

Article

Public Discourse Topics and Emotions toward Acupuncture for Chronic Low Back Pain on Chinese Social Media

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Abstract: Background: Chronic low back pain (CLBP) is a leading global cause of disability. This study investigated dominant topics, emotional profiles, and unmet information needs in Chinese social media discussions regarding acupuncture for CLBP, reflecting how public share experiences and evaluate treatment in the digital sphere. Methods: We analyzed 281,263 comments from Xiaohongshu, Weibo, Toutiao, and Zhihu (January 2023–June 2025). Topic modeling was conducted using BERTopic with large language model–assisted refinement. Fine-grained emotion analysis was performed using the EmoAtlas framework, classifying texts into eight emotions based on Plutchik's theory. Results: Fourteen refined topics were identified and grouped into five dimensions: Treatment Effectiveness, Treatment Process Description, Healthcare Access, Cultural and Theoretical Interpretation, and Patient Experience. Treatment Process Description was the largest dimension (30.59%), while Treatment Effectiveness and Pain Relief the leading topic (n=41,286). Emotion analysis showed that Treatment yielded the highest positive sentiment (44.8%), Healthcare Access was most neutral (35.8%), and Patient Experience was significantly negative (67.5%). Key discussions focused on costs, insurance, provider selection, and first-time consultation concerns. Conclusion: Chinese social media discussions regarding acupuncture for CLBP are multidimensional and emotionally distinct. Discourse extends beyond clinical efficacy to include embodied experiences, psychological burdens, and cultural frameworks. These findings provide evidence for patient-centered care and illustrate how acupuncture is understood and negotiated in digital public health contexts.

Keywords: Chronic Low Back Pain; Acupuncture Treatment; Social Media; Topic Modeling; Large Language Model; Emotion Analysis

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1. Introduction

Chronic low back pain (CLBP) represents a major global public health challenge and is currently recognized as the leading cause of years lived with disability worldwide. Epidemiological data from 2020 show that CLBP affected nearly 619 million individuals. Driven by global aging and population growth, this number is expected to climb to 843 million by 2050 [1]. Although many individuals experience partial or temporary recovery following an initial episode of low back pain, recurrence and chronicity remain common; nearly 70% of patients report short-term improvement [2,3], while approximately 23.3% progress to persistent chronic pain [4]. In China, the burden of CLBP is particularly pronounced. Domestic research indicates that upwards of four-fifths of the adult population encounters a minimum of one occurrence of lumbar discomfort throughout their lives [5], making CLBP the second leading contributor to disease burden in mainland China [6,7]. The condition imposes substantial socioeconomic costs through direct

healthcare expenditures, reduced productivity, and work absenteeism, with broad consequences for individuals, families, healthcare systems, and society as a whole [8,9].

The management of CLBP has undergone a significant paradigm shift over the last decade. Historically, clinical practice relied heavily on pharmacological interventions, particularly opioids, which have contributed to a global drug abuse crisis and rising concerns over addiction and adverse events [10]. In response, international health organizations have advocated for non-pharmacological and non-invasive interventions as first-line treatment options for chronic pain [11]. This shift was formally reinforced by the 2023 World Health Organization clinical guideline on the non-surgical management of chronic primary low back pain, which emphasizes holistic, integrated, and person-centered care [12]. Within this context, acupuncture, a core modality of Traditional Chinese Medicine involving the stimulation of specific acupoints, has gained growing clinical recognition [13]. Recent high-quality clinical evidence, including the large-scale "BackInAction" trial, has validated acupuncture's efficacy in reducing pain-related disability and improving physical function [14,15], particularly among older adults who are often more susceptible to the side effects of traditional analgesics [16].

Despite this clinical validation, the perception of acupuncture remains complex, existing at the intersection of traditional theories, such as the concept of Qi and meridians and modern neurophysiological research. Advanced neuroimaging studies using functional magnetic resonance imaging have begun to map the central mechanism of acupuncture analgesia, demonstrating its ability to modulate brain networks involved in sensory, affective, and cognitive processing, such as the default mode network and the limbic system [17]. Nevertheless, the certainty of evidence for acupuncture is often categorized as low to very low in systematic reviews due to inherent challenges in participant blinding and the prevalence of the placebo effect in needle-based interventions [18]. This tension between clinical guidelines, scientific uncertainty, and patient experience contributes to divergent interpretations of acupuncture's value and effectiveness, prompting many individuals to seek additional information and peer support outside conventional healthcare settings [19].

In recent years, social media platforms have become important sources of public health data. They offer access to patient experiences that are often missing from conventional clinical reports. Platforms such as X (formerly Twitter), Reddit, and YouTube now serve as online spaces where individuals with chronic conditions share personal stories, seek support from peers, and exchange information about treatment outcomes [20,21]. The analysis of user-generated content enables researchers to better understand lived experiences, unmet information needs, and patient priorities that may not be fully addressed within formal clinical encounters [22]. This approach, commonly referred to as infodemiology or infoveillance, supports the monitoring of public sentiment and facilitates the identification of gaps between healthcare delivery and patient expectations [23,24]. From a public health perspective, examining such discourse is essential for improving health communication, supporting shared decision-making, and advancing patient-centered care.

The theoretical significance of analyzing health-related discourse on social media extends beyond mere description. It offers an additional perspective for examining patient-centered care frameworks [25,26]. Understanding the emotional tone of patient discussions is also important, as emotional experiences strongly influence how patients interpret their condition, interact with healthcare systems, and adopt self-management strategies [21,27]. Previous research indicates that chronic pain narratives on social media are often dominated by negative emotions such as "fear" and "sadness," reflecting the functional disability and individual suffering associated with the disease [28]. However, discussions surrounding acupuncture often display more nuanced or pragmatic emotional tones, with users reporting symptom relief, reduced inflammatory flare-ups, and justification for choosing non-pharmacological interventions [19,29]. Understanding these emotional dimensions is therefore central to evaluating public perceptions of acupuncture within chronic pain management.

To systematically analyze large volumes of unstructured social media text, natural language processing (NLP) techniques have become indispensable. Over the past decade, NLP has evolved from rule-based keyword approaches to advanced topic modeling and large language model (LLM)-based methods capable of capturing nuanced psychological and emotional patterns in public discourse. Topic modeling algorithms such as BERTopic enable the identification of latent thematic structures within large text corpora, while sentiment analysis techniques facilitate multidimensional assessments of public attitudes [30]. By integrating topic modeling with fine-grained emotional analysis, researchers can construct a comprehensive map of public discourse that complements clinical evidence and amplifies patient voices [31].

Despite the increasing volume of social media research in healthcare, the specific intersection of acupuncture, CLBP, and Chinese social media platforms remains under-explored. Previous studies have demonstrated the value of NLP in understanding public discourse related to various conditions, such as traditional Chinese medical treatments [32], irritable bowel syndrome [33], dementia, and broad chronic pain experiences [28,29]. Comparative analyses of acupuncture-related discussions on international platforms, such as X, have further illustrated how cultural contexts shape online discourse in English- and Japanese-speaking communities [34]. However, much of this literature remains focused on Western-centric or international platforms, leaving a critical knowledge gap regarding the Chinese digital landscape. Given the widespread use of social media in China and the central role of Traditional Chinese Medicine in everyday healthcare decision-making, Chinese social media platforms offer a uniquely informative context for examining public perceptions of acupuncture.

The application of advanced NLP methods to Chinese social media discussions of acupuncture for CLBP is particularly valuable for several reasons. First, CLBP is associated with significant emotional burden and social stigma, which may encourage patients in China to seek anonymous online spaces for support and information [35]. Second, perceptions of acupuncture are deeply embedded in culturally specific concepts such as balance, dampness (*shiqi*), and life-nurturing (*yangsheng*), which are actively constructed and negotiated in online discourse [36]. Third, traditional clinical research frequently fails to capture the lived experience and real-time discussion of patients navigating the failures of conventional treatments [37]. Consequently, there is an urgent need for a comprehensive investigation that utilizes advanced NLP methods to unveil the specific topics and sentiments towards public discourse surrounding acupuncture for CLBP in the Chinese digital sphere.

Accordingly, this study addresses the following research questions:

- RQ1: What are the dominant topics in Chinese social media discussions regarding acupuncture for CLBP?
- RQ2: What emotional profiles characterize public discourse on acupuncture for CLBP on Chinese social media platforms?
- RQ3: What unmet information needs can be identified within public discourse regarding acupuncture for CLBP?

To answer these questions, the present study analyzes discussions related to acupuncture treatment for CLBP across multiple Chinese social media platforms, including Xiaohongshu, Weibo, Toutiao and Zhihu. Advanced NLP techniques are applied, including topic modeling using BERTopic with the LLM(Qwen) model to fine-tune the topic representations and fine-grained emotional classification using the EmoAtlas framework grounded in Plutchik's psychological emotion theory. By integrating thematic and emotional analyses of large-scale user-generated data, this study contributes to the emerging literature on digital public health surveillance and patient-centered evaluation of non-pharmacological pain management strategies.

The remainder of this paper is organized as follows. Section 2 describes the data collection procedures and analytical methods. Section 3 presents the empirical results, including dominant discussion topics and emotional characteristics. Section 4 discusses the findings in relation to existing literature and their implications for public health-

oriented, patient-centered care and the dissemination of Traditional Chinese Medicine. Finally, Section 5 concludes the study by outlining limitations and future directions for research on digital information surveillance in chronic pain management.

2. Materials and Methods

This study employed a retrospective, observational design to analyze largescale user-generated textual data from multiple Chinese social media platforms. By integrating topic modeling and fine-grained emotional analysis, the study aimed to systematically examine public discourse surrounding acupuncture treatment for CLBP. The analytical framework combined unsupervised topic mining using BERTopic with emotion profiling based on the EmoAtlas framework, enabling a multidimensional characterization of thematic structures and emotional patterns in online discussions. The methodological pipeline consisted of four stages: data acquisition, data preprocessing, LLM-assisted topic modeling, and emotion analysis.

2.1. Data Sources and Acquisition

In this study, Xiaohongshu, Weibo, Toutiao and Zhihu were selected as data sources. These platforms were chosen based on their high user activity, public accessibility, and diverse user demographics, which include both healthcare professionals and laypersons. In contrast, professional medical platforms such as Dingxiangyuan primarily targeted clinicians and therefore do not adequately represent general public discourse. Private communication tools such as WeChat and QQ were excluded due to restricted data accessibility and ethical concerns related to private messaging environments. Collectively, the selected platforms functioned as prominent venues for public health discussion in China, making them particularly suitable for capturing spontaneous, user-driven perceptions and emotional expressions related to acupuncture and chronic pain management. This approach aligns with prior health-related social media research conducted on Chinese platforms [38,39], which emphasizes the importance of publicly accessible, user-generated content for infodemiological analysis.

Data collection was conducted using a predefined keyword-based retrieval strategy designed to capture a broad range of discussions related to acupuncture and CLBP. Keywords included variations and synonyms in Chinese corresponding to: "acupuncture for chronic low back pain / acupuncture treatment for chronic low back pain / electroacupuncture for chronic low back pain / electroacupuncture analgesia / acupuncture pain relief", etc. A customized web crawling tool was implemented using Python 3.11 and the MediaCrawler. The urllib library was employed for HTTP requests and content parsing [40]. Only publicly accessible comments and corresponding likes, forwards, saves were retrieved, without applying filters based on IP address, or user gender, thereby protecting personal privacy and minimizing selection bias. The total number of social media comments obtained is 511,235 from January 2023 to June 2025 and the proportion of comments from different platforms was shown in Table 1.

Table 1. Distribution of Social Media Comments Related to Acupuncture Treatment for CLBP.

Platform	Time Period Covered	Raw Collected Comments (n)	Valid Comments After Cleaning (n)	Proportion of Valid Dataset (%)
Xiaohongshu	Jan 2023 –June 2025	186,742	102,315	36.38
Weibo	Jan 2023 –June 2025	149,506	84,197	29.93
Toutiao	Jan 2023 –June 2025	101,884	56,041	19.92

Zhihu	Jan 2023 –June 2025	73,103	38,710	13.77
Total		511,235	281,263	100.00

2.2. Data Preprocessing and Cleaning

To enhance data quality and analytical reliability, a multi-step preprocessing procedure was applied using Python-based libraries, including NumPy and custom text-processing scripts. The automated preprocessing consisted of the following steps: First, identical or near-duplicate entries were removed to prevent redundancy; Second, the HTML tags, special characters, emojis, and non-textual symbols were eliminated; Third, missing timestamps or user identifiers were labeled as "NULL" to preserve dataset structure; Fourth, all text was converted to lowercase to improve algorithmic consistency; Fifth, the Chinese word segmentation tool jieba [41] was applied to enhance compatibility with topic modeling and sentiment analysis algorithms. Sixth, a customized Chinese stop-word list (e.g., "acupuncture," "hospital") based on Baidu was used to remove high-frequency but semantically insignificant terms [42].

Following automated cleaning, a rigorous manual screening process was conducted to ensure topical relevance and data integrity. To validate the screening protocol, two independent researchers performed a double-blind review of a randomly sampled subset of 10,000 comments. The inter-rater reliability was assessed using Cohen's Kappa [43], yielding a score of $k = 0.86$, indicating a high level of agreement. Any remaining discrepancies within this subset were resolved through consultation with a third senior researcher, adhering to established qualitative research protocols used in prior social media health studies. Comments were excluded if they met any of the following criteria: Entries containing acupuncture-related keywords but unrelated to CLBP; Comments consisting solely of emojis, advertisements, discount codes, or extremely short texts (e.g., one to two words); Repeated promotional or bot-generated comments; Entries that could not be retrieved due to deleted accounts, broken links, or platform restrictions. After cleaning, deduplication, and non-Chinese text filtering, 281,263 valid textual comments remained for analysis (Table 1).

2.3. Topic Modeling with LLM-Assisted Labeling

Topic modeling was performed using BERTopic, a transformer-based framework that combines dense semantic embeddings, clustering, and class-based term frequency-inverse document frequency (c-TF-IDF) to generate interpretable topic representations [44]. In contrast to conventional bag-of-words topic models, BERTopic uses contextualized embeddings to preserve semantic similarity across short and noisy texts, making it suitable for user-generated social media data. Recent health-related applications have shown that BERTopic can recover coherent themes from large-scale online discourse [45] and support relevant interpretation of patient-centered discussions [46,47]. In the present study, BERTopic was implemented with the Chinese-language encoder (hfl/chinese-roberta-wwm-ext) to identify latent thematic structures in comments related to acupuncture treatment for chronic low back pain (CLBP). The embedding model was selected to improve semantic representation for Chinese short texts, including colloquial expressions, symptom descriptions, and treatment-related terminology. Topic generation proceeded in the standard BERTopic pipeline: sentence embeddings were first computed; dimensionality reduction and density-based clustering were then applied to partition semantically similar comments; finally, c-TF-IDF was used to extract high-weight representative terms for each cluster. This procedure produced an initial set of machine-generated topic clusters that retained high lexical specificity but also contained semantically adjacent micro-topics.

To improve interpretability and reduce fragmentation, topic labels were subsequently refined using a human-in-the-loop, LLM-assisted strategy. LLMs have increasingly been used to support thematic summarization and category refinement in computational social science and qualitative health research, particularly when machine-generated topic labels are lexically sparse or difficult to interpret [48]. Recent studies have

shown that model-assisted summarization can improve descriptive clarity, but that expert review remains necessary to preserve domain validity and analytic consistency [49]. In this study, topic representations generated by BERTopic were therefore further processed with Qwen3, a LLM developed by Alibaba Cloud. According to the Qwen3 technical report, the model family includes dense and mixture-of-experts variants up to 235 billion parameters and was designed for high-level multilingual reasoning and generation tasks [50]. For each initial topic cluster, representative documents and keyword lists extracted by BERTopic were provided to Qwen3 through a standardized prompt. The model was instructed to generate a concise and semantically descriptive topic label in a fixed format. This step was intended to reduce redundancy in cluster naming, normalize expression across semantically similar clusters, and improve readability for subsequent coder review. The standardized prompt was as follows:

"I have a topic that contains the following documents: [DOCUMENTS].

The topic is described by the following keywords: [KEYWORDS].

Based on the information above, extract a short but highly descriptive topic label. Use the following format: topic: <topic label>."

After LLM-assisted labeling, a manual topic consolidation procedure was conducted to merge related clusters into analytically meaningful topics. This stage was included because social media corpora often produce multiple overlapping clusters that refer to closely related aspects of the same broader issue. A comparable strategy of combining computational topic discovery with structured human review has been recommended in recent health informatics and computational text-analysis research, especially when working with sensitive, patient-generated, or clinically nuanced discourse [51]. The manual consolidation proceeded in four steps. First, all initial topic labels, representative keywords, and example comments were exported into a coding matrix. Second, three coders independently reviewed each cluster and assigned it to a provisional conceptual grouping based on semantic similarity, treatment context, and relevance to the study objectives. During this stage, the coders examined not only the LLM-generated label but also the underlying high-frequency words and exemplar comments to reduce over-reliance on the generated summary alone. Inter-coder consistency for this initial grouping stage was assessed using Fleiss' Kappa [52], which showed a high level of agreement $k = 0.88$. Third, the provisional groupings were compared in two rounds of discussion meetings. Disagreements were resolved through consensus, with particular attention paid to distinguishing adjacent but conceptually different categories. Fourth, the final identified topics and corresponding dimensions were reviewed by a senior acupuncture physician to ensure that the topic structure remained clinically and contextually plausible, particularly for treatment-related terms, Traditional Chinese Medicine (TCM) explanatory concepts, and procedure-specific discussions. To support transparency and reliability, coding decisions were documented throughout the consolidation process, including notes on cluster merges, label revisions, and reasons for retaining or separating adjacent topics. This iterative process yielded a reduced and more interpretable final topic set and corresponding dimension naming. The aim of this stage was not to override the unsupervised model output, but to consolidate fine-grained machine-generated clusters into broader topics suitable for reporting and interpretation in a public health study.

2.4. Emotion Analysis Using the EmoAtlas Framework

Emotion analysis was conducted using EmoAtlas, a neuro-symbolic text analysis framework that combines psychologically validated emotion lexicons with AI-based syntactic parsing to extract interpretable emotional profiles from text [53]. EmoAtlas operationalizes Plutchik's eight basic emotions—trust, joy, surprise, anticipation, anger, disgust, fear, and sadness—and distinguishes emotion profiling from simple valence classification by representing texts as multidimensional emotional vectors rather than as only positive or negative outputs [54]. The framework supports both text-level and word-level analysis and has been shown to provide interpretable, computationally efficient, and reproducible results across multiple languages, including Chinese.

In this study, the cleaned Chinese comments were analyzed. For each comment T , EmoAtlas identified the set of emotion-bearing words contained in the text according to the underlying emotion lexicon. Let $n_e(T)$ denote the observed number of words in text T , associated with emotion e , where $e \in \{trust, joy, surprise, anticipation, anger, disgust, fear, sadness\}$. The raw emotional score for each emotion can therefore be written as:

$$s_e(T) = n_e(T)$$

Because raw counts are sensitive to text length and lexical density, EmoAtlas further evaluates whether the observed emotional signal exceeds random expectation by comparing each text against a reference baseline. Following the EmoAtlas framework, the statistical emotional profile is expressed as a z-score:

$$Z_e(T) = \frac{n_e(T) - \mu_e(m)}{\sigma_e(m)}$$

Where m is the number of words in T that elicit at least one emotion, $\mu_e(m)$ is the expected count of words associated with emotion e under random sampling, and $\sigma_e(m)$ is the corresponding standard deviation. In EmoAtlas, these expected values are estimated against a reference lexicon or baseline corpus, allowing the analyst to determine whether a given emotional signal is overrepresented relative to chance. Values outside the conventional rejection region $|Z| < 1.96$ indicate that the emotional content of the text differs significantly from random expectation at the 0.05 level.

For the present study, each social media comment was processed to obtain an eight-dimensional emotional vector:

$$E(T) = [Z_{trust}, Z_{joy}, Z_{surprise}, Z_{anticipation}, Z_{anger}, Z_{disgust}, Z_{fear}, Z_{sadness}]$$

These comment-level emotional vectors were then aggregated to the topic and dimension levels. If a topic k contains N_k comments, the average emotional profile of that topic was computed as:

$$\bar{E}_{e,k} = \frac{1}{N_k} \sum_{i=1}^{N_k} Z_e(T_i)$$

Likewise, if a broader dimension d contains M_d comments, the dimension-level emotion score was calculated as:

$$\bar{E}_{e,k} = \frac{1}{M_k} \sum_{i=1}^{M_k} Z_e(T_i)$$

To facilitate interpretation, the eight emotions were additionally grouped into three higher-order categories based on Plutchik's theory: positive (*trust, joy*), neutral (*surprise, anticipation*), and negative (*anger, disgust, fear, sadness*). For each topic or dimension, the percentage of each category was calculated as:

$$P_c = \frac{\sum_{e \in c} \bar{E}_e}{\sum_{e=1}^8 \bar{E}_e} \times 100\%$$

Where c denotes the positive, neutral, or negative emotion set.

Each textual comment was processed through EmoAtlas to generate an emotional profile based on the frequency and syntactic association of emotion-laden words. Emotional intensities were calculated by comparing observed emotion word distributions against reference baselines, allowing for statistical identification of overrepresented emotional states. The resulting emotion vectors enabled the characterization of dominant emotional patterns across topics, facilitating analysis of public perceptions of acupuncture treatment for CLBP.

3. Results

3.1. Time Period Results

The temporal distribution of CLBP-related comments across the four social media platforms is illustrated in Figure 1. All platforms exhibited a synchronized growth trajectory over the first four observation periods, culminating in a simultaneous peak during the July 2024–December 2024 window. This was followed by a universal decline across all channels in the final period (January 2025–June 2025). In terms of volume, Xiaohongshu consistently served as the primary venue for discourse, maintaining the highest number of valid comments throughout the study. Its volume grew by approximately 85.1% from the initial period to its peak of 28,540 comments. Weibo

followed a nearly identical growth curve, nearly doubling its initial volume by its late-2024 peak (24,600 comments). While Toutiao and Zhihu recorded lower absolute volumes, they demonstrated similar relative stability. The ranking of platforms by comment volume remained unchanged across all five periods. Notably, the gap between the leading platform (Xiaohongshu) and the second (Weibo) remained relatively constant, while both significantly outperformed the more information-centric platforms (Toutiao and Zhihu).

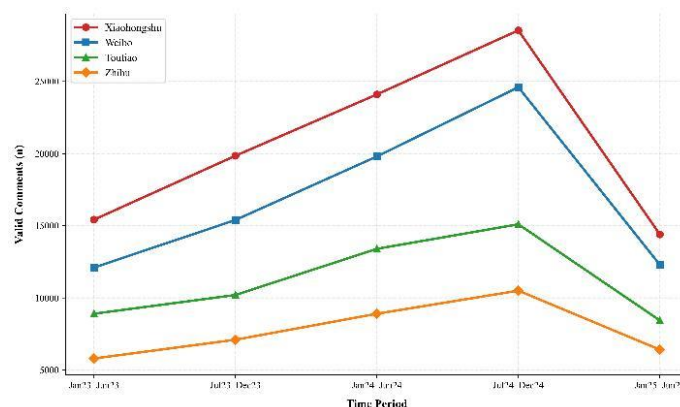


Figure 1. CLBP-related Comments Time Period in Four Social Media Platforms.

The time-period distributions of user engagement metrics are shown in Figure 2, which reports likes, forwards, and saves across the same five periods for each platform. Across the full observation window, Xiaohongshu recorded the highest total number of likes (890,595) and saves (346,940). Weibo, while second in likes (690,673), recorded the highest number of forwards at 309,600, which is significantly higher than the 60,430 forwards recorded on Xiaohongshu. Zhihu displayed a notable ratio of saves to likes; with 195,860 likes, it recorded 164,980 saves, a higher proportion compared to the like-to-save ratios on Weibo and Toutiao. Across all platforms, the peak period for both comment volume and engagement metrics was the second half of 2024 (July to December).

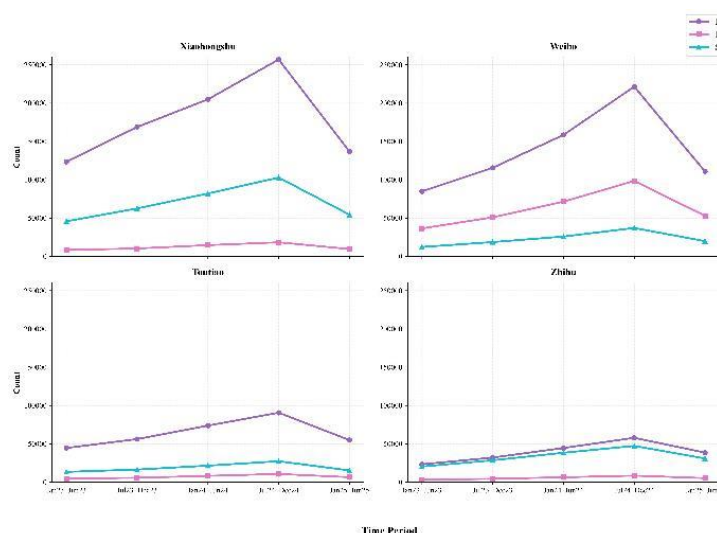


Figure 2. Time Period Situation of Comments' Engagement Metrics.

Across all four platforms, the highest values for comment volume and engagement metrics were concentrated in Jul 2024–Dec 2024. In Jan 2025–Jun 2025, each platform showed lower counts for comments, likes, forwards, and saves than in the preceding period. Figures 1 and 2 together present the time-period distribution of discussion volume and engagement metrics across Xiaohongshu, Weibo, Toutiao, and Zhihu.

3.2. Topic Mining Results

Using BERTopic with the hfl/chinese-roberta-wwm-ext encoder, and setting the model hyperparameters to 86/7, the initial topic modeling procedure generated 529 topic clusters. Because many of these machine-generated clusters were highly fragmented and not sufficiently interpretable for reporting, a subsequent refinement procedure was conducted. Specifically, the BERTopic-derived labels, representative keywords, and exemplar comments were first processed through Qwen3 using a standardized prompt to produce short descriptive topic labels. These preliminary labels and cluster contents were then subjected to a manual topic consolidation procedure, in which three coders independently reviewed semantically adjacent clusters and assigned them to provisional higher-order groupings. Inter-coder consistency for this initial grouping stage was high (*Fleiss'* $\kappa = 0.88$). Disagreements were subsequently resolved through two rounds of discussion, and the resulting topic structure was further reviewed by a senior acupuncture physician to ensure clinical and contextual plausibility. Through this combined process of LLM-assisted labeling and manual consolidation, the initial 529 clusters were reduced to 14 refined topics. Finally, two researchers translated the finalized topic labels into English. The resulting topics are presented in Table 2.

Table 2. Topics Identified in Chinese Social Media Discussions on Acupuncture Treatment for CLBP.

Topics	Translated Keywords
Topic 0: Treatment Effectiveness and Pain Relief	pain relief, effective, improvement, symptoms, lumbar pain, obvious effect, recovery
Topic 1: Treatment Experience and Needling Sensations	soreness, numbness, tingling, deqi, needle sensation, warmth, tolerable
Topic 2: Treatment Frequency and Duration	sessions, course of treatment, several times, weekly, persistent treatment, how long
Topic 3: Electroacupuncture and Instrument-Assisted Therapy	electroacupuncture, current, stimulation, electrode, device, stronger effect
Topic 4: Comparison with Medication and Rehabilitation	physiotherapy, painkillers, massage, rehabilitation, exercise, better than, combined therapy
Topic 5: Side Effects and Safety Concerns	bruising, bleeding, dizziness, soreness, burn, adverse reaction, safe or not
Topic 6: Hospital and Doctor Recommendations	hospital, doctor, practitioner, specialist, department, recommendation, appointment
Topic 7: Treatment Costs and Medical Insurance	cost, price, session fee, expensive, reimbursement, insurance, affordability
Topic 8: Psychological Burden and Pain-Related Distress	anxiety, frustration, insomnia, suffering, stress, repeated pain, emotional exhaustion
Topic 9: Traditional Chinese Medicine Explanations of Pain	meridian, qi, dampness, cold, blockage, constitution, yang deficiency
Topic 10: Self-Management and Daily Care Strategies	stretching, posture, sitting, sleeping, exercise, hot compress, lifestyle adjustment
Topic 11: Information Seeking and Treatment Expectations	does it work, how many sessions, suitable or not, what to expect, first time, consultation
Topic 12: Personal Recovery Narratives and Peer Support	my experience, finally improved, sharing journey, encouragement, same problem, support
Topic 13: Evidence and Placebo Debate	placebo, scientific evidence, useless, belief, controversial, evidence-based, trust

Subsequently, the research team reviewed the refined topics and organized them into five dimensions, namely "Treatment Effectiveness", "Treatment Process Description, Healthcare Access", "Cultural and Theoretical Interpretation", and "Patient Experience", with reference to the preceding theoretical discussion (Figure 3). Specifically, Topics 0 and 4 were grouped under the "Treatment Effectiveness" dimension, considering that they

were generally associated with perceived therapeutic outcomes and comparisons with other treatment options. Topics 1, 2, 3, and 5 were included in the "Treatment Process Description" dimension, as these topics were largely related to treatment sensations, treatment course, technical modalities, and safety-related issues. Topics 6, 7, and 11 were categorized into the "Healthcare Access" dimension, considering that they appeared to involve provider selection, treatment cost, insurance coverage, and consultation-related concerns. Topics 9 and 13 were grouped into the "Cultural and Theoretical Interpretation" dimension, as they were interpreted as reflecting, at least in part, Traditional Chinese Medicine explanatory concepts as well as broader discussions of scientific legitimacy and placebo-related debates. Finally, Topics 8, 10, and 12 were placed under the "Patient Experience" dimension, as they were considered to be more closely related to psychological burden, self-management practices, and peer-supported recovery narratives.

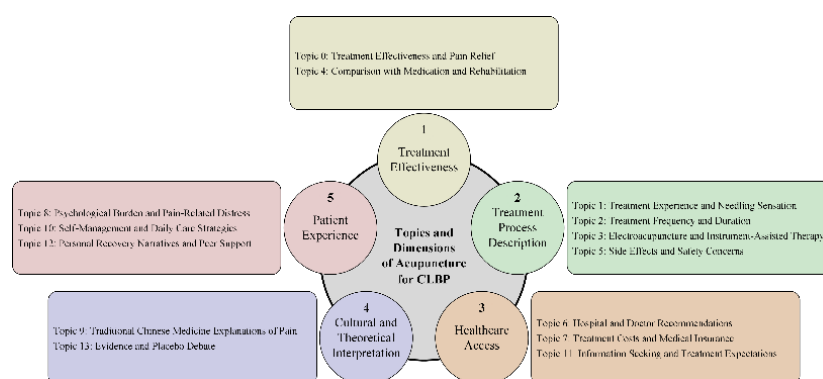


Figure 3. Topics and Corresponding Five Dimensions.

Moreover, Figure 4 further presents word clouds for the five dimensions derived from topic-group clustering. These visualizations were generated using weighted log-odds scores, which estimate how strongly each term is associated with a given target corpus relative to all remaining comments while incorporating a small Bayesian prior to stabilize low-frequency terms [55]. Terms with higher positive scores are therefore more distinctive of the corresponding dimension. In the word clouds, larger font size indicates greater distinctiveness and relative prominence within that dimension.



Figure 4. Word Cloud Map of Representative Keywords for Five Dimensions.

Finally, the fourteen refined topics were distributed across the five dimensions, as shown in Figure 5. Together, these topics accounted for 265,633 comments. Given that the full valid corpus contained 281,263 comments, the remaining 15,630 comments were classified as residual low-coherence clusters or miscellaneous content not retained in the final fourteen topic interpretation. Among the five dimensions, the "Treatment Process

Description" dimension accounted for the largest share (30.59%) of the interpretable corpus. This dimension included four topics: Topic 1: Treatment Experience and Needling Sensation (29,774), Topic 2: Treatment Frequency and Duration (25,184), Topic 3: Electroacupuncture and Instrument-Assisted Therapy (16,709), and Topic 5: Side Effects and Safety Concerns (14,382). Comments in this dimension focused on treatment sensations, treatment schedules, device-assisted procedures, and post-treatment reactions. Representative comments included: "The needle felt sore and numb at first, but my lower back felt more relaxed afterward," "I've already had acupuncture twice this week, but I'm still not sure how long a full course should last," "Electroacupuncture feels stronger than ordinary acupuncture," and "There was a little bruising after treatment-is that normal?"

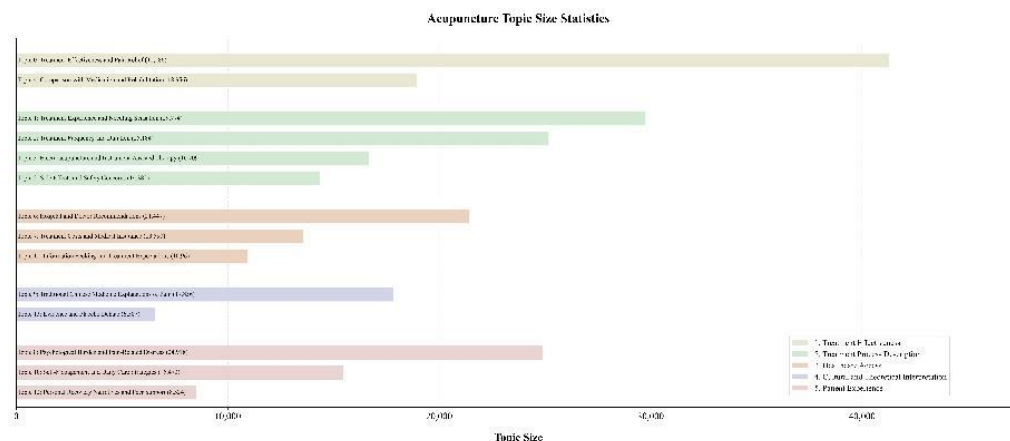


Figure 5. Distribution of Fourteen Topics in Five Dimensions.

At the topic level, Topic 0: Treatment Effectiveness and Pain Relief was the largest single topic in the corpus, with 41,286 comments. In the figure, this topic appears under the Treatment Effectiveness dimension and exceeds the size of all other individual topics. Comments in this topic mainly referred to pain relief, stiffness reduction, symptom change, and daily functioning after treatment. Representative comments included: "After three sessions, the pain when getting up in the morning was clearly reduced," "The soreness in my waist is not completely gone, but it is much lighter than before," and "The effect was not immediate, but after several treatments I gradually felt improvement."

The broader "Treatment Effectiveness" dimension contained two topics: Topic 0: Treatment Effectiveness and Pain Relief (41,286) and Topic 4: Comparison with Medication and Rehabilitation (18,956). Together, these two topics formed one of the largest dimension-level groupings in the figure. Comments under Topic 4 involved comparisons between acupuncture and other approaches, including painkillers, massage, physiotherapy, and rehabilitation exercises. Representative comments included: "Painkillers only helped for a short time, but acupuncture seems to last longer," and "I tried physiotherapy before, but acupuncture worked better for my stiffness."

The "Healthcare Access" dimension included three topics: Topic 6: Hospital and Doctor Recommendations (21,447), Topic 7: Treatment Costs and Medical Insurance (13,590), and Topic 11: Information Seeking and Treatment Expectations (10,967). In the figure, Topic 6 was the largest topic within this dimension. Comments in this group referred to hospitals, doctors, specialists, treatment costs, insurance reimbursement, and consultation-style questions. Representative comments included: "Which hospital has a good acupuncture department for low back pain?" "Each session is quite expensive-can medical insurance cover it?" and "I'm going for my first treatment tomorrow; what should I expect?"

The "Cultural and Theoretical Interpretation" dimension consisted of two topics: Topic 9: Traditional Chinese Medicine Explanations of Pain (17,836) and Topic 13: Evidence and Placebo Debate (6,587). In the figure, Topic 9 was visibly larger than Topic 13 within this dimension. Comments in this group included Traditional Chinese Medicine

terminology and statements related to scientific evidence or placebo. Representative comments included: "My doctor said this is caused by dampness and blockage in the meridians," and "Is acupuncture really scientific, or is it mostly a placebo effect?"

The "Patient Experience" dimension contained three topics: Topic 8: Psychological Burden and Pain-Related Distress (24,918), Topic 10: Self-Management and Daily Care Strategies (15,473), and Topic 12: Personal Recovery Narratives and Peer Support (8,524). Within this dimension, Topic 8 was the largest. Comments referred to repeated pain episodes, anxiety, sleep disturbance, self-care routines, and personal recovery stories. Representative examples included: "The pain keeps coming back, and I feel more anxious every night," "I can't sit or sleep properly, so I have to stretch and use hot compresses every day," and "I also had chronic low back pain for a long time, and I only improved little by little, so don't give up."

3.3. Emotion Analysis Results

As shown in Figure 6, the results are presented at two levels. At the dimension level, donut charts display the proportions of positive, neutral, and negative emotions within each of the five dimensions. At the topic level, heatmaps report the percentage distribution of the eight specific emotions for each topic included in each dimension. In the heatmaps, color categories distinguish positive, neutral, and negative emotional attributes, and the shading intensity corresponds to the relative proportion of each emotion.

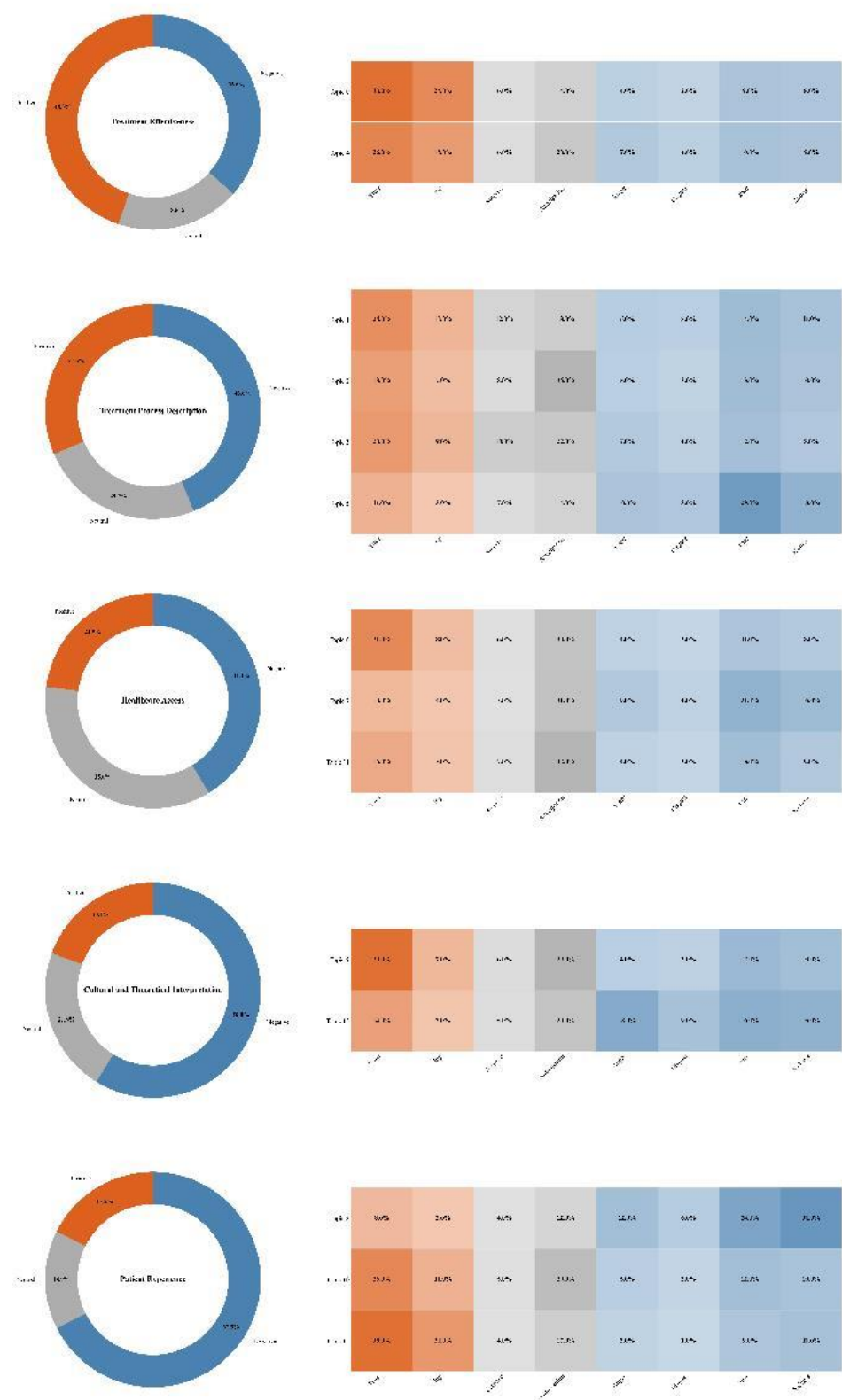


Figure 6. Emotions Distribution of Five Dimensions and Fourteen Topics.

The "Treatment Effectiveness" dimension, the emotional distribution of the two constituent topics showed a relatively high concentration of positive emotions (44.8%). Topic 0: Treatment Effectiveness and Pain Relief was characterized primarily by Trust (33.0%) and Joy (24.0%), which were the two largest components of its emotional profile. The remaining six emotions were all below 15%. A similar pattern appeared in Topic 4:

Comparison with Medication and Rehabilitation, where Trust (26.0%) and Joy (18.0%) were again the largest two emotions. In this topic, Anticipation also occupied a relatively large proportion (20.0%), while the negative emotions remained below 10%. At the topic level, these two topics displayed the highest positive emotional composition among the dimensions shown in Figure 6.

The "Treatment Process Description" dimension contained four topics and showed greater internal variation in the distribution of specific emotions. In Topic 1: Treatment Experience and Needling Sensation, the highest percentages were recorded for Trust (24.0%). Topic 2: Treatment Frequency and Duration displayed the highest Anticipation value within this dimension (36.0%). In Topic 3: Electroacupuncture and Instrument-Assisted Therapy, the most prominent emotion was Anticipation (22.0%). Topic 5: Side Effects and Safety Concerns showed a different composition from the other three topics in this dimension. Its highest emotional proportion was Fear (29.0%). The proportions of Joy (3.0%) and Disgust (8.0%) were lower than the corresponding values of the leading emotions. Across the four topics in this dimension, Anticipation and Trust were recurrent in Topics 1–3, whereas Fear and Sadness were most prominent in Topic 5.

In the "Healthcare Access" dimension, the three topics were marked by comparatively large proportions of Anticipation. Topic 6: Hospital and Doctor Recommendations showed Trust (31.0%) and Anticipation (30.0%) as the two largest emotions. Topic 7: Treatment Costs and Medical Insurance had the highest proportion of Anticipation (31.0%), while Fear (21.0%) and Sadness (16.0%) were also prominent. Its positive emotions were lower, with Trust (10.0%) and Joy (4.0%). Topic 11: Information Seeking and Treatment Expectations showed the highest Anticipation score among all 14 topics (42.0%). In all three topics of this dimension, Anticipation occupied one of the top positions, and in two of the three topics it was the largest single emotion.

The "Cultural and Theoretical Interpretation" dimension consisted of two topics with different emotional compositions. In Topic 9: Traditional Chinese Medicine Explanations of Pain, Trust (29.0%) and Anticipation (29.0%) were equal as the two largest emotional components. These were followed by Fear (12.0%), Sadness (10.0%), Joy (7.0%), Surprise (6.0%), Anger (4.0%), and Disgust (3.0%). In Topic 13: Evidence and Placebo Debate, the distribution was more weighted toward negative emotions. Anticipation (20.0%) remained relatively high, but the largest negative components were Anger (18.0%), Fear (16.0%), and Sadness (15.0%). Positive emotions were less represented in this topic, with Trust (14.0%) and Joy (3.0%). Among all topics displayed in Figure 6, Topic 13 recorded the highest Anger score.

The "Patient Experience" dimension showed the strongest concentration of negative emotions at the dimension level and contained three topics with clearly differentiated profiles. In Topic 8: Psychological Burden and Pain-Related Distress, the largest emotions were Sadness (31.0%) and Fear (24.0%). In Topic 10: Self-Management and Daily Care Strategies, the most prominent emotions were Anticipation (29.0%) and Trust (26.0%). Compared with Topic 8, this topic contained higher positive and neutral shares. Topic 12: Personal Recovery Narratives and Peer Support showed the highest Trust proportion in the topic set (35.0%) and a relatively high Joy value (20.0%). The remaining emotions were all below 20%. Within this dimension, Topics 8 and 12 occupied different positions in the eight-emotion distribution, with Topic 8 showing the highest Sadness score among all 14 topics and Topic 12 showing the highest Trust score.

Across the full set of dimensions and topics shown in Figure 6, several distributional patterns can be directly observed. At the dimension level, Treatment Effectiveness had the largest positive share (44.8%), Healthcare Access had the largest neutral share (35.8%), and Patient Experience had the largest negative share (67.5%). At the topic level, the highest Trust value appeared in Topic 12: Personal Recovery Narratives and Peer Support (35.0%), the highest Joy value in Topic 0: Treatment Effectiveness and Pain Relief (24.0%), the highest Surprise value in Topic 3: Electroacupuncture and Instrument-Assisted Therapy (18.0%), the highest Anticipation value in Topic 11: Information Seeking and Treatment Expectations (42.0%), the highest Anger value in Topic 13: Evidence and

Placebo Debate (18.0%), the highest Disgust value also in Topic 13: Evidence and Placebo Debate (9.0%), the highest Fear value in Topic 5: Side Effects and Safety Concerns (29.0%), and the highest Sadness value in Topic 8: Psychological Burden and Pain-Related Distress (31.0%). These results provide the complete dimension-level and topic-level emotional distributions based on the EmoAtlas framework and the three-category grouping shown in Figure 6.

4. Discussion

This study examined large-scale Chinese social media discussions on acupuncture treatment for CLBP and identified a multidimensional public discourse structure composed of five dimensions: Treatment Effectiveness, Treatment Process Description, Healthcare Access, Cultural and Theoretical Interpretation, and Patient Experience. By integrating topic mining with emotion profiling, the study extends previous social media research on chronic pain and acupuncture by focusing specifically on the Chinese digital context. Overall, the findings respond directly to the three research questions proposed in this study. The results show that public discourse would be multidimensional, that emotional profiles would vary across topics rather than converge into a single sentiment orientation, and that Chinese social media would contain both culturally embedded interpretations and practical unmet information needs.

With respect to "RQ1: What are the dominant topics in Chinese social media discussions regarding acupuncture for CLBP?" The topic structure indicates that public discussion of acupuncture for CLBP is dominated by both treatment effectiveness and treatment process description. A first notable finding is that "Treatment Process Description" dimension accounted for the largest share of the corpus, while Treatment Effectiveness and Pain Relief was the largest single topic. This distribution suggests that online discussions were organized not only around whether acupuncture "works," but also around how treatment is delivered, felt, repeated, and tolerated. This pattern is consistent with previous chronic pain social media studies showing that patients frequently discuss treatment trajectories, bodily symptoms, clinicians, and day-to-day management rather than abstract medical categories alone. In Reddit-based chronic pain research, commonly occurring expressions have included pain, doctor, back, feel, and time, reflecting the practical and experiential orientation of patient discourse rather than strictly diagnostic language [20]. Similarly, work on chronic pain self-reports from Twitter found that social media narratives contain substantial information about alternative therapies, side effects, and self-management strategies [29]. The present findings extend those observations to Chinese social media and to acupuncture-specific discourse, where needling sensations, treatment course, electroacupuncture, and safety concerns appeared as prominent topics.

The prominence of "Treatment Effectiveness" dimension also fits prior research on public attitudes toward acupuncture. In a Japanese web-based survey, acupuncture was perceived as effective by a substantial proportion of respondents for chronic low back pain, and attitudes toward acupuncture were associated with health literacy, prior acupuncture experience, and the number of health information sources consulted [19]. In the present study, the largest topic centered on pain relief, symptom improvement, and functional recovery, while a second effectiveness-related topic focused on comparisons with medication, physiotherapy, massage, and rehabilitation. Taken together, these results indicate that acupuncture is discussed in relation to a broader treatment repertoire rather than as an isolated therapeutic option. That structure is also compatible with previous chronic pain community research showing that discussions of pain management often combine pharmacological, physical, behavioral, and device-based strategies rather than following a single treatment logic [32].

The results for "RQ2: What emotional profiles characterize public discourse on acupuncture for CLBP on Chinese social media platforms?" show that emotional profiles varied substantially across dimensions and topics. At the dimension level, Treatment Effectiveness contained the highest proportion of positive emotions, Healthcare Access

contained the highest proportion of neutral emotions, and Patient Experience contained the highest proportion of negative emotions. At the topic level, trust and joy were concentrated in treatment-effectiveness and recovery-related content, anticipation was especially prominent in expectation- and consultation-related content, and fear and sadness were concentrated in side-effect and psychological burden topics. This differentiation is consistent with the design rationale of the EmoAtlas framework, which distinguishes eight emotions rather than collapsing all content into positive versus negative polarity. The EmoAtlas framework showed that this finer-grained approach can capture emotional profiles with greater interpretability than simple valence-only classification. In the present study, that granularity was especially useful because consultation-related anticipation, relief-related trust, controversy-related anger, and burden-related sadness occupied different locations in the topic structure [56].

The findings for the Patient Experience dimension are especially consistent with prior literature on chronic pain expression online. Earlier studies have shown that social media and online health communities often contain narratives of sleep disruption, emotional strain, repeated symptom episodes, and social support seeking. The Reddit-based chronic pain modeling study found that pain reports encode not only bodily symptoms but also temporality, emotional impact, and contextual disruption. More recent work on peer support in chronic pain forums has further shown that online chronic pain communities are structured around evolving emotional expression and peer interaction [28]. In the present study, these patterns reappeared in a Chinese acupuncture context: psychological burden and pain-related distress carried the highest sadness and fear values, while recovery narratives and peer support carried high trust and joy. This suggests that acupuncture-related discussion is embedded within the broader emotional ecology of chronic pain communication rather than being restricted to procedure-specific talk.

The results for "RQ3: What unmet information needs can be identified within public discourse regarding acupuncture for CLBP?" are most clearly reflected in the Healthcare Access dimension. Topics related to hospital and doctor recommendations, treatment costs and insurance, and treatment expectations indicate that a substantial share of public discourse was devoted to care navigation rather than to treatment outcomes alone. Anticipation was the most prominent emotion in these topics, and the highest anticipation score in the entire topic set appeared in the topic on treatment expectations. Earlier chronic pain studies have similarly found that online communities contain a large volume of requests for practical advice, information about clinicians, and descriptions of barriers to care [32]. From a patient-centred care perspective, this matters because person-centred chronic pain management is commonly described as a dialogue in which patients want information about options, expected outcomes, and the practical implications of treatment choices. The current results therefore identify a set of unmet information needs that includes treatment duration, treatment suitability, first-visit preparation, provider selection, and affordability.

These findings have direct implications for public health-oriented, patient-centred care. The WHO guideline emphasizes that CLBP care should be tailored to the mix of physical, psychological, and social factors affecting patients, rather than organized around a single biomedical endpoint [57]. The current topic structure closely mirrors that broader model: treatment effect, treatment process, patient experience, access, and interpretive frameworks all appeared as distinct but connected dimensions. This suggests that patient-facing communication about acupuncture for CLBP may be more effective when it addresses not only efficacy evidence, but also practical treatment course, common sensations, safety, costs, self-management, and expectation setting. In the chronic pain literature, patient-centred care has been described as requiring shared decision-making, better attention to patient priorities, and more explicit communication about options and likely outcomes. The present findings provide empirical support for that orientation by showing what people actually discuss and ask about when they talk about acupuncture in public digital settings.

The Cultural and Theoretical Interpretation dimension is particularly important for understanding the role of acupuncture in the public sphere and for discussing its implications for Traditional Chinese Medicine (TCM) dissemination. One topic in this dimension used TCM explanatory terms such as meridians, qi, dampness, and constitution, while the other centered on evidence, placebo, and scientific legitimacy. That dual structure indicates that Chinese social media discourse about acupuncture moves across at least two interpretive registers: one rooted in TCM concepts and another oriented toward contemporary standards of scientific explanation. This is compatible with earlier work showing that the legitimacy of acupuncture in public discourse is socially constructed through media narratives and public attitudes. In Hong Kong newspaper discourse, for example, acupuncture has been shown to be legitimated through authorization, rationalization, and moral evaluation [58]. Comparative social media research on acupuncture topics in English and Japanese has likewise shown that cultural context shapes both vocabulary and thematic emphasis [34]. The present study adds Chinese social media evidence to that literature by showing that cultural explanation and scientific debate coexist within the same public discourse field.

From the perspective of TCM dissemination, this coexistence has several implications. First, dissemination is not only a matter of increasing visibility; it is also a matter of how explanatory language is received, translated, compared, and contested in public communication. Recent work on the transcultural dissemination of TCM has emphasized that new media and social media platforms are important channels for communicating TCM concepts in more dynamic and intuitive ways [59]. The present findings suggest that, in domestic Chinese digital settings, dissemination is already occurring through a mixture of symptom narratives, treatment accounts, practical advice, and theory-related discussion. Second, the emotional profile of this dimension indicates that not all TCM-related discourse is affectively similar: the TCM-explanation topic contained high trust and anticipation, whereas the evidence-and-placebo debate topic contained the highest anger score in the whole corpus. For public communication, this means that dissemination of acupuncture-related knowledge is likely to involve both explanatory translation and explicit response to skepticism.

The platform-level time-series results further contextualize these findings. Across Xiaohongshu, Weibo, Toutiao, and Zhihu, valid comment volume and engagement increased through the second half of 2024 and then declined in the final period. Xiaohongshu produced the largest number of valid comments and the highest counts of likes and saves, while Weibo recorded the highest number of forwards. These platform differences are relevant because earlier research on pain-related communication on X/Twitter showed that social media interactions can reveal not only what patients discuss but also how information circulates between different audiences [60]. In the present study, the coexistence of high-volume discussion, strong saving behavior, and forwarding activity across platforms indicates that acupuncture for CLBP is not restricted to a narrow niche of conversation but circulates in multiple communicative formats.

On the whole, the research questions are well answered by the results. RQ1 is answered by the identification of five dimensions and fourteen topics, with treatment process and treatment effect occupying the most prominent positions. RQ2 is answered by the differentiated emotional structure captured by EmoAtlas, especially the contrast between effectiveness-related trust/joy, expectation-related anticipation, and burden-related fear/sadness. RQ3 is answered by the visibility of unmet information needs in the healthcare-access topics, where treatment expectations, provider choice, cost, and insurance emerged repeatedly. In the widest context, these findings position acupuncture-related social media discourse at the intersection of public health communication, patient-centred chronic pain care, and the contemporary dissemination of TCM. They show that Chinese social media is not merely a venue for expressing attitudes toward acupuncture, but also a space where treatment options are compared, symptoms are narrated, healthcare decisions are rehearsed, and TCM concepts are publicly negotiated.

5. Conclusions

This study provides a comprehensive map of the digital discourse surrounding acupuncture for CLBP in China. By analyzing 281,263 comments across four major social media platforms, we identified a multidimensional topic structure where discussions of treatment processes and practical healthcare access often overshadow abstract clinical efficacy. The integration of the EmoAtlas framework revealed that public sentiment is not a monolithic response but is highly differentiated, which ranging from relief-driven trust to skepticism-fueled anger and burden-related sadness.

Several limitations warrant acknowledgment. First, while the dataset is extensive, it primarily represents a younger, digitally active demographic, potentially underrepresenting the elderly population most affected by CLBP. Second, the reliance on textual data excluded the rich multimodal content (images and videos) characteristic of platforms like Xiaohongshu. Finally, the cross-sectional nature of the data precludes drawing causal inferences regarding shifts in public opinion.

These findings suggest that patient-centered care for CLBP should extend beyond clinical outcomes to address practical navigation needs, such as cost transparency, provider selection, and realistic expectation setting for needling sensations. Future research should pursue longitudinal designs to track how discourse evolves in response to new clinical guidelines or public health policies. Additionally, combining social media infoveillance with traditional clinical surveys would provide a more holistic understanding of the patient journey.

Ultimately, this research demonstrates that social media is a vital repository of the lived experience of CLBP publics. For the healthcare community, these digital insights offer a roadmap for improving health communication and the cultural dissemination of TCM in a modern, digital society.

Data availability statement: The original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

Author contributions: TS: Conceptualization, Writing – original draft, Project administration. HD: Conceptualization, Investigation, Funding acquisition. YY: Visualization. LL: Methodology, Writing – review & editing. YZ: Software. JZ: Methodology, Data curation, Writing – review & editing. HD: Validation, Supervision.

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