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

Abstract

Stress is viewed as the leading cause of public mental health issues. Positive events, however, could act as a buffer against stress. Since the stress-buffering effect of positive events in previous studies was 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=29,232) from a high school student group (n=500) to examine the relationship between positive events and stress-buffering pattern based on microblog content and behavioral characteristics. Through a pilot study we found that the stress-buffering pattern of school scheduled positive events (n=259) was manifested in both the reduction of stress intensity, the shorter duration of stress intervals, and talking less about academic words on micro-blog. Hypothetical tests for stress-buffering pattern and monotonic effect of stress changes were further conducted based on automatical extracted positive events (n=1,914) from microblogs. The stress-buffering pattern of positive events was closely correlated with posting behavior (ratio = 80.65%, SD=1.96), stress change mode (ratio = 67.74%, SD=2.04) and microblog linguistic expressions (ratio = 74.19%, SD=2.07). Positive events conducted most intensive stress-buffering impact on stress from 'family life' (ratio = 83.87%, SD=2.72), followed by 'peer relationships' (ratio = 71.77%, SD=4.04) and 'school life' (ratio = 67.74%, SD=2.71) dimensions. Positive events buffered monotonous stress changes at both the early (11.88% reduction) and late stages (5.88% reduction). This study could inform the use of social network to reach and track the mental status transition of adolescents under stress. The theoretical and practical implications, limitations of this study and future work were discussed.

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

1. Introduction

Life is always full of ups and downs. Accumulated stress could drain inner resources, leading to psychological maladjustment, depression and even suicidal behaviours (Nock et al., 2008). According to the latest report released by American Psychological Association in 2018, 91% of youngest 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 are suffering from psychological stress, and nearly 30% of them have a risk of depression (Youth and Center, 2019). Stress-induced mental health problems are becoming an important social issue worldwide.

Studies have found that the occurrence of positive events could exert protective effects on emotional distress, that is, *stress-buffering* (Cohen et al., 1984; Needles and Abramson, 1990; Folkman and Moskowitz, 2010; Shahar and Priel, 2002; Folkman, 1997). As an essential process in human's stress coping system, stress-buffering helps individuals get out of overwhelmed status (Susan, 1984; Wheeler and Frank, 1988; Cohen and Hoberman, 2010). Thus, tracking the state of stress-buffering is important for understanding the mental status of stressed individuals.

However, the dynamic process of stress-buffering was difficult to track due to the lack of effective scientific methods. Previous studies have been based on static perspective, focusing on one-time measurement of positive events and stress-buffering state after events (Kleiman et al., 2014; Santos et al., 2013; Chang et al., 2015). In addition, the subjective self-reporting was susceptible to many factors, such as social appreciation and pressure from measurement scenarios (Kanner et al., 1981b; Alden et al., 2008; Mcmillen and Fisher, 1998; Jun-Sheng, 2008). There is a lack of research on the stress-buffering characteristics that individuals actually exhibit at the behavioral level.

As social networks have penetrated into people' lives, new opportunities are emerging for timely, content-rich and non-invasive detection of users' mental states. Scholars have shown the feasibility to sense users' stress and stressor events (Xue et al., 2014; Lin et al., 2014; Li et al., 2017a), and predict future stress through social networks (Li et al., 2015c, 2017c). The current study aims to contribute to this growing area of interdisciplinary research by examining the potential relationship between positive events and stress-buffering pattern from adolescents' microblog content and behavioral characteristics.

2. Literature review

2.1. Stress-buffering function of positive life 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). The protective effect of positive events was hypothesized to operate in both directly (i.e., the more positive events people experienced, the less stress they perceived) and indirectly 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).

Due to the immature inner status and lack of experience, adolescents exhibit more sensitive to stressors (i.e., exams, heavy homework, isolated by classmates, family transitions), living with frequent, long-term stress (Vitelli, 2014). In this situation, positive events could help reinforce adolescents' sense of well-being (Coolidge, 2009), restore the capacity for dealing with stress (Doyle et al., 2003), and also have been linked to medical benefits, such as improving mood, serum cortisol levels, and lower levels of inflammation and hyper coagulability (Jain et al., 2010; Caputo et al., 1998). The present study will be based on the consensus conclusions from the above studies that positive events could conduct stress-buffering effect on stressed adolescents.

2.2. Assessing the stress-buffering effect of positive events

To assess the stress-buffering effect of positive events, scholars have conducted many studies based on self-support methods, including Hassles and Uplifts Scales (Kanner et al., 1981b), Interpretation of Positive Events Scale (Alden et al., 2008), Perceived Benefit Scales (Mcmillen and Fisher, 1998), Adolescent Self-Rating Life Events Checklist (Jun-Sheng, 2008). For example, (Mcmillen and Fisher, 1998) proposed the Perceived Benefit Scales as a new measure of self-reported positive life changes after traumatic stressors (i.e., lifestyle changes, family closeness, community closeness). (Jun-Sheng, 2008) investigated 282 college students using the Adolescent Self-Rating Life Events Checklist, and found that the training of positive coping style is of great benefit to improve the mental health of students. While, the above explorations based on self-report investigations are difficult to exclude interference from external factors (i.e., social appreciation, pressure from measurement scenarios). Meanwhile, due to the lack of manpower and effective scientific methods, most scholars relies on a limited number of measurements, thus continuous measurements of stress-buffering process was difficult to carry out.

2.3. Measures and stress analysis based on social network

As billions of adolescents are recording their life through social networks (e.g., micro-blog, Twitter, Facebook), researchers explored to apply psychological theories into social network based data mining techniques. 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), high dimensional multimedia features (Lin et al., 2014). For example, (Xue et al., 2014) proposed to detect adolescent stress from microblogs utilizing machine learning methods by extracting stress topic words and abnormal posting time. (Li et al., 2017a) proposed to detect stressor events from microblog content and analyze stressful intervals based on posting rate. The above studies focus on the discussion of stress detection on social networks, while the pattern of stress-buffering and the role of positive events in stress coping process is still insufficiently discussed.

2.4. Current study

Given the limitations in the existing literature, this study examined the relationship between positive events and stress-buffering pattern based on adolescents' microblog content and behaviors. Two hypotheses were tested:

H1. The stress-buffering effect of positive events is correlated with a)posting behavior, b)stress change mode and c)microblog linguistic expressions.

H2. Positive events buffers monotonous stress changes at both the early stage (before stress beginning) and late stage (after the end of stress).

In response to the theoretical hypothesis, we propose new measurement methods in a non-invasion way based on public social network data. Two research questions are proposed:

RQ1. How to (a) automatically extract the positive events experienced by adolescents from microblogs, and (b) identify the time interval impacted by a particular positive event.

RQ2. How to quantify the stress-buffering effect of positive events based on above microblog characteristics.

To answer above questions, a pilot study was firstly conducted on the microblog data set (n=29,232) of a group of high school students (n=500) associated with the school's scheduled positive events (n=259) and stressor events (n=518). After observing the posting behaviors and contents of stressed students under the influence of positive events, several implications were discussed to guide the next step research. In study 2, we examined the relationship between the stress-buffering pattern of automatically extracted positive events and adolescents' microblog characteristics. A Chinese linguistic parser model was applied to extract structural positive events. We depicted an adolescent's stressful behaviors in three groups of measures (posting behaviour, stress change mode, linguistic expressions), and modeled the stress-buffering effect as the statistical difference in two comparative situations. In study 3, we tracked the dynamic process of stress-buffering pattern, and quantify the monotonous stress-buffering impact in temporal order.

3. Study1: a pilot study on the stress-buffering pattern of school scheduled positive events

3.1. Data collection

We built our dataset based on two sources: 1) the microblogs of students coming from Taicang High School, collected from January 1st, 2012 to February 1st, 2015; and 2) list of scheduled school events, with exact start and end time. We filtered out 124 active students according to their posting frequency from over 500 students, and collected their microblogs throughout the whole high school career. Totally 29,232 microblogs were collected in this research, where 236 microblogs per student on average, 1,387 microblogs maximally and 104 posts minimally. To protect the privacy, all usernames were anonymized during the experiment.

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

Type	Date	Content	Grade
stressor event	2014/4/16	*first day of mid-term exam*	grade1,2
positive event	2014/11/5	*campus art festival*	grade1,2,3

3.2. Measures

Scheduled positive events. The list of weekly scheduled school events (from February 1st, 2012 to August 1st 2017) were collected from the school's official website [1], with detailed event description and grade involved in the event. There were 122 stressor events and 75 positive events in total. Examples of scheduled positive and stressor events in high school life are listed shown in Table 1. There were 2-3 stressor events and 1-2 positive event scheduled per month in current study. Figure 1 shows three examples of a student's stress fluctuation during three mid-term exams, where the positive event *campus art festival* was scheduled ahead of the first exam (*example a*), the positive event *holiday* happened after the second exam (*example b*), and no scheduled positive event was found nearby the third exam (*example c*).

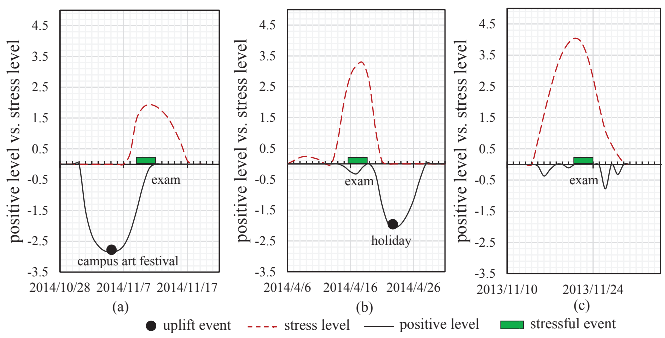


Figure 1: Examples of school scheduled positive events, stressful events, and a student's stress fluctuation

Stress detected from microblogs. Since our target was to track the stress-buffering effect 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 during each day was aggregated by calculating the average stress of all posts. The positive level (0-5) of each post was identified based on the frequency of positive words (details are presented in study 2).

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

3.3. Method

To further observe the effect of positive events on stressed students, we collected all stressful intervals surround the scheduled exams over the 124 students during their high school career applying the interval detection method in (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, positive event) occured. We called the set of such stressful intervals as **SI**; 2) In the other comparative sets, the stressful interval was impacted by a positive event, we called the set of such stressful intervals as **U-SI**. Thus the difference under the two situations (sets) could be seen as the stress-buffering effect conducted by the positive event. we identified 518 exam related stressful intervals (SI) and 259 stressful intervals impacted by four typical scheduled positive events (U-SI) ('practical activity', 'new year party', 'holiday', 'sports meeting') from the students' microblogs. Five measures during the above two conditions were considered: the *accumulated stress*, the *average stress* (per day), the *length of stressful intervals*, the *frequency of academic topic words*, and the *ratio of academic stress among all types of stress*. The average value of each measure over all eligible slides was calculated.

3.4. Results

As shown in figure 2, comparing each measure of scheduled exam intervals under the two situations: 1) existing neighbouring positive events (U-SI) or 2) no neighbouring scheduled positive events (SI), we found that students during exams with neighbouring positive events exhibited less average stress intensity (78.13% reduction in average stress, 95.58% reduction in cumulative stress) and shorter duration of stress intervals (23.30% reduction). Further, the frequency of academic topic words (table 2 for examples) and the ratio of academic stress in each interval were calculated. Results in figure 2 shows that most students talked less about the upcoming or just-finished exams when positive events happened nearby, with lower frequency (84.65% reduction) and lower ratio (89.53% reduction).

Table 2: Examples of academic topic words from microblogs.

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

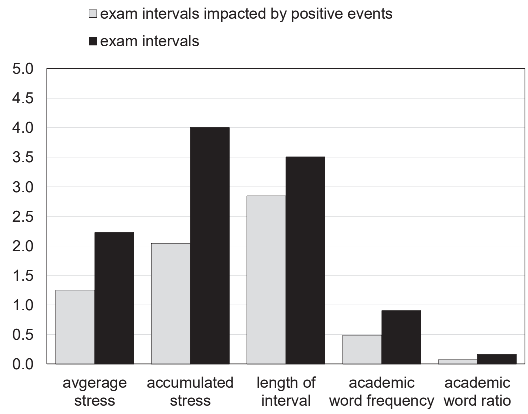


Figure 2: Comparing students' stress during exam intervals in two situations: 1) intervals affected by neighboring positive events (U-SI), 2) no positive events occurred nearby (SI)

The statistic result shows clues about the stress-buffering effect of scheduled positive events, which is constant with the psychological theory (Cohen et al., 1984; Cohen and Hoberman, 2010; Needles and Abramson, 1990), indicating the reliability and feasibility of the microblog data set. However, this is an observation based on specific scheduled events, and cannot satisfy the need for automatic, timely, and continuous perception of stress-buffering process. Therefore, next, in study 2 we will propose a framework to automatically detect positive events and its impact interval. Based on this, the relationship between stress-buffering effect of automatically extracted positive events and microblog characteristics will be examined.

4. Study2: relationship between stress-buffering effect of automatically extracted positive events and microblog characteristics

4.1. Positive events automatically extracted from microblogs

Since events in study 1 are scheduled and limited, in this part we first introduce the procedure to extract positive event and its intervals from microblogs, thus to extend our study to various types of positive events expressed in microblogs.

Linguistic structure. Let $u = [type, \{doer, act, description\}]$ be a positive event, where the element *doer* is the subject who performs the *act*, and *descriptions* are the key words related to u. According to psychological scales (Kanner et al., 1981a; Jun-Sheng, 2008), adolescents' positive events mainly focus on six aspects, as $\mathbb{U}$ = { 'entertainment', 'school life', 'romantic', 'pear relationship', 'self-cognition', 'family life'}.

Table 3: Examples of topic words for 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	beloved, favor, guard, anniversary, concern, tender, deep feeling, care, true love, promise, cherish, kiss, embrace, dating, reluctant, honey, sweetheart, swear, love, everlasting, goddess	138
pear relation	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

Lexicon. We constructed our lexicon for six-dimensional positive events from two sources. The basic positive words are selected from the psychological lexicon SC-LIWC (e.g., *expectation*, *joy*, *love* and *surprise*) (Tausczik and Pennebaker). Then we built six topic lexicons by expanding basic positive words from adolescent microblogs, containing 452 phrases in 'entertainment', 273 phrases in 'school life', 138 phrases in 'romantic', 91 phrases in 'peer relationship', 299 phrases in 'self-recognition' and 184 phrases in 'family life', with totally 2,606 phrases, as examples shown in table 3. Additionally, we labeled *doer* words (i.e., *teacher*, *mother*, *I, we*) in the positive lexicon.

Parser relationship. For each post, after word segmentation, we parsed current sentence to find its linguistic structure, and then matched the main linguistic components with positive topic lexicon in each dimension. The parser model in Chinese natural language processing platform (Che et al., 2010) was adopted in this part, which identified the central verb of current sentence first, namely the *act*, and constructed the relationship between the central verb and corresponding *doer* and *description* components. By searching these main elements in positive event related lexicons, we identified the existence and type of positive events. Due to the sparsity of posts, *act* might be empty. *Descriptions* were collected by searching all nouns, adjectives and adverbs. In such way, we extracted structured positive events from microblogs.

Examples of adolescents' microblogs describing positive events are listed in table 4. For the post 'Thanks all my dear friends hosting the party. Happiest birthday!!!', we translated it into *doer='friends', act = 'expecting', description = 'party'*, and *type = 'entertainment'*. To check the accuracy of positive event extraction, in study 3, we identified positive events and its corresponding stress-buffering effect from microblogs, and compared the results with positive events in school planning.

Table 4: Structured extraction of positive events from microblogs.

I am really looking forward to the spring outing on Sunday now. (doer:*I*, act:*looking forward*, description:*spring outing*)
My holiday is finally coming [smile]. (doer:*My holiday*, act:*coming*, description:*[smile]*)
First place in 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 all my dear friends hosting the party. Happiest birthday!!! (doer:*friends*, act:*thanks*, description:*party, birthday*)
I know my mom is the one who support me forever, no matter when and where. (doer:*mom*, act:*support*)
Expecting Tomorrow' Adult Ceremony[Smile][Smile] (act: *expecting*, description:*Adult Ceremony*)

Impact Interval of Positive Event. Next, we identified the impact interval of each positive event thus to further study its stress-buffering pattern. Splitting interval is a common time series problem, and here we identified the target interval in three steps. In the first step, we extracted positive events, stressor events (Li et al., 2017a) and filtered out candidate intervals after a smoothing process. Since the stress series detected from microblogs were discrete points, the loess method was adopted to highlight characteristics of the stress curve (see Appendix A.1). In the second step, applying the Poisson based statistical method (Li et al., 2017a), we judged whether each candidate interval was a confidential stressful interval. Finally, we divided the stressful intervals into two sets: the SI set and the U-SI set, according to its temporal order with neighboring positive events (see Appendix A.2).

4.2. Measures

We examined the relationship between positive events and stress-buffering pattern through three groups of measures: posting behavior, stress intensity, and linguistic expressions.

Posting behaviors. Stress could lead to abnormal posting behaviors, reflecting user's changes in social engagement activity (Liang et al., 2015). In this study, we considered four measures of posting behaviors in each time unit (day), and presented each measure as a corresponding series. The first measure was *posting frequency*, representing the total number of posts per day. Research in Li et al. (2017a) indicated that overwhelmed adolescents tended to post more to express their stress for releasing and seeking comfort from friends. The second measure *stressful posting frequency* per day was based on existing stress detection result and highlights the stressful posts among all posts. The third measure was the *positive posting frequency*, indicating the number of positive posts per day. The forth measure *original frequency* was the number of original posts, which filters out re-tweet and shared posts. Compared to forwarded posts, original posts indicated higher probability that users were talking about themselves. Thus in each interval, user's posting behavior was represented as a four-dimension vector.

Stress change mode. The global stress change mode during a stressful interval was depicted through four measures: *sequential stress level, length, RMS,* and *peak*. Basically, *stress level* per day constructed a sequential measure during a stressful interval, recording stress values and fluctuation on each time point. As positive events might conduct impact on stressed adolescents, and postpone the beginning or promote the end of a stressful interval, we took *length* as the second factor representing the interval stress change mode. To quantify the intensity of stress fluctuations, *RMS* (root mean square) of stress values through the interval was adopted as the third measure. *Peak* value was adopted as the forth measure to show the maximal stress value in current interval.

Linguistic expressions. Positive and stressful expressions were extracted from the post content. The first linguistic measure was the frequency of *positive word*, which represented the positive emotion in current interval. The second measure was the frequency of *positive event topic words* in six dimensions, reflecting the existence of positive events. (Li et al., 2014) showed that self-mentioned words showed high probability that the current stressor event was related to the author, rather than the opinion about a public event or life events about others. Another important factor was wether existing *self-mentioned words* (i.e., *'I','we','my'*). Except positive-related linguistic descriptions, we also took stressful linguistic characters as measures, while also offered information from the complementary perspective. The frequency of *stressor event topic words* in five dimensions represented the degree of attention for each type of stressor event. The frequency of *pressure words* reflected the degree of general stress emotion during the interval.

Next, based on the above measures, we quantified the difference between SI and U-SI sets, thus to track the stress-buffering pattern of positive events.

4.3. Method

In our problem, there were two sets of stressful intervals to compare: the SI set and the U-SI set, containing stressful intervals not affected by positive events and stressful intervals impacted by positive events, respectively. The basic elements in each set were stressful intervals. Each interval was modeled as a multi-dimensional vector according to the three groups of measures in section 4.2. Thus we formulated this comparison problem as finding the correlation between the two sets of multi-dimension points. Specifically, we adopted the multivariate two-sample hypothesis testing method Li et al. (2017b); Johnson and Wichern (2012) to model such correlation. In this two-sample hypothesis test problem, the basic idea is judging whether the multi-dimension points (i.e., stressful intervals) in set SI and set U-SI were under different statistical distribution. Assuming the data points in SI and U-SI were randomly sampled from distribution F and G, respectively, then the hypothesis was denoted as:

$$H_0 : F = G \quad versus \quad H_1 : F \neq G. \qquad (1)$$

Under such hypothesis, H_0 indicates points in SI and U-SI were under similar distribution, while H_1 means points in SI and U-SI were under statistically different distributions, namely positive events conducted obvious stress-buffering effect on current user. Since each point in the two sets (SI and U-SI) was depicted in multi-dimensions, here we took the KNN (K-Nearest Neighbor) Schilling (1986) based method to judge the

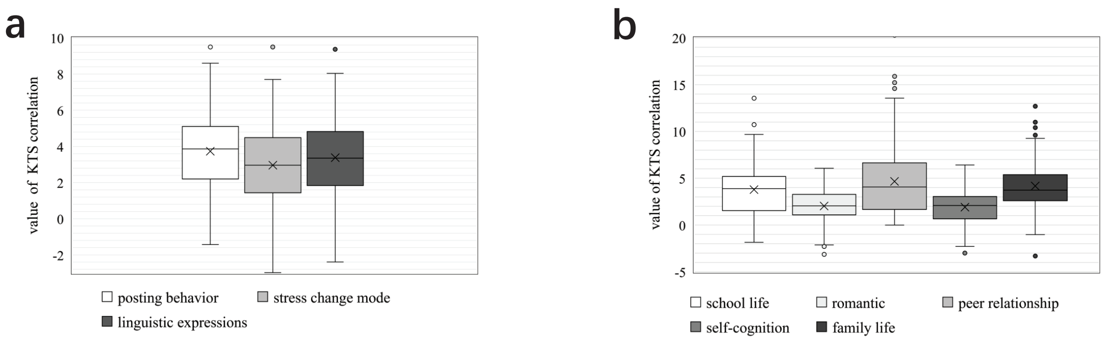


Figure 3: Stress-buffering pattern of positive events. Figure a) shows correlation of each microblog measure, and figure b) shows stress-buffering effect on five dimensions of stress. 'KTS' means KNN-based correlation method.

existence of significant difference between SI and U-SI. For simplify, we used the symbol A_1 to represent set SI, and A_2 represent set U-SI. In the KNN algorithm, for each point ℓ_x in the two sets A_1 and A_2, we expected its nearest neighbors (*the most similar points*) belonging to the same set of ℓ_x. The model derivation process was presented in Appendix B.

4.4. Results

Stress-buffering Pattern of scheduled positive events. Basically, we focused on four scheduled positive events: *practical activity*, *holiday*, *new year party* and *sports meeting*. For each of the four scheduled positive events, we quantified the stress-buffering effect based on corresponding SI and U-SI interval sets of the 124 students.

Table 5: Quantify the impact of scheduled positive school events using KTS (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%

Table 5 shows the experimental results, where 54.52%, 78.39%, 63.39%, 58.74% significant stress-buffering effect were detected for the four specific scheduled positive events, with the total ratio to 69.52% (α =1.96 for p=0.025). We adopted the commonly used Pearson correlation algorithm to compare with the two sample statistical method in this study. The Euclidean metric was used to calculate the distance between two n dimension points X and Y. Experimental results show that our KNN-based two sample method (denoted as KTS) outperformed the baseline method with the best improvement in *new year party* to 10.94%, and total improvement to 6.00%.

The correlation of positive events a) in each group of microblog measure and b) towards five dimensions of stress were shown in box-plots 3. The stress-buffering pattern of positive events was closely correlated with posting behavior (ratio = 80.65%, n=100, SD=1.96), stress change mode (ratio = 67.74%, n=84, SD=2.04) and microblog linguistic expressions (ratio = 74.19%, n=92, SD=2.07). Positive events conducted most intensive stress-buffering impact on 'family life' (ratio = 83.87%, n=104, SD=2.72), followed by 'peer relationships' (ratio = 71.77%, n=89, SD=4.04) and 'school life' (ratio = 67.74%, n=84, SD=2.71) dimensions. The correlation values 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.

5. Study3: Testing the monotonous stress changes of stress-buffering from adolescents' microblogs

5.1. Method

To verify the monotonous stress changes at both the early and late stress-buffering stages, for each stressful interval in SI (n=2,582) and U-SI (n=1,914), we compared its stress intensity with the front and rear adjacent intervals using t-test method. Detailed algorithms are presented in Appendix C.

Table 6: Monotonous stress intensity changes in U-SI and SI intervals compared with adjacent intervals.

	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%

5.2. Result

Here four situations were considered and compared, as shown in table 6. The *ratio of intervals* detected with monotonous increase from the *front interval* to *stressful interval* (denoted as *front*→ *I*), and monotonous decrease from the *stressful interval* to the *rear interval* (denoted as *I* → *rear*) were listed. 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* → *rear* was decreased from 79.55% to 75.13%. The most obvious monotonous decrease in *front*→ *I* were conducted by positive events in family life dimension (12.89% reduction); and the most obvious monotonous decrease in *front*→ *I* were 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 teens.

6. Exploratory study: Integrating the stress-buffering effect into stress prediction

Stress prediction model. To measure the effectiveness of our method for quantifying the restoring impact of positive events, we integrate the impact of positive events into traditional stress series prediction problem, and verify whether the restoring pattern of positive events could help improve the prediction performance. Here we choose the SVARIMA (Seasonal Autoregressive Integrated Moving Average) algorithm Shumway and Stoffer (2006), which is proved to be suitable for teens' linear stress prediction problem Li et al. (2015c), due to the seasonality and non-stationarity of teens' stress series. The basic stress prediction is conducted using SVARIMA approach, in the set of stressful intervals impacted by positive events (U-SI). Since stressor events cause the fluctuation of stress series from normal states, to eliminate the interference, we simply consider the prediction problem in those stressful intervals rather than randomly picked out stress series. The impact of positive events are utilized as adjust values to modify the stress prediction result. Four metrics are adopted to measure the stress forecasting problem, where *MSE*, *RMSE* and *MAD* measure absolute errors and *MAPE* measures relative errors.

We integrate the impact of positive events into stress prediction. The experimental set contains 1,914 stressful intervals under the impact of positive events (U-SI). As shown in Table 7, the original prediction result using only SVARIMA method achieves 0.1281 MSE, 0.3579 RMSE, 0.3604 MAPE and 0.1482 MAD ($L = 7$, $\alpha = 0.5$). Then we integrate the impact of each type of positive events into stress prediction. Specifically, for positive with obvious restoring impact (under the L&S&P pattern), the average stress level during historical restoring intervals are integrated to modify the result, with adjusting the parameter α (details see 6). After the modification, the prediction performance achieves 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).

Predicting stress under different windows. We present the prediction result under the impact of positive events under different lengths of prediction windows, ranging from 1 to 10 days, as shown in 4. With the window length increasing, the prediction error shows decreasing trend in all metrics. The reason is that longer prediction window takes more previous predicted results, and the error accumulates with more predicted values taken into the next step prediction. Among the five dimensions of events, the prediction for school life stress achieves the best performance. On one side, more positive events and stressors about school life events are detected from teens mi-

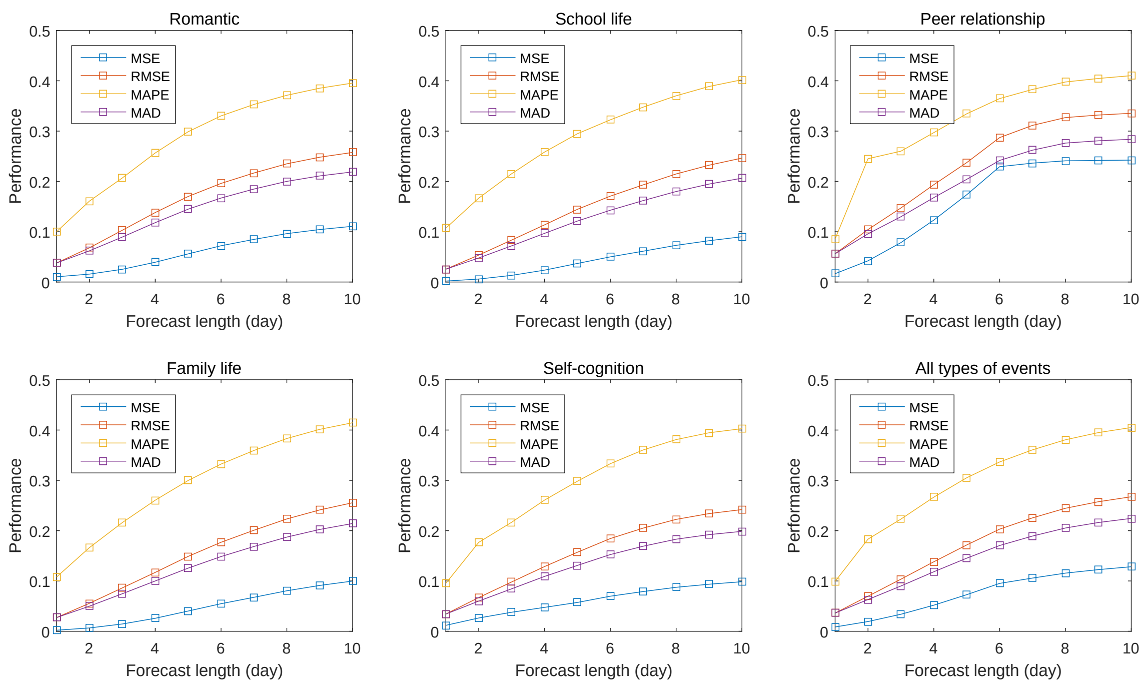
Table 7: Compare the stress forecast performance under three stress-buffering measures of positive events.

	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 4: Teens' stress forecast performance under different lengths of predicting windows.



croblogs, providing sufficient data in prediction. On the other side, stress coming from school life is the most common stress in the student group, with relative stable periodicity and high frequency.

Contribution of each restoring measure. We conduct experiments with different restoring patterns included respectively to show its contribution to the impact of positive events during prediction. Four groups of situations are considered here, as shown in Table 7, considering 1) all the stress intensity, linguistic expression and post behavior measures (the L&S&P pattern), 2) any two of the three measures included (the L|S, L&P, and S&P patterns), 3) only one of the three measures included (the L, S, or P patterns), and 4) none measure included. We integrate the impact of positive events under the four situations into stress prediction using the parameter α, as overlapping $\alpha \times S_{historical}$, where $S_{historical}$ is the average stress level in historical restoring intervals. The detailed adjust process of α is presenting in section 6. Here we present the prediction result when $\alpha = 0.5$ in each dimension of stress respectively. Results show that the correlation in the L&S&P pattern outperforms other patterns (0.0649 MSE, 0.2548 RMSE, 0.2638 MAPE and 0.0858 MAD), showing the effectiveness of considering all the three correlations.

Parameter settings. The parameter α is adjusted when integrate the impact of positive events into stress prediction. For each of the four groups of restoring patterns, we adjust α in the effect of $\alpha \times L$. We calculate the corresponding prediction result for each teen respectively, and show the result of the whole testing group using the averaging performance. Figure **??** shows the changing trend under the L&S&P pattern. ...

The prediction error decreases first and then increases, and the best performance is achieved when α is 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 the impact of positive event into stress prediction could be adopted. In this paper we adopt the simple one to verify the effectiveness of our model in quantifying the impact of positive events, and the setting of parameter α could be changed due to different individuals and data sets.

7. Discussion and conclusion

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.

8. 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 the key challenges in the future work.

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Table 8: Algorithm 1: Selecting candidate stressful intervals impacted by positive events.

A candidate interval $I =< w_1, \cdots, w_i, \cdots, w_m >$ is identified with following rules:
① $s'_1 = 0$, $s'_m = 0$. $\forall s'_j \in \{s'_2, \cdots, s'_{m-1}\}$, $s'_j > 0$.
② Let w_i be the biggest wave in current candidate interval, with $peak(w_i) = \omega$, $\forall$ wave $w_j \in I$, $peak(w_j) <= peak(w_i)$.
③ For w_k before the interval biggest wave w_i , i.e., $\forall w_k \in< w_1, \cdots, w_{i-1} >$, $peak(w_{k+1}) >= peak(w_k)$, $vally(w_{k+1}) >= peak(w_k)$.
④ For w_k behind the interval biggest wave w_i, i.e., $w_k \in< w_i, \cdots, w_m >$, $peak(w_{k+1}) <= peak(w_k)$, $vally(w_{k+1}) <= peak(w_k)$.

Appendix A. Identifying stressful intervals impacted by positive events

Appendix A.1. Selecting candidate intervals impacted by positive events

Let the sub-series $w_{<a,b>} = \{s'_a, \cdots, s'_b\}$ be a stress *wave* series, where $s'_v = vally(w_{<a,b>})$ is the minimum stress value, $s'_p = peak(w_{<a,b>})$ is the maximal stress value during $\{s'_a, \cdots, s'_b\}$, and $s'_a \leq s'_{a+1} \leq \cdots \leq s'_p \leq s'_{p+1} \leq \cdots \leq s'_b$. Candidate stressful intervals are selected following Algorithm 1.

Appendix A.2. Dividing intervals into U-SI set or SI set

For each candidate interval, a Poisson based probability model Li et al. (2017a) is adopted to measure how confidently the current interval is a stressful interval. Here the stressful posting rates under stress (λ_1) and normal conditions (λ_0) are modeled as two independent poisson process:

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

where $i \in \{0, 1\}$, $n = 0, 1, \cdots, \infty$. We expect that $\lambda_1 > \lambda_0$, and measure the probability as $P(\lambda_1 > \lambda_0|N_1, T_1, N_0, T_0)$, where N_1, N_0 are the number of stressful posts, and T_1, T_0 are time duration corresponding to λ_1 and λ_0. Without loss of generality, we assume a Jeffreys non-informative prior on λ_1 and λ_0, and infer 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 $\beta = P(\lambda_1 > \lambda_0|I_1, I_0) \in (0, 1)$ indicates the confidence whether I_1 is a stressful interval.

Next, we filter out two sets of stressful intervals: stressful intervals not affected by positive events (SI), and stressful intervals under the effect of positive events (U-SI). For a detected stressful interval $I =< t_1, \cdots, t_n >$, we consider the temporal order between I and any detected positive event u happening at time point t_u:

1). If the positive event u happens during the stressful interval, i.e., $t_u \in [t_1, t_n]$, the positive interval I is judged as $I \in U - SI$.

2). For the positive event happening nearby a stressful interval, we also consider the probability that it conducts impact on the teen's stressful interval. 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.

Appendix B. Modeling the stress-buffering pattern of positive events

For each interval, three groups of behavioral measures are considered: *posting behavior*, *stress change mode* and *linguistic expressions*, indicated as $\boldsymbol{< D_p, D_s, D_l >}$, respectively. To measure the correlation for each group of measures, the Euclidean distance is adopted to calculate the distance of structured points in A_1 and A_2.

For each point $\ell x \in A = A_1 \bigcup A_2$, let $NN_r(\ell_x, A)$ be the function to find the $r-$th nearest neighbor of ℓ_x. Specifically, three sub-functions of $NN_r(.)$ are defined as $PNN_r(.)$, $SNN_r(.)$ and $LNN_r(.)$, corresponding to user's posting behaviors, stress change mode and linguistic expressions in each stressful interval, respectively.

For point ℓ_x with posting behavior matrix $\boldsymbol{D^x_p}$, stress change mode matrix $\boldsymbol{D^x_s}$, and linguistic expression matrix $\boldsymbol{D^x_l}$, the r-th nearest neighbor of ℓ_x in each measure is denoted as:

$$\begin{aligned} PNN_r(\ell_x, A) &= \{y|min\{\|\mathbf{D}^x_p - \mathbf{D}^y_p\|_2\}, y \in (A/\ell_x)\} \\ SNN_r(\ell_x, A) &= \{z|min\{\|\mathbf{D}^x_s - \mathbf{D}^z_s\|_2\}, z \in (A/\ell_x)\} \\ LNN_r(\ell_x, A) &= \{w|min\{\|\mathbf{D}^x_l - \mathbf{D}^w_l\|_2\}, w \in (A/\ell_x)\} \end{aligned} \tag{B.1}$$

The r-th nearest neighbor considering all three groups of measures is denoted as:

$$NN_r(\ell_x, A) = \{v|min\{a \times \|\mathbf{D}^x_p - \mathbf{D}^v_p\|_2 + \tag{B.2}$$

$$b \times \|\mathbf{D}^x_s - \mathbf{D}^v_s\|_2 + c \times \|\mathbf{D}^x_l - \mathbf{D}^v_l\|_2\}, v \in (A/\ell_x)\} \tag{B.3}$$

In this study, we set $a = b = c = 1/3$. Next, let $I_r(\ell_x, A1, A2)$ be the function denoting whether the r-th nearest neighbor is in the same set with ℓ_x:

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

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:

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

The value of $T_{k,n}$ shows how differently the points in the two testing sets (SI and U-SI) perform in three groups of measures. If the value of $T_{r,n}$ is close to 1, it can be shown that the two underlying distributions F and G for SI and U-SI are significantly different, indicating current positive events conduct obvious restoring impact on the teens' stress series. Let $\lambda_1 = |A_1|$ and $\lambda_2 = |A_2|$, the statistic value Z is denoted as:

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

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

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

where μ_r is the expectation and $\sigma_r{}^2$ is the variance of Z. Based on hypothesis test theory Johnson and Wichern (2012), when the size of the testing set (λ_1 and λ_2) are large enough, Z obeys a standard Gaussian distribution.

Thus we judge whether the positive events have conducted significant restoring impact on the teen's stress series 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 is true.

Appendix C. Identifying the monotonous stress changes of stress-buffering

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 length of I^{front} and I^{rear} are 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 as SI^{front} and SI^{rear}. Similarly, for the set of stressful intervals $USI = < UI_1, UI_2, \cdots, UI_M >$ impacted by positive events, the corresponding sets of adjacent front and rear intervals are denoted as USI^{front} and USI^{rear}. We compare the intensity of stress changes in following four situations, where $g(.)$ is the function comparing two sets.

① $g(SI, SI^{front})$ returns if intensive change happens when stressful intervals begin.

② $g(SI, SI^{rear})$ returns if stress changes intensively after the stressful intervals end.

③ $g(USI, USI^{front})$ returns if intensive change happens when stressful intervals affected by positive events appears.

④ $g(USI, USI^{rear})$ returns if stress changes intensively after stressful intervals affected by positive events end.

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

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

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