Journal of Computational Social Science (2026) 9:7
https://doi.org/10.1007/s42001-025-00438-z

RESEARCH ARTICLE

The emotional trajectory of non-suicidal self-injury: sentiment analysis using social media data

Ziyue Zhu[1] · Michelle Yik[1]

Received: 2 January 2025 / Accepted: 2 October 2025

Abstract
Studies using self-report data have shown that emotion is related to non-suicidal self-injury (NSSI). However, the specific roles of emotion in the initiation and continuation of this type of behavior remain unmapped. This study conducted a sentiment analysis of social media posts to map the emotional trajectory of NSSI behavior in China. We collected data from 462,287 social media posts by 398 females who disclosed their NSSI behavior on Weibo, mainland China's most popular social media platform. Using a lexicon-based sentiment analysis approach, we assigned sentiment scores to each post at the person-per-date level, then subjected these scores to latent growth modeling to map the emotional trajectory of NSSI behavior. During the four days preceding NSSI disclosure, the Weibo users showed significant increases in arousal (β = .317; p = .014), positive emotions (β = .175; p = .022), and negative emotions (β = .805; p = .032). During the four days following NSSI disclosure, they experienced significant decreases in positive emotions compared with the preceding four days ($diff_{\beta}$ = .318; p = .003), with no significant changes in negative emotions or arousal. Our findings indicated that the levels of arousal, positive emotions, and negative emotions all rose in the four days preceding NSSI disclosure. However, contrary to the common notion that NSSI may improve mood, our results showed that positive emotions decreased following the disclosure.

Keywords Non-suicidal self-injury · Emotional trajectory · Social media · Sentiment analysis · Circumplex model of affect

The authors thank Jacky Feng, Jo Jo Lai, Mary Ma, Nicolson Siu, and Winnie Yang for their comments on earlier drafts of this article.

✉ Michelle Yik
Michelle.Yik@ust.hk

[1] Division of Social Science, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong, China

Published online: 19 November 2025

1 Introduction

"People assume you aren't sick unless they see the sickness on your skin" [1].

Non-suicidal self-injury (NSSI), which typically manifests as skin wounds caused by cutting, carving, or scraping [2], refers to the deliberate destruction of one's own body tissue without any intention of dying [3]. NSSI behavior has long been a public health issue, particularly in mainland China, which is home to the world's second-largest national population. In a study of 17,622 mainland Chinese adolescents and young adults, 17% of the participants reported that they had self-injured during the previous year [4], a slightly higher figure than that reported for Western samples (15%; see [5]). A meta-analysis of findings published in Chinese reported a significantly higher NSSI rate among females (18%) than males (16%) [6]. However, most NSSI studies have focused on Western samples, leaving the Chinese (female) population understudied. Using a large sample of Chinese females who disclosed their NSSI behavior on a social media platform, we sought to map the emotional trajectory of NSSI behavior.

2 Emotion and NSSI

To address the public health concern of destructive NSSI behavior, researchers have investigated its underlying mechanism and identified emotion as a pivotal factor. Nock and Prinstein [3] proposed that NSSI behavior can serve as an emotion regulation strategy (e.g., to alleviate unpleasant feelings or generate desired feelings) and as an interpersonal tool (e.g., to seek help or avoid negative social interactions). Other researchers have focused on the impact of different emotions on NSSI behavior. The affect regulation model suggests that NSSI may be a strategy to alleviate negative emotions or emotional arousal [7, 8], while the sensation seeking model considers NSSI a way to generate positive emotions such as excitement or exhilaration [9].

These models primarily concentrate on the valence of emotions, which they categorize as either positive or negative. However, according to the circumplex model of emotion [10, 11], emotions are structured along two dimensions: valence (i.e., pleasantness versus unpleasantness) and arousal (i.e., activation versus deactivation). In most NSSI research, the arousal dimension has been largely overlooked. As arousal refers to a sense of mobilization and energy [12, 13] and NSSI involves physical action, it is reasonable to suspect that arousal plays an important role in NSSI behavior. In this study, we investigated the trajectories of positive emotion, negative emotion, and emotional arousal in the context of NSSI behavior.

3 Previous findings

Several studies have investigated the association between NSSI and emotions. Using cross-sectional designs, the emotional functions of NSSI behavior have been carefully investigated and documented (see [14, 15]). For example, using the Functional Assessment of Self-Mutilation framework [16], a widely used scale for assessing the functions of NSSI, NSSI behavior has been shown to increase desired feelings (e.g., "to feel something, even if it is pain") and decrease undesired feelings (e.g., "to stop bad feelings") [17–19]. However, cross-sectional designs have been criticized for their inability to examine the daily and dynamic emotional experiences of those who engage in NSSI behavior, while their reliance on self-reports makes them susceptible to recall bias and response bias [20, 21].

To capture the unfolding of real-time emotions experienced during NSSI behavior, researchers have relied on diary studies. Although the focus of such studies has differed (e.g., specific emotions or general positive/negative emotions), most diary studies have reached a similar conclusion: individuals experience a high level of negative emotions before engaging in NSSI behavior [14]. This finding implies that individuals engage in NSSI to cope with negative emotions, as hypothesized by the affect regulation model [7, 8]. However, no consistent conclusions have been drawn regarding post-NSSI emotions. Some studies have reported increased positive emotions [22, 23], while others have reported decreased positive emotions [24] or no clear pattern [25].

In summary, research has yielded inconsistent findings regarding the types of emotions experienced following NSSI behavior. More evidence is thus required to map the consequences of NSSI behavior. Although diary studies are valuable for gaining insights into the detailed emotional experiences of those who engage in NSSI behavior, a growing concern is the high frequency of intrusive daily assessments required. These may cause discomfort, particularly for emotionally disturbed individuals [26].

4 The present study

Over the last decade, the use of social media has grown considerably [27]. This has enabled individuals to share or report their daily activities, including NSSI behavior, through text and images [28]. Social media have provided useful platforms for examining NSSI non-intrusively [29], while minimizing response distortion and recall bias. However, previous research has focused only on the potential risks and benefits associated with exposure to or sharing of NSSI-related content on social media [30, 31]. Meanwhile, research on the emotions associated with NSSI behavior, and particularly the trajectory of such emotions, is lacking.

In this study, we explored the emotions associated with NSSI behavior in a large sample of Chinese females in natural settings. By analyzing their spontaneous emotional expressions in social media posts, we conducted a non-intrusive investigation of the emotional experiences and expressions of females who have engaged in NSSI behavior. Specifically, we wished to (1) describe individuals' linguistic patterns of expression when disclosing their NSSI behavior on social media; (2) depict individuals' daily emotional trajectories throughout the month preceding their NSSI disclosure; and (3) compare the short-term emotional changes in the four days preceding and four days following their NSSI disclosure. Regarding short-term emotional changes, we expected that (1) emotional arousal and negative emotions would increase before the NSSI disclosure but decrease after the disclosure [22, 25, 32] and

(2) positive emotions would decrease before the NSSI disclosure but increase after the disclosure [22, 23].

5 Method

5.1 Data collection strategy

To examine the emotional experiences and expressions of individuals who engage in NSSI, we analyzed posts by Chinese females who disclosed their NSSI on Weibo. Specifically, we used keyword searching to scrape NSSI-related Weibo posts from 1 March to 1 October 2023. We identified and traced the publishers of these posts, then extracted all the public posts and profiles from identified female users who disclosed their NSSI on Weibo using a custom Python crawler. Finally, a lexicon-based sentiment analysis assigned arousal and valence scores to each post at the person-by-date level.

5.2 Data scraping

We collected posts by female users who publicly disclosed their NSSI on Weibo, the most popular social media platform in mainland China [33]. A Python-based crawler program searched for posts containing the Chinese keywords "紫餐" (a homonym of NSSI) and "割手" (cutting the wrist),[1] published between 1 March to 1 October 2023. This search yielded 13,483 posts. We reviewed these posts to identify those constituting the initiation, processing, and/or completion of an NSSI event, or to determine the specific date on which the NSSI event occurred. We categorized posts that fit any of these criteria as an NSSI disclosure (see [34]). From these 13,483 posts, we identified 530 users who posted one distinct NSSI disclosure event. To ensure a minimum threshold of posts for analysis (at least 100 posts, as recommended by [35]) while excluding potential chatbot accounts, we applied specific criteria. We excluded 132 users whose previous posts were not publicly accessible or whose accounts displayed an unusually high or low number of posts. Specifically, we excluded accounts with post counts exceeding two standard deviations from the mean of 1729, which translated to more than 5829 posts or fewer than 100 posts (see [37]). Ultimately, we analyzed 462,287 posts from 398 users. On average, each user published 1,162 posts (ranging from 109 to 5,245) during the data collection period. The mean length of time since account registration was 1,684 days (ranging from 92 to 5,138 days).

5.3 Data cleaning

Before assigning sentiment scores to the posts, we conducted data cleaning. For sentiment analysis, we retained only the content generated by the 398 target users, and removed noise such as hyperlinks, usernames, and tags [38]. Appendix A provides further details.

[1] We did not search for the keyword "自残" (NSSI in Chinese) as its use is not allowed on Weibo [36].

5.4 Sentiment analysis

After data cleaning, we used a lexicon-based approach to assign arousal and valence scores to the post texts at the person-per-date level. That is, for each user, on each specific date, we aggregated the emotional scores of all their posts from that day. We then applied the Chinese Sentiment Lexicon for Internet 2.0 (CSLI 2.0), which was developed based on a Weibo corpus [39]. CSLI 2.0 includes 10,164 Chinese words, each with an arousal score ranging from 0 (low arousal) to 8 (high arousal), and a valence score ranging from −4 to 0 (negative emotion) and from 0 to 4 (positive emotion) (e.g., "难受" [feeling bad]: arousal score = 3.714; valence score = − 2.571). For word tokenization we used Jieba, for the custom lexicon we imported CSLI 2.0, and for the stopword list we imported the Harbin Institute of Technology Stopwords List. Consistent with previous studies [22, 23, 40], we separated the valence score into distinct positive and negative emotions when depicting emotional trajectory [41, 42].

5.5 User profiles

For user identification, we collected publicly available profile data from the 398 Weibo users included in the study, including user ID, gender, region, and username. Recognizing that high-frequency internet use may lead to negative mental health outcomes [43], we included the total number of user posts and account registration time as control variables in the latent growth modeling analysis, consistent with previous research [44, 45]. These variables served as proxies for the degree of social media use.

6 Data analysis strategy

6.1 Descriptive statistics and visualization

To provide an overview of the distribution of emotions contained in the collected posts, we created an emotion map using RStudio with R version 4.3.1 [46] to visualize the distribution of arousal and valence scores. To illustrate the linguistic pattern of expressions used by individuals when disclosing their NSSI behavior, we generated a word cloud displaying the most frequently used words in NSSI disclosures using the Wordcloud package in Jupyter Notebook with Python 3.0. To depict individuals' daily emotional trajectories, we generated time-series plots for arousal, positive emotions, and negative emotions for one month preceding NSSI disclosure (see [47]) using RStudio with R version 4.3.1 [46].

6.2 Latent growth modeling

To compare the short-term emotional changes before and after NSSI disclosure, we used Mplus Version 8.10 [48] to fit two symmetrical latent growth models. One model captured the four days preceding the NSSI disclosure, and the other captured the four days following disclosure. The four-day window was chosen because time-series plots indicate a low point on the fourth day (see [49, 50]). We applied these two latent growth models to arousal, positive emotions, and negative emotions. Latent growth modeling is widely used for analyzing variable trends over time, particularly in emotion and personality research [51, 52].

7 Results

7.1 Descriptive statistics: emotion map and word cloud

Figure 1 plots the valence and arousal scores of all 462,287 posts, comparing the emotional features of posts published on days with and without NSSI disclosures. We classified the posts as positive (negative) when their valence scores were above 0 (below 0) and as high arousal (low arousal) when their arousal scores were above 4 (below 4) (see [39]).

The overall distribution of emotions in the dataset covered both positive and negative areas of the valence–arousal plane (see Fig. 1). Consistent with previous studies, we found significant quadratic relationships between valence and arousal on both NSSI non-disclosure days ($F_{2,458,378} = 9.221*10^4$; $p < 0.001$; $R^2 = 0.287$) and disclosure days ($F_{2,3,903} = 7.922*10^2$; $p < 0.001$; $R^2 = 0.288$). This finding indicates that

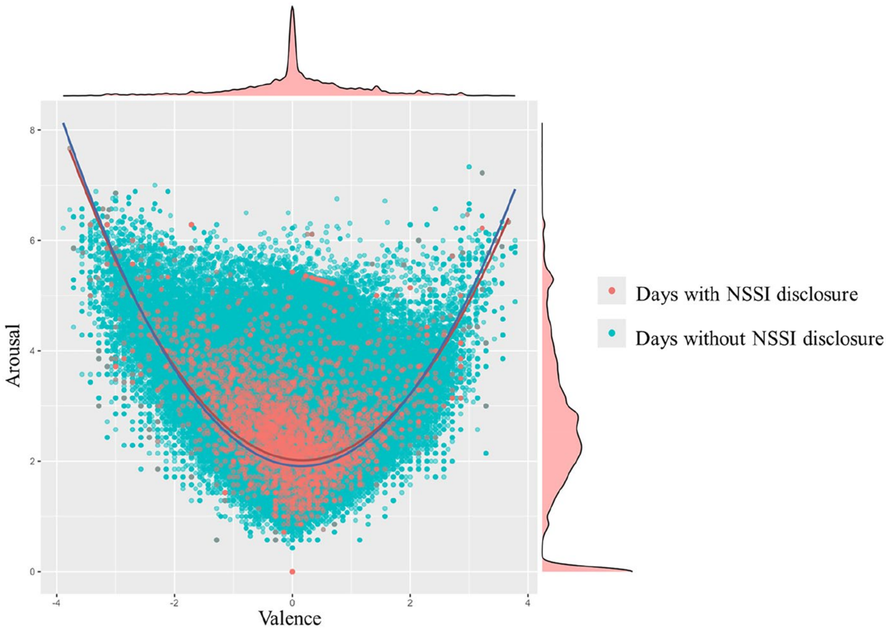


Fig. 1 Emotion map of 462,287 posts from 398 users. NSSI = non-suicidal self-injury; 3,906 posts were published on days with NSSI disclosure, while 458,381 posts were published on days without NSSI disclosure. The marginal density plots were created along the axes to visualize the distribution of emotions at varying levels of valence and arousal

increases in valence in both directions (positive and negative) were accompanied by a rising level of arousal [38, 53].

For the 458,381 posts published on days without NSSI disclosure, emotions were scattered across the plane. These posts tended to be accompanied by low arousal (68.1% for arousal < 4; 12.2% for arousal > 4) and were more positive (45.2% for valence > 0) than negative (35.1% for valence < 0). Additionally, we classified 79,478 (17.3%) posts as neutral (valence = 0, arousal = 0).

In contrast, the 3,906 posts published on NSSI disclosure days revealed a more negative distribution of emotions (42.8% for valence < 0; 41.7% for valence > 0) with a higher proportion of lower arousal (74.1% for arousal < 4; 10.3% for arousal > 4) than on non-disclosure days. Moreover, disclosure days had a lower proportion (13.2%) of neutral posts (valence = 0, arousal = 0) than NSSI non-disclosure days (17.3%). These findings suggest that, compared with non-disclosure days, individuals expressed more negative emotions and lower arousal on days when they disclosed NSSI behavior on social media.

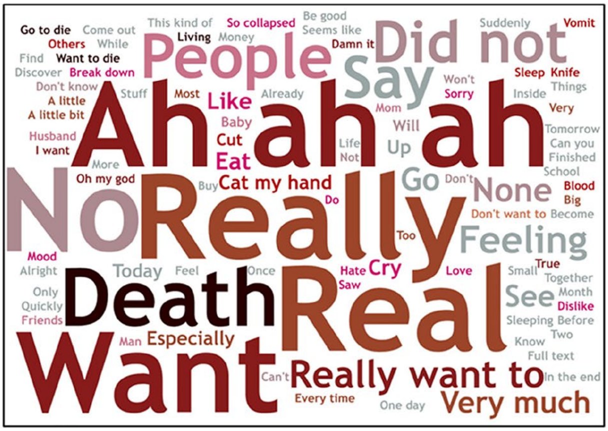
To further explore the higher prevalence of emotional (i.e., non-neutral), and especially negative, characteristics and linguistic patterns of posts on NSSI disclosure days, we generated two word clouds. Figure 2A presents the original Chinese words, and Fig. 2B presents their English translations. Both visualizations present the same 100 most common words in posts published on NSSI disclosure days, along with their valence and arousal scores from CSLI 2.0. A larger font size indicates a higher frequency of use. As the Chinese words and their English equivalents differed in length, the positions of the words varied between the two visualizations.

The most common word in posts published on NSSI disclosure days was "好" (good/really), which appeared 311 times with a valence score of 2.143 and an arousal score of 2.714. In these disclosure posts, "好" was frequently paired with "想" (want to), with the combination "好想" (really want to) appearing 181 times, indicating a strong urge or desire. To investigate why more negative emotions were expressed on NSSI disclosure days than on non-disclosure days, we examined the use of the word "死" (death), which appeared 250 times with a valence score of –3.000 and an arousal score of 3.714. The word "死" was frequently associated with verbs expressing desire or intention; related terms such as "想死" (want to die) and "去死" (go to die) appeared a total of 98 times. This characteristic usage of words and expressions related to death and suicide may contribute to the observed high frequency of negative valence and low arousal scores in posts on NSSI disclosure days.

8 Emotional trajectory preceding NSSI disclosure

To visualize the emotional trajectory preceding the Weibo users' disclosure of NSSI, we aggregated their posts on a daily basis, designating the day of NSSI disclosure as Day 0, the previous day as Day -1, and so on. Using these aggregated data, we averaged the users' daily valence and arousal scores to generate the arousal and valence scores for each date. For comparison, we specifically divided valence into positive and negative emotions.

Word	Valence	Arousal	Word	Valence	Arousal
好	2.143	2.714	一点	-0.286	0.857
啊啊啊	0.667	5.222	知道	0.429	1.571
真的	1.000	1.714	人生	0.571	2.286
死	-3.000	3.714	有点	-0.286	1.714
想	0.143	1.571	最	0.571	3.429
没	-0.286	1.143	老公	1.571	2.857
很	0.286	1.857	别人	-0.143	0.857
感觉	0.286	2.143	尼玛	-2.714	5.571
没有	-0.286	1.000	好了	1.571	1.857
特别	0.714	2.143	发现	0.571	1.429
喜欢	2.857	4.143	朋友	2.143	2.143
哭	-2.143	4.000	更	0.143	1.714
会	1.429	1.857	明天	0.714	1.857
宝宝	1.429	2.857	快	0.571	3.143
不想	-1.143	1.429	去死	-3.429	6.286
觉得	0.143	1.286	好像	0.111	1.222
一下	0.143	0.857	出来	0.286	1.857
根	-3.143	5.571	能不能	0.000	1.286
崩溃	-3.143	6.286	非常	0.857	3.143
已经	0.143	1.857	一起	0.571	1.857
爱	2.857	3.857	到底	-0.286	2.143
不是	-0.286	1.286	太	0.143	2.714
不要	-0.714	3.000	活着	1.571	2.714
卧槽	-1.714	6.286	突然	0.000	2.571
对不起	-1.000	2.000	心情	1.143	1.714
妈妈	1.143	2.857	讨厌	-2.571	4.429
不会	-0.429	1.429	好好	1.571	2.429
想死	-2.444	5.333	不能	-0.286	2.143
不知道	-0.286	1.429	大	0.286	1.714
睡觉	0.429	1.429	吐	-1.571	4.429



Word	Valence	Arousal	Word	Valence	Arousal
Really	2.143	2.714	A little	-0.286	0.857
Ah ah ah	0.667	5.222	Know	0.429	1.571
Real	1.000	1.714	Life	0.571	2.286
Death	-3.000	3.714	A little bit	-0.286	1.714
Want	0.143	1.571	Most	0.571	3.429
Did not	-0.286	1.143	Husband	1.571	2.857
Very much	0.286	1.857	Others	-0.143	0.857
Feeling	0.286	2.143	Damn it	-2.714	5.571
None	-0.286	1.000	Alright	1.571	1.857
Especially	0.714	2.143	Discover	0.571	1.429
Like	2.857	4.143	Friends	2.143	2.143
Cry	-2.143	4.000	More	0.143	1.714
Will	1.429	1.857	Tomorrow	0.714	1.857
Baby	1.429	2.857	Quickly	0.571	3.143
Don't want to	-1.143	1.429	Go to die	-3.429	6.286
Feel	0.143	1.286	Seems like	0.111	1.222
Once	0.143	0.857	Come out	0.286	1.857
Hate	-3.143	5.571	Can you	0.000	1.286
Break down	-3.143	6.286	Very	0.857	3.143
Already	0.143	1.857	Together	0.571	1.857
Love	2.857	3.857	In the end	-0.286	2.143
Not	-0.286	1.286	Too	0.143	2.714
Don't	-0.714	3.000	Living	1.571	2.714
Oh my god	-1.714	6.286	Suddenly	0.000	2.571
Sorry	-1.000	2.000	Mood	1.143	1.714
Mom	1.143	2.857	Dislike	-2.571	4.429
Won't	-0.429	1.429	Be good	1.571	2.429
Want to die	-2.444	5.333	Can't	-0.286	2.143
Don't know	-0.286	1.429	Big	0.286	1.714
Sleeping	0.429	1.429	Vomit	-1.571	4.429

Fig. 2 Word cloud of the 100 most frequently used words in posts published on NSSI disclosure days. The English word cloud is translated from Chinese. From the 100 words presented in the word cloud, 60 are documented in CSLI 2.0 with their corresponding valence and arousal. “紫餐” was translated as “Cat my hand” to reflect its homophonic relationship with “Cut my hand.”

Figure 3A illustrates the daily trajectory of negative and positive valence in the month leading up to the NSSI disclosures of the Weibo users included in the analysis, with magnitudes ranging from 0 to 4. While the valence trajectory fluctuated, these users tended to express negative emotions in their posts, as their scores for negative emotions were consistently higher than those for positive emotions. Notably, we observed a continuous rise in the intensity of negative emotions in the four days immediately preceding NSSI disclosure. In contrast, we observed no clear pattern for positive emotions in the four days immediately preceding NSSI disclosure.

Similarly, Fig. 3B depicts the daily trajectory of arousal, which also exhibited a fluctuating pattern. Notably, we observed more pronounced changes near NSSI dis-

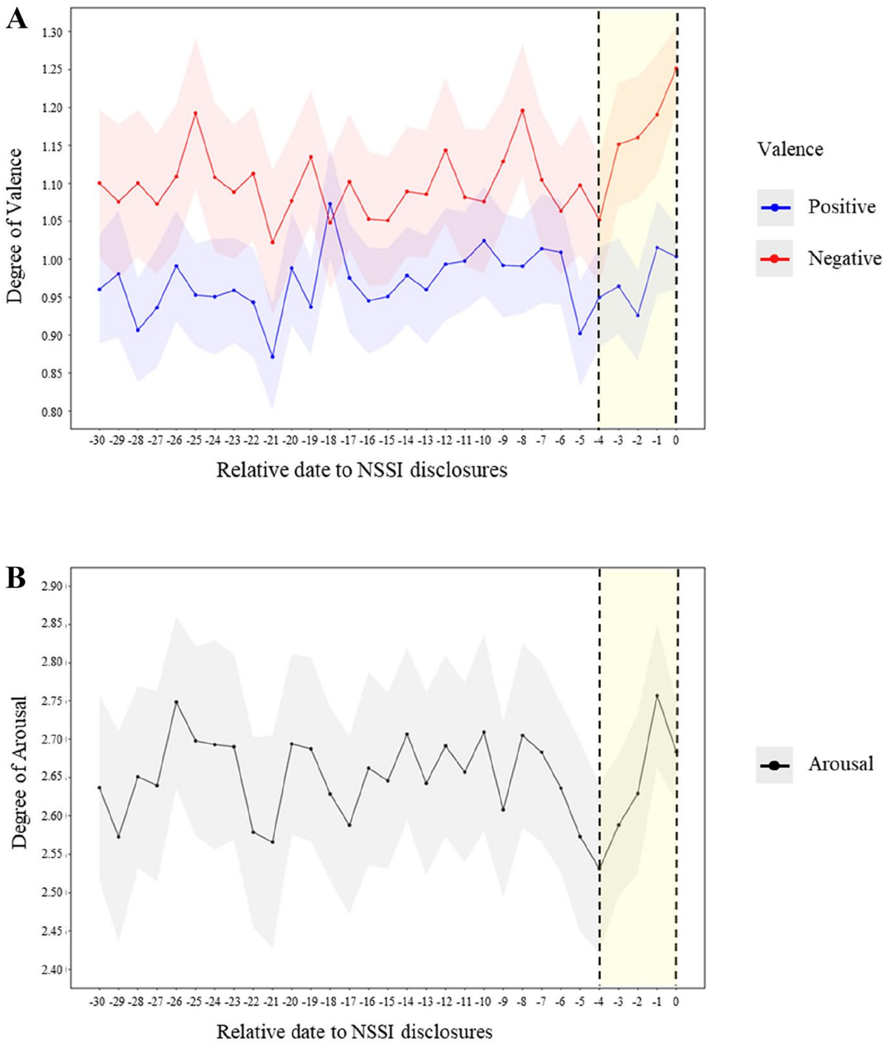


Fig. 3 Daily valence and arousal trajectories in the month preceding the Weibo users' NSSI disclosures. The shaded areas indicate the 95% bootstrap confidence ribbons: light red indicates negative emotions, blue indicates positive emotions, and gray indicates emotional arousal

closures than at other times: a dramatic decline in arousal occurred from Day -8 to Day -4, followed by a rapid increase that peaked on Day -1.

To test the one-month trajectory, we conducted hierarchical linear modeling with the number of posts and registration time as control variables [44]. We found that both positive and negative emotions increased during the month preceding NSSI disclosure. However, we identified no significant pattern for arousal across the one-month period (see Appendix B).

9 Short-term emotional trajectory: latent growth modeling

As previous studies have noted, NSSI may be associated with short-term emotional changes [54]. Using least squares regression via the *R* package bcp [55], we identified a turning point in both negative emotions and arousal corresponding to a notable low on Day -4, as illustrated in Fig. 3. We thus investigated changes in emotional states four days before (highlighted in the vertical yellow shaded bands) and after NSSI disclosure, using symmetric latent growth models for comparative analysis. We applied both linear and non-linear latent growth models to examine these short-term emotional patterns. Specifically, the mean slope in the pre- and post-NSSI models represented emotional changes (a positive slope indicated an increase and a negative slope indicated a decrease).

Table 1 presents the results of the latent growth models for arousal, negative emotions, and positive emotions as outcome variables. We evaluated model fit using the root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker–Lewis index (TLI), and standardized root mean squared residual (SRMR). CFI and TLI values greater than .90, RMSEA values below .06, and SRMR values below .08 indicate excellent fit [56].[2]

9.1 Arousal

First, we tested the pre-NSSI models. Both linear (RMSEA = 0; CFI = 1; TLI = 1; SRMR = 0.051) and non-linear (RMSEA = 0; CFI = 1; TLI = 1; SRMR = 0.034) models demonstrated excellent fit. The results suggest that the level of arousal exhibited a significant linear increase over the four days preceding NSSI (β = 0.317; p = 0.014), while we observed no significant non-linear pattern (p = 0.091). Next, we tested the post-NSSI models. The non-linear model demonstrated a good fit (RMSEA = 0.019; CFI = 0.911; TLI = 0.823; SRMR = 0.039), while the linear model exhibited a poor fit (RMSEA = 0.043; CFI = 0.257; TLI = 0.071; SRMR = 0.061). However, we detected no significant pattern in either the linear (p = 0.398) or non-linear (p = 0.955) model. Comparing the non-linear models before and after NSSI, we observed a significant difference in intercepts ($\text{diff}_i = -1.080$; p = 0.049). This indicated that the intercept for the pre-NSSI model was considerably lower than that for the post-NSSI model. This finding implies that the level of arousal on Day 0 was significantly higher than that on Day -4, further substantiating the observed increase in arousal in the four days preceding NSSI disclosure.

9.2 Negative emotions

In the pre-NSSI period, the non-linear model showed a better fit (RMSEA = 0; CFI = 1; TLI = 1; SRMR = 0.039) than the linear model (RMSEA = 0.022; CFI = 0.572; TLI = 0.465; SRMR = 0.054). These results suggest that negative emotions exhib-

[2] In cases where the model is saturated (CFI = 1; RMSEA = 0), greater emphasis should be placed on assessing the significance of the path coefficients rather than the model fit indices when comparing models [57, 58].

Table 1 Estimation of Short-term Emotional Trajectory Before and After NSSI Disclosure

Measure	Pre-NSSI		Post-NSSI	
	Linear	Non-linear	Linear	Non-linear
Arousal				
Mean intercept	1.751***	1.429**	2.682***	2.662***
Mean slope	0.317*	0.878	− 0.102	− 0.026
Mean quadratic slope		− 0.130		− 0.021
Intercept on registration time	− 0.018	0.000	− 0.041	− 0.039
Intercept on post number	0.125***	0.146**	0.041	0.041
Slope on registration time	− 0.003	− 0.040	0.015	0.009
Slope on post number	− 0.034**	− 0.066	− 0.002	− 0.004
Quadratic slope on registration time		0.009		0.002
Quadratic slope on post number		0.007		0.000
Negative emotions				
Mean intercept	0.802**	0.427	1.482***	1.302***
Mean slope	0.155	0.805*	− 0.077	− 0.016
Mean quadratic slope		− 0.149		− 0.021
Intercept on registration time	− 0.027	− 0.018	− 0.039	− 0.032
Intercept on post number	0.062*	0.104**	0.004	0.023
Slope on registration time	− 0.001	− 0.014	− 0.020	− 0.054
Slope on post number	−0.014	− 0.089*	0.023	0.037
Quadratic slope on registration time		0.003		0.014
Quadratic slope on post number		0.017*		− 0.007
Positive emotions				
Mean intercept	0.283	0.545	1.190***	1.115***
Mean slope	0.175*	− 0.283	− 0.143	0.041
Mean quadratic slope		0.105		− 0.048
Intercept on registration time	0.005	− 0.011	− 0.045*	− 0.039
Intercept on post number	0.083***	0.065*	0.018	0.023
Slope on registration time	− 0.009	0.020	0.014	− 0.005
Slope on post number	− 0.013	0.018	0.005	− 0.003
Quadratic slope on registration time		− 0.007		0.005
Quadratic slope on post number		− 0.007		0.002

NSSI = non-suicidal self-injury; Pre-NSSI = four days before NSSI; Post-NSSI = four days after NSSI. $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

ited a significant non-linear increase over the four days preceding NSSI disclosure ($\beta = 0.805$; $p = 0.032$), while we detected no significant linear pattern for the change in negative emotions ($p = 0.131$). In the post-NSSI period, both linear (RMSEA = 0; CFI = 1; TLI = 1; SRMR = 0.031) and non-linear (RMSEA = 0; CFI = 1; TLI = 1; SRMR = 0.052) models demonstrated an excellent fit. However, we observed no significant pattern for the change in negative emotions after NSSI disclosure for either linear ($p = 0.537$) or non-linear ($p = 0.965$) models. A comparison of the pre- and post-NSSI non-linear models revealed that the intercept of the pre-NSSI model was significantly lower than that of the post-NSSI model ($\text{diff}_i = -0.874$; $p = 0.042$). This implies that negative emotions were significantly higher on Day 0 than during the previous four days, further supporting the finding that negative emotions increased in the four days preceding NSSI disclosure.

9.3 Positive emotions

In the pre-NSSI period, the linear model (RMSEA= 0.044; CFI= 0.683; TLI= 0.604; SRMR= 0.068) showed an acceptable fit, while the non-linear model (RMSEA= 0.056; CFI= 0.682; TLI= 0.365; SRMR= 0.062) showed a poor fit. Positive emotions exhibited a significant linear increase over the four days preceding NSSI disclosure (β = 0.175; p = 0.022), but we detected no significant non-linear pattern for the change in positive emotions (p = 0.349). In the post-NSSI period, both linear (RMSEA= 0; CFI= 1; TLI= 1; SRMR= 0.043) and non-linear (RMSEA= 0; CFI= 1; TLI= 1; SRMR= 0.028) models demonstrated excellent fit. We observed a marginally significant pattern for the linear change in positive emotions ($\beta = -0.143$; p= 0.062) after NSSI disclosure but not for the non-linear model (p = 0.887). This implies that individuals experienced a linear drop in positive emotions after NSSI disclosure.

A comparison between the pre- and post-NSSI linear models further supported this conclusion. The slope of the pre-NSSI model (β = 0.175; p = 0.022) was significantly greater (diff_β = 0.318; p = 0.003) than that of the post-NSSI model ($\beta = -0.143$; p = 0.062), suggesting a decrease in positive emotions after NSSI disclosure compared with before NSSI disclosure. At the same time, the intercept of the pre-NSSI model was significantly lower than that of the post-NSSI model ($\text{diff}_i = -0.908$; p = 0.001), suggesting that positive emotions were significantly higher on Day 0 than in the previous four days, further supporting the conclusion that positive emotions increased before NSSI disclosure.

10 Discussion

Using a lexicon-based sentiment analysis approach, this study revealed that individuals' emotional arousal, positive emotions, and negative emotions all increased during the four days preceding their NSSI disclosure on Weibo. The increase in negative emotions was the most significant. Furthermore, we found that positive emotions were lower in the post-NSSI period than in the pre-NSSI period, but we identified no other pattern for the post-NSSI emotional trajectory.

Our findings of increasing negative emotions and arousal during the pre-NSSI period echo past studies. NSSI behavior may be motivated by a combination of heightened negative emotions and emotional arousal, indicating that such behavior is more likely to occur following elevated levels of these emotional states. Empirical support for the hypothesis that individuals experience significant negative emotions and emotional arousal before engaging in NSSI behavior (the affect-regulation model; see [7, 8]) is well-documented. Self-reported diary studies have similarly found increasing negative emotions pre-NSSI [22–25, 59]. In terms of arousal, self-injurers have been found to suffer from higher levels of arousal under negative stimulation, using both physiological [60] and self-report assessment [61].

However, contrary to the hypothesis that negative emotions and arousal should decrease following NSSI, our findings indicate a lack of reduction in negative emotions and arousal post-NSSI. Additionally, our findings indicate a decrease in positive emotions following NSSI. This contrasts with the sensation-seeking model [9], which suggests that NSSI serves to generate desired emotions such as excitement and exhilaration.

Regarding the prevailing assumption of emotional experience after NSSI, the discrepancies between our findings and those of previous studies do not necessarily mean that NSSI brings no reduction (improvement) in negative (positive) emotions. Rather, our findings may highlight the potential interpersonal help-seeking functions associated with the online expression of NSSI, such as communicating distress, fostering feelings of connection, and obtaining support [62–64]. First, individuals may continue to express their suffering rather than revealing their relief after engaging in NSSI to elicit sympathy and obtain desired social reactions, which are key benefits of this behavior [65]. The evidence indicates that the suffering of vulnerable individuals (e.g., crying babies, hospitalized persons, or those with physical disabilities) effectively elicits compassion [66, 67]. Second, individuals may avoid revealing their positive emotions after engaging in NSSI if they believe society will perceive them negatively. Given the social stigma surrounding NSSI in China, where it is viewed as deviant and immoral [68, 69], happiness derived from this behavior may be perceived as "evil joy." Lastly, it is also possible that emotions fluctuate immediately after engaging in NSSI [25, 32] but diminish rapidly in subsequent days, which our analysis of social media data failed to capture. These hypotheses warrant further exploration.

This study has several limitations. First, we used a lexicon-based sentiment analysis approach. This method may not be as effective and accurate for scoring sentiments as other machine learning algorithms, such as support vector machines [70] or generative AI-based sentiment classification [71]. While machine learning algorithms commonly classify positive and negative sentiments, their effectiveness in distinguishing high/low arousal in texts remains unverified. Thus, we chose to use the lexicon-based approach with CSLI 2.0 [39], which was developed based on Weibo text, the same platform from which we sourced our data. Future studies could apply other algorithms to pursue better performance in sentiment detection.

Second, our study focused on female Weibo users who actively disclosed their NSSI behavior. Future studies should expand the study scope to cover different societal segments to better understand the role of emotion in the initiation and continuation of the NSSI phenomenon.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s42001-025-00438-z.

Funding Open access funding provided by Hong Kong University of Science and Technology

Data availability The processed datasets are available from the authors on request.

Declarations

Conflict of interest The authors declare no competing interests.

References

1. Roy, E. (2014, July 3). *The first step*. Goodreads. https://www.goodreads.com/book/show/22708771-the-first-step.
2. Nock, M. K., & Prinstein, M. J. (2004). A functional approach to the assessment of self-mutilative behavior. *Journal of Consulting and Clinical Psychology, 72*(5), 885–890. https://doi.org/10.1037/0022-006X.72.5.885
3. Nock, M. K. (2009). Why do people hurt themselves? New insights into the nature and functions of self-injury. *Current Directions in Psychological Science, 18*(2), 78–83. https://doi.org/10.1111/j.1467-8721.2009.01613.x
4. Wan, Y. H., Hu, C. L., Hao, J. H., Sun, Y., & Tao, F. B. (2011). Deliberate self-harm behaviors in Chinese adolescents and young adults. *European Child & Adolescent Psychiatry, 20*, 517–525. https://doi.org/10.1007/s00787-011-0213-1
5. Swannell, S. V., Martin, G. E., Page, A., Hasking, P., & St John, N. J. (2014). Prevalence of non-suicidal self-injury in nonclinical samples: Systematic review, meta-analysis and meta-regression. *Suicide and Life-Threatening Behavior, 44*(3), 273–303. https://doi.org/10.1111/sltb.12070
6. Pan, Z., Mao, S., Tang, H., Fu, Y., Sun, W., Liao, Z., Li, J., Qiu, H., Zhu, J., & Huang, P. (2016). Meta-analysis on non-suicidal self-injury among college students in China. *Chinese Journal of School Health*, *37*(6), 878–881. https://doi.org/10.16835/j.cnki.1000-9817.2016.06.020
7. Favazza, A. R. (1992). Repetitive self-mutilation. *Psychiatric Annals, 22*(2), 60–63. https://doi.org/10.3928/0048-5713-19920201-06
8. Haines, J., Williams, C. L., Brain, K. L., & Wilson, G. V. (1995). The psychophysiology of self-mutilation. *Journal of Abnormal Psychology, 104*(3), 471–489. https://doi.org/10.1037/0021-843X.104.3.471
9. Edmondson, A. J., Brennan, C. A., & House, A. O. (2016). Non-suicidal reasons for self-harm: A systematic review of self-reported accounts. *Journal Of Affective Disorders, 191*, 109–117. https://doi.org/10.1016/j.jad.2015.11.043
10. Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39*(6), 1161–1178. https://doi.org/10.1037/h0077714
11. Yik, M., Russell, J. A., & Steiger, J. H. (2011). A 12-point circumplex structure of core affect. *Emotion, 11*(4), 705–731. https://doi.org/10.1037/a0023980
12. Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review, 110*(1), 145–172. https://doi.org/10.1037/0033-295X.110.1.145
13. Reich, J. W., & Zautra, A. J. (2002). Arousal and the relationship between positive and negative affect: An analysis of the data of Ito, Cacioppo, and Lang (1998). *Motivation and Emotion, 26*, 209–222. https://doi.org/10.1023/A:1021773013487
14. Hepp, J., Carpenter, R. W., Störkel, L. M., Schmitz, S. E., Schmahl, C., & Niedtfeld, I. (2020). A systematic review of daily life studies on non-suicidal self-injury based on the four-function model. *Clinical Psychology Review, 82*, Article 101888. https://doi.org/10.1016/j.cpr.2020.101888
15. Taylor, P. J., Jomar, K., Dhingra, K., Forrester, R., Shahmalak, U., & Dickson, J. M. (2018). A meta-analysis of the prevalence of different functions of non-suicidal self-injury. *Journal Of Affective Disorders, 227*, 759–769. https://doi.org/10.1016/j.jad.2017.11.073
16. Lloyd, E., Kelley, M. L., & Hope, T. (1997). *Self-mutilation in a community sample of adolescents: Descriptive characteristics and provisional prevalence rates.* Paper presented at the annual meeting of the Society for Behavioral Medicine, New Orleans, LA. https://doi.org/10.31390/gradschool_disstheses.6546
17. Leong, C. H., Wu, A. M., & Poon, M. M. (2014). Measurement of perceived functions of non-suicidal self-injury for Chinese adolescents. *Archives of Suicide Research, 18*(2), 193–212. https://doi.org/10.1080/13811118.2013.824828

18. Roley-Roberts, M. E., Zielinski, M. J., Hurtado, G., Hovey, J. D., & Elhai, J. D. (2017). Functions of nonsuicidal self-injury are differentially associated with suicide ideation and past attempts among childhood trauma survivors. *Suicide and Life-Threatening Behavior, 47*(4), 450–460. https://doi.org/10.1111/sltb.12306
19. Yen, S., Kuehn, K., Melvin, C., Weinstock, L. M., Andover, M. S., Selby, E. A., Solomon, J. B., & Spirito, A. (2016). Predicting persistence of nonsuicidal self-injury in suicidal adolescents. *Suicide and Life-Threatening Behavior, 46*(1), 13–22. https://doi.org/10.1111/sltb.12167
20. Yik, M. (2007). Culture, gender, and the bipolarity of momentary affect. *Cognition and Emotion, 21*, 664–680. https://doi.org/10.1080/02699930600823702
21. Robinson, M. D., & Clore, G. L. (2002). Belief and feeling: Evidence for an accessibility model of emotional self-report. *Psychological Bulletin, 128*, 934–960. https://doi.org/10.1037/0033-2909.128.6.934
22. Andrewes, H. E., Hulbert, C., Cotton, S. M., Betts, J., & Chanen, A. M. (2017). Ecological momentary assessment of nonsuicidal self-injury in youth with borderline personality disorder. *Personality Disorders: Theory, Research, and Treatment, 8*(4), 357. https://doi.org/10.1037/per0000205
23. Muehlenkamp, J. J., Engel, S. G., Wadeson, A., Crosby, R. D., Wonderlich, S. A., Simonich, H., & Mitchell, J. E. (2009). Emotional states preceding and following acts of non-suicidal self-injury in bulimia nervosa patients. *Behaviour Research and Therapy, 47*(1), 83–87. https://doi.org/10.1016/j.brat.2008.10.011
24. Houben, M., Claes, L., Vansteelandt, K., Berens, A., Sleuwaegen, E., & Kuppens, P. (2017). The emotion regulation function of nonsuicidal self-injury: A momentary assessment study in inpatients with borderline personality disorder features. *Journal of Abnormal Psychology, 126*(1), 89. https://doi.org/10.1037/abn0000229
25. Armey, M. F., Crowther, J. H., & Miller, I. W. (2011). Changes in ecological momentary assessment reported affect associated with episodes of nonsuicidal self-injury. *Behavior Therapy, 42*(4), 579–588. https://doi.org/10.1016/j.beth.2011.01.002
26. d'Abrera, J., Holland, A., Landt, J., Stocks-Gee, G., & Zaman, S. (2013). A neuroimaging proof of principle study of Down's syndrome and dementia: Ethical and methodological challenges in intrusive research. *Journal of Intellectual Disability Research, 57*(2), 105–118. https://doi.org/10.1111/j.1365-2788.2011.01495.x
27. Stieglitz, S., Mirbabaie, M., Ross, B., & Neuberger, C. (2018). Social media analytics–Challenges in topic discovery, data collection, and data preparation. *International Journal of Information Management, 39*, 156–168. https://doi.org/10.1016/j.ijinfomgt.2017.12.002
28. Wang, Y., Tang, J., Li, J., Li, B., Wan, Y., Mellina, C., O'Hare, N., & Chang, Y. (2017). Understanding and discovering deliberate self-harm content in social media. *Proceedings of the 26th International Conference on World Wide Web*, 93–102. https://doi.org/10.1145/3038912.3052555
29. Ho, S., Lwin, M. O., Chen, L., & Chen, M. (2020). Development and validation of a parental social media mediation scale across child and parent samples. *Internet Research, 30*(2), 677–694. https://doi.org/10.1108/INTR-02-2018-0061
30. Arendt, F., Scherr, S., & Romer, D. (2019). Effects of exposure to self-harm on social media: Evidence from a two-wave panel study among young adults. *New Media & Society, 21*(11–12), 2422–2442. https://doi.org/10.1177/1461444819850106
31. Zhu, L., Westers, N. J., Horton, S. E., King, J. D., Diederich, A., Stewart, S. M., & Kennard, B. D. (2016). Frequency of exposure to and engagement in nonsuicidal self-injury among inpatient adolescents. *Archives of Suicide Research, 20*(4), 580–590. https://doi.org/10.1080/13811118.2016.1162240
32. Kranzler, A., Fehling, K. B., Lindqvist, J., Brillante, J., Yuan, F., Gao, X., Miller, A. L., & Selby, E. A. (2018). An ecological investigation of the emotional context surrounding nonsuicidal self-injurious thoughts and behaviors in adolescents and young adults. *Suicide and Life-Threatening Behavior, 48*(2), 149–159. https://doi.org/10.1111/sltb.12373
33. Gao, Q., Abel, F., Houben, G. J., & Yu, Y. (2012). A comparative study of users' microblogging behavior on Sina Weibo and Twitter. In: Masthoff, J., Mobasher, B., Desmarais, M.C., & Nkambou, R. (Eds). *Lecture Notes in Computer Science*: Vol. 7379. *User Modeling, Adaptation, and Personalization* (pp. 88–101). Springer. https://doi.org/10.1007/978-3-642-31454-4_8
34. Coppersmith, G., Ngo, K., Leary, R., & Wood, A. (2016). Exploratory analysis of social media prior to a suicide attempt. *Proceedings of the Third Workshop on Computational Linguistics and Clinical Psychology*, 106–117. https://doi.org/10.18653/v1/W16-0311

35. Coppersmith, G., Dredze, M., Harman, C., & Hollingshead, K. (2015). From ADHD to SAD: Analyzing the language of mental health on Twitter through self-reported diagnoses. *Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology*, 1–10. https://doi.org/10.3115/v1/w15-1201
36. Weibo Terms of Service, (2021, May 27). *The Community Convention of Weibo*. https://service.account.weibo.com/h5/roles/gongyue
37. Yates, A., Cohan, A., & Goharian, N. (2017). Depression and self-harm risk assessment in online forums. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. https://doi.org/10.48550/arXiv.1709.01848
38. Chen, X., & Yik, M. (2022). The emotional anatomy of the Wuhan lockdown: Sentiment analysis using Weibo data. *JMIR Formative Research, 6*(11), Article e37698. https://doi.org/10.2196/37698
39. Zhao, J., Li, M., Yao, J., & Qin, G. (2019). The development of the Chinese sentiment lexicon for internet. *Frontiers in Psychology, 10*, 2473. https://doi.org/10.3389/fpsyg.2019.02473
40. Bruckbauer-Schwed, M., Kaiser, T., Plöderl, M., & Laireiter, A.-R. (2023). Dynamic complexity of positive and negative affects in NSSI – A daily diary study. *PsychArchives*. https://doi.org/10.23668/psycharchives.13937
41. Sailunaz, K., & Alhajj, R. (2019). Emotion and sentiment analysis from Twitter text. *Journal Of Computational Science, 36*, Article 101003. https://doi.org/10.1016/j.jocs.2019.05.009
42. Rodrigues, R. G., das Dores, R. M., Camilo-Junior, C. G., & Rosa, T. C. (2016). SentiHealth-cancer: A sentiment analysis tool to help detecting mood of patients in online social networks. *International Journal of Medical Informatics, 85*(1), 80–95. https://doi.org/10.1016/j.ijmedinf.2015.09.007
43. Marchant, A., Hawton, K., Stewart, A., Montgomery, P., Singaravelu, V., Lloyd, K., Purdy, N., Daine, K., & John, A. (2017). A systematic review of the relationship between internet use, self-harm and suicidal behaviour in young people: The good, the bad and the unknown. *PLoS ONE, 12*(8), Article e0181722. https://doi.org/10.1371/journal.pone.0181722
44. Barak, A., & Dolev-Cohen, M. (2006). Does activity level in online support groups for distressed adolescents determine emotional relief. *Counselling and Psychotherapy Research, 6*(3), 186–190. https://doi.org/10.1080/14733140600848203
45. Coyne, S. M., Rogers, A. A., Zurcher, J. D., Stockdale, L., & Booth, M. (2020). Does time spent using social media impact mental health? An eight year longitudinal study. *Computers in Human Behavior, 104*, Article 106160. https://doi.org/10.1016/j.chb.2019.106160
46. R Core Team. (2023). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/
47. Mereish, E. H., Peters, J. R., Brick, L. A., Killam, M. A., & Yen, S. (2023). A daily diary study of minority stressors, suicidal ideation, nonsuicidal self-injury ideation, and affective mechanisms among sexual and gender minority youth. *Journal of Psychopathology and Clinical Science, 132*(4), 372–384. https://doi.org/10.1037/abn0000813
48. Muthén, L. K., & Muthén, B. O. (2023). Mplus user's guide: Statistical analysis with latent variables (version 8.10). *Muthén & Muthén*. https://www.statmodel.com/download/usersguide/MplusUserGuideVer_8.pdf
49. Doerr, B., Fischer, P., Hilbert, A., & Witt, C. (2017). Detecting structural breaks in time series via genetic algorithms. *Soft Computing, 21*, 4707–4720. https://doi.org/10.1007/s00500-016-2079-0
50. Östman, Ö., Bergström, L., Leonardsson, K., Gårdmark, A., Casini, M., Sjöblom, Y., Haas, F., & Olsson, J. (2020). Analyses of structural changes in ecological time series (ASCETS). *Ecological Indicators, 116*, Article 106469. https://doi.org/10.1016/j.ecolind.2020.106469
51. Jackson, D. L. (2010). Reporting results of latent growth modeling and multilevel modeling analyses: Some recommendations for rehabilitation psychology. *Rehabilitation Psychology, 55*(3), 272. https://doi.org/10.1037/a0020462
52. Larsen, R. J., Augustine, A. A., & Prizmic, Z. (2009). A process approach to emotion and personality: Using time as a facet of data. *Cognition and Emotion, 23*(7), 1407–1426. https://doi.org/10.1080/02699930902851302
53. Yik, M., Mues, C., Sze, I. N. L., Kuppens, P., Tuerlinckx, F., De Roover, K., Kwok, F. H. C., Schwartz, S. H., Abu-Hilal, M., Adebayo, D. F., Aguilar, P., Al-Bahrani, M., Anderson, M. H., Andrade, L., Bratko, D., Bushina, E., Choi, J. W., Cieciuch, J., Dru, V., & Russell, J. A. (2023). On the relationship between valence and arousal in samples across the globe. *Emotion, 23*(2), 332–344. https://doi.org/10.1037/emo0001095

54. Paul, T., Schroeter, K., Dahme, B., & Nutzinger, D. O. (2002). Self-injurious behavior in women with eating disorders. *American Journal of Psychiatry, 159*(3), 408–411. https://doi.org/10.1176/appi.ajp.159.3.408
55. Erdman, C., & Emerson, J. W. (2008). bcp: An R package for performing a Bayesian analysis of change point problems. *Journal of Statistical Software*, *23*, 1–13. https://doi.org/10.18637/jss.v023.i03
56. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118
57. Steeger, C. M., & Gondoli, D. M. (2013). Mother–adolescent conflict as a mediator between adolescent problem behaviors and maternal psychological control. *Developmental Psychology, 49*(4), 804. https://doi.org/10.1037/a0028599
58. Zhang, L., Xue, X., & Zhao, J. (2019). Discrimination perception, academic achievement in rural left behind children: Longitudinal mediation role of depression. *Journal of Psychological Science, 42*(3), 584.
59. Snir, A., Rafaeli, E., Gadassi, R., Berenson, K., & Downey, G. (2015). Explicit and inferred motives for nonsuicidal self-injurious acts and urges in borderline and avoidant personality disorders. *Personality Disorders: Theory, Research, and Treatment, 6*(3), 267. https://doi.org/10.1037/per0000104
60. Nock, M. K., & Mendes, W. B. (2008). Physiological arousal, distress tolerance, and social problem-solving deficits among adolescent self-injurers. *Journal of Consulting and Clinical Psychology, 76*(1), 28. https://doi.org/10.1037/0022-006X.76.1.28
61. Glenn, C. R., Blumenthal, T. D., Klonsky, E. D., & Hajcak, G. (2011). Emotional reactivity in nonsuicidal self-injury: Divergence between self-report and startle measures. *International Journal of Psychophysiology, 80*(2), 166–170. https://doi.org/10.1016/j.ijpsycho.2011.02.016
62. Brown, W. (2020). States of injury: Power and freedom in late modernity. *Princeton University Press*. https://doi.org/10.2307/j.ctvzgb898
63. Mirichlis, S., Boyes, M., Hasking, P., & Lewis, S. P. (2023). What is important to the decision to disclose nonsuicidal self-injury in formal and social contexts? *Journal Of Clinical Psychology, 79*(8), 1816–1825. https://doi.org/10.1002/jclp.23503
64. Haliczer, L. A., & Dixon-Gordon, K. L. (2023). Social stressors, emotional responses, and NSSI urges and behaviors in daily life. *Journal of Affective Disorders, 338*, 601–609. https://doi.org/10.1016/j.jad.2023.06.043
65. Hooley, J. M., & Franklin, J. C. (2018). Why do people hurt themselves? A new conceptual model of nonsuicidal self-injury. *Clinical Psychological Science, 6*(3), 428–451. https://doi.org/10.1177/2167702617745641
66. Oveis, C., Horberg, E. J., & Keltner, D. (2010). Compassion, pride, and social intuitions of self-other similarity. *Journal of Personality and Social Psychology, 98*(4), 618–630. https://doi.org/10.1037/a0017628
67. Zahn-Waxler, C., Friedman, S. L., & Cummings, E. M. (1983). Children's emotions and behaviors in response to infants' cries. *Child Development, 54*(6), 1522–1528. https://doi.org/10.2307/1129815
68. Wang, Y. Z., Meng, X. D., Zhang, T. M., Weng, X., Li, M., Luo, W., Huang, Y., Thornicroft, G., & Ran, M. S. (2023). Affiliate stigma and caregiving burden among family caregivers of persons with schizophrenia in rural China. *International Journal of Social Psychiatry, 69*(4), 1024–1032. https://doi.org/10.1177/00207640231152206
69. Hinshaw, S. P., & Stier, A. (2008). Stigma as related to mental disorders. *Annual Review of Clinical Psychology, 4*(1), 367–393. https://doi.org/10.1146/annurev.clinpsy.4.022007.141245
70. Suthaharan, S. (2016). Support vector machine. In: *Machine Learning Models and Algorithms for Big Data Classification: Thinking with Examples for Effective Learning* (pp. 207–235). https://doi.org/10.1007/978-1-4899-7641-3_9
71. Gilardi, F., Alizadeh, M., & Kubli, M. (2023). ChatGPT outperforms crowd workers for text-annotation tasks. *Proceedings of the National Academy of Sciences, 120*(30), Article e2305016120. https://doi.org/10.1073/pnas.2305016120

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.