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

Abstract

Stress ~~was~~ 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 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 ~~the two situations:~~ two situations, namely, 1) existing neighboring ~~scheduled positive~~ positive scheduled events (n=75) and 2) no neighboring positive events, we found that students ~~during~~ taking exams with neighboring positive events appeared ~~exhibited less stress intensity~~ to exhibit less intense stress and more stable stress fluctuations. Most students talked less about exams when positive events ~~happened nearby, with~~ occurred nearby, at a lower frequency and a lower ratio. Hypothetical tests for stress-buffering effects of positive events and ~~monotonous changes of~~ 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 ~~microblogs. Results showed~~ the microblogs. The results showed that the stress-buffering effects of positive events were closely correlated with adolescents~~ stress change~~' 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~~, while~~; however, the total frequency of microblogs ~~didn't appear obvious change~~ did not appear to change significantly under the impact of positive events. The study also showed that positive events buffered ~~monotonous changes of~~ monotonic changes in stress intensity caused by stressor events. Based on these theoretical findings, the stress-buffering patterns ~~of~~ around positive events were further incorporated ~~into the problem of adolescent stress prediction and improved predictive performance~~ for stress prediction in adolescents, and the predictive performance was improved. This study could inform the use of social ~~network to reach and track the mental status transition of~~ networks to estimate and track mental health transitions in adolescents under stress. The theoretical and practical implications, limitations of this study and future work ~~were~~ 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 ~~behaviours~~ behaviors (?). Compared ~~with adults,~~ to adults, young people exhibit ~~more exposure to stressdue to the~~ high levels of stress due to their immature inner status and lack of experience (?). According to the latest report released by the American Psychological Association in 2018, 91% of ~~youngest~~ young adults had experienced physical or emotional symptoms due to stress in the past month compared to 74% of adults (?). More than 30 million Chinese adolescents ~~are suffering~~ suffer from psychological stress, and nearly 30% of them ~~have~~ are at a risk of depression (?). 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 ~~directly and indirectly ways by~~ direct and indirect ways by ~~'~~'*buffering*' (??), with respect to physiological, psychological, and social coping resources (??). Researchers indicated that positive events mitigated the ~~relation~~ relationship between negative events and maladjustment in samples of adolescents experiencing family transitions (?). The written expression of positive feelings ~~had also been proven to prompt increased cognitive re-organization among~~ also prompted increased cognitive reorganization in an undergraduate student group (?). Positive events ~~also have~~ have also been linked to medical benefits, such as ~~improving~~ improved mood, serum cortisol levels, and lower levels of inflammation and hypercoagulability (??). Thus, tracking the state of the stress-buffering effect is important for understanding the mental status of stressed individuals.

Existing solutions: Previous studies have ~~been focusing on conducting measurement of~~ focused on measuring positive events and stress-buffering ~~state~~ states after events through questionnaires~~, including Hassles & Uplifts Scales (?),~~. including the Hassles and Uplifts Scale (?), the Perceived Benefit Scales ~~(?)~~ ~~,~~ (?), the Interpretation of Positive Events Scale (?) and the

Adolescent Self-Rating Life Events Checklist ~~(?). Recent~~ (?). Recently, scholars have demonstrated the feasibility to sense and predict users' stress from social networks (????????) through content (linguistic text, emoticons, and pictures) and behavioral (abnormal posting time ~~,~~ and comment/response actions) measures.

If we view the aforementioned traditional studies on positive events as static sensing of stress-buffering, this study approaches the problem ~~to the dynamic process of stress-buffering and aims at~~ stress-buffering as a dynamic process and aims to find a solution at both ~~microblogging content~~ the microblogging-content and behavioral levels under the hypothesis that the occurrence of positive events can be reflected in adolescents' microblogs. ~~Since the subjective self-report~~ Subjective self-reported investigations are susceptible to many factors, such as ~~social appreciation and pressures~~ 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 ~~researches stopped at~~ studies stopped the analysis of stress, and none went further to capture positive events that may play a key role in adolescents' ~~stress coping mechanism~~stress-coping mechanisms. For example, ~~it is hiking tomorrow that~~ 'hiking tomorrow' might simultaneously occur and be expressed in microblogs with ~~losing~~ 'failing the exam today~~.If we couldn't~~'. If do not know anything about positive events, is the ~~stress unilaterally detected is~~ 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 ~~stressful adolescents~~ adolescents who are coping with stress.

Our work: To this end, this paper ~~proposes to study adolescent stress in a~~ studies adolescent stress from the dual perspective of stress generation and stress-buffering ~~, and view it~~ 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~~ around positive events and further predict future stress under such mitigation. Exploiting the stress-buffering effects of positive events is also advantageous in handling the confusing situation of whether an adolescent who ~~doesn't~~ does not express stressful information ~~from microblogs~~ in microblog 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 ~~to depict~~ for depicting stress-buffering ~~?~~ effects? 2) What is the latent connection between positive events and adolescents' stress-buffering reflections ~~from~~ in microblogs? 3) How ~~to~~ can extract positive events and ~~its impact interval~~ their impact interval be extracted from microblogs?

A pilot study was ~~firstly~~ first conducted on the microblog data (n=27,346) of a group of high school students (n=500) associated with the school's ~~scheduled positive~~ positive scheduled events (n=75) and stressor events (n=122). Stressful intervals were divided into two comparative categories: intervals impacted by ~~scheduled positive~~ positive scheduled events (denoted ~~as~~ by U-SI, n=259) and intervals not impacted by ~~scheduled positive~~ positive scheduled events (denoted ~~as~~ by SI, n=518). After observing the posting behaviors and ~~contents of~~ 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 ~~from~~ 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 period-level: stress change~~ stress buffering at the period level: stress-change modes, linguistic expressions and posting ~~behaviours~~behav Positive events buffered ~~monotonous changes of stress intensityMonotono~~ ~~changes of~~ monotonic changes in stress intensity. 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 ~~its~~ the stress-buffering effects into each time unit and integrated such ~~effect into stress prediction~~an effect into the stress prediction model.

In this paper, to ~~realize automatically extraction of~~ automatically extract positive events, we ~~stood~~ 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, ~~pear relationship~~peer relationships, self-cognition, and family life) and extended the SC-LIWC lexicons ~~to~~ into 2,606 phases. Stressful intervals (SI) and stressful intervals impacted by positive events (U-SI) were identified according to ~~temporal orders~~their temporal order.

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

2. Literature Review

2.1. Stress-buffering Function of Positive Events

Positive events have been verified as protective factors against daily stress (**??**), loneliness (**?**), suicide (**?**) and depression (**?**). ~~Through~~ By exploring naturally occurring daily stressors, (**?**) found that over time, the experience of positive emotions ~~functions to assist~~ assists high-resilient individuals ~~to recover~~ in recovering effectively from daily stress. Through a three-week longitudinal study, (**?**) examined the correlation between employee stress and health and positive life events ~~,~~and concluded that naturally occurring positive events are correlated with decreased stress and improved health. (?) 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 ~~found to be~~ weaker for those who experienced a ~~high~~ large number of positive life events, as opposed to those who experienced a ~~low~~ small number of positive life events. This ~~is assistant~~ finding agrees with the conclusion made by (?) that positive events ~~acted~~ 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 ~~made~~ conducted by (?), strategies of positive psychology were also ~~checked as potentially~~ identified as potential tools for the prophylaxis and treatment of depression, helping to reduce symptoms and ~~for prevention of~~ prevent relapses.

The protective effect of positive events was hypothesized to operate in both ~~directly~~ direct (i.e., the more positive events people experienced, the less stress they perceived) and ~~indirectly ways by~~ indirect ways by ~~'~~'*buffering*' the effect of stressors (??), with respect to physiological, psychological, and social coping resources (??). (?) identified three classes of coping mechanisms that were associated with positive ~~emotion~~ emotions during chronic stress: positive reappraisal, problem-focused coping, and the creation of positive events. Due to ~~the~~ their immature inner status and lack of experience, adolescents exhibit more ~~sensitive~~ sensitivity to stressors (i.e., exams, heavy homework ~~, isolated~~ load, isolation by classmates, family transitions), ~~living~~ and live with frequent, long-term stress (?). In this situation, positive events could help reinforce adolescents' sense of well-being (?) ~~,~~ and restore the capacity ~~for dealing with~~ to handle stress (?) ~~, and also have~~ and have also been linked to medical benefits, such as ~~improving~~ improved mood, serum cortisol levels, and lower levels of inflammation and ~~hyper coagulability~~ hypercoagulability (??). 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 many studies based on self-support methods. For example, (?) ~~conducted Hassles & Uplifts Scales,~~ 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~~ life-events approach. To measure the negative interpretations of positive social events, (?) proposed the Interpretation of Positive Events Scale ~~, and analyzed~~ and analyzed the relationship between social interaction anxiety and the tendency to interpret positive social events in a threat-maintaining manner. (?) proposed the Perceived Benefit Scales as ~~the~~ new measures of self-reported positive life changes after traumatic stressors, including lifestyle changes, material gain, increases in ~~self efficacy~~self-efficacy, family closeness, community closeness, faith in people, compassion, and spirituality. Specific ~~for~~ to college students, (?) ~~investigated in 282 college students using~~ administered the Adolescent Self-Rating Life Events Checklist ~~,~~ to 282 college students and found that ~~the training of positive coping style~~ training in positive coping styles was of great benefit to improve the mental health of students. The above explorations ~~based on self-report investigationswere~~ are based on self-reported investigations; therefore, it is difficult to exclude the interference from external factors (i.e., social ~~appreciation, pressure~~ pressure and pressure from measurement scenarios). ~~Meanwhile~~Moreover, due to the lack of ~~manpower~~ personnel and effective scientific methods, most scholars have relied on a limited number of measurements~~, thus~~; 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 ~~life~~ lives through social networks (e.g., ~~micro-blog~~microblogs, Twitter, and Facebook), researchers ~~explored to apply psychological theories into social network based~~ have explored applying psychological theories to social network-based data mining techniques ~~, thus~~ to better understand ~~user' psychological status~~ users' psychological statuses from the self-expressed public data source. Multiple content and user behavioral measures have been ~~proven~~ proven effective in user mental health analysis, including time series curve analysis of stress (??), topic words (?), abnormal posting time (?), online shopping behaviors (?), human mobility features (?), comment/response actions (?) and ~~high dimensional~~ high-dimensional multimedia features (?). For example, (??) proposed ~~to detect~~ detecting adolescent stress from a single post utilizing machine learning methods by extracting ~~stressful topic words~~ topic words indicating stress, abnormal posting time, and interactions with friends. (?) constructed a deep neural network to combine the high-dimensional ~~picture~~ semantic information into stress ~~detecting~~detection. Based on the stress ~~detecting result~~detection results, (?)?? adopted a series of ~~multi-variant~~ multivariate time series prediction techniques (i.e., ~~Candlestick Charts, fuzzy Candlestick line, Seasonal Autoregressive Integrated Moving Average model~~candlestick charts, fuzzy candlestick lines, and seasonal autoregressive integrated moving average models) to predict future stress ~~trend. Taking the~~ trends. Taking linguistic information into consideration, (?) employed a ~~Nonlinear autoregressive with External Input Neural Network~~ nonlinear autoregressive with external input neural network to predict a ~~teen~~teenager's future stress level ~~referred~~ by referring to the impact of ~~co-experiencing~~ co-experienced stressor events of similar companions. (?) proposed ~~to detect~~ detecting stressor events from microblog content and ~~analyze~~ analyzing stressful intervals based on the posting rate. All of the above studies focused on the discussion of stress detection ~~on~~ 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 ~~process. Thuswe push forward~~ processes. Thus, we extend the study from how to find stress to the next~~more meaningful~~, more meaningful, stage: how to cope with stress.

2.3. *Correlation Analysis Models for Multivariate Time Series*

Basic correlation analysis models on time series ~~focused~~ focusing on univariate data have been well studied. As the most widely adopted model, the Pearson correlation ~~analysis~~ coefficient ? measures the linear correlation between two variables X and Y. One inevitable defect of ~~Pearson correlation~~

the Pearson correlation coefficient is its sensitivity to ~~outlier values~~outliers. To overcome such ~~drawback, SpearmanRank correlation ? and Kendall Rank correlation~~ drawbacks, Spearman's rank correlation coefficient ? and the Kendall rank correlation coefficient ? were proposed based on ~~Pearson correlation. While Pearson correlation~~ the Pearson correlation coefficient. While the Pearson correlation coefficient estimates linear relationships, Spearman~~correlation~~ 's correlation coefficient estimates monotonic relationships (~~whether linear or not~~regardless of linearity), and are calculated as the Pearson correlation coefficient between the rank values of two variables. The Kendall ~~Rank correlation~~ rank correlation coefficient mainly assesses the similarity of the orderings of the data when ranked by each of the quantities. The above correlation ~~models are usually~~ metrics are primarily used to estimate the relationship between single-dimensional variables, and cannot be adopted directly in social ~~network based scenario~~network-based scenarios.

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

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

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

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

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

figs/exampleWave-eps-converted-to.pdf

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 ~~stressful intervals surround~~ the stressful

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

intervals surrounding the scheduled exams ~~over~~ for the 121 students during their high school career, applying the interval detection method ~~in~~ from (**?**). 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) ~~occured~~occurred. 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~~. 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~~ induced by the positive event. We identified 518 ~~exam related~~ exam-related stressful intervals (~~SI~~SIs) and 259 stressful intervals impacted by four typical ~~scheduled positive events (U-SI) ('~~ positive scheduled events (U-SIs) ('practical activity', ~~'new year~~ 'New Year party', ~~'~~'holiday', ~~'sports meeting'~~ 'sporting event') from the students' microblogs. Six measures ~~in~~ 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 **?**, 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 ~~stress of all~~ amount of stress from all the posts. Examples of ~~academic related keywords were listed in table~~ academic-related keywords are listed in Table **??**. The average value of each measure over all eligible slides was calculated.

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

figs/activity-eps-converted-to.pdf

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

Results. As shown in figure **??**, comparing each measure of scheduled exam intervals under the two situations ~~: ~~(1) existing ~~neighbouring positive~~ positive neighboring events (U-SI) and 2) no ~~neighbouring scheduled positive~~ neighboring positive scheduled events (SI)), we found that students ~~during exams with neighbouring positive events appeared exhibited~~ with exams and positive neighboring events appeared to exhibit 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). ~~Further~~Furthermore, the frequency of academic topic words (~~table~~ see Table **??** for examples) and the ratio of academic stress in each interval were calculated. Most students talked less about exams when positive events ~~happened nearby ,~~ occurred nearby with lower frequency (84.65% reduction) and lower ratio (89.53% reduction). The ~~statistic result shows~~ statistical results show clues about the impact of ~~scheduled positive~~ positive scheduled events, which is ~~constant with the~~ consistent with psychological theory (**???**), indicating the reliability and feasibility of the microblog ~~data set~~dataset. However, this ~~is an observation~~ observation is based on specific scheduled events, and cannot satisfy the need for automatic, timely, and continuous perception of the stress-buffering process. Therefore, ~~next, we will~~ we propose a framework to automatically detect positive events and ~~its~~ their impact interval. Based on this framework, the relationship between the impact of automatically extracted positive events and ~~adolecents~~adolescents' microblogging characteristics will be discussed.

4. Framework

We first introduce the procedure to extract positive ~~event and its~~ 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 ~~*descriptions*~~*description* ~~are~~ is the key words related to u. According to psychological scales (??), ~~adolescent positive events~~ positive events for adolescents mainly focus on six dimensions~~, as~~: $\mathbb{U}$ = { ~~'~~'entertainment', ~~'~~'school life', ~~'romantic '~~'romantic relationships', 'peer relationships', ~~'pear relationship', '~~'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) (?). Then, we built six topic lexicons by expanding basic positive words from ~~adolescent~~ the adolescents' microblogs, containing 452 phrases in ~~'~~'entertainment', 273 phrases in ~~'~~'school life', 138 phrases in ~~'romantic~~ 'romantic relationships', 91 phrases in ~~'~~'peer relationship', 299 phrases in ~~'~~'self-recognition' and 184 phrases in ~~'~~'family life', ~~with totally~~ for a total of 2,606 phrases~~, as examples shown in table~~. Examples are shown in Table ??. Additionally, we labeled *doer* words (i.e., *teacher*, *mother*, *I*~~, we~~ and *we*) in positive lexicons.

4.1.1. Linguistic Parser Model

Positive events were identified through a Chinese natural language processing platform (?). 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. ~~The~~ A linguistic 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 ~~were~~ 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 ??. For ~~the post '~~example, the post 'Thanks all my dear friends for hosting the party. Happiest birthday!!!' ~~, it~~ 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 (?) 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: Extracted positive~~ Step 1: Positive events, stressor events and ~~filtered out candidate intervals~~ 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 ~~neighboured stressed~~ neighboring stressful days. Since the stress series detected from the microblogs were discrete points, the locally weighted regression (?) method was adopted to highlight the characteristics of the stress curve.

~~Step2: Judged stressful intervals~~ Step 2: Intervals were judged as stressful or not through hypothesis testing. A ~~Poisson based~~ Poisson-based probability model was adopted to measure how ~~confidently~~ confident we are that the current interval was a stressful interval. Here, the stressful posting rates under ~~stress~~ stressful λ_1 and normal conditions λ_0 were modeled as two independent ~~poisson process~~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 ~~$N_1, N_0$ are the number~~ N_1 and N_0 are the numbers of stressful posts ~~, and T_1, T_0 are time duration~~ and T_1 and T_0 are the time durations corresponding to λ_1 and λ_0, respectively. Without loss of generality, we assume a Jeffreys ~~non-informative~~ noninformative prior on λ_1 and λ_0 ~~, and inferred~~ and infer the posterior distribution $P(\lambda_1|N_1)$ and $P(\lambda_0|N_0)$ according to Bayes' Rule. Thus~~for~~, for the 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 the confidence~~ indicates confidence in whether I_1 was a stressful interval.

Step 3: ~~Divided stressful intervals into~~ 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 ~~happening~~ occurring at time point t_u in three cases:

1) If the positive event u ~~happened~~ 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 ~~happened nearby~~ occurred near a stressful interval, ~~considering~~ the probability that it ~~conducted impact on~~ had an impact on the current stressful interval ~~. Here~~ 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 ~~divided into~~ classified into the U-SI set.

4.2. Hypothesis Test for the Relationship ~~between~~ 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 ~~multi-dimensional vector depicted~~ multidimensional vector depicting the microblogging characteristics of the current adolescent. Specifically, ~~the~~ a multivariate two-sample hypothesis ~~testing method~~ test ?? was adopted to model such a relationship. The basic idea was ~~judging~~

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, theater, 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 marks, 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, teammate, 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's Adult Ceremony [smile] [smile] (act: *expecting*, description: *Adult Ceremony*)

~~whether the multi-dimension~~ to determine whether the multidimensional points (i.e., the stressful intervals) in set SI and set U-SI ~~were under~~ follow different statistical distributions. Assuming the data points in SI and U-SI were randomly sampled from distribution F and G, respectively, then the hypothesis ~~was denoted as~~ 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 ~~indicated~~ indicates that points in SI and U-SI ~~were under~~ follow a similar distribution, while H_1 ~~meant~~ means points in SI and U-SI ~~were under~~ follow statistically different distributions, namely~~positive events conducted~~, positive events had obvious stress-buffering ~~effecte~~effects.

4.2.1. Statistical Model of the Stress-buffering Effect

We ~~took the K-Nearest Neighbor based~~ used a K-nearest-neighbor-based method (?) to judge the existence of a significant difference between set SI and set U-SI. For ~~simplify~~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 ~~belonging to~~ 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 was denoted ~~as~~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 ~~with~~ 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, ~~it could be shown that~~ then the two underlying distributions F and G for SI and U-SI were significantly different, indicating current positive events ~~conducted~~ had an obvious stress-buffering impact on the ~~teens~~adolescents' stress series. Let $\lambda_1 = |A_1|$ and $\lambda_2 = |A_2|$, the ~~statistic~~ statistical value Z ~~was denoted as~~is denoted by:

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

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

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

where μ_r ~~was~~ is the expectation and $\sigma_r{}^2$ ~~was~~ is the variance of Z. Based on hypothesis ~~test~~ testing theory (?), when the size of the testing set ~~was~~ is large enough, Z ~~obeyed~~ obeys a standard Gaussian distribution. Thus, we judged whether the positive events ~~conducted significant stress buffering~~ 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 ??, three groups of ~~mircoblogging~~ microblogging measures were introduced to depict ~~multi-dimension~~ the multidimensiona characteristics of each stressful interval $\ell_x \in A$, indicated as an linguistic expression matrix $\boldsymbol{D}_l^x$, ~~posting behavior~~ a posting-behavior figs/gray/stress-eps-converted-to.pdf

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}.

matrix $\boldsymbol{D}_p^{\boldsymbol{x}}$ and ~~stress change mode~~ a stress-change-mode matrix $\boldsymbol{D}_s^{\boldsymbol{x}}$. Correspondingly, three ~~sub-functions~~ subfunctions of $NN_r(.)$ were defined~~as~~: $PNN_r(.)$, $SNN_r(.)$ and $LNN_r(.)$.

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

The r-th nearest neighbor was ~~re-calculated~~ 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~~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 was denoted ~~as~~ by $S =< s_1, s_2, \cdots, s_n >$, where $s_i \in S$ ~~was~~ is the average stress value of microblogs posted ~~in~~ on day i. The four measures ~~were denoted as~~ 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 ~~into positive emotion fluctuations during~~ to positive emotional fluctuations in an interval, which might reflect the complementary changes to stress. To show the occurrence of ~~above mentioned~~ the abovementioned measures, we present a 7×5 ~~gray-scale~~ grayscale map for each measure in Figure **??**. The x-axis (ranging from P1 to P6) ~~represent~~ represents each dimension of positive events (P={~~academic, romantic,~~ school life, romantic relationships, peer relationships, ~~peer relationship,~~ self-cognition, family life, entertainment}), and the last column ~~represent no positive event happening in the observation~~ represents no positive events occurring in the observed interval. The y-axis (ranging from S1 to S5) ~~represent~~ represents each dimension of stressor events (E={~~academic, romantic,~~ school life, romantic relationships, peer relationships, ~~peer relationship,~~ self-cognition, family life}). The color of each point in ~~a gray-scale map depended~~ 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 ~~were presented by~~ are presented as follows:

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

For example, in ~~figure~~ Figure **??** (a), point (P4,S1) ~~was the value of average stress~~ is the average stress value in all $\mathbf{I}_{<1,4>}$ intervals, where stress was caused mainly by ~~academic events~~ school life (S1) and impacted by positive events related to self-cognition (P4). Figure **??** exhibited four ~~stress change modes (subgraph~~ stress-change modes (subgraphs (a) to (d)) and four corresponding positive emotion change modes (~~subgraph~~ subgraphs (e) to (h)) in both the SI and U-SI sets. ~~Statistical~~ The statistical results showed that the occurrence of positive events significantly reduced ~~accumulated~~ 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 ~~obvious increase of all positive change modes (subgraph~~ 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 intensity~~ positive-intensity change modes initially reflected stress-buffering effects of different types of positive events on each dimension of stressor events.

Linguistic expressions. For each microblog, we identified its linguistic expressions applying the segmentation model and parser model ~~in~~ from section **??**. The first measure was the frequency of stressful emotional words based on four categories (anger, anxiety, hate, sad) ~~of LICW lexicons, represented~~ from LIWC lexicons, representing general stress during ~~a~~ an interval (**?**). The second measure was the frequency of positive emotional words, which were identified based on the surprise, joy, expectation and love categories of ~~LICW~~ the LIWC 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 **??** (a) and (b) ~~showed~~ 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 ~~subgraph~~ subgraphs (a) and (b) was different compared to ~~column~~ columns P1 to P6. Specifically, positive events from romantic, peer relationship and family life showed obvious ~~reduction~~ reductions in stressful emotional words caused by peer relationship and family life stressor events (subgraph **??** (a)). Figure **??** ~~showed~~ shows the distribution of stressful topic words when different positive events occurred. Here~~we showed~~, we shows the statistical results during stressful intervals caused by ~~academic~~ school-life and self-figs/gray/emotion-eps-converted-to.pdf

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}.

figs/gray/topicOffset-eps-converted-to.pdf

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}.

cognition stressor events. The frequency of ~~academic stress~~ stressful academic topic words (~~subgraph~~ subgraphs (a1) and (b1)) and ~~academic positive~~ positive academic topic words (~~subgraph~~ subgraphs (a2) and (b2)) showed ~~not clear regular. Further~~ no clear regularity. Furthermore, we explored the offset ~~result~~ for each dimension of stressful and positive topic words, as shown in ~~subgraph~~ subgraphs (a3) and (b3). The offset results showed obvious stress-buffering results ~~, since~~ because stressful topic words showed ~~decrease in column~~ a decrease in columns P1 to P5 in subgraph (a3), and positive topic words exhibited ~~increase in column~~ increases in columns P1 to P5 in subgraph (b3). These ~~revealed~~ findings reveal that the occurrence of positive events offset the impact of stressor events ~~through talking about positive topicsat the same time~~by simultaneously discussing positive topics.

Posting behaviors. Stress ~~could~~ can lead to abnormal posting behaviors, reflecting ~~user' s~~ users' changes in social engagement ~~activity~~ activities (**?**). We considered four measures of posting behaviors here. The first measure was the frequency of stressful microblogs, highlighting stressful microblogs among all microblogs. Research in **?** indicated that overwhelmed adolescents tended to post more microblogs expressing their stress for ~~releasing and seeking~~ 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 ~~forth measure was~~ fourth measure was the frequency of forwarded microblogs, showing the number of ~~re-tweet~~ retweets and shared microblogs. Figure **??** ~~summarized~~ summarizes the distribution of the above four measures in the U-SI and SI sets. ~~Results in subgraph~~ The results in subgraphs (a) and (b) ~~showed decrease of~~ show a decrease in stressful microblogs and ~~increase of~~ an increase in positive microblogs when positive events occurred. Subgraph (d) ~~indicated~~ indicates that adolescents tended to forward more microblogs when positive events ~~happened~~occurred, while subgraph (c) showed that the frequency of all microblogs ~~didn't appear obvious change~~ did not appear to change significantly under the impact of positive events.

4.2.3. ~~*Monotonous*~~ *Monotonic Model of Stress-buffering*

To further verify the ~~monotonous changes of~~ 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 intervalsrespectively~~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~~ rear-adjacent interval of I. The ~~length~~ 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 ~~were denoted as~~ 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 ~~adjacent front intervals and adjacent rear intervals were denoted as~~ front-adjacent intervals and rear-adjacent intervals are denoted by USI^{front} and USI^{rear},

Table 5: Monotonic stress-intensity changes in the U-SI and SI intervals compared with adjacent intervals. *Front*$\rightarrow I$ represents a monotonic increase from the front interval to the current stressful interval I. $I \rightarrow$ *rear* represents a monotonic decrease from interval I to its rear-adjacent interval.

	School life		Romantic relationships		Peer relationships		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%

figs/gray/post-eps-converted-to.pdf

Figure 7: Comparing posting behaviors 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}.

respectively. We compared the intensity of stress changes in the following four situations, where $g(.)$ ~~was~~ is the function comparing two sets:

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

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

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

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

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

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

where μ_{SI} and $\mu_{SI^{rear}}$ ~~were~~ are the mean stress values of intervals in sets SI and SI^{rear}, respectively, and σ_{SI} and $\sigma_{SI^{rear}}$ ~~were the variance~~ 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 ~~comparison for~~ 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 $g(SI^{front}, SI)$.

5. Experiments

5.1. Stress-buffering Effect of Positive Events

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

	Practical activities	Holidays	New Year parties	Sporting events	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%

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

figs/cor-eps-converted-to.pdf

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

~~Stress-buffering~~ The stress-buffering effects measured by three groups of ~~microblog~~ microblogging characteristics and towards the five dimensions of stressor events ~~were shown in box-plots~~ are shown in box plots **??**, using the statistical ~~value~~ α ~~computed through~~ value computed via the KTS method. ~~Results~~ The 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~~ 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~~ had the 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'~~ 'school life' (ratio = 68.55%, n=85, SD=2.71)~~dimensions. Statistics~~ . The α ~~in 'peer relation~~for 'peer relationships' exhibited the highest 75th percentile ~~while~~ and the lowest 25th percentile, showing a relatively random and unstable stress-buffering effect on this dimension. Comparing the hypothesis test results on ~~scheduled positive~~ the positive scheduled events (ratio = 69.52%) and automatically extracted positive events (ratio = 74.21%), the ~~result~~ results indicated the feasibility of automatically extracting positive events from microblogs.

Next, to verify ~~monotonous changes of~~ monotonic changes in stress intensity when ~~an~~ a positive event impacted a stressful interval, for each interval in the SI and U-SI sets, we quantified its monotonous stress changes by comparing ~~with the front and rear adjacent~~ it with the front- and rear-adjacent intervals, respectively. Four situations proposed in section **??** were considered and are compared in table **??**. The ratio of intervals detected with ~~monotonous~~ the monotonic increase from the front interval to the current stressful interval I (denoted ~~as~~ by $front \to I$), and ~~ratio of monotonous~~ the ratio of the monotonic decrease from I to its ~~rear~~ rear-adjacent interval (denoted ~~as~~ by $I \to rear$) ~~were~~ are summarized. Under the effect of positive events, the ratio of intensive stress increase in $front \to I$ was ~~decreased~~ reduced from 78.51% to 70.17%; ~~and~~ the ratio of intensive stress decrease in $I \to rear$ was ~~decreased~~ reduced from 79.55% to 75.13%. The most obvious ~~monotonous~~ monotonic decrease in $front \to I$ was ~~conducted by~~ related to positive events in ~~family life~~ the 'family life' dimension (12.89% reduction)~~;~~ , and the most obvious monotonous decrease in $front \to I$ was also ~~conducted by~~ related to positive events in ~~family life~~ the 'family life' dimension (6.65% reduction). The experimental results ~~indicated~~ indicate the effectiveness of the ~~two sample method~~ two-sample methods for quantifying the effect of positive events ~~,~~and the rationality of the assumption that positive events could help ease the 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 the stress-buffering effects of positive events, we integrate the impact of positive events into a stress prediction problem ~~,~~ and verify whether considering the stress-buffering effects of positive events could help improve the stress prediction performance.

Stress prediction model. The ~~SVARIMA (Seasonal Autoregressive Integrated Moving Average)algorithm was proved~~ SVARIMA (seasonal autoregressive integrated moving average) algorithm was proven to be suitable for the adolescents' stress prediction problem (**??**), due to the seasonality and ~~non-stationarity of~~ nonstationarity of the stress series. Since stressor events cause the fluctuation ~~of~~ in the stress series from normal states, we focused the prediction problem on stressful intervals rather than randomly ~~picked out~~ selected stress series. Thus~~the~~ , basic stress prediction was conducted using the SVARIMA approach in the set of stressful intervals impacted by positive events (U-SI). Stress-buffering effects of positive events were adopted as adjust the values to modify the stress prediction results. Four metrics were adopted to measure ~~stress forecasting performance, where~~ the stress-forecasting performance: *MSE*, *RMSE* and *MAD* ~~measured absolute errors~~measure the absolute errors, and *MAPE* measures the relative errors. For all real stress ~~value~~ values $\overline{s_i}$ and predicted stress ~~value~~ values s_i in ~~predicting~~ a prediction

Table 7: Adolescents' stress prediction performance when ~~combined~~ combining 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 relationships	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 relationships	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 relationships	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 relationships	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*.

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 ??, the original prediction performance using only the SVARIMA method achieved ~~0.1281 MSE , 0.3579 RMSE , 0.3604 MAPE and 0.1482 MAD~~ an MSE of 0.1281, an RMSE of 0.3579, a MAPE of 0.3604 and a MAD of 0.1482 ($L = 7, \beta = 0.5$). Then, we integrated the stress-buffering impact of each dimension of positive events ~~into~~ for stress prediction. Specifically, for positive events ~~conducted~~ leading to significant stress-buffering effects on the current adolescent, the average stress value during historical U-SI intervals ~~were~~ was integrated to modify the result by adjusting the parameter β. After modification, the prediction performance achieved ~~0.0649 MSE~~ an MSE of 0.0649, an RMSE of 0.2548, a MAPE of 0.2638 and a MAD of 0.0858, ~~0.2548 RMSE , 0.2638 MAPE and 0.0858 MAD ,~~ reducing the prediction errors efficiently (~~with~~ the MSE, RMSE, MAPE and MAD were 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~~ to show each pattern's contribution to stress prediction. Four groups of situations were considered here, as shown in Table ??, considering 1) all three groups of measures, namely~~stress change~~ , stress-change modes, linguistic expressions and ~~post~~ posting 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~~ of the measures included. We integrated the effect of positive events under the four situations ~~into~~ for stress prediction by ~~overlapping paramiter~~ the overlapping parameter $\alpha \times S_{historical}$, where $S_{historical}$ ~~was~~ is the average stress value in the historical U-SI intervals. Here, we present the prediction result when $\beta = 0.5$ in each dimension of stress~~respectively. Results showed that~~ . The results showed that the stress-buffering pattern in the L&S&P pattern outperformed the other patterns (~~0.0649 MSE, 0.2548 RMSE, 0.2638 MAPEand 0.0858 MAD~~MSE=0.0649 , RMSE=0.2548, MAPE=0.2638 and MAD=0.0858), showing the effectiveness of all three groups of measures.

Stress prediction performance under different observation ~~windows~~windo lengths. We further explored ~~to combine~~ combining stress-buffering effects into future stress prediction under different ~~length~~ lengths of observation windows, ranging from 1 to 10 days, as shown in Figure ??. With ~~window length increasing,~~ increasing window length, the prediction errors showed ~~increasing trend in all~~ an increasing trend across all the metrics. The reason might be that a longer prediction window ~~took more previous predicted results , and errors accumulates~~ resulted in more previously predicted results and errors accumulating with more predicted values are taken into the next step of prediction. Among the five dimensions of stressor events, ~~prediction for school life~~ the prediction for school-life stress achieved the best performance. One reason might be that more positive events and stressors about ~~school life~~ school-life events were detected from adolescents' microblogs, providing sufficient data in the prediction process. On the other ~~side~~hand, stress coming from school life was the most common ~~stress in student group, with relative~~ source of stress in the student group with relatively stable periodicity, which was more suitable for the current prediction model.

~~Parameter settings.~~ ~~Parameter~~ β was adjusted when ~~integrated~~ the impact of positive events was integrated into stress pre-

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

figs/predictWindow2-eps-converted-to.pdf

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

figs/thresh-eps-converted-to.pdf

diction. For each of the four groups of stress-buffering patterns, ~~we~~ We adjust β ~~in~~ to the effect of $\beta \times L$. We calculated the corresponding prediction result for each adolescent ~~respectively,~~ as follows: and showed the result of ~~whole~~ the entire testing group in the average performance. Figure ?? ~~showed~~ shows the changing trend under the L&S&P pattern. ~~Prediction~~ The 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~~ approximately0.52, with an MSE of 0.0649, and RMSE of 0.2548, a MAPE of 0.2638 and a MAD of 0.0858 as the average performance of the ~~whole experimental data set~~entire experimental dataset. Multiple methods for integrating the stress-buffering impact of positive ~~event~~ events into stress prediction could be adopted in the future. In this paper~~we adopted the simple one~~, we adopted a simple method to verify the effectiveness of our model in quantifying the impact of positive events. The setting of ~~parameter~~ β could be changed ~~due~~ according to different individuals and ~~data sets~~datasets.

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~~ stress buffering were not only manifested in self-reported subjective feelings ~~, but also in~~ but also at the 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~~ stress-change modes on stressed adolescents, and verified that positive events buffered ~~monotonous stress changes~~ monotonic changes in stress at both the early and late stages. Second, this study implemented ~~the innovation of~~ innovative methods. Through building a complete technical framework, we realized 1) the automatic extraction of positive events, as well as users' ~~behavior~~ behaviors and content measures from microblogs ~~,~~ and 2) the quantification of relationships between the stress-buffering effects of positive events and microblogging measures. Third, this article showed practical significance. It realized the 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~~ stress resistance in adolescents; On the other hand, it could provide supplementary advice to schools and parents about ~~'when to arrange~~ when to schedule positive events to ease the 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~~ The results showed that when positive events were scheduled neighboring stressful events, students exhibited less ~~stress intensity~~ intense stress and shorter stressful time intervals ~~from~~ based on their microblogs. The study also found that most students talked less about the upcoming or just-finished exams when positive events ~~happened nearby, with~~ occurred nearby, at a lower frequency and a lower ratio. The results substantiated previous studies reporting the protective effect of positive events on adolescents (??) using laboratory methods. Based on this conclusion, this article carried out more in-depth follow-up studies.

The second ~~groups of results were~~ group of results was presented in study 2, ~~examining~~ which examined the stress-buffering pattern of positive events through microblog content and behavioral measures. ~~As basis, a~~ A complete solution was provided for automatically detecting positive events based on microblog semantics, which were ~~totally~~ completely different from traditional questionnaire methods, enabling timely, fraud-proof and continuous detection. ~~In order to eliminate the~~ To eliminate possible errors in positive event detection and avoid false overlays, ~~we~~ We first used four ~~scheduled positive~~ positive scheduled events to examine significant stress-buffering effects. ~~Results showed the event '~~The results showed that the event 'holiday' exhibited the highest proportion of significant stress-buffering effects. However, this conclusion was questionable because the ~~frequency~~ frequencies of the above four events ~~was~~ were different and might affect the experimental results. Next, the stress-buffering effect of automatically extracted positive events ~~were~~ was tested based on three groups of stress-buffering measures. The most intensive stress-buffering effects were shown in ~~'~~the 'school life' and ~~'peer relationship~~'peer relationships' dimensions. *Posting behaviors* exhibited the most significant correlations among the three groups of measures. This finding resonated with the study ??, 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 process. Since more complex situations were simplified in the present exploration, the goals were still salient for stress-buffering ~~researches~~ studies from social networks.

7. Limitations and future work

This study has a number of limitations. First, it used ~~the microblog data set~~ a microblog dataset collected from social networks of high school students, and chose the scheduled school events as the ground truth in the pilot study. This method could be seen as ~~a~~ relative fuzzy verification~~method~~, because individual events (i.e., ~~’~~‘lost love’, or ~~’~~‘received a birthday present’) might also ~~conduct~~ have additional impact. Therefore, the data ~~observation~~ observations in the pilot study were not 100% rigorous and ~~needed~~ need further verification. ~~A~~ An improvement might be ~~conducted~~ implemented by inviting participants to complete related scales (e.g., positive and stressor scales) ~~, thus~~ to label part of the ~~data set,~~ dataset 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~~ , which ignores the additive and collective effects of multiple positive events ~~which might happened~~ that might happen at the same time. Thus, our future research might investigate the overlap effects of multiple positive events, as well as the frequent ~~co-appearing~~ coappearance patterns of different types of positive events ~~, thus~~ to provide more accurate stress-buffering guidance for individual adolescents.

Based on our current research implications, more factors could help analyze stress-buffering patterns among adolescents more comprehensively in future research. One factor is how personality (**??**) 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 (**??**) in social networks plays. This factor leaves clues in the messages under each post, and the behaviors (i.e., ~~retweet, the like numbers~~retweets and the number of likes) of friends. For ~~examples~~example, (**?**) showed that the number of Facebook friends was associated with stronger perceptions of social support, which in turn correlated with reduced stress and greater sense of well-being. The corresponding experimental design ~~, and the online-offline~~ and the online/offline complementary verification will be challenges in ~~the~~ future work.

8. ~~Reference~~References