Stress-Buffering Pattern of Positive Events on Adolescents: An Exploratory Study Based on Social Networks

Abstract

Stress is viewed as the leading cause of mental health issues. Positive events, however, could act as a buffer against stress. Since the stress-buffering effects of positive events in previous studies were mainly examined by subjective self-reporting, continuous tracking research at individual behavioral levels still remains to be explored. In this study, we collected microblogs (n=27,346) from a group of high school students (n=500) to examine the relationship between positive events and stress-buffering patterns at both the content and behavioral levels. Through a pilot study of scheduled exam intervals under two situations, namely, 1) existing neighboring positive scheduled events (n=75) and 2) no neighboring positive events, we found that students taking exams with neighboring positive events appeared to exhibit less intense stress and more stable stress fluctuations. Most students talked less about exams when positive events occurred nearby, at a lower frequency and a lower ratio. Hypothetical tests for stress-buffering effects of positive events and monotonic changes in the stress intensity under the impact of positive events were further conducted based on automatically extracted positive events (n=1,914) from the microblogs. The results showed that the stress-buffering effects of positive events were closely correlated with adolescents' stress-change modes, microblog linguistic expressions, and posting behaviors. The occurrence of positive events was verified to offset the impact of stressor events through talking about positive topics at the same time. Adolescents tended to post more forwarded microblogs, more positive microblogs and less stressful microblogs when positive events appeared; however, the total frequency of microblogs did not appear to change significantly under the impact of positive events. The study also showed that positive events buffered monotonic changes in stress intensity caused by stressor events. Based on these theoretical findings, the stress-buffering patterns around positive events were further incorporated for stress prediction in adolescents, and the predictive performance was improved. This study could inform the use of social networks to estimate and track mental health transition in adolescents under stress. The theoretical and practical implications, limitations of this study and future work are discussed.

Keywords: stress-buffering effect, positive events, microblogs, adolescents

1. Introduction

Motivation: Life is always full of ups and downs. Accumulated stress could drain inner resources, leading to psychological maladjustment, depression and even suicidal behaviors (Nock et al., 2008). Compared to adults, young people exhibit high levels of stress due to their immature inner status and lack of experience (Vitelli, 2014). According to the latest report released by the American Psychological Association in 2018, 91% of young adults had experienced physical or emotional symptoms due to stress in the past month compared to 74% of adults (APA, 2018). More than 30 million Chinese adolescents suffer from psychological stress, and nearly 30% of them are at a risk of depression (Youth and Center, 2019). Stress-induced mental health problems are becoming an important social issue worldwide.

On the other hand, positive life events, such as satisfying social interactions, excellent academic performance and pleasant entertainment activities, could exert protective effects on emotional distress in both direct and indirect ways by '*buffering*' (Shahar and Priel, 2002; Cohen and Hoberman, 2010), with respect to physiological, psychological, and social coping resources (Cohen et al., 1984; Needles and Abramson, 1990). Researchers indicated that positive events mitigated the relationship between negative events and maladjustment in samples of adolescents experiencing family transitions (Doyle et al., 2003). The written expression of positive feelings could prompt increased cognitive reorganization in undergraduate students (Daniel L., 2009). Positive events have also been linked to medical benefits, such as improved mood, serum cortisol levels, and lower levels of inflammation and hypercoagulability (Caputo et al., 1998; Jain et al., 2010). Thus, tracking the state of the stress-buffering effect is important for understanding the mental status of stressed individuals.

Existing solutions: Previous studies have focused on measuring positive events and stress-buffering states after events through questionnaires, including the Hassles & Uplifts Scales (Kanner et al., 1981b), the Interpretation of Positive Events Scale (Alden et al., 2008), the Adolescent Self-Rating Life Events Checklist (Jun-Sheng, 2008) and the Perceived Benefit Scales (Mcmillen and Fisher, 1998). Recently, scholars have demonstrated the feasibility to sense and predict users' stress from social networks (Xue et al., 2013, 2014; Lin et al., 2014; Li et al., 2015b,c,a, 2017a,c) through content (linguistic text, emoticons and pictures) and behavioral (abnormal posting time and comment/response actions) measures.

If we view the aforementioned traditional studies as static sensing of stress-buffering, this study approaches the stress-buffering as a dynamic process and aims to find a solution at both the microblogging-content and behavioral levels under the hypothesis that the occurrence of positive events can be reflected in adolescents' microblogs. Self-report investigations are susceptible to many factors, such as social pressure and pressure from measurement scenarios, but microblogging characteristics at the behavioral level are objective expressions that can assist in identifying content characteristics.

Another difference from the previous studies lies in that, despite the unique advantages of social networks over traditional survey methods in offering self-expressed content and behavioral information, previous microblog-based studies stopped at the analysis of stress, and none went further to capture positive events that may play a key role in adolescents' stress-coping mechanisms. For example, 'hiking tomorrow' might simultaneously occur and be expressed in microblogs with 'failing the exam today'. If do not know anything about positive events, is the unilaterally detected stress the real stressful state of the current youth? Understanding stress-buffering patterns of positive events is helpful in precisely predicting and guiding adolescents who are coping with stress.

Our work: To this end, this paper studies adolescent stress from the dual perspective of stress generation and stress-buffering and views stress as the superposition effect of stressors and positive events. By investigating the connection between positive events and stress changes reflected through adolescents' microblogging content and behaviors, we discover stress-buffering patterns of positive events and further predict future stress under such mitigation. Exploiting stress-buffering effects of positive events is also advantageous in handling the confusing situation whether an adolescent who doesn't express stressful information from microblogs is actually under stress.

However, capturing the stress-buffering process of positive events is not a trivial task. Three fundamental challenges need to be addressed: 1) What are the criteria for depicting stress-buffering effects? 2) What is the latent connection between positive events and adolescents' stress-buffering reflections in microblogs? 3) How can identify positive events and their impact interval be extracted from microblogs?

A pilot study was first conducted on the microblog data (n=27,346) of a group of high school students (n=500) associated with the school's positive scheduled events (n=75) and stressor events (n=122). Stressful intervals were divided into two comparative categories: intervals impacted by positive scheduled events (denoted by U-SI, n=259) and intervals not impacted by positive scheduled events (denoted by SI, n=518). After observing the posting behaviors and microblog content of the stressed students in both the SI and U-SI groups, several implications were discussed to guide the next step of the study. Motivated by the implications of the pilot study, we modeled the connection between positive events and adolescents' stress-buffering reflections as the statistical difference in two comparative situations SI and U-SI. Three groups of measures were adopted to depict adolescent stress buffering at the period level: stress-change modes, linguistic expressions and posting behaviors. Monotonic changes in stress intensity buffered by positive events were measured in temporal order. As an exploration, according to the occurrence of automatically extracted positive events, we covered the stress-buffering effects into each time unit and integrated such an effect into the stress prediction model.

In this paper, to automatically extract positive events, we built upon and extended previous stress and event detection works. A Chinese linguistic parser model was applied to extract positive events in the linguistic structure *[type, (act, doer, description)]*. We followed the categorization of adolescents' positive events in six dimensions (entertainment, school life, romantic, peer relationships, self-cognition and family life) and extended the SC-LIWC lexicons into 2,606 phases. Stressful intervals (SI) and stressful intervals impacted by positive events(U-SI) were identified according to their temporal order.

The rest of the paper is organized as follows. We review the literature in section 2 and introduce the pilot study in section 3. The procedure for extracting positive events is presented in section 4.1. The connection between positive events and adolescents' stress buffering from microblogs are discussed and modeled in section 4.2. We present the experimental results in section 5.1 and extend the study to integrating stress-buffering patterns into future stress prediction in section 5.2. Future work is discussed in section 6.

2. Literature Review

2.1. Stress-buffering Function of Positive Events

Positive events have been verified as protective factors against daily stress (Ong et al., 2006; Bono et al., 2013), loneliness (Chang et al., 2015), suicide (Kleiman et al., 2014) and depression (Santos et al., 2013). By exploring naturally occurring daily stressors, (Ong et al., 2006) found that over time, the experience of positive emotions assisted high-resilient individuals in recovering effectively from daily stress. Through a three-week longitudinal study, (Bono et al., 2013) examined the correlation between employee stress and health and positive life events. They concluded that naturally occurring positive events were correlated with decreased stress and improved health. (Chang et al., 2015) investigated the protective effect of positive events in a sample of 327 adults and found that the positive association between loneliness and psychological maladjustment was weaker for those who experienced a large number of positive life events, as opposed to those who experienced a small number of positive life events. This finding agrees with the conclusion made by (Kleiman et al., 2014) that positive events act as protective factors against suicide individually and synergistically when they co-occurred, by buffering the link between important individual differences in risk variables and maladjustment. In the survey concluded by (Santos et al., 2013), strategies of positive psychology were also identified as potential tools for the prophylaxis and treatment of depression, helping to reduce symptoms and prevent relapses.

The protective effect of positive events was hypothesized to operate in both direct (i.e., the more positive events people experienced, the less stress they perceived) and indirect ways by '*buffering*' the effect of stressors (Cohen and Hoberman, 2010; Shahar and Priel, 2002), with respect to physiological, psychological, and social coping resources (Cohen et al., 1984; Needles and Abramson, 1990). (Folkman and Moskowitz, 2010) identified three classes of coping mechanisms that were associated with positive emotions during chronic stress: positive reappraisal, problem-focused coping, and the creation of positive events. Due to their immature inner status and lack of experience, adolescents exhibit more sensitivity to stressors (i.e., exams, heavy homework load, isolation by classmates, family transitions), and live with frequent, long-term stress (Vitelli, 2014). In this situation, positive events could help reinforce adolescents' sense of well-being (Daniel L., 2009) and restore the capacity to handle stress (Doyle et al., 2003). Positive events have also been linked to medical benefits, such as improved mood, serum cortisol levels, and lower levels of inflammation and hypercoagulability (Jain et al., 2010; Caputo et al., 1998). The present study will be based on the consensus conclusions from the above studies.

To assess the stress-buffering effect of positive events, scholars conducted various studies based on self-support methods. For example, (Kanner et al., 1981b) developed the Hassles and Uplifts Scale and concluded that the assessment of daily hassles and uplifts might be a better approach to the prediction of adaptational outcomes than the usual life-events approach. To measure the negative interpretations of positive social events, (Alden et al., 2008) proposed the Interpretation of Positive Events Scale and analyzed the relationship between social interaction anxiety and the tendency to interpret positive social events in a threat-maintaining manner. (Mcmillen and Fisher, 1998) proposed the Perceived Benefit Scales as new measures of self-reported positive life changes after traumatic stressors, including lifestyle changes, material gain, increases in self-efficacy, family closeness, community closeness, faith in people, compassion, and spirituality. Specific to college students, (Jun-Sheng, 2008) administered the Adolescent Self-Rating Life Events Checklist to 282 college students and found training in positive coping styles was of great benefit to improve the mental health of students. The above explorations are based on self-report investigations; therefore, it is difficult to exclude the interference from external factors (i.e., social pressure and pressure from measurement scenarios). Moreover, due to the lack of personnel and effective scientific methods, most scholars have relied on a limited number of measurements; thus, continuous measurements of the stress-buffering process were difficult to carry out.

2.2. Measures and Stress Analysis from Social Networks

As billions of adolescents are recording their lives through social networks (e.g., microblogs, Twitter and Facebook), researchers have explored applying psychological theories to social network-based data mining techniques to better understand user' psychological statuses from the self-expressed public data source. Multiple content and user behavioral measures have been proven effective in user mental health analysis, including time series curve analysis of stress (Li et al., 2015b,a), topic words (Xue et al., 2013), abnormal posting time (Xue et al., 2014), online shopping behaviors (Zhao et al., 2016), human mobility features (Jin et al., 2016), comment/response actions (Liang et al., 2015) and high-dimensional multimedia features (Lin et al., 2014). For example, (Xue et al., 2013, 2014) proposed detecting adolescent stress from a single post utilizing machine learning methods by extracting topic words indicating stress, abnormal posting time, and interactions with friends. (Lin et al., 2014) constructed a deep neural network to combine the high-dimensional pictorial information into stress detection. Based on the stress detection results, (Li et al., 2015c,a,b) adopted a series of multivariate time series prediction techniques (i.e., candlestick charts, fuzzy candlestick lines and the seasonal Autoregressive Integrated Moving Average model) to predict future stress trends. Taking linguistic information into consideration, (Li et al., 2017c) employed a nonlinear autoregressive with external input neural network to predict a teenager's future stress level by referring to the impact of co-experienced stressor events of similar companions. (Li et al., 2017a) proposed detecting stressor events from microblog content and analyzing stressful intervals based on the posting rate. All of the above studies focused on the discussion of stress detection in social networks. This paper starts from a completely new perspective and focuses on the stress-buffering effect of positive events in adolescents' stress coping processes. Thus, we extend the study from how to find stress to the next more meaningful stage: how to cope with stress.

2.3. Correlation Analysis Models for Multivariate Time Series

Basic correlation analysis models on time series focusing on univariate data have been well studied. As the most widely adopted model, the Pearson correlation coefficient (Cohen et al., 1988) measures the linear correlation between two variables X and Y. One inevitable defect of the Pearson correlation coefficient is its sensitivity to outliers. To overcome such drawbacks, Spearman's rank correlation coefficient (Spearman, 1987) and the Kendall rank correlation coefficient (Mcleod, 2011) were proposed based on the Pearson correlation coefficient. While the Pearson correlation coefficient estimates linear relationships, Spearman's correlation coefficient estimates monotonic relationships (regardless of linearity), and are calculated as the Pearson correlation coefficient between the rank values of two variables. The Kendall rank correlation coefficient mainly assesses the similarity of the orderings of the data when ranked by each of the quantities. The above correlation metrics are primarily used to estimate the relationship between single-dimensional variables, and cannot be adopted directly in social network-based scenarios.

For multivariate time series analysis, two-sample models are widely adopted. Such models are built to check whether two samples come from the same underlying distribution, which is assumed to be unknown. Correspondingly, various kernel-based (Scholkopf et al., 2006) and distance-based models (Schilling, 1986) have been proposed. (Scholkopf et al., 2006) proposed to transform the distance between two variables and nearest neighbors into a reproducing kernel Hilbert pace and to solve the problem using the maximum mean discrepancy. (Schilling, 1986) adopted an r-nearest-neighbor-based model to partition two sets of event-driven time series data. The global proportion of right divided neighbors was calculated to estimate whether there existed a statistically significant difference between the two sets. This paper adopted an r-nearest-neighbor-based two-sample model in our problem to measure the distance and correlation between two multidimensional variables depicting the stress-buffering patterns of positive events.

3. Data Observation: A Pilot Study on the Stress-buffering Effect of School-Scheduled Positive Events

Microblogs. Microblogs of students from Taicang High School were collected from January 1, 2014, to September 1, 2017. We filtered out 121 active students out of over 500 students according to their posting frequency and collected their microblogs throughout their whole high school career. In total, 27,346 microblogs were collected in this study, where each student post an average of 226 microblogs, and maximum of 1,421 microblogs and a minimum of 102 microblogs. To protect the privacy, all the usernames were anonymized during the experiment.

Scheduled events. The list of weekly scheduled school events, with a detailed description of the event (grade and exact start and end time), were collected from the school's official website[1] from February 1, 2014 to August 1 2017. There were 126 stressor events and 75 positive events in total. Examples of positive scheduled and stressor events in high school life are listed in Table 1. There were 2-3 stressor events and 1-2 positive events scheduled per month in the current study. Figure 1 shows three examples of a student's stress fluctuations around three midterm exams, where a positive event *campus art festival* was scheduled ahead of the first exam (*example a*), a positive event *holiday* occurred after the second exam (*example b*), and no positive scheduled event was found near the third exam (*example c*).

Table 1: Examples of school-scheduled positive and stressor events.

Type	Date	Content	Grade
stressor event	2017/4/16	first day of the mid-term exam	grades 1 and 2
positive event	2016/11/5	campus art festival	grades 1, 2, and 3

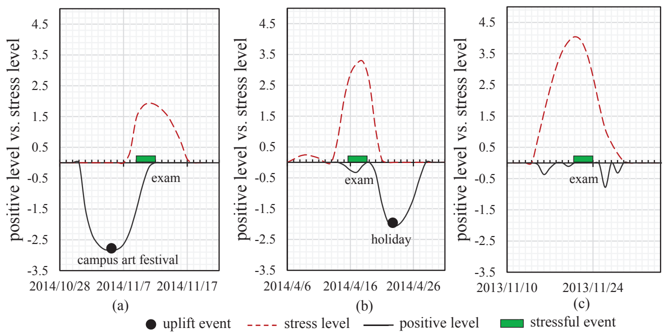


Figure 1: Examples of school-scheduled positive events, stressor events, and a student's stress fluctuations

To further observe the effect of positive events on stressed students, we collected all the stressful intervals surrounding the scheduled exams for the 121 students during their high school career, applying the interval detection method from (Li et al., 2017a). For each student, we divided all the stressful intervals into two sets: 1) In the original sets, stress was caused by a stressor event, lasting for a period, and no other intervention (namely, a positive event) occurred. We called the set of such stressful intervals **SI**; 2) In the other comparative sets, the stressful interval was impacted by a positive event. We called the set of such stressful intervals **U-SI**. Thus, the difference under the two situations (sets) could be seen as the stress-buffering effect induced by the positive event. We identified 518 exam-related stressful intervals (SI) and 259 stressful intervals impacted by four typical positive scheduled events (U-SI) ('practical activity', 'New Year party', 'holiday', 'sporting event') from the students' microblogs. Six measures for the above two conditions were considered: the *accumulated value of stress*, the *average value of stress* (per day), the *maximal value of stress* (per day), the *RMS value of stress*, the *frequency of academic topic words*, and the *ratio of academic stress among all types of stress*. Since our target was to track the impact of positive events for students under stress, based on previous research Xue et al. (2013), we detected the stress level (ranging from 0 to 5) for each post. For each student, the stress value per day was aggregated by calculating the average amount of stress from all the posts. Examples of academic-related keywords are listed in Table 2. The average value of each measure over all eligible slides was calculated.

Table 2: Examples of academic-related keywords.

exam, fail, review, score, test paper, rank, pass, math, chemistry homework, regress, fall behind, tension, stressed out, physics, nervous, mistake, question, puzzle, difficult, lesson, careless

Results. As shown in Figure 2, comparing each measure of scheduled exam intervals under the two situations (1) existing positive neighbouring events (U-SI) and 2) no neighbouring positive scheduled events (SI)), we found that students with exams and positive neighbouring events appeared exhibited less stress intensity (78.13% reduction in average stress, 95.58% reduction in cumulative stress, and 57.20% reduction in maximal stress) and more stable stress fluctuations (47.93% reduction in the RMS values of stress). Furthermore, the frequency of academic topic words (see Table 2 for examples) and the ratio of academic stress in each interval were calculated. Most students talked less about exams when positive events occurred nearby with lower frequency (84.65% reduction) and lower ratio (89.53% reduction). The statistical results show clues about the

[1] http://stg.tcedu.com.cn/col/col82722/index.html

impact of positive scheduled events, which is consistent with psychological theory (Cohen et al., 1984; Cohen and Hoberman, 2010; Needles and Abramson, 1990), indicating the reliability and feasibility of the microblog dataset. However, this observation is based on specific scheduled events, and cannot satisfy the need for automatic, timely, and continuous perception of the stress-buffering process. Therefore we propose a framework to automatically detect positive events and their impact intervals. Based on this framework, the relationship between the impact of automatically extracted positive events and adolecents' microblogging characteristics will be discussed.

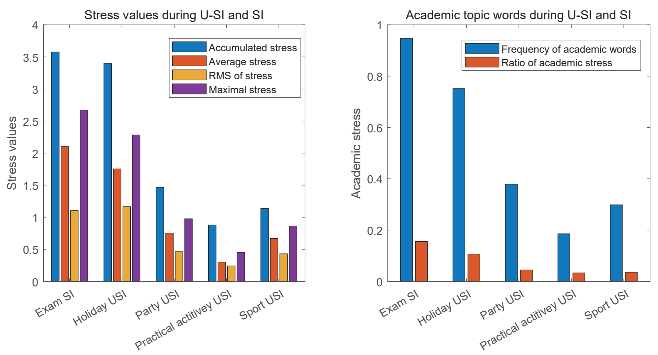


Figure 2: Comparing average stress value for all students during exam intervals in two situations: 1) intervals affected by positive neighboring events (U-SI) and 2) no positive events occurred (SI).

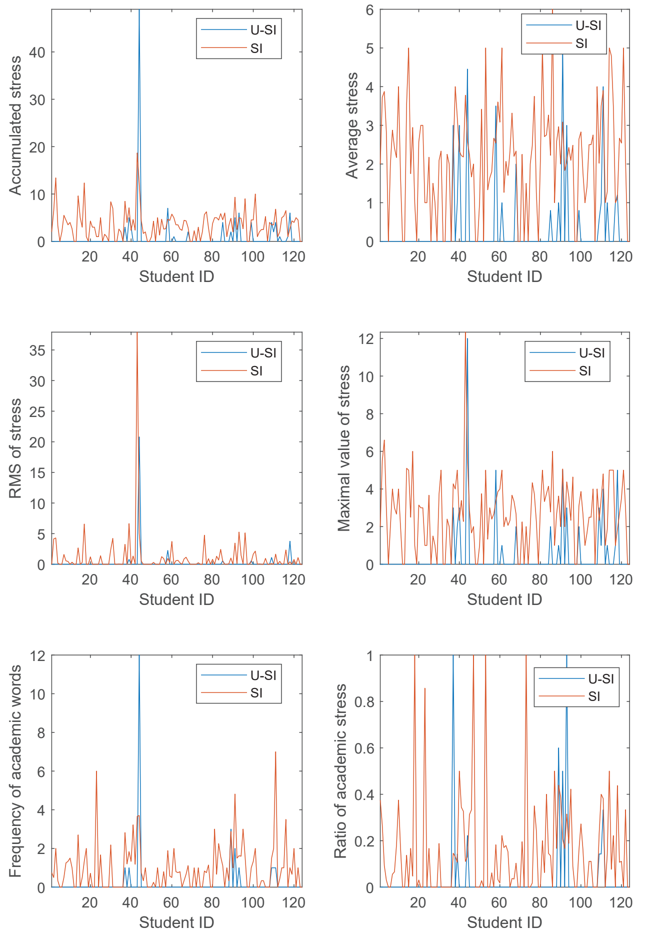


Figure 3: Comparing students' stress fluctuations during exam intervals in the SI and U-SI sets.

4. Framework

We first introduce the procedure to extract positive events and their intervals from microblogs. Based on this procedure, we present a statistical model to depict the relationship between positive events and adolescents' stress-buffering patterns through three groups of content and behavioral measures.

4.1. Discovery of Positive Events from Microblogs

Let $u = [type, \{doer, act, description\}]$ be a positive event, where the element *doer* is the subject who performs the *act*, and *description* is the list of key words related to u. According to psychological scales (Jun-Sheng, 2008; Kanner et al., 1981a), positive events for adolescents mainly focus on six dimensions: $\mathbb{U}$ = { 'entertainment', 'school life', 'romantic relationships', 'peer relationships', 'self-cognition', 'family life'}. We constructed our lexicon for six-dimensional positive events from two sources. The basic positive words are selected from the psychological lexicon C-LIWC (expectation, joy, love, and surprise) (Tausczik and Pennebaker). Then, we built six topic lexicons by expanding basic positive words from the adolescents' microblogs, containing 452 phrases in 'entertainment', 273 phrases in 'school life', 138 phrases in 'romantic relationships', 91 phrases in 'peer relationships', 299 phrases in 'self-recognition' and 184 phrases in 'family life', for a total 2,606 phrases. Examples are shown in Table 3. Additionally, we labeled *doer* words (i.e., *teacher*, *mother*, *I* and *we*) in positive lexicons.

4.1.1. Linguistic Parser Model

Positive events were identified through a Chinese natural language processing platform (Che et al., 2010). For each post, after word segmentation, we parsed each sentence to find its linguistic structure and then matched the main linguistic components with positive topic lexicons in each dimension. A lin-

Table 3: Examples and statistics for topic phrases in the six-dimensional lexicons of positive events.

Dimension	Example words	total
entertainment	hike, travel, celebrate, dance, swimming, ticket, shopping, air ticket, theatre, party, Karaoke, self-driving tour, game, idol, concert, movie, show, opera, baseball, running, fitness, exercise	452
school life	reward, come on, progress, scholarship,admission, winner, diligent, first place, superior hardworking, full mark, praise, goal, courage, progress, advance, honor, collective honor	273
romantic relationships	beloved, favor, guard, anniversary, concern, tender, deep feeling, care, true love, promise, cherish, kiss, embrace, dating, reluctant, honey, sweetheart, swear, love, everlasting, goddess	138
peer relationships	listener, company, pour out, make friends with, friendship, intimate, partner, team-mate, brotherhood	91
self-cognition	realize, achieve, applause, fight, exceed, faith, confidence, belief, positive, active, purposeful	299
family life	harmony, filial, reunite, expecting, responsible, longevity, affable, amiability, family, duty	184

Table 4: Examples of automatically extracted positive events from the adolescents' microblogs.

I am really looking forward to the spring outing on Sunday. (doer:*I*, act:*looking forward*, description:*spring outing*)
My holiday is finally coming [smile]. (doer:*My holiday*, act:*coming*, description:*[smile]*)
First place on my lovely math exam!!! In memory of it. (description:*first place, math, exam, memory*)
You are always here for me like sunshine. (doer:*You*, description:*sunshine*)
Thanks to all my dear friends for hosting the party. Happiest birthday!!! (doer:*friends*, act:*thanks*, description:*party, birthday*)
I know my mom is the one who will support me forever, no matter when and where. (doer:*mom*, act:*support*)
Expecting tomorrow' Adult Ceremony[Smile][Smile] (act: *expecting*, description:*Adult Ceremony*)

guistic parser model was applied to identify the central verb of the current sentence, namely, the *act*. It constructed the relationship between the central verb and corresponding *doer* and *description* elements. By searching these elements in positive topic lexicons, the existence of positive events was identified. Due to the sparsity of posts, the element *act* might be empty. *Descriptions* were collected by searching all nouns, adjectives and adverbs. Examples of positive events extracted from the adolescents' microblogs are listed in Table 4. For example, the post 'Thanks all my dear friends for hosting the party. Happiest birthday!!!' was processed as *doer='friends', act = 'expecting', description = 'party'*, and *type = 'entertainment'*.

4.1.2. Impact Intervals of Positive Events

We followed and extended the method in (Li et al., 2017a) to identify the impact interval of each positive event to further study its stress-buffering pattern. The target interval was identified in three steps.

Step1: Positive events, stressor events and filtered-out candidate intervals were extracted. For each candidate interval, we set its length to more than 3 days and a maximum gap of 1 day between two neighboring stressful days. Since the stress series detected from the microblogs were discrete points, the locally weighted regression (Cleveland and Devlin, 1988) method was adopted to highlight the characteristics of the stress curve.

Step2: Intervals were judged as stressful or not through hypothesis testing. A Poisson-based probability model was adopted to measure how confident we are that the current interval was a stressful interval. Here, the stressful posting rates under stressful λ_1 and normal conditions λ_0 were modeled as two independent Poisson processes:

$$Pr[N = n|\lambda_i] = \frac{e^{-\lambda_i T}(\lambda_i T)^n}{n!} \tag{1}$$

where $i \in \{0, 1\}$ and $n = 0, 1, \cdots, \infty$. We expected that $\lambda_1 > \lambda_0$ and measured the probability as $P(\lambda_1 > \lambda_0|N_1, T_1, N_0, T_0)$, where N_1 and N_0 are the numbers of stressful posts and T_1 and T_0 are the time durations corresponding to λ_1 and λ_0, respectively. Without loss of generality, we assumed a Jeffreys noninformative prior on λ_1 and λ_0 and inferred the posterior distribution $P(\lambda_1|N_1)$ and $P(\lambda_0|N_0)$ according to Bayes' Rule. Thus, for current interval I_1 and historical normal interval I_0, the quantified probability $\beta = P(\lambda_1 > \lambda_0|I_1, I_0) \in (0, 1)$ indicated confidence in whether I_1 was a stressful interval.

Step 3: The stressful intervals were divided into an SI set and a U-SI set. For a detected stressful interval $I =< t_1, \cdots, t_n >$, we considered the temporal order between I and any detected positive event u occurring at time point t_u in three cases:

1) If the positive event u occurred during the stressful interval, i.e., $t_u \in [t_1, t_n]$, the positive interval I was judged as $I \in U - SI$.
2) If the positive event occurred near a stressful interval, the probability that it had an impact on the current stressful interval was considered. Here, the gap between t_u and I is limited to ξ, i.e., if $t_u \in [t_1 - \xi, t_1) \cup (t_n, t_n + \xi]$, then $I \in U - SI$. If a stressful interval satisfies none of the above conditions, we classify it into the SI set.
3) Other stressful intervals were classified into the U-SI set.

4.2. Hypothesis Test for the Relationship Between Positive Events and Adolescents' Stress-buffering Patterns

We formulated the relationship between positive events and adolescents' stress-buffering patterns as a comparison problem between two sets of stressful intervals: the SI set and the U-SI set. Each interval was modeled as a multidimensional vector depicting microblogging characteristics of the current adolescent. Specifically, a multivariate two-sample hypothesis test (Li et al., 2017b; Johnson and Wichern, 2012) was adopted to model such a relationship. The basic idea was to determine whether the multidimensional points (i.e., the stressful intervals) in SI and U-SI were under different statistical distributions. Assuming the data points in SI and U-SI were randomly sampled from distribution F and G, respectively, then the hypothesis can be denoted as follows:

$$H_0 : F = G \quad versus \quad H_1 : F \neq G. \tag{2}$$

Under such a hypothesis, H_0 indicates that points in SI and U-SI follow a similar distribution, while H_1 means points in SI and U-SI follow statistically different distributions, namely positive events had obvious stress-buffering effects.

4.2.1. Statistical Model of the Stress-buffering Effect

We used a K-nearest-neighbor-based method (Schilling, 1986) to judge the existence of a significant difference between set SI and set U-SI. For simplification, we used the symbol A_1 to represent set SI and A_2 to represent set U-SI. For each point ℓ_x in the two sets, we expected its top-k similar points to belong the same set of ℓ_x. The Euclidean distance was adopted to calculate the distance of structured points here. For each point $\ell x \in A = A_1 \bigcup A_2$, let $\mathbf{D}^y$ be the feature vector of ℓ_x and $NN_r(\ell_x, A)$ be the function to find the $r-$th nearest neighbor of ℓ_x. The r-th nearest neighbor of ℓ_x is denoted by:

$$NN_r(\ell_x, A) = \{y|min\{||\mathbf{D}^x - \mathbf{D}^y||_2\}, y \in (A/\ell_x)\} \tag{3}$$

Let $I_r(\ell_x, A1, A2)$ be the function denoting whether the r-th nearest neighbor was in the same set as ℓ_x:

$$I_r(\ell_x, A_1, A_2) = \begin{cases} 1, & if \ell_x \in A_i \&\& NN_r(\ell_x, A) \in A_i, \\ 0, & otherwise \end{cases} \tag{4}$$

Let $T_{r,n}$ denote the proportion that pairs containing two points from the same set among all pairs formed by $\ell_x \in A$ and its k nearest neighbors:

$$T_{k,n} = \frac{1}{n \times k} \sum_{i=1}^{n} \sum_{j=1}^{k} I_j(x, A_1, A_2) \tag{5}$$

The value of $T_{k,n}$ showed how differently the points in the two testing sets (SI and U-SI) performed. If the value of $T_{r,n}$ was close to 1, then the two underlying distributions F and G for SI and U-SI were significantly different, indicating current positive events had an obvious stress-buffering impact on the adolescents' stress series. Let $\lambda_1 = |A_1|$ and $\lambda_2 = |A_2|$, the statistical value Z is denoted as:

$$Z = (nr)^{1/2}(T_{r,n} - \mu_r)/\sigma_r \tag{6}$$

$$\mu_r = (\lambda_1)^2 + (\lambda_2)^2 \tag{7}$$

$$\sigma_r{}^2 = \lambda_1\lambda_2 + 4\lambda_1{}^2\lambda_2{}^2 \tag{8}$$

where μ_r is the expectation and $\sigma_r{}^2$ is the variance of Z. Based on hypothesis testing theory (Johnson and Wichern, 2012), when the size of the testing set is large enough, Z obeys a standard Gaussian distribution. Thus, we judged whether the positive events had a significant stress-buffering impact as follows: if $f(SI, USI) = (nr)^{1/2}(T_{r,n} - \mu_r)/\mu_r{}^2 > \alpha$ ($\alpha = 1.96$ for $P = 0.025$), then the hypothesis H_1 was true.

In section 4.2.2, three groups of microblogging measures were introduced to depict the multidimensional characteristics of each stressful interval $\ell_x \in A$, indicated as a linguistic expression matrix $\boldsymbol{D_l^x}$, a posting behavior matrix $\boldsymbol{D_p^x}$ and a stress-change-mode matrix $\boldsymbol{D_s^x}$. Correspondingly, three subfunctions of $NN_r(.)$ were defined: $PNN_r(.)$, $SNN_r(.)$ and $LNN_r(.)$.

$$\begin{aligned} PNN_r(\ell_x, A) &= \{y|min\{||\mathbf{D}_p^x - \mathbf{D}_p^y||_2\}, y \in (A/\ell_x)\} \\ SNN_r(\ell_x, A) &= \{z|min\{||\mathbf{D}_s^x - \mathbf{D}_s^z||_2\}, z \in (A/\ell_x)\} \\ LNN_r(\ell_x, A) &= \{w|min\{||\mathbf{D}_l^x - \mathbf{D}_l^w||_2\}, w \in (A/\ell_x)\} \end{aligned} \tag{9}$$

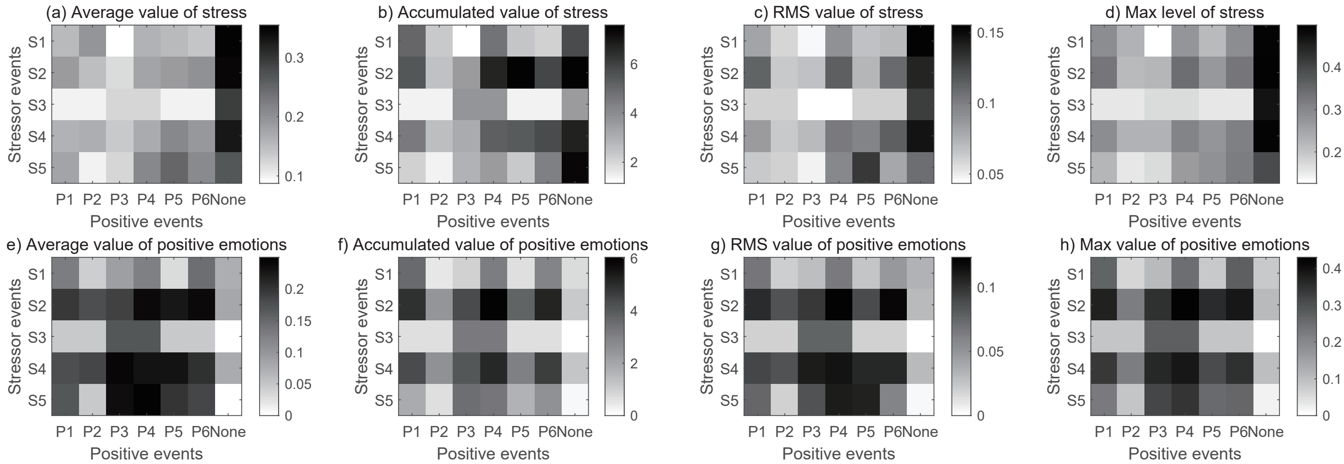


Figure 4: Comparing stress change modes during stressful intervals in two situations: 1) intervals affected by positive neighboring events (U-SI) and 2) no positive events occurred nearby (SI). P_{1-6}={school life, romantic relationships, peer relationships, self-cognition, family life, entertainment}, E_{1-5}={school life, romantic relationships, peer relationships, self-cognition, family life}.

The r-th nearest neighbor was recalculated as:

$$NN_r(\ell_x, A) = \{v | min\{a \times \|\mathbf{D}_p^x - \mathbf{D}_p^v\|_2 + \tag{10}$$

$$b \times \|\mathbf{D}_s^x - \mathbf{D}_s^v\|_2 + c \times \|\mathbf{D}_l^x - \mathbf{D}_l^v\|_2\}, v \in (A/\ell_x)\} \tag{11}$$

In this study, we set $a = b = c = 1/3$.

4.2.2. Measures

Stress-change modes. Inspired by the pilot study, four measures were adopted to quantify the intensity of stress changes during a stressful interval: the average value of stress, the accumulated value of stress, the RMS value of stress, and the maximal value of stress. For an interval $I =< t_1, t_2, \cdots, t_n >$ with length $|I| = n$ (day), the stress series is denoted by $S =< s_1, s_2, \cdots, s_n >$, where $s_i \in S$ is the average stress value of microblogs posted on day i. The four measures are denoted as follows:

$$\begin{aligned}
&V_{accumulate}(I) = \sum_{i=1}^{n}(s_i)\\
&V_{average}(I) = \frac{1}{n}V_{accumulated}(I)\\
&V_{RMS}(I) = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}(s_i)^2}\\
&V_{maximal}(I) = max(I) = \{s_i | \forall s_j \in I \& j \neq i, s_i \geq s_j\}
\end{aligned} \tag{12}$$

Similarly, we applied the four measures to positive emotional fluctuations in an interval, which might reflect the complementary changes to stress. To show the occurrence of the above mentioned measures, we present a 7×5 grayscale map for each measure in Figure 4. The x-axis (ranging from P1 to P6) represents each dimension of positive events (P={school life, romantic relationships, peer relationships, self-cognition, family life, entertainment}), and the last column represent no positive event happening in the observation interval. The y-axis (ranging from S1 to S5) represent each dimension of stressor events (E={academic, romantic, peer relationship, self-cognition, family life}). The color of each point in the grayscale map depends on the average value of the current measure over the corresponding set of intervals. For a set of intervals $\mathbf{I}_{<e,p>} =< I_1, I_2, \cdots, I_m >$, where the stress was caused by stressor events $e \in E$ and impacted by positive events $p \in P$, the measures are presented as follows:

$$\begin{aligned}
&V_{accumulated}(\mathbf{I}_{<e,p>}) = \sum_{i=1}^{m} V_{accumulated} I_i\\
&V_{average}(\mathbf{I}_{<e,p>}) = \frac{1}{m}\sum_{i=1}^{m} I_i\\
&V_{RMS}(\mathbf{I}_{<e,p>}) = \sqrt{\frac{1}{m}\sum_{i=1}^{m} I_i^2}\\
&V_{maximal}(\mathbf{I}_{<e,p>}) = \{max(V_{maximal}(I_i)) | i \in [1, m]\}
\end{aligned} \tag{13}$$

For example, in Figure 4 (a), point (P4,S1) is the average stress value in all $\mathbf{I}_{<1,4>}$ intervals, where stress was caused mainly by school life (S1) and impacted by positive events related to self-cognition (P4). Figure 4 exhibited four stress-change modes (subgraphs (a) to (d)) and four corresponding positive emotion change modes (subgraphs (e) to (h)) in both the SI and U-SI sets. The statistical results showed that the occurrence of positive events significantly reduced the average stress (subgraph (a)), accumulated stress (subgraph (b)) and maximal stress (subgraph (d)), and slowed down the fluctuations (subgraph (c)) during stressful intervals. On the other hand, the occurrence of positive events caused an obvious increase in all the positive-change modes (subgraphs (e) to (h)), especially in stressful intervals caused by romantic and self-cognition events. The above statistics on stress and positive change modes initially reflected stress-buffering effects of different types of positive events on each dimension of stressor events.

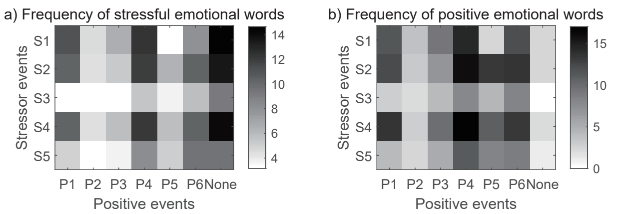


Figure 5: Comparing stressful emotions and positive emotions during stressful intervals in the SI and U-SI sets. P_{1-6}={school life, romantic relationships, peer relationships, self-cognition, family life, entertainment}, E_{1-5}={school life, romantic relationships, peer relationships, self-cognition, family life}.

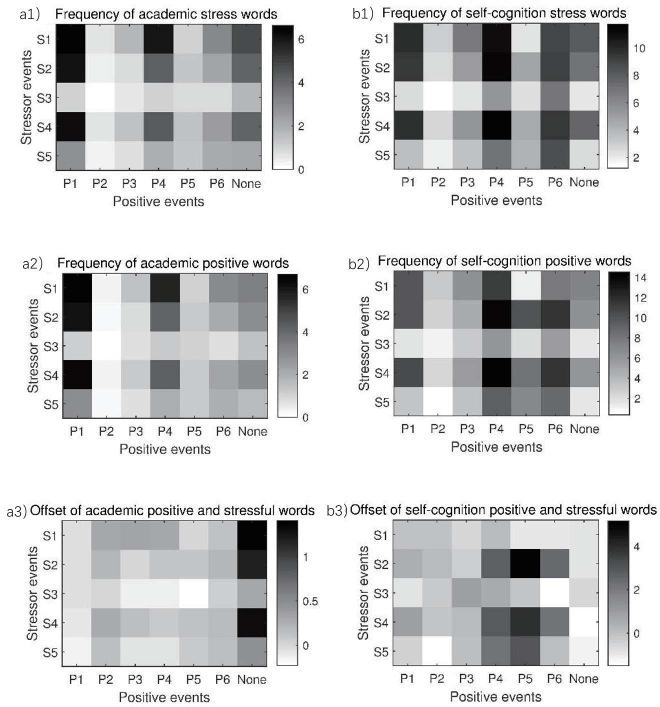


Figure 6: Offset frequency of topic words during stressful intervals in the SI and U-SI sets. P_{1-6}={school life, romantic relationships, peer relationships, self-cognition, family life, entertainment}, E_{1-5}={school life, romantic relationships, peer relationships, self-cognition, family life}.

Linguistic expressions. For each microblog, we identified its linguistic expressions applying the segmentation model and parser model from section 4.1. The first measure was the frequency of stressful emotional words based on four categories (anger, anxiety, hate, sad) from LICW lexicons, representing general stress during an interval (Tausczik and Pennebaker). The second measure was the frequency of positive emotional words, which were identified based on the surprise, joy, expectation and love categories of the LICW lexicons. The third measure was the frequency of topic words in the five dimensions of stressor events, representing the degree of attention for each dimension of stressor events. Figure 5 (a) and (b) shows the frequency of stressful emotional words and positive emotional words, respectively. Generally, positive events showed stress-buffering effects in these two measures, since the last column in subgraphs (a) and (b) is different compared to columns P1 to P6. Specifically, positive events from romantic, peer relationship and family life shows obvious reductions in stressful emotional words caused by peer relationship and family life stressor events (subgraph 5 (a)). Figure 6 shows the distribution of stressful topic words when different positive events occurred. Here, we shows the statistical results during stressful intervals caused by school-life and self-cognition stressor events. The frequency of stressful academic topic words (subgraphs (a1) and (b1)) and positive academic topic words (subgraphs (a2) and (b2)) shows no clear regularity. Furthermore, we explored the offset for each dimension of stressful and positive topic words, as shown in subgraphs (a3) and (b3). The offset results shows obvious stress-buffering results because stressful topic words shows a decrease in columns P1 to P5 in subgraph (a3), and positive topic words exhibit increases in columns P1 to P5 in subgraph (b3). These findings reveal that the occurrence of positive events offset the impact of stressor events by simultaneously discussing positive topics.

Posting behaviors. Stress can lead to abnormal posting behaviors, reflecting users' changes in social engagement activities (Liang et al., 2015). We considered four measures of posting

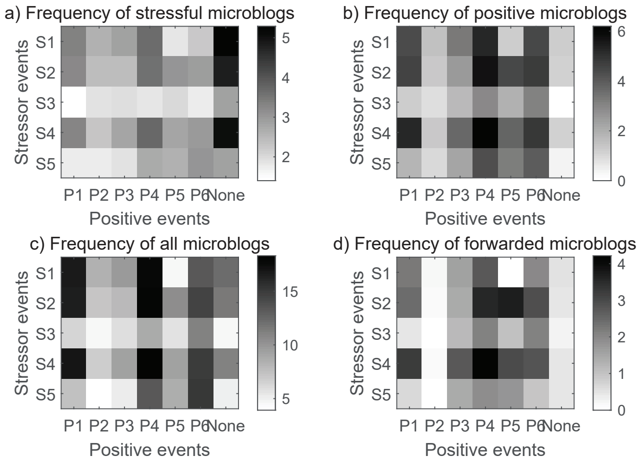


Figure 7: Comparing posting behaviors during stressful intervals in SI and U-SI sets. P_{1-6}={academic, romantic, peer relationship, self-cognition, family life, entertainment}, E_{1-5}={academic, romantic, peer relationship, self-cognition, family life}.

behaviors here. The first measure was the frequency of stressful microblogs, highlighting stressful microblogs among all microblogs. Research in Li et al. (2017a) indicated that overwhelmed adolescents tended to post more microblogs expressing their stress for release and to seek comfort from friends. The second measure was the frequency of positive microblogs, indicating the number of positive microblogs per day. The third measure was the total number of all microblogs per day. The fourth measure was the frequency of forwarded microblogs, showing the number of retweets and shared microblogs. Figure 7 summarizes the distribution of the above four measures in the U-SI and SI sets. The results in subgraphs (a) and (b) show a decrease in stressful microblogs and an increase in positive microblogs when positive events occurred. Subgraph (d) indicates that adolescents tended to forward more microblogs when positive events occurred, while subgraph (c) showed that the frequency of all microblogs did not appear to change significantly under the impact of positive events.

4.2.3. Monotonic Model of Stress-buffering

To further verify the monotonic changes in stress intensity under the impact of positive events, for each stressful interval in the SI (n=2,582) and U-SI (n=1,914) sets, we compared its stress intensity with the front- and rear-adjacent intervals. For a stressful interval $I =< t_i, t_{i+1}, \cdots, t_j >$, let $I^{front} =< t_m, \cdots, t_{i-1} >$ be the adjacent interval before I, and $I^{rear} =< t_{j+1}, \cdots, t_n >$ be the rear-adjacent interval of I. The lengths of I^{front} and I^{rear} were set to $|I|$. For the set of stressful intervals SI composed of $< I_1, I_2, \cdots, I_N >$, the corresponding sets of adjacent front and rear intervals are denoted by SI^{front} and SI^{rear}, respectively. Similarly, for the set of stressful intervals $USI =< UI_1, UI_2, \cdots, UI_M >$ impacted by positive events, the corresponding sets of front-adjacent intervals and rear-adjacent intervals are denoted by USI^{front} and USI^{rear}, respectively. We compared the intensity of stress changes in the following four situations, where $g(.)$ is the function comparing two sets:

1) $g(SI, SI^{front})$ is returned if a stress-intensity change occurred when the stressful intervals began.

2) $g(SI, SI^{rear})$ is returned if a stress-intensity change occurred after the stressful intervals ended.

3) $g(USI, USI^{front})$ is returned if a stress-intensity change occurred when the stressful intervals affected by positive events began.

4) $g(USI, USI^{rear})$ is returned if a stress-intensity change occurred after the stressful intervals affected by positive events ended.

In our problem, taking the comparison between SI and SI^{rear} as an example, the basic computation element $I_k \in SI \cup SI^{rear}$ in both sets was an interval, represented by a multidimensional point. Here, we adopt a t-test as the intensity computation function $g(.)$. The function $g(.) = t_{score} \in$ (-1,1) is represented as:

$$g(SI, SI^{rear}) = \frac{\mu_{SI} - \mu_{SI^{rear}}}{\sqrt{\frac{(n_1-1)\sigma^2_{SI}+(n_2-1)\sigma^2_{SI^{rear}}}{n_1+n_2-2}(\frac{1}{n_1} - \frac{1}{n_2})}} \tag{14}$$

where μ_{SI} and $\mu_{SI^{rear}}$ are the mean stress values of intervals in sets SI and SI^{rear}, respectively, and σ_{SI} and $\sigma_{SI^{rear}}$ are the variance of the stress values of the intervals in sets SI and SI^{rear}, respectively. If $g(SI, SI^{rear}) > \alpha$, the stress intensity in SI^{rear} showed a significant decrease compared with SI (monotonic negative effect). If $g(SI^{front}, SI) < -\alpha$, the stress intensity in SI showed a significant increase compared with SI^{front} (monotonic positive effect). Here, we adopted $\alpha = 1.96$; $P = 0.025$. We conducted a comparison for the above four situations to observe whether the occurrence of positive events relieved the monotonic negative effect of $g(SI, SI^{rear})$ and the monotonic positive effect of $g(SI^{front}, SI)$.

Table 5: Monotonous stress intensity changes in U-SI and SI intervals compared with adjacent intervals. *Front*→ *I* represented monotonous increase from the front interval to current stressful interval *I*. *I* → *rear* represented monotonous decrease from interval *I* to its rear interval.

	school life		romantic		peer relationship		self-cognition		family life		all types	
	U-SI	SI	U-SI	SI	U-SI	SI	U-SI	SI	U-SI	SI	U-SI	SI
# interval	365	514	536	587	128	391	564	609	321	481	1,914	2,582
front → I	72.60%	78.79%	69.03%	77.51%	74.22%	81.59%	70.04%	77.67%	67.91%	77.96%	70.17%	78.51%
I → rear	75.89%	78.40%	74.63%	79.05%	78.13%	82.61%	75.00%	79.15%	74.14%	79.42%	75.13%	79.55%

Table 6: Quantify the stress-buffering effect of scheduled positive events applying KTS model (the KNN-based two sample method adopted in this research) and baseline method.

	practical activity	holiday	new year party	sports meeting	all
size of U-SI	219	339	235	226	1,019
Pearson	55.65%	70.97%	56.45%	54.84%	65.32%
KTS	54.52%	78.39%	63.39%	58.74%	69.52%

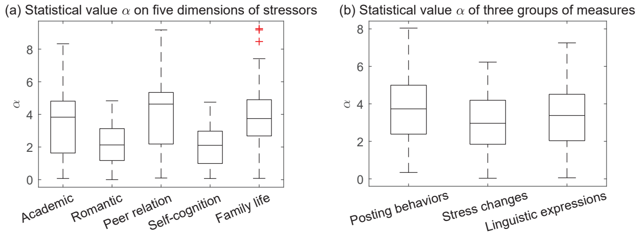


Figure 8: Subgraph (a) showed statistical value α of each group of measures. Subgraph (b) showed stress-buffering effects on five dimensions of stress.

5. Experiments

5.1. Stress-buffering Effect of Positive Events

Basically, we explored the stress-buffering effect of specific positive events based on the framework in section 4. Four scheduled positive events were adopted: practical activity, holiday, new year party and sports meeting. Table 6 showed the experimental results, where 54.52%, 78.39%, 63.39%, 58.74% significant stress-buffering effect were detected for each of the four scheduled positive events, with the total ratio to 69.52% (α =1.96 for p=0.025). Here Pearson correlation algorithm was applied to compare with the statistical model in section 4.2. The Euclidean metric was used to calculate the distance between two n dimension points X and Y. Experimental results showed that our KNN-based two sample method (denoted as KTS) outperformed the baseline method with the best improvement in event *new year party* to 10.94%, and total improvement to 6.00%.

Stress-buffering effects measured by three groups of microblog characteristics and towards five dimensions of stressor events were shown in box-plots 8, using the statistical value α computed through KTS method. Results showed the stress-buffering pattern of positive events was significantly correlated with posting behaviors (ratio = 83.06%, n=103, SD=1.96), stress change modes (ratio = 74.19%, n=92, SD=2.04) and linguistic expressions (ratio = 77.42%, n=96, SD=2.07). Positive events conducted most significant stress-buffering impact on 'family life' (ratio = 84.68%, n=105, SD=2.72), followed by 'peer relationships' (ratio = 79.03%, n=98, SD=4.04) and 'academic' (ratio = 68.55%, n=85, SD=2.71) dimensions. Statistics α in 'peer relation' exhibited the highest 75th percentile while the lowest 25th percentile, showing a relatively random and unstable stress-buffering effect on this dimension. Comparing the hypothesis test results on scheduled positive events (ratio = 69.52%) and automatically extracted positive events (ratio = 74.21%), the result indicated the feasibility of automatically extracting positive events from microblogs.

Next, to verify monotonous changes of stress intensity when an positive event impacted a stressful interval, for each interval in SI and U-SI sets, we quantified its monotonous stress changes by comparing with the front and rear adjacent intervals, respectively. Four situations proposed in section 4.2.3 were considered and compared in table 5. The ratio of intervals detected with monotonous increase from the front interval to current stressful interval I (denoted as *front*→ I), and ratio of monotonous decrease from I to its rear interval (denoted as I → *rear*) were summarized. Under the effect of positive events, the ratio of intensive stress increase in *front*→ I was decreased from 78.51% to 70.17%; and the ratio of intensive stress decrease in $I \rightarrow$ *rear* was decreased from 79.55% to 75.13%. The most obvious monotonous decrease in *front*→ I was conducted by positive events in family life dimension (12.89% reduction); and the most obvious monotonous decrease in *front*→ I was also conducted by positive events in family life dimension (6.65% reduction). The experimental results indicated the effectiveness of the two sample method for quantifying the effect of positive events, and the rationality of the assumption that positive events could help ease stress of overwhelmed adolescents.

5.2. Predicting Future Stress Under the Stress-buffering Effects of Positive Events

To further explore the effectiveness of our method for quantifying stress-buffering effects of positive events, we integrate the impact of positive events into a stress prediction problem, and verify whether considering stress-buffering effects of positive events could help improve stress prediction performance.

Stress prediction model. The SVARIMA (Seasonal Autoregressive Integrated Moving Average) algorithm was proved to be suitable for adolescents' stress prediction problem (Li et al., 2015c; Shumway and Stoffer, 2006), due to the seasonality and non-stationarity of stress series. Since stressor events cause the fluctuation of stress series from normal states, we focused the prediction problem on stressful intervals rather than randomly picked out stress series. Thus the basic stress prediction was conducted using SVARIMA approach in the set of stressful intervals impacted by positive events (U-SI). Stress-buffering effects of positive events were adopted as adjust values to modify stress prediction results. Four metrics were adopted to measure stress forecasting performance, where *MSE*, *RMSE* and *MAD* measured absolute errors and *MAPE* measures relative errors. For all real stress value $\overline{s_i}$ and predicted stress value s_i in predicting sequence $< s_1, \cdots, s_n >$: $MSE = \frac{1}{n}\sum_{i\in[1,n]}(s_i - \overline{s_i})^2$, $RMSE = \frac{1}{n}\sqrt{\sum_{i\in[1,n]}(s_i - \overline{s_i})^2}$, $MAD = \frac{1}{n}\sum_{i\in[1,n]}|s_i - \overline{s_i}|$, $MAPE = \frac{1}{n}\sum_{i\in[1,n]}|s_i - \overline{s_i}|/s_i$.

The experimental set contained 1,914 stressful intervals under the impact of positive events (U-SI). As shown in Table 7, the original prediction performance using only SVARIMA method achieved 0.1281 MSE, 0.3579 RMSE, 0.3604 MAPE and 0.1482 MAD ($L = 7, \beta = 0.5$). Then we integrated the stress-buffering impact of each dimension of positive events into stress prediction. Specifically, for positive events conducted significant stress-buffering effects on current adolescent, the average stress value during historical U-SI intervals were integrated to modify the result by adjusting the parameter β. After modification, the prediction performance achieved 0.0649 MSE, 0.2548 RMSE, 0.2638 MAPE and 0.0858 MAD, reducing the prediction errors efficiently (with MSE, RMSE, MAPE and MAD reduced by 49.34%, 28.81%, 26.80% and 42.11%, respectively).

Contribution of each group of measures. Further, we conducted experiments with different stress-buffering patterns included respectively, thus to show its contribution to stress prediction. Four groups of situations were considered here, as shown in Table 7, considering 1) all three groups of measures, namely stress change modes, linguistic expressions and post behaviors (the L&S&P pattern), 2) any two of the three groups of measures included (the L|S, L&P, and S&P patterns), 3) only one group of measures included (the L, S, or P patterns), and 4) none group of measures included. We integrated the effect of positive events under the four situations into stress prediction by overlapping paramiter $\alpha \times S_{historical}$, where $S_{historical}$ was average stress value in historical U-SI intervals. Here we present the prediction result when $\beta = 0.5$ in each dimension of stress respectively. Results showed that stress-buffering pattern in L&S&P pattern outperformed other patterns (0.0649 MSE, 0.2548 RMSE, 0.2638 MAPE and 0.0858 MAD), showing the effectiveness of all three groups of measures.

Stress prediction performance under different observation windows. We further explored to combine stress-buffering effects into future stress prediction under different length of observation windows, ranging from 1 to 10 days, as shown in Figure 9. With window length increasing, prediction errors showed increasing trend in all metrics. The reason might be that longer prediction window took more previous predicted results, and errors accumulates with more predicted values taken into the next step prediction. Among five dimensions of stressor events, prediction for school life stress achieved the best performance. One reason might be more positive events and stressors about school life events were detected from adolescents' microblogs, providing sufficient data in prediction process. On the other side, stress coming from school life was the most common

Table 7: Adolescents' stress prediction performance when combined different groups of stress-buffering measures separately.

	None				Positive (L)				Positive (S)				Positive (P)			
	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD
School life	0.0856	0.2926	0.4852	0.1146	0.0259	0.1609	0.2991	0.0923	0.0297	0.1723	0.3135	0.0899	0.0223	0.1493	0.3438	0.0931
Romantic	0.0703	0.2651	0.3555	0.1083	0.0291	0.1706	0.2832	0.0919	0.0379	0.1947	0.2941	0.1026	0.0332	0.0835	0.2746	0.1240
Peer relationship	0.2800	0.5292	0.3256	0.1697	0.3140	0.5604	0.3626	0.1202	0.2972	0.5452	0.3060	0.1298	0.2557	0.1472	0.3481	0.1458
Self-cognition	0.0445	0.2110	0.3066	0.1895	0.0345	0.1857	0.2721	0.1653	0.0366	0.1913	0.2557	0.0754	0.0245	0.0862	0.2863	0.1447
Family life	0.1602	0.4002	0.3291	0.1587	0.0889	0.2982	0.2891	0.0944	0.0378	0.1944	0.2952	0.0842	0.1827	0.0979	0.3148	0.1131
All	0.1281	0.3579	0.3604	0.1482	0.0985	0.3138	0.3012	0.1128	0.0878	0.2964	0.2929	0.0964	0.1037	0.1128	0.3135	0.1241

	Positive (L&S)				Positive (L&P)				Positive (S&P)				Positive (L&S&P)			
	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD	MSE	RMSE	MAPE	MAD
School life	0.0283	0.1682	0.2934	0.0824	0.0261	0.1616	0.2770	0.0768	0.0342	0.1849	0.2629	0.0590	0.0132	0.1149	0.2364	0.0717
Romantic	0.0219	0.1480	0.2532	0.0839	0.0180	0.1342	0.2644	0.0952	0.0176	0.1327	0.2549	0.0823	0.0251	0.1584	0.2507	0.0891
Peer relationship	0.2361	0.4859	0.3182	0.1300	0.2349	0.4847	0.3283	0.1189	0.2351	0.4849	0.3558	0.1297	0.2341	0.4838	0.3096	0.1093
Self-cognition	0.0329	0.1814	0.2942	0.0946	0.0262	0.1619	0.2791	0.0858	0.0245	0.1565	0.2740	0.0945	0.0144	0.1200	0.2580	0.0739
Family life	0.1489	0.3859	0.2750	0.1244	0.0395	0.1987	0.2853	0.0939	0.0484	0.2200	0.2946	0.0992	0.0378	0.1944	0.2645	0.0848
All	0.0936	0.3060	0.2868	0.1031	0.0689	0.2626	0.2868	0.0941	0.0720	0.2683	0.2884	0.0929	0.0649	0.2548	0.2638	0.0858

[1] Three stress-buffering measures: 'L' represents *linguistic expression*, 'S' represents *stress intensity*, and 'P' represents *posting behavior*.

Figure 9: Adolescents' stress prediction performance under different lengths of observation windows.

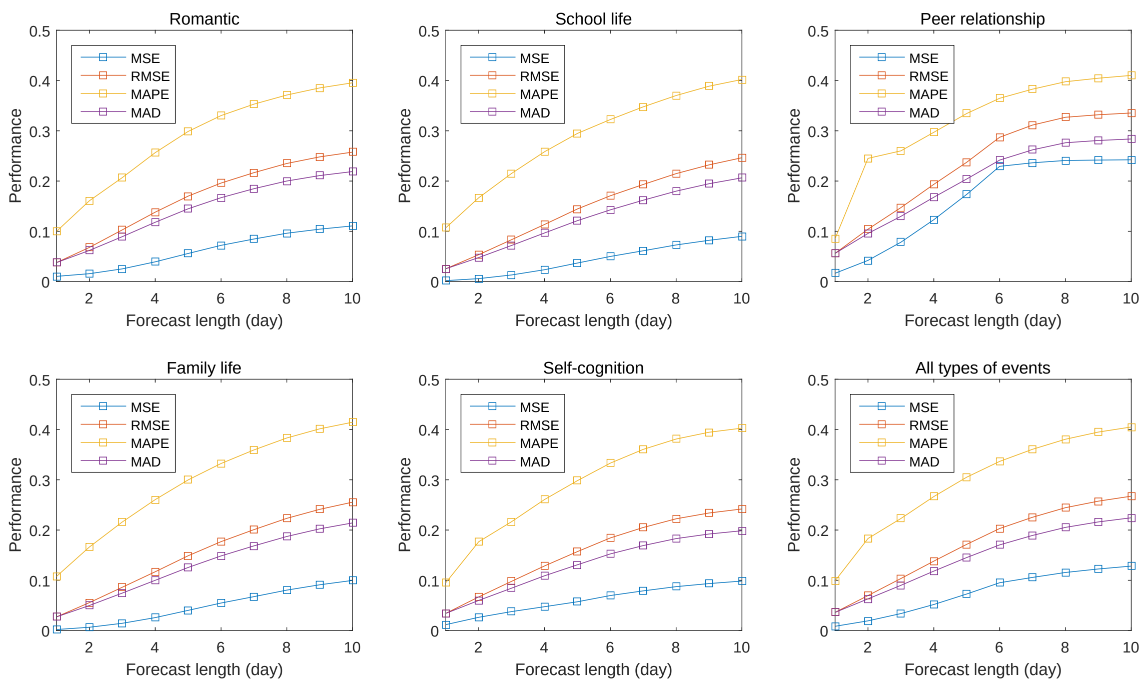
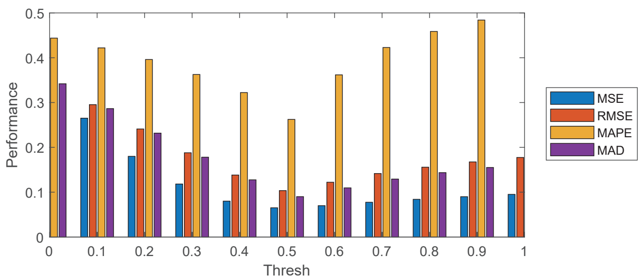


Figure 10: Stress prediction performance under L&S&P stress-buffering pattern of positive events.



stress in student group, with relative stable periodicity, which was more suitable for current prediction model.

Parameter settings. Parameter β was adjusted when integrated impact of positive events into stress prediction. For each of the four groups of stress-buffering patterns, we adjust β in the effect of $\beta \times L$. We calculated the corresponding prediction result for each adolescent respectively, and showed the result of whole testing group in average performance. Figure 10 showed the changing trend under the L&S&P pattern. Prediction errors decreased first and then increased, and the best performance was achieved when β was nearby 0.52, with 0.0649 MSE, 0.2548 RMSE, 0.2638 MAPE and 0.0858 MAD as the average performance of the whole experimental data set. Multiple methods for integrating stress-buffering impact of positive event into stress prediction could be adopted in the future. In this paper we adopted the simple one to verify the effectiveness of our model in quantifying the impact of positive events. The setting of parameter β could be changed due to different individuals and data sets.

6. Discussion

The main contribution of the present study lies in the following three aspects. First, we validated and expanded the theoretical results of previous studies. The characteristics of stress-buffering were not only manifested in self-reported subjective feelings, but also in behavioral level in social networks. We examined the potential relationship between the occurrence of positive events and the posting behaviors, microblog contents and stress change mode on stressed adolescents, and verified that positive events buffered monotonous stress changes at both the early and late stages. Second, this study implemented the innovation of methods. Through building a complete technical framework, we realized 1) automatic extraction of positive events, as well as users' behavior and content measures from microblogs, and 2) quantification of relationships between stress-buffering of positive events and microblogging measures. Third, this article showed practical significance. It realized timely and continuous monitoring of the stress-buffering process of adolescents based on public social network data sources, which could be used to assess the stress resistance of adolescents; on the other hand, it could provide supplementary advice to schools and parents about 'when to arrange positive events to ease stress of adolescents'.

There were three groups of results in this work. In study 1, the scheduled school events with exact time intervals and the microblogs posted by a group of 500 students were collected and statistically analyzed. Results showed that when positive events were scheduled neighboring stressful events, students exhibited less stress intensity and shorter stressful time intervals from their microblogs. The study also found that most students talked less about the upcoming or just-finished exams when positive events happened nearby, with lower frequency and lower ratio. The results substantiated previous studies reporting the protective effect of positive events on adolescents (Cohen and Hoberman, 2010; Shahar and Priel, 2002) using laboratory methods. Based on this, this article carried out more in-depth follow-up studies.

The second groups of results were presented in study 2, examining stress-buffering pattern of positive events through microblog content and behavioral measures. As basis, a complete solution was provided for automatically detecting positive events based on microblog semantics, which were totally different from traditional questionnaire methods, enabling timely, fraud-proof and continuous detection. In order to eliminate the possible errors in positive event detection and avoid false overlays, we first used four scheduled positive events to examine significant stress-buffering effects. Results showed the event 'holiday' exhibited the highest proportion of significant stress-buffering. However, this conclusion was questionable because the frequency of the above four events was different and might affect the experimental results. Next, the stress-buffering effect of automatically extracted positive events were tested based on three groups of stress-buffering measures. The most intensive stress-buffering effects were shown in 'school life' and 'peer relationship' dimensions. *Posting behaviors* exhibited most significant correlations among three groups of measures. This resonated with the study Blachnio et al. (2016); L. Bevan et al. (2014) suggesting that users who tended to share important news on Facebook had a higher level of stress.

This article proposed a novel perspective to better understand the process of stress-buffering. Since more complex situations were simplified in the present exploration, the goals were still salient for stress-buffering researches from social networks.

7. Limitations and future work

This study has a number of limitations. First, it used the microblog data set collected from social networks of high school students, and chose the scheduled school events as the ground truth in the pilot study. This could be seen as a relative fuzzy verification method, because individual events (i.e., 'lost love', or 'received a birthday present') might also conduct additional impact. Therefore, the data observation in the pilot study were not 100% rigorous and needed further verification. A improvement might be conducted by inviting participants to complete related scales (e.g., positive and stressor scales), thus to label part of the data set, and achieve a balance between data volume and accuracy.

Second, this study treated positive events as independent existence and studied the effect of each event separately. This ignored the additive and collective effects of multiple positive events which might happened at the same time. Thus, our future research might investigate the overlap effects of multiple positive events, as well as the frequent co-appearing patterns of different types of positive events, thus to provide more accurate stress-buffering guidance for individual adolescents.

Based on current research implications, more factors could help analyze stress-buffering patterns among adolescents more comprehensively in future research. One factor is how personality (Twomey and O' Reilly, 2017; Shchebetenko, 2019) impacts the stress-buffing effect of positive events, which could be captured from the social media contents. Another key factor is the role the social support (Nabi et al., 2013; L Bevan et al., 2015) in social networks plays. This factor leaves clues in the messages under each post, and the behaviors (i.e., retweet, the like numbers) of friends. For examples, (Nabi et al., 2013) showed that the number of Facebook friends was associated with stronger perceptions of social support, which in turn correlated with reduced stress and greater well-being. The corresponding experimental design, and the online-offline complementary verification will be challenges in the future work.

8. Reference

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