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Online Health Communities as a Double-Edged Sword: A Systematic Review of Emotional Amplification and Anxiety Feedback in Depression-Oriented Networks

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Abstract: *This paper focuses on the "double-edged sword effect" of the depression community in online health communities represented by Xiaohongshu, assessing its ability to provide positive functions such as emotional support, information sharing, and destigmatization, as well as its potential to amplify negative experiences through emotional reinforcement and anxiety feedback loops. A review of the latest evidence integrating social support network structures, digital narratives and peer support, emotional signals such as music and labels, multimodal and temporal approaches, points out that existing studies are mostly cross-sectional or corpora-dependent, with insufficient causal inference, platform interaction and cultural adaptation. Based on this, it is recommended to combine time series, multimodal sensing, and cross-cultural calibration to test the causal effects of algorithms through longitudinal or natural experiments, and to emphasize the need for ethical governance and human-automation interventions to suppress the risk of emotional amplification while preserving the value of social support.*

Keywords: *Online Health Communities; Depression; Emotional Contagion; Anxiety Feedback; Xiaohongshu*

1. Introduction

With the popularity of Internet social platforms, online health communities (OHCs) have become an important field for public mental health research and intervention. Cyberspace provides lower disclosure costs and anonymity for revealing stigmatizing mental problems, allowing behavioral, emotional and visual cues to be aggregated and analyzed, thus offering unprecedented possibilities for monitoring and intervening in problems such as depression, anxiety and suicidal ideation. The language, visual and emotional indicators contained in social media data can not only be used to build recognition tools based on natural language processing and machine learning, but also provide a new source of information for improving the timeliness of clinical practice and policy-making; At the same time, these methods show significant potential in raising public awareness and achieving early warning, but there are still deficiencies in clinical validation and ethical governance [1]. At the same time, public health emergencies have further highlighted the value of online support systems: Isolation and social restrictions during COVID-19 have significantly increased young people's reliance on online social platforms as emotional outlets and mutual aid networks. Relevant studies have shown significant shifts in the volume and thematic structure of depression-related discussions, suggesting that OHCs serve as a window to observe public psychological states in crisis situations. It also became an important field for alleviating feelings of isolation and providing immediate support [2].

However, viewing social media platforms as a single "positive" resource is clearly oversimplified. Platform diversity and user jumps across different media (platform-swinging) create a complex media-dependent ecosystem, and research shows that the way platforms switch and their respective functionalities imply differences that affect individuals' mental states by altering information access, feedback rhythms, and social comparison mechanisms. This leads to a dynamic association between the nature of media dependence and depressive symptoms [3]. This mechanism suggests that the effects of OHCs are not one-way; Online communities can promote healing by providing emotional support, information sharing, and de-stigmatizing discourse, but they can also reinforce negative emotional expression, create emotional resonance or echo room effects, and even exacerbate anxiety and depression tendencies under the influence of platform design and usage habits.

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Existing literature, while revealing these dual effects, often focuses on macro descriptions or cross-sectional text mining, providing less systematic evidence on causal pathways, platform interactions, and cultural context differences, which is particularly evident in non-Western contexts and text-based communities such as Xiaohongshu. Based on the above review, it is necessary to understand the "double-edged sword effect of online health communities" as a multi-level issue. Based on the above review, it is necessary to understand the "double-edged sword effect of online health communities" as a multi-level issue, as summarized in Table 1.

Table 1: Multi-level Issues of the Double-edged sword effect of Online Health communities

Levels/Features	Positive effects (Mechanisms and examples)	Negative effects (Mechanisms and examples)	Research Gaps
Anonymity and low disclosure costs	Lower the threshold for seeking help; Facilitating the expression of sensitive emotions and promoting early identification (such as language/picture cues can be used for early warning)	Low-cost disclosures may lead to an accumulation of excessive negative expressions, reinforcing negative identity	The causal relationship between anonymity and long-term mental health outcomes needs to be quantified
Language and visual cues converge	Rich data sources can support NLP and visual analysis, enhancing clinical screening and timeliness	It can trigger emotional contagion and reverberation room effects, magnifying negative narratives	The effectiveness and cross-cultural applicability of multimodal (image-text) metrics in the Chinese community need to be verified
Platform features and feedback rhythms (likes, comments, recommendations)	Quick feedback provides immediate support and social recognition, alleviating isolation	Uneven or reinforcing feedback can lead to social comparison, anxiety, and exacerbation of symptoms	There is a lack of systematic experimental research on how platform algorithms and interfaces regulate psychological effects
Platform-swinging	Division of labor among different platforms helps to obtain diverse support (such as an anonymous platform + familiar platform combination)	Switching modes to alter information access and comparison benchmarks may have migratory negative effects	There is a scarcity of research on the long-term effects of platform interactions and usage paths on psychological outcomes
Crisis situations (such as COVID-19)	Become an important emotional outlet and mutual support field in isolation and restriction	A shift in the volume and subject of discussion during a crisis can exacerbate the spread of anxiety	The short-term relief effects and long-term side effects of OHCs under crisis conditions require longitudinal studies

On the one hand, OHCs lower the threshold for seeking help through anonymity and popular disclosure channels and provide rich verbal and visual cues for early identification and intervention; On the other hand, the functional differences and usage strategies of the platform may amplify emotional reinforcement and negative feedback loops, causing the support network to turn to risk sources under specific conditions. Given that existing studies are methodologically focused on descriptive text analysis and pay insufficient attention to platform interaction, long-term effects, and clinical validation, this study intends to use a more refined emotional dynamics and usage pattern analysis in Xiaohongshu, a Chinese community with unique social and expressive styles, to test and expand the above theoretical framework.

2. The positive role of online health communities: Social support and psychological healing mechanisms

In online depression communities, the formation of social support networks is both dependent on individual behavior and shaped by the structural characteristics of the networks. An empirical study based on 1,077 members and nearly 75,000 posts revealed two key structural effects in the formation of information support and emotional support networks through an exponential random graph model (ERGM) : reciprocity and transitivity have a significant positive effect in both types of networks, suggesting that support relationships are more likely to form within groups of nodes that are mutually feedback and locally aggregated rather than randomly distributed [4]. The study further noted that individual engagement metrics contribute differently to different types of support: spending more time online and responding to others significantly promotes the formation of information support relationships;

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In emotional support networks, influence, online time, number of posts, and response behavior are all important positive predictors, while new users have significantly difficulty obtaining emotional support [4]. In addition, the study found a significant "entrainment" effect between the information network and the emotional network, but no direct exchange effect across networks was observed, suggesting that information sharing and emotional comfort are functionally interrelated yet maintain a certain degree of independence [4]. Methodologically, ERGM provides a powerful tool for understanding the macrostructure of support relationships, but it has inherent limitations based on observational data - particularly insufficient characterization of discourse content and support quality, difficulty in determining causal relationships, and samples coming from specific cultural contexts (small online communities in China) 2003-2017 - suggests caution in extrapolating its conclusions to other platforms or time periods. The key structural differences between information support and emotional support networks are summarized in Table 2.

Table 2: Comparison of Structural Characteristics of information Support and emotional support Networks in Online Health Communities (Based on ERGM analysis)

Project	Information Support Network	Emotional support network
Research sample (Source)	1,077 members, nearly 75,000 posts (study population)	1,077 members, nearly 75,000 posts (study population)
Structural effects - reciprocity	Significantly positive: Supporting relationships tend to form in reciprocal reciprocal relationships	Significantly positive: Support relationships tend to form in reciprocal reciprocal relationships
Structural effects - transitivity/triangulation	Significantly positive: Supports more formation within locally aggregated node groups	Significantly positive: Supports more formation within the locally aggregated node group
The main individual participates in the predictor	Online duration ↑ and responses to others ↑ can significantly promote the formation of information support	Influence ↑, online duration ↑, number of posts ↑, and reply behavior ↑ are all positive predictors
Relationships between networks	There is significant "entrainment" with the emotional network.	There is a significant "entrainment" with information networks.
Methodology and extrapolation limitations	Based on observational data, it is difficult to characterize discourse content and support quality; Samples come from specific cultures and time periods	Same as left

At the mechanistic level, digital narratives and peer support are seen as an important path for online communities to provide psychological healing. Research on the hybrid approach to postpartum depression shows that online groups can both deliver emotional support and serve as carriers of information education through narrative practice, thereby promoting knowledge acquisition and emotional empathy [5].

Qualitative research interviews with peer volunteers as providers further emphasize the bidirectional healing effect of "being there" : Volunteers who provided support gained a sense of meaning and rehabilitation experience through self-narration and reflection, while frequent interaction, resource sharing and self-disclosure helped build trust with new members and maintain support relationships [6]. These studies collectively suggest that peers build emotional connections and information pathways through shared experiences and visibility, which in turn lead to symptom relief and cognitive reconstruction for members. However, the existing evidence is mostly from specific populations (such as postpartum mothers) or mainly qualitative/mixed methods, and there is still a lack of longitudinal validation of large samples on how narrative works at different stages of psychological illness and the quantitative association between narrative content quality and long-term psychological outcomes.

In response to the demand for scale, intelligent assistive tools have been proposed as supplementary support. In the case of general chatbot architectures based on neural networks, studies have shown that such systems can go beyond the limitations of traditional rule-driven conversations, demonstrate potential in responding to diverse inputs and providing individual emotional support, and have been helpful to individuals seeking help in field experiments [7]. However, such tools still need to be positioned as a complement rather than a replacement for human peer support: first, the community-level impact (including possible spillover effects on the engagement of other users or community norms) has not been fully quantified; Secondly, automated responses face challenges in terms of depth of empathy, contextual sensitivity, and ethical compliance (such as privacy and misleading advice) [7]. Therefore, future designs should aim to promote response behavior and reciprocal mechanisms, combining novices friendly guidance, peer volunteer training, and transparent boundaries of the dialogue system to balance scale accessibility and support quality, thereby more effectively leveraging the positive role of online health communities in emotional support and psychotherapy.

3. The Complexity of Depression online communities: Emotional Expression, risk identification and potential harm

Emotional expression in depression online communities largely presents a map closely related to musical choices and lyric preferences: the interweaving of textual meaning and vocal traits makes certain content not only reflect emotional states but also potentially reinforce existing negative emotions. Based on natural language processing analysis of online listening records and lyrics, the study found that people at risk of depression tend to choose lyrics and tracks with low valence and low arousal, and prefer themes such as denial, self-reference, and ambivalence. These characteristics are semantically consistent with negative self-focus and emotional maintenance mechanisms [8]. Further quantitative studies added that this group of users had a particular preference for the amount of information in lyrics: when classified as "sad" songs, lyrics preferred by the at-risk group tended to be more informative (i.e., less compressible) and showed greater absolute variability in information content over time series [9]. These findings suggest that music lyrics may act as a passive mapping signal of emotional states, or they may work together with semantically rich information and repetitive listening behavior patterns to maintain emotions. However, it is necessary to be vigilant that the existing evidence is mostly correlation analysis, and sample sources (such as Last.fm) and measurement strategies have selective biases against platform culture and user groups. As a result, inferences about causal pathways remain insufficient.

From the perspective of social metadata and behavioral trajectories, the static and dynamic patterns of online tagging systems and listening behavior further enrich the understanding of the complexity of emotional expression. Research that focused on social tags suggests that users at risk of depression are more often associated with tags expressing "sadness" as well as specific genres such as dream-pop and neo-psychedelic, characterizing an emotion-genre coupled cultural ecosystem [10]. Meanwhile, time-varying analyses of the acoustic and emotional characteristics of listening history revealed that the listening behavior of high-risk individuals showed higher repetitiveness and resilience - a preference for a "fixed" consumption pattern of sad music, which reinforces the emotional stability in the low arousal and low price range [11]. The work highlights the importance of combining static preferences with temporal dynamics, but also exposes several methodological limitations, such as the semantic noise of social labels, the transferability of genres and cultural contexts, and the uncertainty of the match between acoustic/textual features and actual subjective experiences.

When applying these signals to research on risk identification and intervention, there are both technical and ethical challenges. Recent work has attempted to enhance transparency and interpretability in social media mental state detection by combining interpretable models with large language models, emphasizing the need to generate user-oriented or clinicer-readable explanations for responsible interventions while providing model determinations [12]. Meanwhile, the scarcity of data and the difficulty of annotation have prompted researchers to use text data augmentation to improve classifier performance, but synthetic or transformed generated data may introduce biases or mask population differences while improving performance, and ethical review and privacy protection remain unavoidable issues [13]. If technological advancements do not go hand in hand with cross-platform validation, sensitivity to cultural differences, and strict ethical frameworks, they can easily lead to abuse risks or misjudgments, especially in scenarios where intervention recommendations may directly affect individual behavior.

Ethnographic studies of peer support and content dissemination mechanisms remind us that online communities can offer understanding and mutual assistance, but they can also amplify risks through emotional reinforcement, anxiety feedback loops, and even the spread of self-harming behaviors. Empirical observations show that young people seeking or sharing self-harm content often turn to platforms for understanding in situations where offline support is scarce; In this process, peer-to-peer empathy and advice constitute the main pattern of interaction, but these interactions sometimes restate victim identity, regulate self-harm narratives, or unintentionally spread harmful techniques, resulting in complex negative consequences [14]. Combining this perspective with the study of music/tagging/listening dynamics, one can imagine a feedback path where algorithms or peer recommendations prompt users to repeatedly engage with lyrics and tracks that align with their negative emotions, emotions are continuously activated and reconcretized in the community discourse, thus forming reinforcement loops; However, this mechanism is not a single "imitative dissemination" process; it involves more of the interaction of seeking identity, emotional regulation strategy imbalance, and

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platform governance measures.

Therefore, for empirical studies on image-text and short-video intensive platforms represented by Xiaohongshu, it is necessary to integrate multimodal signaling, time series analysis and social network analysis in methodology, and avoid simple content deletion policies in intervention design, and prioritize the development of interpretable, culturally adapted and protective intervention strategies for users.

4. Conclusions and Prospects for Future Studies

A review of the full text's discussion on online health communities reveals that depression online communities offer both rare emotional support and information resources for seekers, as well as the risk of amplifying individual negative experiences through emotional reinforcement and anxiety feedback. Empathetic responses, experience sharing and immediate interaction within the community help to reduce stigma, enhance self-efficacy and improve willingness to seek professional help, yet these positive effects often coexist with the group spread of negative emotions: Repeated narration of similar experiences, empathetic retelling, and excessive focus on symptom details may unintentionally reconstruct and reinforce stigma and helplessness, creating a "feedback loop" that perpetuates or worsens anxiety and depression symptoms. This tension is particularly evident on platforms represented by Xiaohongshu, whose media form centered on image and lifestyle presentation, influencer-driven content ecosystem, and recommendation algorithm preference for highly interactive content not only increase visibility and the immediacy of social support, but also amplify the probability of exposure to anxiety-related content. This makes the mechanism of emotional reinforcement and anxiety feedback more likely to be activated. Based on the above theoretical and empirical identification, future research should make targeted adjustments in methodology and problem setting. First, emotional analysis needs to be expanded from a single positive and negative polarity to a multi-dimensional emotional spectrum, identifying the time series and intertransformation paths of specific emotions such as anxiety, despair, and shame, and combining network dissemination analysis to identify the "source" and "amplification node" of emotions. An overview of these future research directions and key implementation paths is provided in Table 3.

Table 3: Overview of Future Research Directions and Key Implementation Paths

Research Directions	Key issues/Objectives	Recommend methods or designs	Expected output/considerations
Emotion Spectrum and propagation analysis	Expand sentiment analysis from positive and negative polarities to dimensions such as anxiety, despair, and shame; Identify the "source" and "amplification node" of emotions	Multidimensional emotion coding, Time series emotion tracking, network propagation analysis (Node influence and propagation path identification)	Identify the diffusion paths and key amplifiers of various negative emotions to guide directed intervention
Longitudinal and causal inference design	Distinguish the causal direction of selective exposure from that of emotion propagation; Evaluate the causal effects of algorithmic or layout changes	Panel data, differences - in differences (DiD), natural experiments (such as platform policy changes), and instrumental variables	Get stronger causal evidence and reduce bias in cross-sectional studies
Multimodal and platform characteristics drivers	Capture the impact of images/short videos/interactions on emotional expression and social comparison; Control platform drivers	Multimodal feature engineering and fusion models for text + image + video; Add platform metrics (recommendation intensity, creation motivation) as covariates	More accurately reflect the emotional dynamics of image-based platforms like Xiaohongshu and avoid text-only bias
Intervention design and effect evaluation	Reduce emotional amplification while preserving social support; Test the effects of different presentation strategies	A/B tests (information presentation, emotion buffer prompts), mixed human + automated high-risk screening, randomized intervention trials	Evaluate which presentation/feedback mechanisms can reduce symptom persistence without weakening empathetic support
Ethics, governance, and interdisciplinary collaboration	Data privacy, informed consent, automated labeling, and suicide risk management	Establish division of responsibilities and emergency processes; Introduce ethical reviews, human oversight, and clinical and social science experts to design together	Ensure the ethical acceptability and clinical safety of research and interventions

Secondly, longitudinal and causal inference design is indispensable: cross-sectional associations cannot distinguish the causal directions of selective exposure and emotional contagion. Therefore, panel data, difference-in-difference, or natural experiments using platform policy changes should be adopted more often to estimate the causal impact of algorithmic recommendations or layout adjustments on emotional trajectories. At the same time, text analysis must be combined with multimodal information (images, short videos, comment interactions) to capture the impact of non-textual cues on emotional

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expression and social comparison on Xiaohongshu, and potential confounding factors such as user characteristics, helt-seeking intentions, and community norms must be strictly controlled in the model to reduce estimation bias.

In terms of intervention design, the research should go beyond the superficial goal of "whether negative content can be reduced" and shift to constructing micro mechanisms that can simultaneously preserve social support values and reduce emotional amplification. Feasible approaches include evaluating the effectiveness of different information presentation methods (such as highlighting rehabilitation experiences rather than symptom details, setting up emotion buffer prompts) through A/B testing, developing a hybrid human + automated screening system that can identify high-risk interactions and trigger timely guidance or professional feedback, and testing psychological educational content and peer mutual guidance in suppressing anxiety feedback and facilitating help referrals The relative efficacy. It is worth emphasizing that the platform's unique economic incentives and content creation ecosystem, such as influencer monetization and brand collaboration, can change the structure and visibility of user narratives. Therefore, any intervention strategy must take into account changes to the platform's algorithmic incentive structure and its external effects while retaining user autonomy and freedom of expression.

At the same time, ethical and governance issues must be incorporated into the agendas of academic research and practical transformation in parallel. Data privacy, informed consent, the risk of labeling due to misjudgment in automated classification, and suicide risk management that may be involved in interventions all require researchers and platforms and clinical service providers to establish clear divisions of responsibility and emergency procedures. Interdisciplinary collaboration is particularly important: computational methods need to be combined with professional judgments in psychology, sociology, and public health to ensure the cultural fit and clinical effectiveness of emotion recognition and intervention. In addition, research reports should transparently disclose potential harms and limitations, and incorporate human oversight and follow-up in the design to assess long-term consequences.

To drive the accumulation in the field, several actionable research questions and test hypotheses can be specifically proposed: for example, whether the intensity of platform recommendations significantly increases the frequency of individuals' exposure to high-anxiety content and through this pathway improves self-reported levels of depression or anxiety; Heterogeneity in inducing social comparison and emotion transfer among different presentation formats (image-dominated vs. text-dominated); And whether interventions led by "rehabilitation narratives" can reduce the risk of symptom persistence without weakening empathetic support. To achieve these goals, it is necessary to integrate refined emotional coding, causal identification strategies, and ethically acceptable experimental designs into long-term observations of platforms such as Xiaohongshu to form a comprehensive evidence base that focuses on both individual disease trajectories and community ecology.

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