

Article

Psychological Carbon Footprint: The Hidden Climate Cost of Negative Emotions

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Abstract: Mental health and climate change are not independent crises, but rather mutually reinforcing systemic challenges. To quantify the hidden climate costs, this paper introduces and operationalizes the concept of psychological carbon footprint (PCF) for the first time, and develops a multi-level association mining computational model termed “Emotion recognition-behavior association-carbon emission accounting” (EBC). Based on massive comment datasets from three major platforms—Xiaohongshu, Douyin, and Weibo—this study employed both manual annotation and automated scoring to identify 17 types of negative emotions and 13 types of behavioral responses. It then used confidence and lift scores to uncover emotion-behavior association pathways and, by integrating carbon emission coefficients, estimated the average daily associated PCF for different emotion types. The study found that: (1) anger (104.21 kg CO_{2e} per instance), despair (101.60 kg CO_{2e} per instance), and feelings of injustice (85.44 kg CO_{2e} per instance) constitute a high-emission cluster, whereas the frequently occurring feelings of helplessness and anxiety are associated with lower carbon emissions, demonstrating an asymmetry between frequency and intensity; (2) Although self-harm tendencies and eating disorders occur infrequently, their associated emissions per unit are extremely high (>100 kg CO_{2e} per instance), with confidence levels of 0.628 and 0.367, respectively, making them key targets for emission reduction; (3) The spatial distribution of negative emotional intensity is highly coupled with China’s Hu Huanyong Line population density pattern and the economic gradient across the eastern, central, and western regions, with comments reflecting high negative emotional intensity concentrated in the eastern coastal provinces. This study further reveals that affect-oriented platforms, represented by Xiaohongshu, exhibit a bias towards internalising an emotional cocoon, whereas topic-oriented platforms, represented by Weibo, exhibit a bias towards externalising a conflict-driven emotional cocoon. For the first time, this paper systematically operationalises the analytical framework and computational model for quantifying the psychological carbon footprint, uncovering the hidden climate cost of negative emotions. These findings provide deep insights and empirical evidence for developing synergistic strategies that address both mental health and climate mitigation.

Keywords: psychological carbon footprint; negative emotions; EBC multi-level association mining computational model; climate cost; social media comments



1. Introduction

As the global climate crisis and challenges to sustainable development grow increasingly severe, the analysis of greenhouse gas emissions is gradually expanding beyond traditional sectors such as energy, industry, and transportation to encompass broader social behaviors and psychological factors [1,2]. A growing number of scholars have begun to investigate the intrinsic link between human psychological states and environmental behaviour, namely that mental health issues not only affect individual quality of life and social productivity but may also indirectly drive carbon emissions through a series of social behavioural chains [3]. Chen [4] argued that environmental and social issues cannot be understood in isolation, as they are interconnected within complex systems of mutual interaction. Boluda-Verdú et al. [5] conducted a cross-sectional survey of psychological states and pro-environmental behaviours in adult samples across multiple countries and regions, and found that moderate levels of anxiety can promote individual green actions, whereas excessive anxiety may trigger psychological distress and emotional compensatory consumption that is detrimental to low-carbon behaviours. Shahin et al. [6], using large-sample household surveys and multiple regression analysis, found that individuals with high psychological stress and emotional instability exhibit a stronger preference for private car use and reduced public transportation usage, thereby potentially increasing carbon emissions. At the healthcare system level, the medical and health system, including psychological counselling and psychiatric services, accounts for more than 4.4% of global carbon emissions [7]. The systematic review by Keil et al. [8] revealed that the share of carbon emissions attributable to healthcare varies across countries, ranging from 1.5% to 9.8%, with hospital services constituting the core source of emissions and showing an overall upward trend. As a result, the potential impact of mental health on environmental sustainability remains a neglected area [9].

In recent years, mental health issues have shown a trend toward global expansion, characterized by an increasingly younger demographic, greater professionalization, and greater diversity [10,11]. According to data from the World Health Organization [12], approximately 970 million people (about one-eighth of the global population) were affected by mental disorders in 2019, with depression and anxiety being the most common; at the same time, approximately one in seven adolescents aged 10–19 suffered from a mental disorder. In China, data from the Report on National Mental Health Development in China (2021–2022) [13] indicate that the risk of depression among adolescents has approached 24.6%, while more than 40% of the working population experience anxiety or chronic stress. The Lancet-WPS Major Report on Depression [14] estimates that 5% of adults worldwide suffer from depression each year. In high-income countries, approximately half of those with depression remain undiagnosed or untreated, while in low- and middle-income countries, this figure rises to 80% to 90%. Mental health issues not only pose health risks but also lead to the consumption of medical resources, medications, and supplies, as well as behavioral deviations, thereby creating potential environmental externalities. These psychological struggles may drive carbon emissions through both direct and indirect channels: the direct channel manifests as emotional consumption, such as fast fashion, food delivery, high-carbon foods, frequent short-distance travel, and heavy use of electronic devices; these behaviors directly contribute to household energy consumption, transportation emissions, and carbon emissions from supply chains. Indirect pathways manifest as the use of healthcare resources (outpatient care, hospitalizations, pharmaceutical production, and the operation of mental health counseling centers) and the burden on social systems (nursing homes, funeral services, etc.) resulting from mental health issues, as well as indirect carbon emissions generated through energy use and material consumption [2]. However, the academic community currently lacks a systematic research framework and quantitative methods to examine the mechanisms linking mental health issues to carbon emissions. Existing carbon footprint assessment systems focus on physical consumption and emissions along the supply chain [15,16], and do not adequately capture the behavioral chains triggered by mental states and their associated carbon emissions. Accordingly, this paper introduces the concept of Psychological Carbon Footprint (PCF), defined as the greenhouse gas emissions resulting from the direct and indirect behavioural chains triggered by a single negative emotional cue (e.g., anxiety, depression, burnout, loneliness) in an individual or group. It encompasses direct carbon emissions driven by emotions, such as consumption, travel, and use of electronic devices, as well as indirect emissions arising from medical services, the production of pharmaceuticals and supplies, and the operation of social systems. Importantly, the PCF captures emissions from behavioral responses to negative emotions rather than the emotions themselves, and the observed associations are probabilistic rather than deterministic.

This study aims to construct a multi-level association mining computational model termed Emotion Recognition-Behavior Association-Carbon Emission Accounting (EBC). Specifically, social media comments were scraped from three widely influential and representative platforms in China—Xiaohongshu, Douyin, and Weibo. Using a combination of manual annotation and automated scoring, 17 categories of negative emotions (including powerlessness, anxiety, anger, depression, sadness, fear, and grievance) were identified, along with 13

types of behavioral responses (such as rumination, emotional venting, self-isolation, interpersonal conflict, social avoidance, self-harm tendencies, and eating disorders). Association pathways within the EBC framework were then mined using confidence and lift measures, and the psychological carbon footprint associated with each emotion type was estimated by integrating behavioral carbon emission coefficients. Through this framework, the study reveals the mechanisms by which negative emotions translate into carbon emissions via specific behavioural pathways, thereby providing empirical evidence for emotion-focused psychological interventions and synergistic carbon reduction strategies.

2. Variable Selection, Methodology, and Data Sources

The overall research workflow comprises four main steps. First, comment data were collected from the platforms via web crawlers, followed by text cleaning and preprocessing. Second, a hybrid approach combining manual annotation with automated scoring was employed to identify emotion categories and intensity levels (Grades I–V) in the comments, as well as to annotate behavioral responses. Third, the confidence and lift metrics from association rule mining were used to quantify the strength of emotion–behavior associations and to identify typical emotion–behavior pathways. Fourth, integrating a behavioral carbon emission coefficient matrix, the per-instance PCF associated with different emotional states was calculated, followed by analyses of spatial differentiation and platform heterogeneity.

2.1. Social Media Data Extraction Using Web Crawlers

This study constructs a modular crawling framework to address the challenges of collecting heterogeneous data from multiple platforms. The framework employs a multi-source adaptation mechanism to dynamically switch scraping rules, achieving data coverage across platforms such as Xiaohongshu, Douyin, and Weibo.

Xiaohongshu is a lifestyle-sharing platform with a predominantly young, urban, female user base, where content centers on consumption and daily life. Users tend to form homogeneous communities, and behavioral responses are biased toward internalizing patterns such as rumination and self-isolation. Douyin is a short-video platform characterized by algorithm-driven, pan-entertainment content. Its user base is more demographically diverse, generating a more balanced but less intense emotional structure. Weibo functions as a hybrid of microblogging and public forum, attracting an ideologically diverse user base. Its public-facing, event-driven nature facilitates externalizing emotions such as anger, often channeled through interpersonal conflict. These platform characteristics shape the emotional distributions and emotion–behavior pathways observed across platforms.

A parallel crawling strategy with multiple starting URLs is adopted in this study to distribute anti-scraping pressure and improve collection efficiency and robustness. To preserve the semantic structure of the text, a word order arc mechanism is introduced. Define an ordered arc $a_{i,j} = (w_i, w_j)$ between any two tokens in $S = [w_1, w_2, \dots, w_n]$ to represent a linear sequence relationship between token w_i and token w_j . The arc weight is defined as follows:

$$w_{i,j} = f_{i,j} \cdot \lambda_{i,j} \quad (1)$$

Here, $f_{i,j}$ represents the co-occurrence frequency of the word pair (w_i, w_j) in the corpus, and $\lambda_{i,j}$ is the positional weight factor, which is used to characterize the contribution of word order to semantics. By traversing the text, a directed weighted graph $G = (V, E)$ is constructed, where nodes V represent words and edges E represent sequential arcs, fully preserving the original text's word order structure and semantic information. Additionally, the framework integrates a direct connection mechanism to primary DNS servers, automatically switching access paths when domain name resolution is blocked, thereby effectively circumventing anti-crawling restrictions.

2.2. Data Encoding and Sentiment Intensity Measurement Based on Manual Annotation and Automated Scoring

This study employs a hybrid approach combining manual annotation with automated scoring to systematically measure the intensity of emotions in comments from three major social media platforms: Xiaohongshu, Douyin, and Weibo. Based on classical theories in emotional psychology and the linguistic characteristics of social media, the study first developed a five-level emotional intensity coding system. The five intensity levels are defined as follows: Level 1 represents mild emotional expression with minimal behavioral implications; Level 2 indicates moderate emotional expression; Level 3 corresponds to strong emotional expression with noticeable psychological distress; Level 4 denotes intense emotional expression accompanied by

functional impairment or significant behavioral consequences; Level 5 represents extreme emotional expression with suicidal ideation or severe behavioral outcomes. The coding rules are shown in Figure 1.

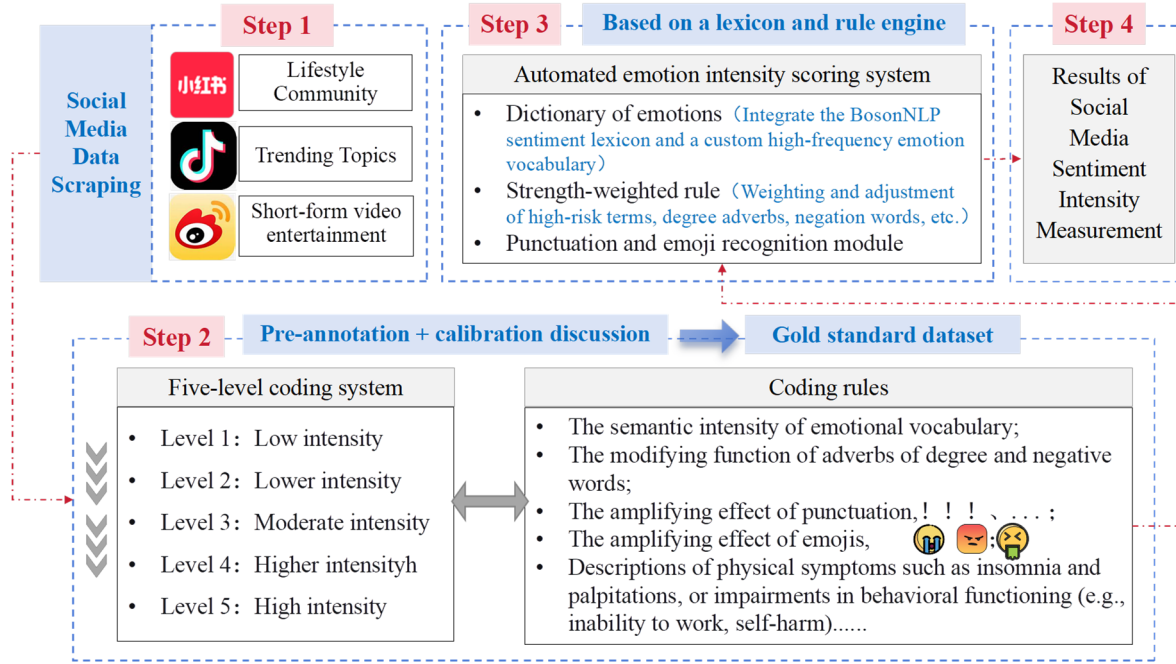


Figure 1. Coding rules for social media comments and measurement of sentiment intensity. Note: In step 1, the three icons are Xiaohongshu, Douyin, and Weibo in sequence.

To ensure coding reliability, the research team recruited six research assistants with backgrounds in psychology or communication studies and provided them with systematic training, including three rounds of pre-annotation and calibration discussions. The 15% proportion was selected because it provided a sufficiently large and representative training set ($N = 1245$) for model development, while leaving the remaining 85% for robust validation. Given the imbalanced distribution of some emotion categories, this split helps ensure adequate representation of minority categories in both the training and validation sets. Two annotators independently completed the annotation, and after consensus was reached through deliberation, Krippendorff's α coefficient was calculated to be 0.87, indicating that annotation consistency had reached an acceptable level. These manually annotated results served as the gold standard dataset for subsequent automated model training and validation.

Building on manual annotation, this study further developed an automated emotion intensity scoring system based on a lexicon and rule engine. The core components of the system include: (1) a sentiment lexicon integrating the BosonNLP sentiment dictionary and a custom lexicon of high-frequency emotion words; (2) intensity weighting rules that apply semantic direction modifications to high-risk vocabulary, degree adverbs, and negations; and (3) a punctuation and emoji recognition module that standardises scoring for repeated punctuation marks and emojis. The system ultimately outputs an emotion intensity score ranging from 1 to 5 for each comment based on a comprehensive weighted formula (see Equation (2)). Finally, ten-fold cross-validation yielded a weighted F1 score of 0.86 for the automated scoring system, demonstrating that the data encoding approach combining manual annotation with automated scoring used in this study can support efficient large-scale data processing.

$$\text{Score} = \text{clip}\left(\sum_{i=1}^n (\text{Base}(w_i) \times \prod_k \text{Mod}_k(w_i)) \times \prod_j \text{Enhance}_j, 1.5\right) \quad (2)$$

Here, $\text{Base}(w_i)$ represents the base sentiment score. For each sentiment word w_i in the review text, its base intensity value is retrieved from the sentiment lexicon:

$$\text{Base}(w_i) = \begin{cases} v_{\text{dict}}(w_i), & \text{if } w_i \in \text{Dict} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Here, Dict refers to a composite dictionary that integrates the BosonNLP sentiment lexicon with a custom-built high-frequency emotion lexicon, and $v_{\text{dict}}(w_i) \in [1, 5]$.

For each emotional word w_i , adjust its intensity based on the constituents it modifies:

$$\text{Mod}_k(w_i) = \begin{cases} \beta_{hr} & \text{if } w_i \in \omega_{hr} \\ \gamma_{adv}(w_i) & \text{if } w_i \text{ is adjacent to a degree adverb} \\ -1 & \text{if } w_i \text{ is adjacent to a negation word} \\ 1 & \text{otherwise} \end{cases} \quad (4)$$

Here, ω_{hr} denotes the set of high-risk words, $\beta_{hr} \in [1.5, 2.0]$; $\gamma_{adv}(w_i) \in [1.2, 1.5]$, where the value is determined by the semantic intensity of the adverb of degree; **adjacent** is defined as the absence of any other emotional words between the emotional word and the modified word.

Apply global sentiment enhancement to the entire comment:

$$\text{Enhance} = 1 + 0.2 \cdot 1_{\text{punc}}(x) + 0.3 \cdot 1_{\text{emoji}}(x) \quad (5)$$

Here, $1_{\text{punc}}(x)$ and $1_{\text{emoji}}(x)$ are punctuation and emoji detection functions that return a value of 1 when the corresponding feature appears, and 0 otherwise. The final score is clipped to the range $[1, 5]$ using the `clip` function and rounded to the nearest integer:

$$\text{Score} = \min(5, \max(1, [S + 0.5])) \quad (6)$$

2.3. Mining Emotion-Behavior Association Rules

To quantify the strength of the association between different emotions and specific behaviors, this study employs the confidence and lift metrics from association rule mining. Let N be the total number of comments, n_{ij} the co-occurrence frequency of emotion category E_i and behavior category B_j , n the total frequency of emotion E_i (where $n = n_i + 1$), and $n \cdot j = \sum_i n_{ij}$ the total frequency of behavior B_j . Then, confidence is defined as:

$$\text{Conf}(E_i \rightarrow B_j) = \frac{n_{ij}}{n_i} \quad (7)$$

The above expression represents the conditional probability of behaviour B_j occurring given the presence of emotion E_i . Lift is defined as:

$$\text{Lift}(E_i \rightarrow B_j) = \frac{\text{Conf}(E_i \rightarrow B_j)}{n \cdot j / N} \quad (8)$$

A lift value greater than 1 indicates that the emotion has a positive facilitative effect on the behaviour, a value equal to 1 indicates independence, and a value less than 1 indicates inhibition. Given the sparsity of emotion-behaviour co-occurrence in social media comments, and the fact that certain behaviours (e.g., self-harm and medical help-seeking), although infrequent, exhibit strong dependencies on specific emotions, this study adopts a relatively low confidence threshold (≥ 0.2) to retain potentially important pathways. At the same time, we require lift > 1.5 to ensure that the associations are of practical positive significance. Specifically, the presence of the emotion increases the probability of the behaviour by more than 50%. It should be emphasized that the emotion-behavior associations identified in this study are probabilistic rather than deterministic. The confidence and lift measures used below are designed to capture the strength of statistical co-occurrence between emotions and behaviors, not to imply that a given emotion invariably or causally leads to a specific behavior.

2.4. Data Sources and Diagram of the Step-by-Step Data Cleaning Process

To construct the EBC multi-level association mining model for PCF, this study employed a modular web crawling framework to collect public comments containing expressions of negative emotions from three major mainstream social media platforms in China. It is important to emphasise that only comment samples containing both explicit emotional expressions and behavioural responses were retained for analysis; comments that featured emotions without behaviours, or behaviours without emotions, were excluded from subsequent analyses. Since negative sentiment comments often contain sensitive language, and platforms impose access restrictions and anti-crawling measures on them, while such content is also prone to being hidden or throttled, obtaining raw data presents significant challenges. The crawling strategy is guided by sentiment-related keywords (such as

“helplessness”, “anxiety”, and “anger”) and expands the scope of data collection by incorporating trending topics on the platform (such as “workplace stress”, “emotional distress”, “social events”, and “life challenges”). Of the more than 120,000 social media comments initially crawled, approximately 28.6% of the samples contained explicit expressions of negative sentiment; among these negative comments, the proportion of samples that contained both emotional and behavioral reactions was approximately 25.6%, resulting in a final dataset of 34,300 raw comments. The entire data acquisition and processing workflow consisted of four stages: raw data scraping, content cleaning and structuring, dual-dimension (emotion-behavior) coding, geographic information mapping, and manual verification and review. This process ultimately yielded 8795 high-quality, valid samples for subsequent association rule mining and carbon emissions accounting. The detailed data cleaning process is illustrated in Figure 2.

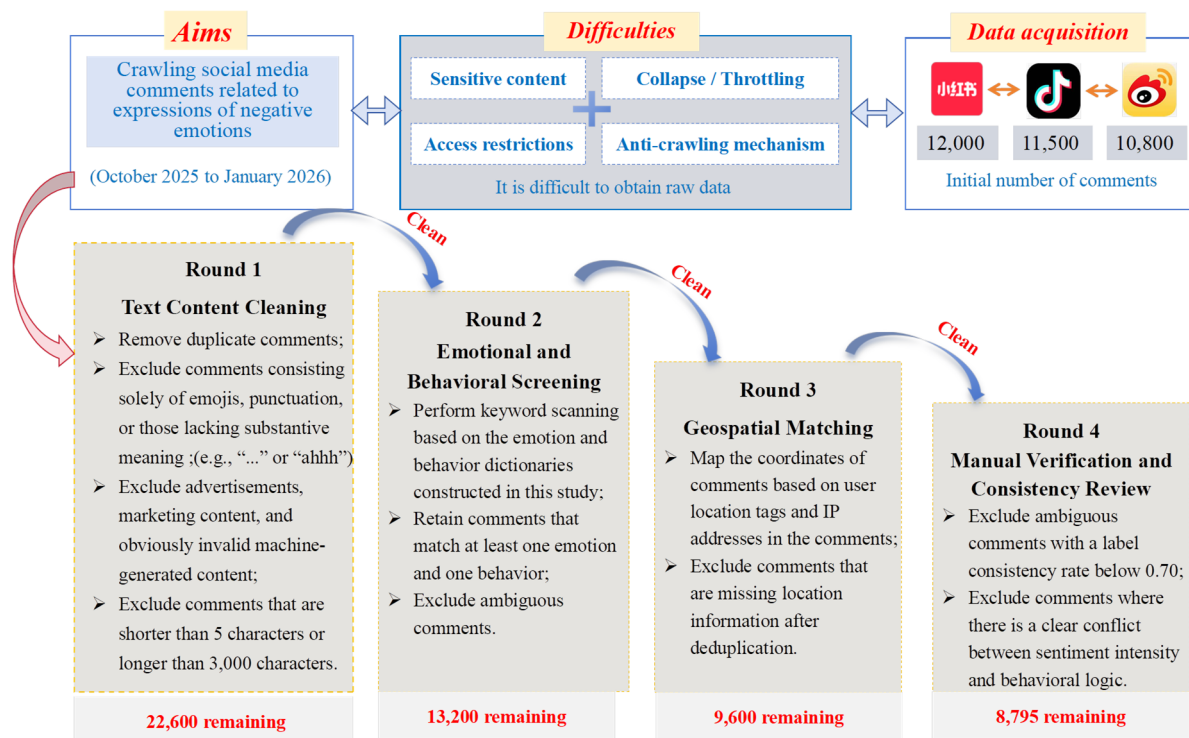


Figure 2. Diagram of step-by-step data cleaning.

Ultimately, this study identified 17 categories of negative emotions (including helplessness, anger, anxiety, sadness, irritability, low self-esteem, depression, despair, fear, feeling wronged, loneliness, envy, numbness, confusion, disappointment, jealousy, and no obvious emotion), as well as 13 categories of behavioral responses (including rumination, emotional outbursts, self-withdrawal, interpersonal conflict, social avoidance, avoidance behaviors, somatic symptoms, no obvious behavior, self-neglect, impairment in work or study, sleep problems, eating disorders, and tendencies toward self-harm). The classification was primarily based on classic theories in emotional psychology [17,18] and a coding system constructed from social media linguistic features.

3. Results of the Emotion-Behavior Correlation Analysis

3.1. Sentiment Text Analysis Based on Three Major Chinese Social Media Platforms

This section draws on negatively oriented social media comment data collected from three major platforms, specifically Xiaohongshu, Douyin, and Weibo.

Figure 3 presents the characteristics of negative emotional expressions by users of three major mainstream social media platforms in China, specifically Xiaohongshu, Douyin, and Weibo, revealing significant heterogeneity across platforms in terms of emotional dimensions, intensity, and distribution patterns. Observations from Figure 3a,b indicate that Xiaohongshu users exhibit an extremely concentrated pattern of negative emotions. Powerlessness emerges as the dominant emotion, with a frequency exceeding 1300 occurrences, significantly higher than all other categories. This is followed by Anger with approximately 550 occurrences and Anxiety with approximately 400 occurrences, after which subsequent emotions such as Sadness and Irritation show an exponential and rapid decline in frequency. Furthermore, the emotional structure of Xiaohongshu users is characterised by single-peak dominance and an extremely short tail. Emotions including Sadness, Depression,

Despair, Fear, and Resentment exhibit low frequency but high intensity. This pattern is highly consistent with Xiaohongshu's content ecosystem, which centres on lifestyle sharing, consumption decisions, and emotional resonance. When confronted with issues such as consumer traps, life difficulties, and social topics, users are more prone to feelings of powerlessness and anger, and their emotional expressions are highly homogeneous.

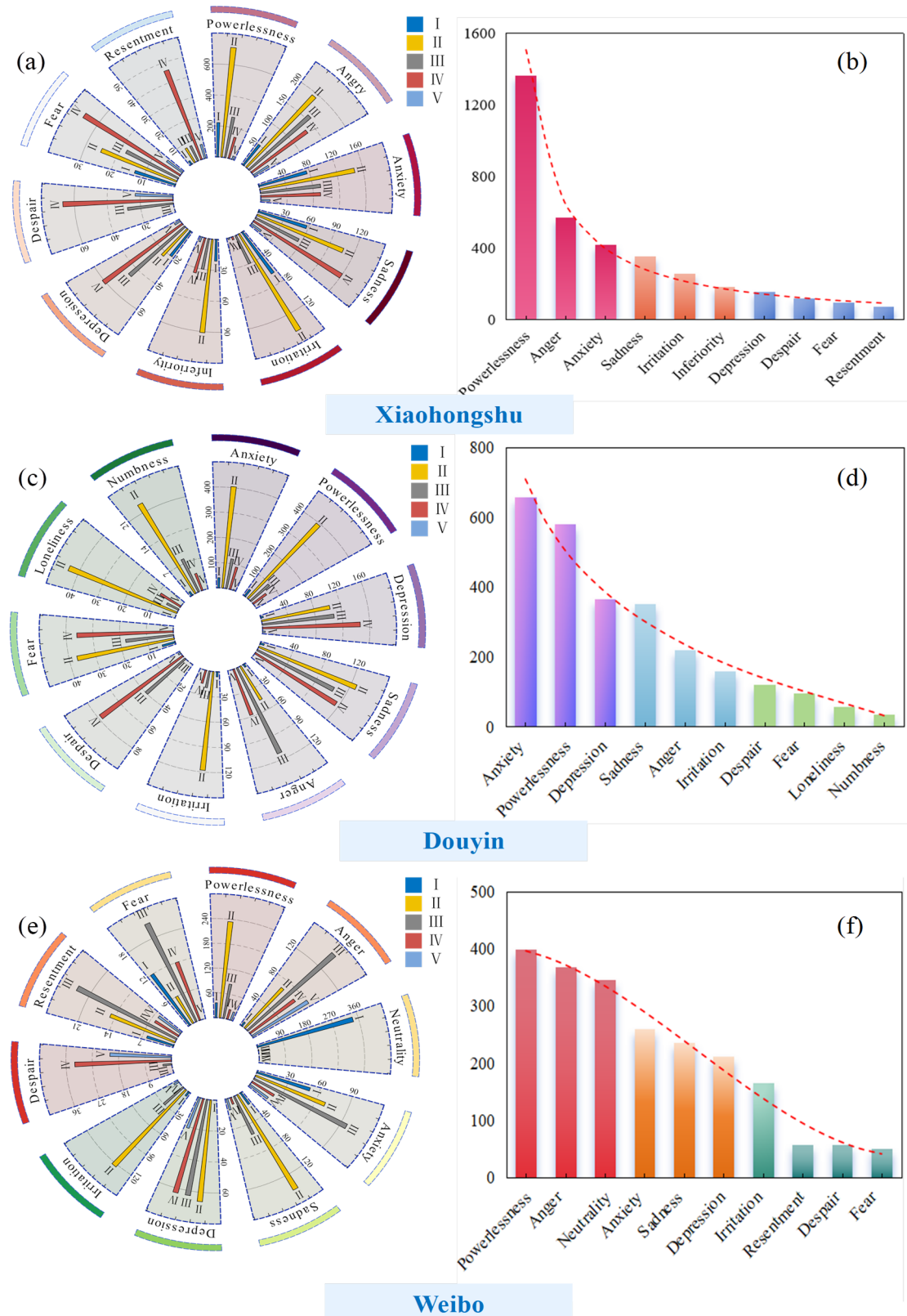


Figure 3. Emotion text analysis using three major social media platforms in China. Note: Panels (a–f) represent Xiaohongshu, Douyin, and Weibo, respectively. For each platform, the two panels display the five-tier presentation and total frequency ranking of the top 10 negative emotions.

Observations from Figure 3e,f reveal that the top four emotions expressed by Weibo users are Powerlessness with approximately 400 occurrences, Anger with approximately 370 occurrences, Neutrality with approximately 350 occurrences, and Anxiety with approximately 260 occurrences. The overall frequency base is significantly higher than that of Douyin, and the decay curve is the gentlest among the three platforms, indicating that the frequency differences across emotion categories are the smallest and the distribution is the most even. In summary, as a public opinion forum and a central arena for the discussion of social hot-topics and public issues, Weibo elicits user emotional expressions that are more public-oriented and critical in nature. Consequently, emotions pertaining to social issues, including Anger, Powerlessness, and Resentment, account for a higher proportion. The emotional structure on Weibo is more complex and diverse, with extreme emotional expressions being more pronounced.

3.2. Sentiment Analysis of Text Based on Chinese Provinces

This section further analyzes the characteristics of negative emotional expressions among social media users from a geospatial perspective. Based on the geolocation data in the comments, we mapped the comments to China's provinces and counted the number of comments for each emotional intensity level (1–5), as shown in Figure 4.

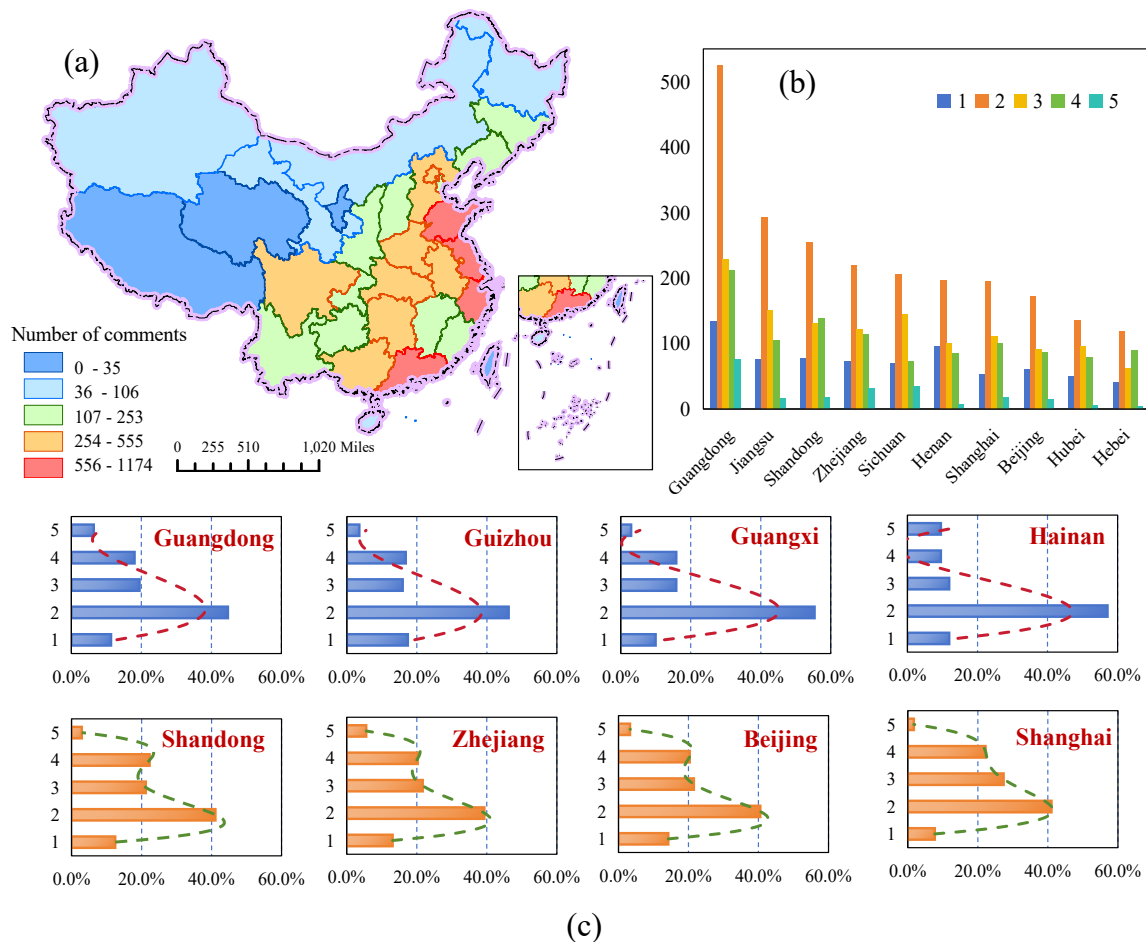


Figure 4. Sentiment analysis of text based on typical provinces. Note: (a) shows the spatial distribution of the number of emotional comments posted; (b) shows the distribution of five-tier emotional comments in typical provinces; (c) decomposes the hierarchical structure of negative emotions in eight representative provinces.

Composition of emotional intensity grades in social media comments across typical provinces in China. Emotional intensity is classified into five levels: Grade 1 (mild), Grade 2 (moderate), Grade 3 (strong), Grade 4 (intense with functional impairment), and Grade 5 (extreme with suicidal ideation or severe behavioral consequences).

As shown in Figure 4a, social media comment counts in China exhibit a pronounced spatial differentiation. High-intensity areas corresponding to Grades 4 and 5 are concentrated in economically developed and densely populated eastern and southern provinces including Guangdong, Fujian, Zhejiang, Jiangsu, and Shandong, forming a contiguous high-value belt. Low-intensity areas corresponding to Grades 1 and 2 are concentrated in economically less developed frontier and inland regions, primarily in Northwest and Northeast China. This spatial pattern is highly coupled with the population distribution pattern defined by the Hu Line in China as well as the

east-central-west economic gradient, validating the strong correlation between social media comment counts and regional economic development, population size, and internet activity. Figure 4b presents the structure of negative emotion intensity grades across the top ten provinces by comment count. It can be observed that all provinces are dominated by low-to-moderate intensity negative emotions corresponding to Grades 2 and 3, while the proportions of high-intensity negative comments corresponding to Grades 4 and 5 are relatively low in all cases. In terms of provincial differences, municipalities such as Beijing and Shanghai are similarly characterised by predominantly low-to-moderate intensity negative emotions, yet they exhibit a slightly higher proportion of high-intensity comments. This reflects the greater concentration of social issues and the higher intensity of emotional expression characteristic of metropolitan regions. Figure 4c decomposes the structure of negative emotion intensity grades across eight representative provinces. It can be seen that the southern and southwestern provinces, including Guangdong, Guizhou, Guangxi, and Hainan, are dominated by low-intensity negative emotions corresponding to Grades 1 and 2. In these provinces, Grade 2 accounts for more than 40 percent of comments, while the proportions of Grades 3 through 5 are extremely low, and the fitted curve exhibits a unimodal concentrated pattern, indicating a homogeneous structure dominated by low intensity. In contrast, the eastern developed provinces and municipalities, including Shandong, Zhejiang, Beijing, and Shanghai, are predominantly characterised by moderate-intensity emotions corresponding to Grades 2 and 3, with significantly higher proportions of Grade 3 and above. Their emotional structure is notably more diverse. This divergence suggests that the level of economic development and the structure of social pressures significantly influence the expression intensity of negative emotions among internet users, with online expression in eastern developed regions being more pronounced in both emotional intensity and issue contentiousness.

3.3. Exploring the Relationship between Emotions and Behavior

3.3.1. Sankey Diagram-Based Analysis of Emotion-Intensity-Behavior Flow

This section uses a Sankey diagram to visualize the multi-stage flow from emotion type through emotion intensity to behavioral response. The Sankey diagram intuitively illustrates how emotion intensity levels are distributed across different emotional states and which specific behavioral responses are subsequently associated with these intensity levels. By constructing this three-stage flow relationship, the study aims to reveal which emotions are more likely to be accompanied by high-intensity expression and which behavioral patterns ultimately arise from high-intensity emotions. In doing so, the analysis provides an intuitive representation of the core pathways and critical nodes through which negative emotions translate into behavior.

In Figure 5, the left-hand nodes represent the primary negative emotions including powerlessness, anger, anxiety, depression, and irritation. The middle nodes represent emotional expression intensity levels from level I to level V. The right-hand nodes represent 13 typical behavioural responses, with line width reflecting co-occurrence frequency or conditional probability. With respect to the flow pattern from emotions to intensity levels, powerlessness, anger, and anxiety constitute the three core input emotions. The flow of powerlessness is highly concentrated at the lower intensity level II, while also branching to low-intensity level I, moderate-intensity level III, and relatively high-intensity level IV, reflecting its broad coverage as a diffuse negative emotion. Anger exhibits a wide intensity span, primarily covering the moderate to high levels of II, III, and IV, indicating that anger experiences are not concentrated at a single intensity but instead show a stratified distribution across the moderate-to-high intensity range. Anxiety is predominantly distributed at level II intensity, with additional branching to moderate-intensity level III, consistent with its chronic and generalised emotional characteristics. Emotions such as sadness, depression, and irritation show comparatively smaller flows, mostly converging at Intensity levels II and III. Low-frequency emotions including loneliness and numbness are concentrated at levels III and IV, highlighting their association with moderate-to-high intensity emotional experiences.

Level II carries the largest flow volume, primarily toward rumination, emotional venting, and self-isolation, indicating that moderate-to-high intensity emotions are core drivers of maladaptive behaviors. Lower intensity (Level I) manifests mainly as internalized distress. Moderate intensity (Level III) elicits more diverse interpersonal responses including conflict and social avoidance. High (Level IV) and extremely high (Level V) intensities, though smaller in volume, are heavily concentrated on extreme outcomes such as self-harm tendency, somatic symptoms, and eating abnormalities, constituting the highest-risk pathways.

From the perspective of the structural characteristics of the full flow pathway, the translation of negative emotions into behaviour exhibits a clear hierarchical differentiation of pathways. The first pathway is the predominant maladaptive pathway, driven by the three core emotions of powerlessness, anxiety, and anger. These emotions are mediated by moderate-to-high intensity at level II and ultimately translated into common maladaptive behaviours including rumination, emotional venting, and self-isolation. This represents the most representative

transformation pattern of negative emotions among social media users. The second pathway is the moderate interpersonal dysfunction pathway, driven primarily by sadness and depression. Through the transmission of moderate-intensity emotions at level III, these emotions trigger behaviours characterised by interpersonal dysfunction such as interpersonal conflict and social avoidance, revealing the systemic impact of moderate negative emotions on users' social connections. The third pathway is the high-risk crisis pathway, originating from extreme emotions, including anger and despair. Amplified by high or extremely high intensity at levels IV and V, these emotions ultimately induce severe psychosomatic problems such as self-harm tendencies and somatic symptoms.

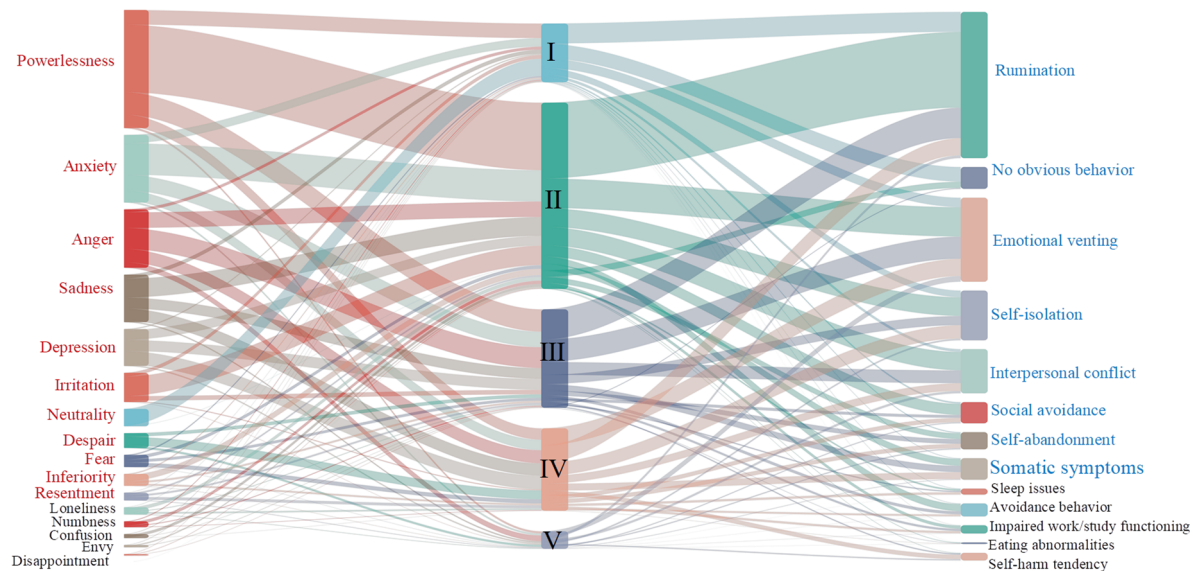


Figure 5. Sentiment-intensity-behavior flow analysis based on a sankey diagram.

Extending the analysis based on the emotional characteristics of the three platforms described earlier, distinct platform-specific transformation patterns emerge. On Xiaohongshu, where powerlessness serves as the core emotion, the high-flow pathway follows powerlessness to Level II to rumination or self-isolation, consistent with the logic of emotional coping in lifestyle-oriented sharing scenarios. On Douyin, which features anxiety and powerlessness as dual core emotions, the pathways are more diverse, following anxiety or powerlessness to level II or level III to emotional venting or interpersonal conflict, reflecting the behavioural diversity arising from the diffuse nature of its emotional landscape. On Weibo, where anger and powerlessness are central, the pathway follows anger to level IV to self-harm tendency or social avoidance, representing a high-risk trajectory and highlighting the extreme behavioural consequences of high-intensity anger within the public opinion arena. From a psychological mechanism perspective, emotion intensity plays a critical mediating role in the translation of negative emotions into behaviour. Moderate-to-high intensity emotions predominantly drive everyday maladaptive behaviours, whereas high to extremely high intensity emotions serve as core predictors of extreme psychological crises.

3.3.2. Typical Associations between Emotional and Behavioral Pathways Based on Confidence and Lift

To quantify the association between emotional types and behavioral categories, this study employed Cramér's V coefficient and the chi-square test. The results showed that Cramér's $V = 0.4454$, $p < 0.001$, indicating a significant moderate association between the two. For the statistical analysis of the direct association between emotional types and behavioral categories, please refer to Figure 6.

The emotion-behaviour association heatmap clearly reveals the specific behavioural transformation patterns of different emotions. Specifically, rumination is the primary associated behaviour for most negative emotions, including powerlessness at 47.4%, anxiety at 65.6%, and jealousy at 50.0%. This indicates that rumination serves as a key vehicle for the sustained amplification of negative emotions. Emotional venting, in contrast, is the core behavioural expression for emotions including anger at 44.7%, sadness at 44.1%, and irritation at 38.3%. This reflects the adaptive tendency of high-arousal negative emotions to release internal tension and seek immediate relief through externalising behaviours. To better quantify the strength and specificity of emotion-behaviour associations, this study further calculated the confidence and lift between emotion types and behaviour categories, as shown in Figure 7a,b. Confidence represents the conditional probability of a specific behaviour occurring given the presence of a given emotion, whereas lift measures the degree to which the emotion facilitates the behaviour,

with a value greater than one indicating a positive association. Through these two metrics, emotion-behaviour pathways with strong predictive power and specificity can be identified, providing probabilistic weights for the subsequent quantification of the psychological carbon footprint or PCF.

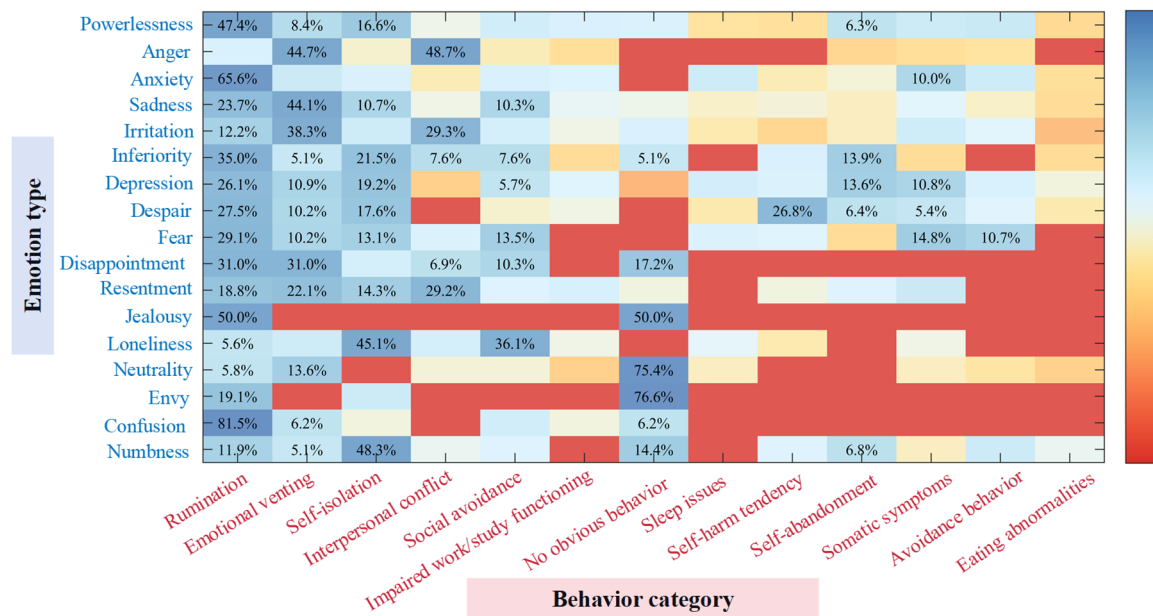


Figure 6. Schematic illustration of the relationship between emotional types and behavioral categories.

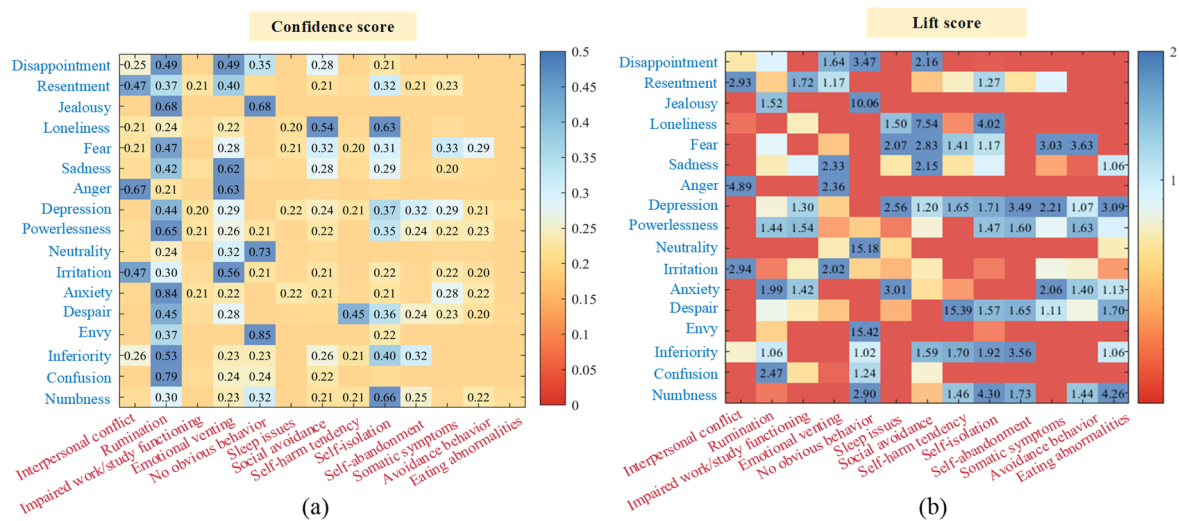


Figure 7. Calculation of confidence and lift between emotion types and behavior categories.

The confidence analysis heatmap in Figure 7a reveals that emotions including anxiety at 0.84, confusion at 0.79, Jealousy at 0.68, and powerlessness at 0.65 exhibit extremely high conditional probabilities with rumination, indicating that rumination serves as the core cognitive carrier for most negative emotions. Meanwhile, emotions including anger at 0.63, sadness at 0.62, irritation at 0.56, and disappointment at 0.49 show significant associations with emotional venting, establishing emotional venting as the core behavioural expression for these high-arousal negative emotions and reflecting an individual's innate tendency to release tension outwardly when confronted with intense emotional impacts. Furthermore, distinct differentiation exists in the behavioural transformation patterns across different emotions. Loneliness is highly coupled with self-isolation at 0.63 and social avoidance at 0.54, whereas numbness exhibits a strong conditional association with self-isolation at 0.66. These findings illustrate the differentiated behavioural externalisation pathways of various negative emotions.

The lift analysis heatmap in Figure 7b reveals that the lift values for pathways such as resentment with Interpersonal conflict at 2.93, jealousy with no obvious behaviour at 10.06, anxiety with sleep issues at 3.01, powerlessness with avoidance behaviour at 1.63, and numbness with self-isolation at 4.30 are all significantly

greater than one. This confirms that these emotion-behaviour combinations exhibit non-random and strongly driven associations.

3.3.3. Joint Analysis of Confidence and Lift

High-Frequency Strong Correlation Analysis

Based on the screening criteria for high-frequency, strong associations (confidence level ≥ 0.5 and lift > 1.5), this study identified a total of 12 typical emotion-behavior pathways, as shown in Table 1.

Table 1. High-frequency strong correlation analysis.

Emotional Types	Behavioral Categories	Emotional Types	Behavioral Categories
Jealousy	Rumination	Loneliness	Self-isolation
Powerlessness	Rumination	Numbness	Self-isolation
Anxiety	Rumination	Sadness	Emotional venting
Inferiority	Rumination	Irritation	Emotional venting
Confusion	Rumination	Anger	Emotional venting
Loneliness	Social avoidance	Anger	Interpersonal conflict

The pathways described above exhibit clear emotion-behaviour clustering characteristics. As shown in Table 1, rumination serves as a common behavioural outlet for multiple negative emotions. Five emotions, namely jealousy, powerlessness, anxiety, inferiority, and confusion, all feature rumination as their primary associated behaviour. This pattern suggests that regardless of whether the source of the emotion is self-evaluation in the case of inferiority, social comparison in the case of jealousy, or cognitive uncertainty in the case of confusion, individuals tend to cope with psychological distress through persistent and repetitive rumination. Notably, the pathways for powerlessness and anxiety are consistent with the findings of the preceding sankey diagram analysis, further validating the generality of rumination as a core coping strategy for internalised emotions.

Analysis of Low-Frequency, High-Risk Associations

Based on the screening criteria for low-frequency, high-risk associations ($0.2 \leq$ confidence level < 0.5 and lift > 2.0), this study identified several pathways in which emotions exert a strongly specific facilitative effect on behavior, despite their low absolute frequency in the sample (see Table 2). These pathways are primarily concentrated in somatic symptoms, sleep problems, social avoidance, and severe behavioral reactions (self-neglect, self-harm).

Table 2. Analysis of low-frequency, high-risk associations.

Emotional Types	Behavioral Categories	Emotional Types	Behavioral Categories
Disappointment	Social avoidance	Depression	Sleep issues
Resentment	Interpersonal conflict	Depression	Self-abandonment
Loneliness	Sleep issues	Depression	Somatic symptoms
Fear	Sleep issues	Irritation	Interpersonal conflict
Fear	Social avoidance	Anxiety	Sleep issues
Fear	Somatic symptoms	Anxiety	Somatic symptoms
Fear	Avoidance behavior	Despair	Self-harm tendency
Sadness	Social avoidance	Inferiority	Self-isolation

Sleep issues represent a common high-risk outlet for depression, loneliness, fear, and anxiety, with lift values exceeding 2.0 in all cases, highlighting the central role of the emotion-sleep axis in psychological distress. Somatic symptoms are specifically associated with fear and anxiety, confirming the tendency toward somatisation of high-arousal emotions. Social avoidance appears across three emotions, namely disappointment, fear, and sadness, with lift values significantly above 2.0, indicating its function as a cross-emotional avoidance strategy. Beyond sleep issues and somatic symptoms, depression is also specifically associated with self-abandonment. The lift value for the association between despair and self-harm tendency is substantially higher than 2.0, and although the confidence is relatively low, the clinical risk is extremely high.

4. Estimation and Comparison of Psychological Carbon Footprints

This section further maps behavioral responses to greenhouse gas emissions to construct a quantitative PCF model.

4.1. Activity-Based Carbon Emission Factors

To translate emotion-driven behavioural responses into quantifiable greenhouse gas emissions, this study constructed a behavioural carbon emission coefficient matrix. The selection of coefficients followed a three-tier principle. First priority was given to peer-reviewed LCA studies conducted in the Chinese context. Second priority was assigned to internationally recognized databases including Ecoinvent and IPCC, followed by regional calibration using China-specific parameters. Third priority was applied to healthcare-related behaviors, for which we used input-output data from the China Health Statistics Yearbook. Where multiple sources existed, we selected the most recent and contextually relevant estimates. To assess robustness, we conducted a sensitivity analysis varying key coefficients within $\pm 30\%$. The relative ranking of emotion types by PCF remained stable, and the main qualitative conclusions were unaffected. The PCF estimates should therefore be interpreted as order-of-magnitude approximations rather than precise values.

For emotional venting, social avoidance, and self-isolation, we disaggregated each behavior into sub-activities and derived coefficients from recent Chinese LCA studies. Details of the sub-activity breakdown and emission sources are provided in Table 3 and Appendix B. Rather than offering precise point estimates, we aim to provide order-of-magnitude approximations that capture the relative scale of emissions across different emotions and behaviors.

Table 3. Carbon emission factors for activities.

Code	Behavioral Categories	Emission Factor (kgCO _{2e} /Instance)	Break Down into Sub-Activities	References
B01/B07	Rumination /No obvious behavior	0	Purely cognitive activity; no consumption of matter or energy	Lenzen et al. [2]
B02	Emotional venting	2.83	Food delivery, fast fashion (jeans, single-wear), non-essential online shopping (delivery only)	Zhong et al. [19]; Li et al. [20]; Kang et al. [21]
B03/B10	Self-isolation /Self-abandonment	2.82	Additional household electricity use (lighting, appliances), additional household heating (northern regions, 45% of the population), additional household cooling (southern regions, 55% of the population), and online streaming entertainment	Wu et al. [22]
B04	Interpersonal conflict	14.36	Emergency treatment, production of oral antibiotics	National Health Commission [23]; Taylor et al. [24]
B05	Social avoidance	7.80	Additional carbon emissions per trip, calculated based on trip distance (15 km), the difference in emissions between alternative modes of transportation and public transit (≈ 0.21 kg/km), an empty-run rate adjustment ($\times 1.35$), and a trip completion rate adjustment ($\div 0.7$)	Ministry of Housing and Urban-Rural Development [25]; This study calculates
B06	Impaired work/study functioning	4.05	Additional office energy consumption (increased electricity use for computers, lighting, air conditioning, etc.), increased consumption of coffee and energy drinks, and increased commuting (using ride-hailing services instead of public transportation after overtime)	Wu et al. [26]; Li et al. [27]; Wu et al. [22]
B08	Sleep issues	0.51	Production and use of sleep aids; reduced daytime productivity (embedded carbon)	Taylor et al. [24]; Espie et al. [28]
B09	Self-harm tendency	115.86	Emergency care, inpatient treatment (average of 3 days), psychological crisis intervention, and drug manufacturing (antibiotics, antidepressants, etc.)	National Health Commission [23]; Li [29]; Lenzen et al. [2]; Haider et al. [30]

Table 3. *Cont.*

Code	Behavioral Categories	Emission Factor (kgCO _{2e} /Instance)	Break Down into Sub-Activities	References
B11	Somatic symptoms	16.08	The entire outpatient care process (including consultations, examinations, medical supplies, and building energy consumption); pharmaceutical production (antibiotics, antidepressants, etc.); and transportation to and from medical appointments (private cars, ride-hailing services, and public transportation)	National Health Commission [23]; Haider et al. [30]; Yusuf et al. [31]
B12	Avoidance behavior	−4.1	Cancel non-essential travel (private cars/ride-hailing services) and reduce in-home activities (substitute activities)	Zhou et al. [32]; National Bureau of Statistics [33]
B13	Eating abnormalities	103.10	Binge eating/emotional eating, psychotherapy/nutrition counseling, inpatient treatment (average of 3 days)	Poore & Nemecek [34]; Simsek et al. [35]

According to Nolen-Hoeksema's [36] theory of response styles, rumination is an internal psychological process that focuses cognitive resources on internal states and does not involve a chain of overt behaviors. It should be emphasised that although Rumination does not directly generate carbon emissions, it indirectly amplifies the frequency and intensity of other behaviours by prolonging the duration of emotional states, thereby exerting a significant mediating effect on the total psychological carbon footprint. Somatic symptoms refer to physical discomforts experienced by individuals as a result of psychological distress, including anxiety, depression, and related conditions. These symptoms may manifest as headaches, palpitations, or gastrointestinal disturbances, among others. The carbon emissions arising from somatic symptoms are primarily concentrated in medical diagnosis and treatment. According to healthcare carbon emission accounting data from the China Health Statistics Yearbook 2024 [23], the average carbon emission per outpatient visit to a general hospital in China is 14.5 kg CO_{2e}. The entire outpatient process, which includes consultation, physical examination, laboratory tests, consumables usage, and the allocation of building energy consumption, represents the largest contributor to carbon emissions from somatic symptom-related behaviours [37].

Avoidance behaviour refers to the active cancellation of planned consumption or travel activities by individuals due to negative emotions such as fear and anxiety. Its carbon emission effect is negative, representing a net carbon offset. Regarding the cancellation of non-essential travel, according to Zhou et al. (2023) [32] on the life cycle carbon emissions of ride-hailing vehicles, the emission factor for private cars is approximately 0.185 kg CO₂ per kilometre. Assuming an average cancellation of 42 km of travel, this avoids approximately 5.37 kg CO_{2e} per instance [38]. Regarding the incremental increase in home-based activities, staying at home after travel cancellation results in alternative energy consumption including television, lighting, and air conditioning, amounting to approximately 0.5 kg CO_{2e} per instance based on data from the National Bureau of Statistics (2023) [33]. Combining these two sub-activities, the net offset effect of B12 is −4.1 kg CO_{2e} per instance. It is worth noting that this emission reduction comes at the cost of individual well-being and social connectedness, revealing a phenomenon of unequal emissions reduction that may arise in the pursuit of climate goals. Specifically, achieving emission reductions may come at the expense of weakening the social participation of disadvantaged groups.

Eating abnormalities encompass two types of behaviours: binge or emotional eating and severe eating disorders. According to the study by Poore and Nemecek (2018) [34], the additional consumption of 150 to 300 g of red or processed meat during emotional binge eating can generate a substantial additional carbon footprint. In terms of medical or psychological treatment, Simsek et al. (2025) [35] analysed travel-related carbon emissions among 3908 psychiatric outpatients and found an average one-way travel distance of 20.06 km, with total annual travel emissions amounting to 15.6 tonnes of CO_{2e}. The carbon emissions per outpatient visit for treatment were approximately 0.6 to 1.2 kg CO_{2e}. Regarding inpatient treatment, severe eating disorders such as anorexia nervosa accompanied by weight loss exceeding 15 percent and electrolyte disturbances often require hospital admission.

The PCF coefficients for the 13 behaviour categories exhibit a pronounced hierarchical structure (See Figure 8). At the highest emission level are Self-harm tendency at 115.86 kg CO_{2e} per instance and Eating abnormalities at 103.10 kg CO_{2e} per instance. Both behaviours derive their core emission sources from intensive healthcare resource utilisation. The former depends on emergency treatment and inpatient surgery, whereas the latter

combines high-carbon food intake from binge eating with inpatient treatment for severe conditions, together constituting extreme emission hotspots for the psychological carbon footprint. The next highest emission level includes Somatic symptoms at 16.08 kg CO_{2e} per instance and Interpersonal conflict at 14.36 kg CO_{2e} per instance. Their primary emission sources are outpatient diagnosis and treatment as well as oral medication production, representing moderate-intensity, relatively high-frequency medical-dependent behaviours. The next emission tier comprises social avoidance, work or academic impairment, emotional venting, and self-isolation or self-abandonment. Their emissions derive primarily from daily consumption behaviours, increased home energy use, and compensatory commuting. These represent low-frequency yet widespread daily behavioural emissions. The lowest tier consists of Sleep issues at 0.51 kg CO_{2e} per instance, which mainly involve the embedded carbon from sleep aid medication use and reduced daytime productivity, exhibiting the lowest emission intensity.

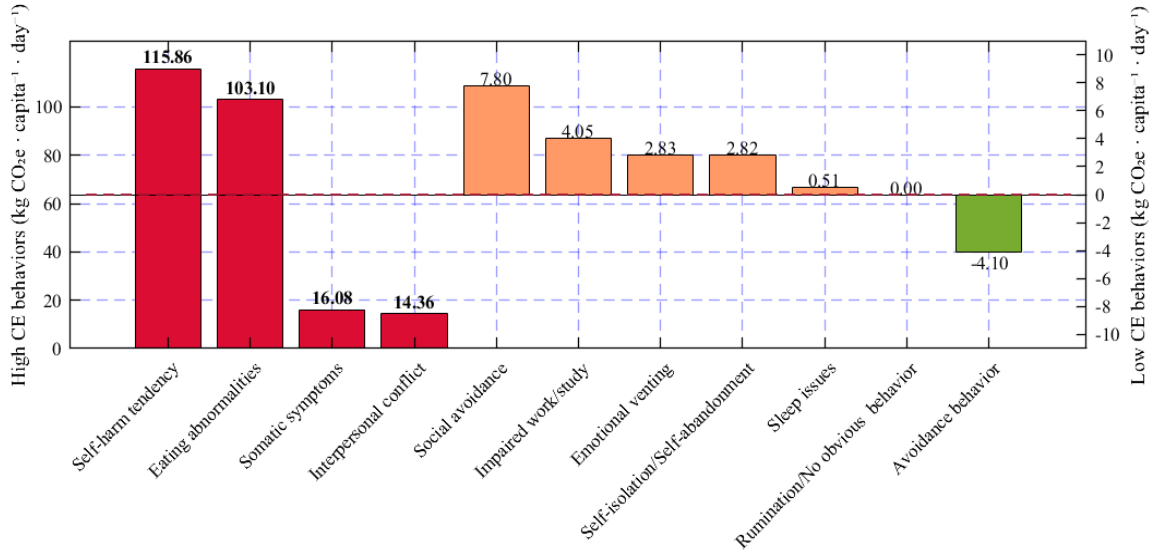


Figure 8. Carbon emission factors for 13 categories of activities.

Overall, the distribution of the psychological carbon footprint exhibits a Pareto-like characteristic in which a small number of high-intensity medical behaviours contribute the majority of emissions, whereas numerous daily behaviours contribute relatively little. This finding suggests that synergistic strategies combining psychological intervention with emission reduction should prioritise high-carbon medical behaviours triggered by high-risk psychological states, including self-harm and eating abnormalities.

4.2. The PCF of Different Emotional Types

Based on the coefficients in Table 1 and the confidence levels of the emotion-behavior pathways in Section 3.3, we calculated the per-capita PCF_e associated with a single emotional event for each typical emotional state:

$$PCF_e = \sum_{b \in B} P(b|e) \times EF_b = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mn} \end{bmatrix} \times \begin{bmatrix} EF_{b1} \\ EF_{b2} \\ \vdots \\ EF_{bn} \end{bmatrix}$$

Here, $B = \{B01, B02, \dots, B13\}$ represents the set of behaviors, and $P(b|e)$ denotes the conditional probability that behavior b occurs given emotion e ; see Appendix A for the specific values of p . EF_b is the carbon emission coefficient for behavior b ; see Table 3 for the specific values.

The psychological carbon footprints for different emotional types were calculated using the above formula, and the results are shown in Figure 9.

As shown in Figure 9, the PCF varies substantially across emotions, with a range of 97.95 kg CO_{2e} per instance, representing a more than sixteen-fold difference between the highest and lowest values. Anger at 104.21, despair at 101.60, and resentment at 85.44 together constitute the top tier, forming an extremely high emission cluster. The PCF values for these three emotions are significantly higher than those for the remaining emotions. Notably, both anger and despair exceed 100 kg CO_{2e} per instance, meaning that a single instance of either emotion

is associated with carbon emissions roughly equivalent to driving a petrol-fuelled private car for 250 km or the electricity consumption of an average urban Chinese household over five days. Although resentment is slightly lower, its PCF remains substantially above that of the fourth-ranked emotion, disappointment, with a difference of 41.7 kg CO_{2e} per instance. The PCF for Anger is marginally higher than that for despair, which can be primarily attributed to its high confidence values for interpersonal conflict at 0.847 and emotional venting at 0.807. Despair, in contrast, is more strongly associated with extreme medical behaviours including self-harm tendency at 0.628 and eating abnormalities at 0.367. Resentment is characterised by elevated levels of both interpersonal conflict at 0.652 and rumination at 0.548, reflecting a response style in which emotional internalisation and externalised conflict coexist. It should be noted that although anger, despair, and resentment exhibit extremely high per-instance carbon emissions, they are typical high-arousal or high-internalisation extreme emotions, and their occurrence frequency in daily social media contexts as well as in real psychological states is relatively limited. In other words, these three types of emotions are not universal, persistent mental states, but rather stress responses triggered by specific stressful situations or major setbacks. Therefore, their higher PCF values reflect the impact intensity of a single emotional event on carbon emissions, rather than their cumulative daily contribution.

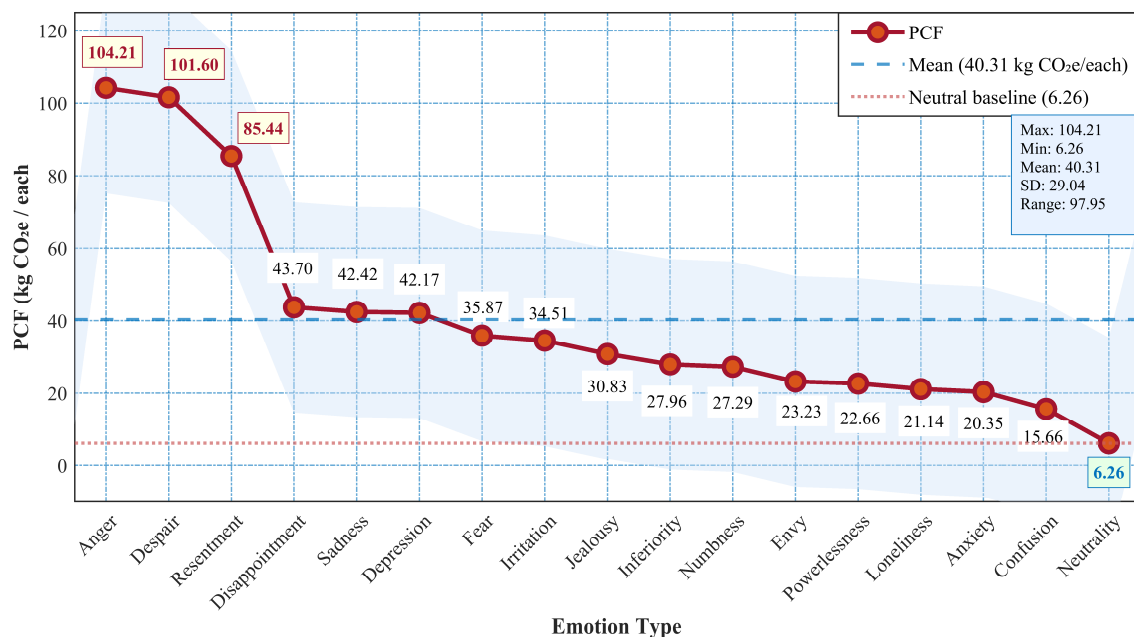


Figure 9. Psychological carbon footprints by emotional type.

The PCF values of the second and third tiers exhibit a continuous gradient distribution. Disappointment at 43.70, sadness at 42.42, and depression at 42.17 form a moderate-to-high emission cluster ranging from 40 to 45 kg CO_{2e} per instance. Although the numerical values of these three emotions are close, their behavioural attributions differ markedly. Disappointment is characterised by high-confidence values for both emotional venting and rumination at 0.670 each. Sadness shows the highest confidence for emotional venting among all emotions, reaching 0.801. Depression is more diffusely associated with self-harm tendency at 0.389 and self-abandonment at 0.496. Closely following are fear at 35.87, irritation at 34.51, and jealousy at 30.83, forming a medium emission cluster ranging from 30 to 40 kg CO_{2e} per instance. Fear is notably characterised by somatic symptoms at 0.508 and social avoidance at 0.495. Irritation ranks second in confidence for Emotional venting with a value of 0.743. Jealousy exhibits an extreme bimodal distribution between rumination and no obvious behaviour, both at 0.860. Together, these two tiers reveal a behavioural dimension gradient ranging from high-arousal emotional venting to cognition-behaviour dissociation.

The fourth tier, comprising eight emotions from Inferiority to Confusion, as well as Neutrality as the lowest value, falls below 30 kg CO_{2e} per instance. Notably, Powerlessness and Anxiety, which appear with high frequency on social media, exhibit relatively low PCF values, confirming the pattern of asymmetry between emotional frequency and carbon emission intensity. In other words, emotions that are widespread but low in behavioural externalisation have a lower per-instance PCF than emotions that occur less frequently yet involve a heavier carbon behavioural chain.

In summary, the psychological carbon footprint exhibits a clear Pareto-like distribution across emotional dimensions. A small number of high-arousal, highly externalising emotions, specifically Anger, Despair, and Resentment, contribute a disproportionately large share of emissions, whereas most negative emotions have a relatively modest carbon impact.

5. Discussion

This study is the first to systematically develop and empirically test a computational model for uncovering the multi-level relationship between “emotion recognition-behavior association-carbon emission accounting” (EBC). It introduces the key concept of the psychological carbon footprint and, based on user-generated content from China’s three major social media platforms, quantifies the pathways of carbon-emitting behaviors associated with various negative emotional states. The findings reveal a long-overlooked, hidden link between mental health and climate change. Specifically:

This study found that negative emotions exert a substantial carbon impact on the external environment through behavioral chains. Anger, despair, and feelings of injustice constitute an “extremely high-level” emissions cluster, with an average daily PCF exceeding 85 kg CO_{2e} per episode (with maximum confidence levels of 0.847, 0.635, and 0.652, respectively), which is higher than the emissions from a gasoline-powered passenger car traveling 250 km.

From the perspective of emotional functioning theory, the high expression of anger observed in this study is supported by the existing literature. Stanley et al. [39] found that ecological anger can significantly promote climate action. However, the present study reveals the other side of anger in the context of interpersonal stress, namely that anger generates substantial carbon costs through interpersonal conflict and emotional venting. Despair falls into the high-emission cluster in this study, with a value of 101.60 kg CO_{2e} per instance, and operates primarily through high-carbon medical behaviours including self-harm and eating abnormalities. Pihkala [40] noted that despair often leads to climate action withdrawal. The distinction of the present study lies in the finding that when despair is directed toward one’s own life state rather than the external environment, its behavioural consequences in our data appear more closely associated with internalised self-harm than with externalised action abandonment. Resentment, with a value of 85.44 kg CO_{2e} per instance, is characterised by the co-occurrence of both rumination and interpersonal conflict at elevated levels. The existing literature has not yet addressed this pattern, and the present study brings resentment within the perspective of the psychological carbon footprint for the first time.

In contrast to the high-emission emotions described above, powerlessness and anxiety, which appear frequently on social media, exhibit relatively low PCF values. This frequency-intensity asymmetry suggests that emotions which are widespread but low in behavioural externalisation have a lower per-instance carbon footprint than emotions that occur less frequently yet involve a heavier carbon behavioural chain. Therefore, environmental policies and psychological interventions cannot focus solely on the frequency of emotional occurrence, but must also identify the behavioural transformation patterns of emotions. These findings provide an important complement to the existing environmental psychology literature. In the domain of transport, Bretter and Pangbourne [41] found that negative emotions toward private cars can predict sustainable travel behaviour. The complementary contribution of the present study lies in showing that certain negative emotions, such as Anger and Resentment, may drive high-carbon travel in the same context. This difference essentially depends on whether the emotion in question has a tendency toward behavioural externalisation. Garg and Lerner [42] found that regional negative emotional climate predicts increased shopping and food consumption behaviours. This aligns with our findings in that both studies identify a link between negative emotional states and increased consumption-related behaviors. Our study extends their finding by disaggregating specific behavioral pathways and quantifying the associated carbon emissions. Brosch [43], in a review on collective emotions and climate action, noted that group emotions can either facilitate collective action or reinforce division. The platform heterogeneity analysis in this study, which identifies high-risk pathways on Weibo and internalising pathways on Xiaohongshu, offers micro-level behavioural evidence for this proposition.

The spatial analysis in this study reveals an ostensibly paradoxical phenomenon: comments expressing high-intensity negative emotions are heavily concentrated in China’s economically developed eastern coastal provinces, including Guangdong, Zhejiang, and Beijing, whereas the central and western regions are predominantly characterized by low-intensity emotions. This pattern superficially suggests that higher economic development is associated with stronger negative emotions. However, a national survey of Chinese social mentality conducted by Feng and Zhang [44], based on a sample of 10,294 participants across the country, indicates that residents of first-tier cities and central urban districts actually exhibit the best mental health status. In contrast, levels of depression and anxiety are higher among residents of peri-urban areas, fringe urban districts, and fifth-tier cities. This finding

initially appears to contradict the conclusion of the present study, but rather provides a critical explanation for understanding the disconnect between the baseline of mental health and the intensity of emotional expression. Specifically, residents of the economically developed eastern regions possess a more robust mental health foundation, which may paradoxically enable them to have greater self-awareness and more open channels for expression when they do experience psychological distress. This, in turn, manifests as discussions of higher-intensity negative emotions in online spaces.

At the platform level, the emotional structures of users on Xiaohongshu, Douyin, and Weibo exhibit significant differentiation. Xiaohongshu users show a high concentration on Powerlessness, with behavioural pathways dominated by rumination and self-isolation. Douyin users display a more dispersed and diffuse emotional distribution. Weibo users show a coexistence of Anger and Powerlessness, and this platform carries the highest behavioural risk. This differentiation offers new empirical anchors for understanding digital-age emotional governance. A quantitative analysis by Wang et al. [45] explains this emotional differentiation through content ecosystem differences. Specifically, Weibo users prioritise public event outcomes, fairness, and justice. Xiaohongshu users interact in highly enclosed, homogeneous lifestyle communities. Douyin, meanwhile, is defined by stronger pan-entertainment and algorithm-driven features. These content ecosystem characteristics are highly consistent with the emotional structure heterogeneity found in this study.

Further research has pointed out that algorithmic recommendations based on users' click preferences continuously reinforce the delivery of homogeneous content, potentially trapping users within persistently polarised emotional echo chambers [46]. The present study further demonstrates that the emotional echo chambers of different platforms possess distinctly different content structures and risk patterns. The echo chamber on Xiaohongshu is biased toward internalising emotions and behaviours, whereas the echo chamber on Weibo is more likely to foster externalising conflicts and extreme expressions [47]. Therefore, differentiated platform governance should move beyond a one-size-fits-all approach. For platforms similar to Xiaohongshu, where rumination and self-isolation dominate, priority should be given to delivering emotion regulation content such as cognitive reappraisal and behavioural activation. For platforms similar to Weibo, where anger and interpersonal conflict prevail, efforts should focus on strengthening conflict de-escalation guidance and the construction of rational discussion mechanisms.

The EBC framework is currently developed and validated using Chinese social media data. Its application to other cultural contexts would require careful adaptation along three dimensions: emotional expression norms, behavioral response patterns, and carbon emission structures. For instance, individualistic versus collectivistic cultures may differ in the willingness to disclose negative emotions publicly; behavioral responses to psychological distress depend on institutional contexts and infrastructure availability; and the carbon intensity of equivalent behaviors varies with national energy mixes and healthcare systems. The EBC framework is designed as a portable methodological architecture, while the specific parameters—emotion lexicons, behavioral taxonomies, and emission coefficients—are inherently context-dependent and should be recalibrated when applied elsewhere. We outline this as a direction for future research rather than claiming cross-cultural generalizability at this stage.

In general, quantifying the Psychological Carbon Footprint carries theoretical, methodological, and policy significance. Theoretically, PCF extends carbon footprint accounting from the material domain into the psychosocial sphere, linking mental health to climate change through behavioural pathways. Methodologically, the EBC framework demonstrates the feasibility of quantifying emotion-driven emissions using social media data, providing a replicable computational architecture for future interdisciplinary research. From a policy perspective, PCF suggests that mental health interventions may yield carbon co-benefits, offering a novel entry point for integrated climate and health governance. Future work should validate the construct through longitudinal designs and experimental tracking, and test its cross-cultural generalizability beyond the Chinese context. Operationalizing PCF as a metric for evaluating mental health programmes or public health messaging could further bridge psychological wellbeing and environmental sustainability.

6. Conclusions and Policy Recommendations

6.1. Conclusions

Addressing the central question of whether and how mental health influences carbon emissions, this study introduces and operationalises the psychological carbon footprint concept, develops the EBC multi-level association mining computational model, and performs a systematic empirical validation using large-scale user comment data from three major Chinese social media platforms, namely Xiaohongshu, Douyin, and Weibo. The main findings are summarised as follows:

- (1) The EBC multi-level association mining computational model constructed in this paper enables multi-level association mining and quantitative accounting of the full chain from negative emotion type → emotional expression intensity → behavioural response → carbon emissions. The model effectively identifies the key pathways and core behavioural mediating nodes through which emotions translate into carbon emissions.
- (2) Negative emotions carry a significant and long-overlooked climate cost, with the psychological carbon footprint varying substantially across different emotion types. The findings reveal that negative emotions are not merely internal experiences of individuals but exert tangible carbon impacts on the external environment through specific behavioural chains. Anger, Despair, and Resentment constitute an extremely high emission cluster, with a PCF exceeding 85 kg CO_{2e} per instance, which is higher than the emissions generated by driving a petrol-fuelled private car for 250 km. In contrast, high-frequency emotions such as Powerlessness and Anxiety exhibit a relatively low PCF, displaying a pattern of frequency–intensity asymmetry. This finding suggests that psychological distress is not only a health issue but also a latent climate issue, challenging the conventional view that psychological problems are soft or inconsequential.
- (3) Negative emotions translate into carbon emissions via specific behavioral pathways. Through joint analysis of confidence and lift, this study identifies multiple high-frequency, strong-association pathways (e.g., anxiety → rumination, anger → interpersonal conflict) and low-frequency, high-risk pathways (e.g., despair → self-harm tendency, fear → somatic symptoms). Although self-harm tendencies and eating abnormalities occur infrequently, their per-instance carbon emissions are extremely high, reaching 115.86 and 103.10 kg CO_{2e}, respectively, marking them as extreme emission hotspots of the psychological carbon footprint. Emotion intensity plays a key mediating role in behavioral translation. Moderate-to-high intensity emotions predominantly drive everyday maladaptive behaviors such as rumination, venting, and self-isolation, whereas extremely high intensity emotions are strongly oriented toward high-carbon medical behaviors.
- (4) The psychological carbon footprint exhibits significant spatial differentiation and platform-specific heterogeneity. Spatial analysis reveals that high-intensity negative emotion comments are concentrated in the economically developed eastern coastal provinces, whereas the central and western regions are predominantly characterised by low-intensity emotions. This pattern is highly coupled with China's Hu Huanyong Line and the east–central–west economic gradient. At the platform level, Xiaohongshu users show a high concentration of emotions on Powerlessness, with behavioural pathways biased toward rumination and self-isolation. Douyin users display a more dispersed emotional distribution. Weibo users exhibit a coexistence of Anger and Powerlessness, and this platform carries the highest behavioural risk. The content ecosystems and algorithmic mechanisms of different platforms have given rise to distinctly different emotional echo chamber patterns. Xiaohongshu tends toward an internalising emotional echo chamber, whereas Weibo tends toward a conflict-externalising echo chamber.

6.2. Policy Recommendations

- (1) Prioritise national mental health and effectively integrate the psychological carbon footprint into the national climate governance system. Mental health issues are not only a matter of public health but also a long-overlooked source of climate costs. It is recommended that national climate change strategies incorporate mental health into a synergistic policy framework for climate governance, with a cross-sectoral mechanism on mental health and climate jointly established by authorities responsible for ecology and environment, health, and development reform.
- (2) Implement differentiated strategies based on emotion type and emission characteristics to optimise resource allocation. This study finds that the PCF varies substantially across different emotion types. High-frequency emotions such as Powerlessness and Anxiety have low per-instance emissions, and should be addressed through universal mental health education and environmental stress reduction to lower their incidence. Low-frequency emotions such as Despair and Self-harm tendency exhibit extremely high per-instance emissions exceeding 100 kg CO_{2e}, and should be managed through the establishment of rapid response mechanisms, with priority given to remote intervention and community rehabilitation as substitutes for high-carbon inpatient care. High-arousal externalising emotions such as Anger and Resentment generate emissions primarily through interpersonal conflict and venting, and should be redirected toward low-carbon alternative behaviours including physical exercise and artistic expression.
- (3) Establish a progressive intervention system by emotion intensity. Level II drives everyday maladaptive behaviors; Levels IV and V point to extreme high-carbon behaviors. Implement tiered responses: self-guided content for Levels I–II, AI support for Level III, and manual crisis intervention for Levels IV–V, prioritizing low-carbon modalities such as remote counseling.

6.3. Limitations

Several limitations of this study should be acknowledged. First, the behavioral responses analyzed are extracted from self-reported social media comments rather than directly observed behaviors. Social media expressions reflect individuals' linguistic representations of their psychological states and behavioral intentions, but they are not equivalent to actual actions. Users may overstate, understate, or selectively disclose their emotional experiences due to social desirability bias, platform norms, or self-presentation strategies. Therefore, the estimated psychological carbon footprint should be interpreted as an indirect estimation rather than a direct measurement of actual emissions. Second, social media users in China are disproportionately younger, more urban, and more educated than the general population, which may limit the generalizability of our findings to broader demographic groups. Third, the classification of emotions and behaviors from unstructured text inevitably involves subjective judgment and potential misclassification, despite our rigorous annotation protocol and acceptable inter-coder reliability. These limitations notwithstanding, we believe the study provides a useful conceptual and methodological foundation for understanding the overlooked climate costs of negative emotions.

Author Contributions

H.C.: conceptualization, methodology, software, supervision, writing—reviewing and editing; Q.S.: data curation, writing—original draft preparation, visualization, investigation. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data are contained within the article.

Conflicts of Interest

Given the role as Editor-in-Chief, Hong Chen had no involvement in the peer review of this paper and had no access to information regarding its peer-review process. Full responsibility for the editorial process of this paper was delegated to another editor of the journal.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

Appendix A

Table A1. Key Emotion-Behavior Confidence Level $P(b|e)$.

Row	Interpersonal Conflict	Rumination	Impaired Work/Study Functioning	Emotional Venting	No Obvious Behavior	Sleep Issues	Social Avoidance
Disappointment	0.429	0.670	0.360	0.670	0.532	0.360	0.463
Resentment	0.652	0.548	0.392	0.581	0.373	0.360	0.386
Jealousy	0.360	0.860	0.360	0.360	0.860	0.360	0.360
Loneliness	0.395	0.416	0.374	0.402	0.360	0.381	0.721
Fear	0.389	0.651	0.360	0.462	0.360	0.389	0.495
Sadness	0.374	0.597	0.378	0.801	0.375	0.370	0.463
Anger	0.847	0.390	0.364	0.807	0.360	0.360	0.368
Depression	0.363	0.621	0.385	0.469	0.361	0.395	0.417
Powerlessness	0.375	0.834	0.389	0.444	0.388	0.365	0.398
Neutrality	0.372	0.418	0.363	0.496	0.730	0.369	0.372
Irritation	0.653	0.482	0.374	0.743	0.389	0.367	0.394
Anxiety	0.367	1.016	0.387	0.404	0.360	0.402	0.391
Despair	0.360	0.635	0.374	0.462	0.360	0.367	0.370
Envy	0.360	0.551	0.360	0.360	0.850	0.360	0.360
Inferiority	0.436	0.710	0.364	0.411	0.411	0.360	0.436
Confusion	0.360	0.790	0.372	0.422	0.422	0.360	0.397
Numbness	0.377	0.479	0.360	0.411	0.504	0.360	0.385

Table A1. Cont.

Row	Self-Harm Tendency	Self-Isolation	Self-Abandonment	Somatic Symptoms	Avoidance Behavior	Eating Abnormalities
Disappointment	0.360	0.394	0.360	0.360	0.360	0.360
Resentment	0.373	0.503	0.386	0.405	0.360	0.360
Jealousy	0.360	0.360	0.360	0.360	0.360	0.360
Loneliness	0.367	0.811	0.360	0.374	0.360	0.360
Fear	0.385	0.491	0.364	0.508	0.467	0.360
Sadness	0.372	0.467	0.368	0.382	0.370	0.364
Anger	0.360	0.370	0.363	0.364	0.365	0.360
Depression	0.389	0.552	0.496	0.468	0.391	0.372
Powerlessness	0.365	0.526	0.423	0.403	0.408	0.364
Neutrality	0.360	0.360	0.360	0.369	0.366	0.363
Irritation	0.363	0.401	0.369	0.400	0.382	0.362
Anxiety	0.367	0.389	0.371	0.460	0.401	0.364
Despair	0.628	0.536	0.424	0.414	0.384	0.367
Envy	0.360	0.403	0.360	0.360	0.360	0.360
Inferiority	0.390	0.575	0.499	0.364	0.360	0.364
Confusion	0.360	0.372	0.360	0.360	0.360	0.360
Numbness	0.385	0.843	0.428	0.368	0.402	0.377

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