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ARTICLE

Effect of Online Social Networking on Emotional Status and Its Interaction with Offline Reality during the Early Stage of the COVID-19 Pandemic in China

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ABSTRACT

Background: During the early stages of the COVID-19 pandemic in China, social interactions shifted to online spaces due to lockdowns and social distancing measures. As a result, the impact of online social networking on users' emotional status has become stronger than ever. This study examines the association between online social networking and Internet users' emotional status and how offline reality affects this relationship. **Methods:** The study utilizes cross-sectional online survey data (n = 3004) and Baidu Migration big data from the first 3 months of the pandemic. Two dimensions of online networking are measured: social support and information sources. **Results:** First, individuals' online social support ($\beta = 0.16$, $p < 0.05$) and information sources ($\beta = 0.08$, $p < 0.01$) are both positively associated to their emotional status during the epidemic. Second, these positive associations are moderated by social status and provincial pandemic control interventions. With regards to the moderation effect of social status, the constructive impact of information sources on emotional well-being is more pronounced among individuals from vulnerable groups compared to those who are not. With regard to the moderation effect of provincial interventions, online social support has the potential to alleviate the adverse repercussions of high rates of confirmed COVID-19 cases and strict lockdown measures while simultaneously augmenting the favorable effects of recovery. **Conclusion:** The various dimensions of social networking exert distinct effects on emotional status through diverse mechanisms, all of which must be taken into account when designing and adapting pandemic-control interventions.

KEYWORDS

COVID-19; emotional status; online social networking; social support; information sources

Introduction

The outbreak of the COVID-19 pandemic had a marked impact on the emotional status of people all over the world. To contain the spread of the virus, many countries implemented public health measures such as social distancing, mobility restrictions, case isolation, and non-essential business closures [1]. These interventions created different levels of economic burden, unemployment risk, travel restrictions, and social isolation for residents [2]. Social isolation and loneliness have negative effects on individuals' mental health, life satisfaction, and subjective well-being [3,4]. In the early stage of the pandemic, Chinese residents suffered from depression, anxiety, and other psychological problems. Further, more severe outbreaks were associated with more severe symptoms [5,6].

In this context, online social networking became an important way to maintain social contact and combat social isolation. For elderly people living alone in China, the use of WeChat and other apps for online social networking during the COVID-19 pandemic helped to increase social connections between generations and to improve their subjective well-being [7]. Professionals also provided psychological counseling services to those quarantined at home through WeChat groups and other platforms to support their mental health [8]. However, studies on the effects of social media use on individuals' mental health during COVID-19 had mixed results. While some studies have shown that WeChat use can regulate the negative impact of social isolation on individuals' mental health and life satisfaction [9], others have shown that in the early periods of the pandemic in 2020, the prevalence of Internet addiction rose to 24.4% among Taiwan junior high school students [10]. Researchers from Brazil found that social media use can have both positive and negative effects on individuals' well-being [11].

This study aims to contribute to existing research both theoretically and methodologically. At the theoretical level, prior research findings on the relationship between online social networking and emotional status have been inconsistent. Limited attention has been paid to macro-level factors or the interplay between online and offline interactions. By integrating social capital theory and the network society, we aim to analyze how social networking serves as a resource for risk management in this study. At the methodological level, we place the impact of online social networking on emotional status in the context of COVID-19. Our research aims to investigate the influence of online social networking on emotional status while also examining how this effect is moderated by individual social status and provincial interventions. Additionally, we combine data from individual-level surveys and provincial-level online big data to generate new insights in this field.

Two dimensions of online social networking

Based on the characteristics and functions of social capital, Putnam distinguished between bonding social capital and bridging social capital [12]. Bonding social capital is generated in dense networks within a group, community, or organization. Its main function is to provide emotional support for individuals. Bridging social capital is generated from a sparse network that crosses group boundaries and connects many individuals with different statuses and attributes. It provides members with heterogeneous information [13]. Similarly, scholars have divided online social networking into two basic types. The first is online social support. Offline interpersonal connections are enhanced through the internet, and comfortable communication with close acquaintances is maintained online. Online social support provides companionship and alleviates loneliness [14]. The second type is online information sources, which involve extensive network communication in online spaces such as virtual communities and social media platforms. Their main function is to obtain and extend heterogeneous information resources [15].

The effect of online social networking on emotional status

Regarding online social support, relationships that offer social support are often marked by depth, mutual benefit, and a strong sense of mindfulness [16]. Typically, family members and close friends constitute the most essential components of an individual's core social network. These types of connections tend to foster communication, promote harmony, and reinforce cohesiveness within a group. Data analyses from numerous countries and regions have consistently demonstrated that more formal and informal connections tend to make people healthier and happier [17]. Besides, dense social networks can help individuals regulate their emotions, cope with stress, and maintain mental resilience during difficult situations [18]. Nonetheless, it is important to investigate whether the emotional impact of online social support during COVID-19 quarantine may differ from the conclusions drawn from studies on offline social support.

Regarding online information sources, during public health crises, the richness and heterogeneity of the online information to which individuals have access can significantly impact their emotional status. Efficient information transfer is a crucial element of risk management during such times. Studies conducted during the pandemic found that the clearer the subjects' understanding of the main symptoms and the progress of COVID-19, the smaller the fluctuations in their physical and mental health status [19]. Other studies on Chinese Internet users also found that high heterogeneity in information sources during the pandemic made it easier for people to maintain their health and positive emotional status [20]. We intend to test these conclusions by focusing on the effect of online information sources on emotional status during the quarantine in China.

The moderating effect of offline factors

(1) Micro level: Social status

The ability to deal with, avoid, and compensate for risks in the face of a pandemic is unequally distributed among different groups [21]. An individual's online social behavior happens in the digital space, where physical subjects are absent. However, the behavioral characteristics, patterns, and psychological effects of online behavior are still shaped by the individual's social status in the offline space [22]. Access to the Internet and how the Internet is used are affected by social status, personality, abilities, and other factors in the offline space [23,24]. Thus, how the use of social media affects emotional status might be moderated by an individual's social status [25].

(2) Macro level: Risk management

The positive effect of social capital on individuals' response to COVID-19 is shaped by community-level factors and macro-level institutional factors [26]. Social networking has an impact on emotional status through its interaction with risk management. For instance, individuals who perceive others as non-compliant with control measures or view government actions as ineffective are more likely to display poor mental health; conversely, those who perceive that the government has taken decisive action tend to have better mental health [27]. China's epidemic prevention and control measures are issued directly by provincial governments under a unified policy framework provided by the central government. Therefore, the pandemic control practices of the provincial governments may affect individuals' emotional status during a pandemic. We will focus on three aspects of risk management practice.

The first is the relative difficulty of risk management, which is measured by the population inflow into the local area before a lockdown. During the early stages of the pandemic, provinces with high inter-provincial population inflow from Wuhan faced stricter prevention and control measures. This influx of people from areas with high rates of infection not only directly impacted residents' emotional status but also perpetuated anxiety through continuous sharing of this information in both online and offline interactions.

The second research focus is the effect of provincial governments' risk management, which can be measured by the cumulative number of confirmed cases in each province. In public health, the number of confirmed cases has been widely used to evaluate the effectiveness of prevention and control measures [28,29]. The effectiveness of prevention and control measures determines the public's understanding, acceptance, and confidence in these measures, as well as their attitude toward future epidemic control measures. It also directly affects their attitude toward future epidemic control measures.

The third research focus is recovery from the pandemic, which can be measured by the relaxation of mobility restrictions once the pandemic was under control. After the pandemic was brought under control, most citizens wished to return to work as soon as possible due to economic pressure [30]. During that time, whether the provincial governments could timely adjust interventions and facilitate the orderly resumption of work proved crucial in reestablishing normalcy and shaping residents' positive attitudes. Consequently, risk management practices at the provincial level might have moderated the impact of online social networking on individuals' emotional status.

To gain a detailed understanding of the correlation between online social networking and emotional status, this study has integrated survey data with provincial-level online big data during the early stages of COVID-19 to address three objectives. Firstly, we examine the relationship between online social networking from two dimensions: online social support and online information sources. Secondly, we investigate how the relationship between online social networking and emotional status is moderated by individuals' social status. Thirdly, we will investigate the moderating effect of provincial interventions on this relationship. Therefore, we propose the following hypothesis. Since online social networking has two dimensions, each hypothesis can be refined as two sub-hypotheses as below:

Hypothesis 1: Online social networking is positively related to users' emotional status.

Hypothesis 1.1: The more online social support an individual receives in the context of pandemic isolation, the more positive their emotional status.

Hypothesis 1.2: The more variety in individuals' online information sources, the more positive their emotional status.

Hypothesis 2: The influence of online social networking on emotional status is moderated by social status.

Hypothesis 2.1: The influence of online social support on emotional status is moderated by social status.

Hypothesis 2.2: The influence of online information sources on emotional status is moderated by social status.

Hypothesis 3: The influence of online social networking on emotional status is moderated by provincial risk management practices.

Hypothesis 3.1: The effect of online social support on emotional status is moderated by provincial risk management practices.

Hypothesis 3.2: The effect of online information sources on emotional status is moderated by provincial risk management practices.

Materials and Methods

Participants and research design

We integrated individual level survey data and provincial level online big data to to conduct our analysis.

1) Individual level: WeChat users online survey

This part of study adopted a cross-sectional research design. In 2020, the number of monthly active users of WeChat reached 1.225 billion [31]. Due to its large user base and the boom in social media usage during the COVID-19 pandemic, many researchers have used data collected from WeChat in behavioral and psychological studies, particularly studies of changes during the COVID-19 pandemic [32]. At the onset of the epidemic, stringent physical distancing measures were enforced nationwide, rendering online surveys almost the only option. We designed a short questionnaire including seven sections: A. Infected respondents or infected acquaintances of respondents; B. Behaviors during the quarantine; C. Social networking during the quarantine; D. Physical and mental health during the quarantine; E. Difficulties and solutions; F. Personal information. We conducted a pilot study with a sample size of 50 and the average survey time was 8 min. After modifications, 60 survey questions were included in the final questionnaire.

We carried out an online survey based on the WeChat sample bank through the data collecting platform named Researcher. The survey was posted online on April 23 and 24, 2020, and the respondents received and completed the questionnaire through the WeChat app on their mobile phones. The data collection platform randomly sampled 30,000 active WeChat users from the Chinese user base, encompassing both urban and rural areas across 31 provinces and over 300 cities. The average age of the users in the sample pool is 30, and they have relatively high levels of education, relatively stable incomes, and are mainly white-collar workers. The survey was completed by 8,019 respondents. To improve the quality of the online survey, three detectors were embedded among survey questions aimed to screen out programs coded to automatically complete questionnaires, multiple entries of a same respondent, and irresponsible answers that were intended to collect a payment for a completed questionnaire. As a result, responses that were careless, incomplete, or repetitive, and automatically completed questionnaires were excluded.

Following the screening process, a final sample of 3,004 valid questionnaires was obtained from all provinces in China.

2) Provincial level: Online big data and provincial statistics

This part of study utilized a multilevel research design, incorporating online big data from different sources and survey data. Online big data sets have become increasingly popular in computational social science research due to their immediacy, continuity, authenticity, and large scale. Besides, they can provide objective records independent of subjective reports [24,33]. The online data used in this study was primarily obtained from two sources:

(1) Baidu Migration data. The population flow data used in this research were drawn from the Baidu Migration data set (https://qianxi.baidu.com/#/). Baidu Migration acquires location data of smartphones in real-time through mobile phone base stations and other devices, anonymously processes the data on an individual level, and calculates overall indicators of daily population flow in different regions. This method accurately reflects the population flow between and within provinces and cities in real-time. To obtain the Baidu Migration data, the authors wrote a crawler program based on the open-source crawler framework Scrapy using Python 3.7. The result was a web-scraping program specifically targeting the Baidu Migration platform. The code used for this is provided in the Appendix. During August to September 2020, the Migration data of more than 300 cities in China in the three months before and after the 2019–2020 Spring Festival was captured from the website. Using the Migration data from the same period in 2019 as a baseline, changes in population flow caused by the COVID-19 pandemic in 2020 were calculated. The daily inter-city population flow data and within-city movement index were then measured to gauge the population inflow from epidemic areas and reflect the strength of the lock-downs in various provinces.

(2) Confirmed cases data. The data on the number of confirmed cases is publicly available and released by the Chinese Center for Disease Control and Prevention. This ensures the accuracy of the data and facilitates comparison with related studies.

Measures

1) Dependent variables

In the WeChat survey, respondents were asked how often they experienced different emotional status, including optimism, calmness, anxiety, and fear. Each state of mind was measured using a 4-point scale with reverse coding for anxiety and fear. Next, we constructed a factor score using principal component factor analysis. The values ranged from 1 to 10, where higher scores represented a more positive emotional status. The Cronbach's α was above 0.8, indicating high validity of this measurement.

2) Independent variables

(1) Online social networking. Online social networking can be divided into two dimensions: online social support and online information sources. To measure online social support, the respondents were asked "Has your online communication with relatives, friends, and acquaintances increased since the beginning of the pandemic?" The survey question used a 4-point scale (0 = "never," 1 = "decrease," 2 = "constant," and 3 = "increase"). To construct a binary variable, "never," "decrease," and "constant" were coded as 0, indicating no increase, and "increase" was coded as 1. For online information sources, the questionnaire asked the respondents about their "sources of information related to the COVID-19," including WeChat, Weibo, news portals, Douyin, Billibilli and other video platforms, and TV broadcasting. This variable was a count variable with answers ranging from 0 to 5; a larger value indicated access to more information channels.

(2) Cumulative confirmed cases. This variable was derived from online data released by CDC. It represented the daily cumulative number of confirmed cases in each province. The cumulative number of confirmed cases in each province on April 23, the date of the survey, was used to represent the severity of the pandemic in the province during the study period.

(3) Population inflow from the epidemic area: This variable was derived from Baidu Migration's online data. As inter-provincial movement of populations from areas with outbreaks was strictly restricted after the Wuhan lockdown on January 23, 2020, this indicator was measured as the percentage of the population flowing into the focal province from Wuhan on January 22. This variable depicted varying levels of difficulty in epidemic prevention and control caused by the geographical location of each province.

(4) Post-pandemic recovery: The population flow index within each province on March 17th was used to measure post-pandemic recovery. March 17th marked the end of the third phase (see Fig. 1 for the division of phases). This date marked the point when the pandemic was initially under control. The population flow index measured the relaxation of lock-downs and the extent to which social life had returned to normal in each province.

3) Control variables

We controlled for two dimensions of social status. The first consisted of demographic characteristics, such as gender and age. To ensure a balanced gender ratio, we set a gender quota during the online survey. Respondents ranged in age from 16 to 84 years old with an average age of 29. To control for the nonlinear effect of age, we also added the square term of age as a control variable. The second set of control variables consisted of social status characteristics, such as education level, occupation type, and family income. In terms of education level, 78% of the WeChat sample had obtained or were in the process of obtaining a bachelor's or junior college degree, while 22% had a high school or lower degree. The majority had middle-class occupations; employers and white-collar workers accounted for 11% and 40%, respectively, and blue-collar workers accounted for 32% of the sample. Economic status was measured by annual household income. In the analysis of moderating effects of social status, annual household income was treated as a categorical variable to eliminate the influence of skewed distribution. Following the calculation methods proposed by

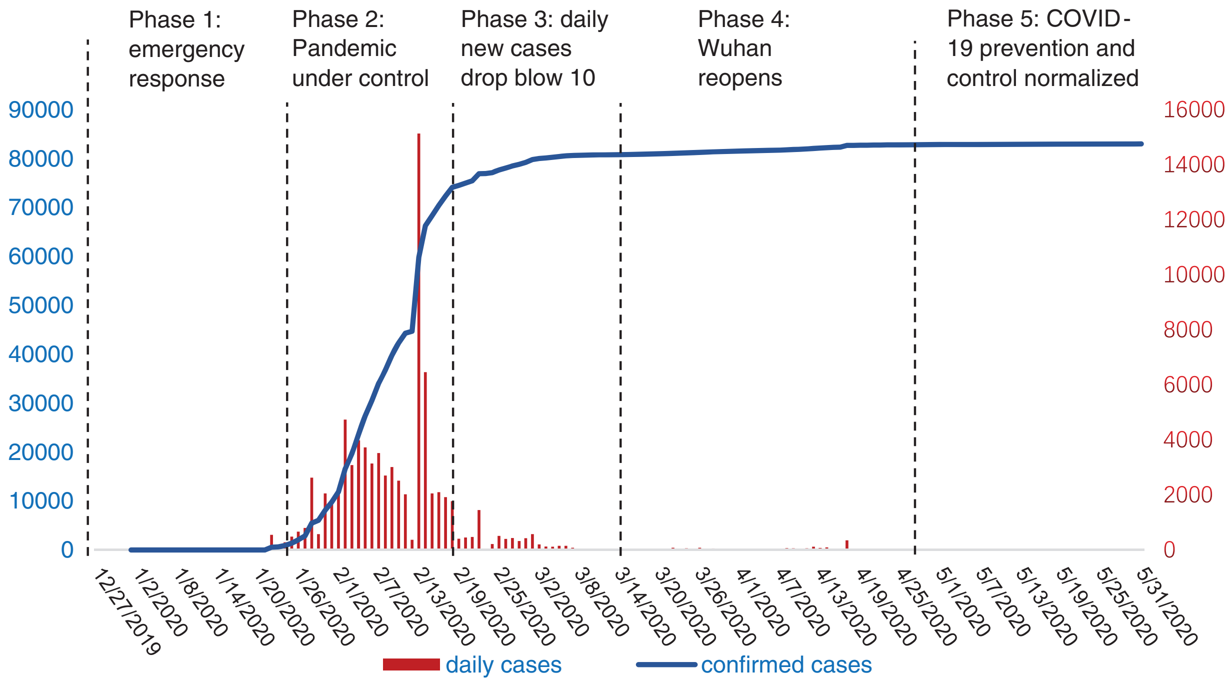

FIGURE 1. Confirmed cases during different phases of the COVID-19 pandemic.

Li et al. [34], people with annual household incomes of less than 88,300 yuan in 2020 were assigned to the low-income group, while those with annual household incomes of more than 300,000 yuan were assigned to the high-income group. We also included a control variable that measured the frequency of going out. The questionnaire asked "How frequently did you go out to parties with others, for shopping or for volunteering or community service, or other outdoor activities during the pandemic?" We calculated a principal component factor score for these "going out" variables, and the values ranged from 1 to 100, where a higher value indicated a higher frequency of going out. Descriptive statistics of these variables are shown in Table 1.

Data analysis and models

In our study, we used Stata version 17.0 to conduct statistical analyses. First, we integrated online big data at the provincial level with survey data at the individual level. The two datasets were linked based on the locations reported by participants in the survey. This integration of datasets facilitated a comprehensive analysis of the research subject. Next, we employed OLS regression to investigate the impact of online social networking on emotional status and determine whether there was an interaction between online social networking and social status.

Furthermore, we adopted a multilevel model to analyze the relationships between provincial-level and individual-level variables. Both the intercept and slope were expressed as functions of the provincial-level independent variables. The model assumes that the intercepts and slopes at the individual level are random and affected by some independent variables at the provincial level. x'_j in Eqs. (2) and (3) represents the provincial-level independent variables in the jth province, which affect the slope of the individual-level independent variable x_{ij} and the intercept in Eq. (1). $\bar{x}_j$ is the mean of the individual-level independent variable x_{ij} in the jth province.

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{ij} + \varepsilon_{ij} \tag{1}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}x'_j + \gamma_{02}\bar{x}_j + \mu_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}x'_j + \gamma_{12}\bar{x}_j + \mu_{1j} \tag{3}$$

Results

Effect of online social networking

OLS regression was used to analyze the effect of online social networking on emotional status. As shown in Table 2, the two dimensions of online social networking, online social support and online information sources, are positively and significantly related to emotional status. The standardized regression coefficients (B) indicates that after eliminating the influence of value range, the coefficient of online social support is larger than that of online information sources. In other words, individuals' online social support during the pandemic had a greater effect on emotional status than online information sources. Among the control variables, going out had a significant negative impact on emotional status. During the pandemic, quarantine and mobility restrictions were widely implemented across the country. People who had to go out for any reason faced a much higher risk of infection than others, leading them to feel more insecure and anxious. Males had a more positive

TABLE 1

Descriptive statistics of the variables

	N	Means/ Percent	SD	Min	Max
Dependent variable					
Emotional status	2,983	7.48	1.84	1	10
Independent variable					
Online social support	3,003	0.63	0.48	0	3
Online information sources	3,004	3.33	1.18	0	5
Control variables					
Going out	3,004	30.30	19.73	1	100
Age	3,003	29.12	7.73	16	84
Square of age/ 100	3,003	9.08	5.52	2.56	70.56
Gender	3,003	50%	0.5	0 = female	1 = male
Household income (Logarithm)	3,003	2.46	1.19	−13.82	8.70
Household income low	609	20.28%			
Medium	2,000	66.60%			
High	394	13.12%			
Education high school and below	657	21.87%			
College	2,135	71.07%			
Masters and above	211	7.02%			
Occupation self-employed	327	10.89%			
White collar	1,154	38.42%			
Blue collar	959	31.92%			
Jobless	563	18.74%			
Confirmed cases (Logarithmic)	31	5.28	1.81	0.69	11.12
Inflow population	31	2.39	13.49	0	94.23
Recover	31	0.99	1.20	0	4.71

emotional status than females. The unemployed group, who faced greater pressure during the pandemic, had a more negative emotional status than the employed.

Interaction between online social networking and social status
To investigate group differences in the effect of online social networking on emotional status, we included interactions

TABLE 2

Effect of online networking on emotional status (n = 2,983)

Variables	B	se	t	*p*	LLCI	ULCI
Online social support	0.16*	0.07	2.30	0.02	0.02	0.30
Online information sources	0.08**	0.03	2.65	0.01	0.02	0.13
Going out	−0.01***	0.00	−5.28	0.00	−0.01	−0.01
Gender	0.15*	0.07	2.13	0.03	0.01	0.28
Age	0.03	0.02	1.19	0.23	−0.02	0.07
Age^2/100	−0.03	0.03	−1.04	0.30	−0.09	0.03
Education 2. College	0.14	0.09	1.58	0.11	−0.03	0.31
3. Masters	−0.07	0.15	−0.45	0.65	−0.37	0.23
Occupation 1. Self-employed	0.01	0.12	0.06	0.95	−0.23	0.24
3. Blue collar	0.01	0.09	0.13	0.90	−0.16	0.18
4. Jobless	−0.35**	0.12	−3.03	0.00	−0.58	−0.13
Household income (Logarithm)	−0.03	0.03	−0.95	0.35	−0.09	0.03
Weight	5.69	4.11	1.39	0.17	−2.36	13.74

Note: Standard errors in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

TABLE 3

Interaction between online social networking and social status (n = 2,983)

Variables	B	se	t	*p*	LLCI	ULCI
Online social support × no college	0.31	0.167	2.79	0.005	0.02	0.14
Online social support × self employed	0.24	0.24	1.02	0.307	−0.22	0.70
Online social support × blue collar	0.21	0.17	0.47	0.636	−0.25	0.41
Online social support × jobless	0.08	0.20	1.09	0.275	−0.17	0.60
Online social support × high income	−0.30	0.17	−1.75	0.081	−0.64	0.04
Online social support × low income	0.13	0.21	0.61	0.544	−0.29	0.54
Information sources × no college	0.25***	0.07	3.83	0.00	0.12	0.38

(Continued)

Table 3 (continued)

Variables	B	se	t	p	LLCI	ULCI
Information sources × self employed	0.25**	0.09	2.73	0.01	0.07	0.44
Information sources × blue collar	0.14*	0.07	1.99	0.05	0.00	0.27
Information sources × jobless	0.41***	0.08	5.16	0.00	0.25	0.56
Information sources × high income	0.03	0.09	0.39	0.70	−0.14	0.20
Information sources × low income	0.22**	0.07	3.09	0.00	0.08	0.35

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

TABLE 4

Interaction between online social networking and provincial factors (n = 2,983)

Variables	B	se	t	p	LLCI	ULCI
Online social support	0.16*	0.07	2.33	0.02	0.03	0.30
Information sources	0.08**	0.03	2.83	0.01	0.02	0.14
ConfIrmed cases	−0.08***	0.02	−4.01	0.00	−0.12	−0.04
Population inflow	−0.51***	0.15	16.59	0.00	6.17	7.82
Recovery	0.02*	0.07	2.55	0.01	0.04	0.32
Online social support × confirmed cases	−0.17***	0.04	−4.57	0.00	−0.24	−0.10
Online social support × population inflow	−1.09***	0.28	−3.87	0.00	−1.65	−0.54
Online social support × recovery	0.52***	0.13	3.91	0.00	0.26	0.78
Information sources × confirmed cases	−0.02	0.02	−0.88	0.38	−0.05	0.02
Information sources × population inflow	−0.04	0.14	−0.27	0.79	−0.32	0.24
Information sources × recovery	0.09	0.05	1.77	0.07	−0.01	0.20

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

with three status variables: occupation type, education level, and family income, based on the OLS model (see Table 3). Occupation type was coded as a four-category variable (self-employed, white-collar, blue-collar, and unemployed). Education level was a binary variable, where 1 represented not having attended university and 0 represented having attended university (including junior college). Household income was a three-category variable.

As shown in Table 3, there is no significant moderation effect of education, occupation, or income on the relationship between online social support and emotional status. This means there were no class differences in the effect of emotional support on positive attitudes during the quarantine. However, the interaction terms between online information sources and the three status variables are significantly positive. This indicates that the positive influence of online information sources on emotional status was stronger for lower occupational status, lower-educated, and low-income groups. There is clearly an interaction between online information sources and individual social status.

Interaction between online social networking and risk management

In Table 4, we tested the influence of provincial-level factors and their interactions with online social networking. The provincial-level independent variables included cumulative confirmed cases, population inflow from epidemic areas, and post-pandemic recovery. Since sample sizes varied between provinces, the average emotional status for each province might have been affected by different sample sizes. To reduce the influence of unbalanced samples from different provinces, a weight was calculated based on the ratio of sample size to the population size in each province. The population weight of each province was then controlled in the multilevel models.

Due to space limitations, we only present coefficients for the main independent variables and interaction terms in Table 4. However, readers interested in obtaining complete results may request them from the authors.

As shown in Table 4, confirmed cases in each province had a significant negative impact (B = −0.08, p-value < 0.001) on the emotional status of Internet users in the province. Inflows of people from Wuhan had a significant negative impact (B = −0.51, p-value < 0.001) on the emotional status of residents in each province. Specifically, the large influx of people from Wuhan created anxiety and fear among the local population. On the other hand, post-pandemic recovery efforts had a significant positive effect (B = 0.02, p-value: 0.01) on individuals' emotional status across all provinces. This suggests that normalization of travel within provinces has contributed to increased positivity among people.

The significantly negative interaction term between social support and confirmed cases indicates that social support amplified the negative impact of confirmed cases on emotional status. In the early phases of the pandemic, online communication between acquaintances functioned as an amplifier, as people reinforced each other's anxiety and fear of infection. Likewise, the significantly negative interaction of online social support and population inflow indicates that online networking between acquaintances amplified the negative impact of population inflows from Wuhan on emotional status. The significantly positive interaction between online social support and recovery indicates that online social support enhanced the positive impact of post-pandemic recovery on emotional status.

The interactions between online information sources and provincial factors show that none of the interaction terms are significant. That is, the richness of online information channels and provincial risk management had independent effects on Internet users' emotional status, and the impact of online information sources on emotional status did not vary because of differences in confirmed cases, population inflows from Wuhan, or the recovery of normal life across 31 provinces.

Discussion

This study tested the impact of two dimensions of online social networking, online social support and online information sources, on emotional status in the early stage of the COVID-19 pandemic. It also analyzed how the effect was moderated by individual social status and provincial factors. The results supported hypothesis 1.1, showing positive effects of online networking on emotional status. This is consistent with some existing research [8,9]. Previous research that identified negative effects on emotional status and mental health has primarily focused on individuals' networking behaviors but often failed to differentiate between different dimensions and mechanisms of social networking [10,11].

Regarding online social support, some research found that online interaction can promote feelings of connection [18], and both giving and receiving social support through online communication can significantly improve an individual's mental health [35]. Regarding online information sources, a survey of WeChat users in China found that high heterogeneity in information sources during the pandemic made it easier for people to maintain their health and positive emotional status [20]. Studies of "echo chambers" have shown that recommendation algorithms on social media platforms tend to homogenize the information people receive [36]. These echo chambers make it unlikely that people will hear different voices, strengthening existing prejudices [37]. In contrast, the heterogeneity of information channels leads to a variety of information content, which played a very important role in avoiding extreme mental states and maintaining optimism during COVID-19 quarantines. Our research finding on Chinese WeChat users corroborates these observations and goes further.

Among the two dimensions of online networking, the positive effect of online social support is stronger, supporting hypothesis 1.2. This might be explained by the deeply embedded culture of guanxi in Chinese society. Online social support, which helps to maintain offline relationships, allows relatives, close friends, and acquaintances to provide help and reduce pressure. Chinese people grow up in a relationship culture and rely on family and acquaintances for emotional support [38]. Communication with members of one's core network is more helpful than information in providing emotional support and staying positive during lock-downs.

Another interesting finding is the different moderating mechanisms underlying the effects of social support and online information sources. The positive effect of social support is moderated by provincial risk management, not by social status. Hypothesis 2.2 is supported, but hypothesis 2.1 is not. The positive effect of online information sources is moderated by social status, not by provincial risk management. Hypothesis 3.1 is supported but hypothesis 3.2 is not. These differences have received inadequate attention yet can be explained by the characteristics of online networking and Chinese culture as follows.

For social status, the positive effect of online social support is relatively uniform among different classes. Lin Nan pointed out that emotional communication often occurs between individuals with homogeneous social status [39]. Since emotional support mainly comes from interpersonal trust, self-disclosure, and psychological support between individuals and their contacts, its positive psychological effect is widely observed within and between social classes. However, the influence of online information sources on emotional status is significantly different for different classes [5,40]. How the use of social media affects emotional status or mental health is related to an individual's digital capability and technical skills, and is also embedded in an individual's position in a stratified social system [25]. Our findings indicate that individuals with lower levels of education, income, and occupational status are more likely to benefit from the positive impact of online information sources. Due to their cultural and economic capital, socially dominant groups have stronger digital skills [41]. Therefore, their online sources to information about the COVID-19 has relatively small impact on their emotional status. However, disadvantaged groups have weaker digital literacy, thus diversified online information sources play a very important role in helping them avoid extreme emotions and stay positive during the pandemic.

Regarding provincial factors, a new finding is that online social support exemplifies either the positive or the negative provincial factors' impact on emotional status. Nevertheless, online information sources have no such interaction with provincial-level offline reality. The effect of online social support on emotional status is moderated by the province's risk management. In provinces with more confirmed cases and larger population inflow from epidemic areas, the positive effect of online social support seems weaker. In provinces with better post-COVID-19 recovery, the positive effect of online social support is stronger. Differences in provincial management led to differences in the emotional status of residents in each province [42]. One possible explanation is that online social support mainly comes from relatives, friends, and acquaintances [20]. Therefore, when gossip about local risk management disseminated together with emotional support through these dense networks [43,44], it is also more easily affected by offline realities and thus clearly moderated by regional differences. On the contrary, online information is transmitted rapidly and is trans-regional. Thus, the richness of online information sources and its impact on emotional status are less influenced by offline governance practices.

This study makes significant contributions to the research field in several aspects. Firstly, it adopts a social capital theory and information society perspective, which is relatively rare in previous studies. Our analysis confirms the positive effect of social support and information sources on emotional status during quarantines, and further depicts the different effect size of these two dimensions. Second, this study extends the scope of online social networking functions and mechanisms. We distinguish between two dimensions of social networking, and reveal subtle difference in their impact on emotional status. We demonstrate that the beneficial impact of online social networking on mental well-being is contingent upon various contextual factors, such as social structure and policies. Furthermore, this study integrates both provincial- and individual-level variables to examine the interplay between virtual and physical spaces. Fourth, the combination of online human behavior big data with survey data will become common in future research [45]. This study represents a valuable endeavor in integrating various forms of data sources.

This study identifies three potential research directions for future investigations. First, exploring different structural dimensions of online social networking based on theoretical integration. Second, interdisciplinary collaboration across fields such as psychology, sociology, communication, public health, and related disciplines could further explore the relationship between online social networking and emotional status. Such collaborations could foster theoretical integration and lead to practical solutions. Lastly, utilizing big data collected from online platforms such as social media, instant messaging applications, online consultations, and search engines to conduct data mining and index construction. This approach can provide empirical data support for theoretical innovation in this field.

The outbreak of COVID-19 has significantly transformed human behavior and altered the dynamics of social interaction in today's information-driven society. The experience of Chinese Internet users during the initial phase of the pandemic offers valuable insights into responding to public health emergencies in other regions undergoing transformation. Firstly, policymakers must pay attention to the emotional effect of online social networking and various anti-pandemic measures. Online networking operates through complex mechanisms during times of pandemic outbreak. Secondly, in societies such as China, social support from loved ones, acquaintances, and friends is the most robust psychological resource for individuals to combat a public health crisis. Social networks should be safeguarded during quarantines and mobility restrictions. Thirdly, facilitating internet access and enhancing digital literacy among marginalized groups could reinforce the constructive impact of online information sources on emotional well-being. Lastly, the psychological impact of social support is subject to moderation by provincial interventions. This indicates that residents' comprehension of regional anti-pandemic measures is strongly influenced by their family and close acquaintances. Therefore, these interventions and their outcomes must be more effectively disseminated through official channels to prevent misconceptions and the propagation of false information [46]. Taken together, all of these factors should be taken into account to enhance the beneficial effects of online networking on emotional well-being and alleviate its adverse consequences.

Conclusion

Several conclusions can be drawn from the results. Firstly, this analysis finds further evidence and more detail for the positive correlation between online networking and emotional status. Among the two dimensions of online networking, the positive effect of online social support is stronger than that of online information sources. Secondly, the practice of risk management at the provincial level also shapes residents' emotional status. Thirdly, the positive effect of online information sources on emotional status is moderated by individuals' social status, and the impact of online social support on emotional status is moderated by provincial risk management.

However, this study is subject to certain limitations. Firstly, the sample of WeChat users may not be entirely representative of the population in each province due to data constraints. Although various measures, such as population weight, were employed to address this issue, it cannot be fully overcome. Secondly, the conclusions may not be generalizable to all Chinese Internet users, as they are not based on a strict random sample. Future studies can address these problems by constructing larger sample pools and expanding online data sources. New measures like matching questionnaire respondents' survey data with their online behavior data can be used to improve the validity of the research.

In summary, the diverse dimensions of online social networking can influence emotional status and interact with real-life situations via distinct mechanisms. These factors and mechanisms should be considered when designing and adjusting pandemic-control interventions. This study advocates for a range of strategies to mitigate the negative impact of future pandemic threats on emotional status and mental health. For instance, supporting online interactions with family, friends, and acquaintances; safeguarding social networks during quarantine measures; improving internet access and digital literacy among disadvantaged groups; and staying vigilant regarding the emotional status and psychological reactions of individuals subject to various local interventions. A comprehensive strategy that encompasses online-offline and provincial-individual level interactions should be developed when formulating emergency responses to public health crises.

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Availability of Data and Materials: The COVID-19 data used in this study are provided by the Chinese Center for Disease Prevention and Control at https://www.chinacdc.cn/. For the control variables, weight is calculated using provincial population, which is available in the "National Data" collected by the Chinese National Bureau of Statistics at https://data.stats.gov.cn/easyquery.htm?cn=E0103. The Baidu population flow data were crawled from the Baidu Qianxi platform at https://qianxi.baidu.com/#/. The WeChat survey data are available on request from the corresponding author.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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Appendix

The core code of the crawler program used to obtain the Baidu population flow data

```
#coding=utf-8
#http://huiyan.baidu.com/migration/internalflowhistory.jsonp?dt=city&id=420100&date=20200213&callback=jsonp_1581579398387_5437718
from bs4 import BeautifulSoup
import urllib.request
import sys
import os
if __name__ == '__main__':
    if len(sys.argv) != 3:
        print(f"usage: {sys.argv[0]} date directory")
    else:
        date = sys.argv[1]
        directory = sys.argv[2]
        if '/' not in directory:
            directory += '/'
        partone = "http://huiyan.baidu.com/migration/internalflowhistory.jsonp?dt=city&id="
        parttwo = "&date="
        files = os.listdir(directory)
        s = u"北京|110000, 天津|120000, 兴安盟|152200, 巢湖|340181, 定安|469021, 屯昌|469022, 澄迈|469023, 临高|469024, 海东地区|630200, 香港|810000, 澳门|820000, 昌都|540300, 昌都地区|540300, 山南|540500, 山南地区|540500, 日喀则|540200, 日喀则地区|540200, 那曲|540600, 那曲地区|540600, 林芝|540400, 林芝地区|540400, 吐鲁番|650400, 吐鲁番地区|650400, 铜仁|520600, 铜仁地区|520600, 毕节|520500, 毕节地区|520500, 广西|450000, 广西壮族自治区|450000, 内蒙古|150000, 内蒙古自治区|150000, 宁夏|640000, 宁夏回族自治区|640000, 新疆|650000, 新疆维吾尔自治区|650000, 西藏|540000, 西藏自治区|540000, 石家庄|130100, 唐山|130200, 秦皇岛|130300, 邯郸|130400, 邢台|130500, 保定|130600, 张家口|130700, 承德|130800, 沧州|130900, 廊坊|131000, |152900, 安徽|340000, 福建|350000, 甘肃|620000, 广东|440000, 贵州|520000, 海南|460000, 河北|130000, 黑龙江|230000, 河南|410000, 湖北|420000, 湖南|430000, 江苏|320000, 江西|360000, 吉林|220000, 辽宁|210000, 青海|630000, 山东|370000, 山西|140000, 陕西|610000, 四川|510000, 云南|530000"......
        cities = s.split(u",")
        print('the number of cities is' + str(len(cities)))
        cdic = {}
        #ids = []
        for city in cities:
            r = city.split(u"|")
            print('city name is:' + r [0] + 'id is:' + r [1])
            if r[1] not in cdic.keys():
                cdic[r[1]] = r[0]
        cnt = 0
        total = len(cdic)
        for id, name in cdic.items():
            request_url = partone + id + parttwo + date
            print('request_url is:' + request_url)
            filename = "城内出行强度." + name + '.' + date + '.html'
            if filename not in files:
                request_page = urllib.request.urlopen(request_url)
                print('filename is:' + filename)
                f = open(directory + filename, "wb")
                f.write(request_page.read())
                f.close()
                cnt += 1
                print(str(cnt) + '/' + str(total))
```