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=27,346) 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=75) 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). Further, the stress-buffering patterns of positive events were incorporated into the prediction of adolescents' future stress. 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

Motivation: 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). Compared with adults, young people exhibit more exposure to stress due to the immature inner status and lack of experience (Vitelli, 2014). 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.

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 *'buffering'* (Shahar and Priel, 2002; Cohen and Hoberman, 2010), with respect to physiological, psychological, and social coping resources (Cohen et al., 1984; Needles and Abramson, 1990). Researchers indicated that positive events mitigated the relation between negative events and maladjustment in samples of adolescents experiencing family transitions (Doyle et al., 2003). The written expression of positive feelings had also been proven to prompt increased cognitive re-organization among an undergraduate student group (Coolidge, 2009). Positive events also have been linked to medical benefits, such as improving mood, serum cortisol levels, and lower levels of inflammation and hypercoagulability (Caputo et al., 1998; Jain et al., 2010). Thus, tracking the state of stress-buffering is important for understanding the mental status of stressed individuals.

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

If we view the aforementioned studies on positive events as static sensing of stress-buffering, this study approaches the problem from the dynamic process of stress-buffering and aims at a solution considering adolescents' both microblogging content and behavioral levels under the hypothesis that the moment in which a positive event occur is related to stress-buffering effects. Since the subjective self-report investigations are susceptible to many factors, such as social appreciation and pressures from measurement scenarios, microblogging characteristics at the behavioral level are objective expressions that can assist content characteristics.

Another difference from the previous studies lies in that, despite the unique advantages of social networks over the survey methods in offering self-expressed content and behavioral information, existing microblog-based researches stopped at the analysis of stress, and none went further to capture positive events that may play a key role in adolescents' stress coping mechanism. For example, it is hiking tomorrow that buffers the stress of losing the exam today. Understanding stress-buffering patterns of positive events is helpful in predicting and guiding stressful adolescents coping with stress.

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

However, capturing the stress-buffering process of positive events is not a trivial task. Three fundamental challenges need to be addressed: 1) What is the latent connection between positive events and adolescents' stress-buffering reflections from microblogs? 2) How to extract positive events and its impact interval from microblogs? 3) What are the criteria to predict future stress under the impact of positive events?

A pilot study was firstly conducted on the microblog data (n=29,232) of a group of high school students (n=500) associated with the school's scheduled positive events (n=75) and stressor events (n=122). Stressful intervals were divided into two comparative categories: intervals impacted by scheduled positive events (denoted as U-SI, n=259) and intervals not impacted by scheduled positive events (denoted as SI, n=518). After observing the posting behaviors and contents of stressed students in both SI and U-SI groups, several implications were discussed to guide the next step study.

Motivated by the implications from the pilot study, we model 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: posting behaviours, stress change modes, linguistic expressions. The monotonous changes of stress intensity caused by positive events were measured in temporal order. As an exploration, according to the occurrence of automatically extracted positive events, we covered its stress-buffering effects into each time unit and integrated such effect into stress prediction.

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

The rest of the paper is organized as follows...

2. Literature Review

2.1. Stress-buffering Function of Positive Events

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

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). (Folkman and Moskowitz, 2010) identified three classes of coping mechanisms that were associated with positive emotion during chronic stress: positive reappraisal, problem-focused coping, and the creation of positive events. 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.

To assess the stress-buffering effect of positive events, scholars conducted many studies based on self-support methods. For example, (Kanner et al., 1981b) conducted Hassles & Uplifts Scales, and concluded that the assessment of daily hassles and uplifts might be a better approach to the prediction of adaptational outcomes than the usual life events approach. To measure negative interpretations of positive social events, (Alden et al., 2008) proposed the Interpretation of Positive Events Scale, and analyzed the relationship between social interaction anxiety and the tendency to interpret positive social events in a threat-maintaining manner. (Mcmillen and Fisher, 1998) proposed the Perceived Benefit Scales as the new measures of self-reported positive life changes after traumatic stressors, including lifestyle changes, material gain, increases in self efficacy, family closeness, community closeness, faith in people, compassion, and spirituality. Specific for college students, (Jun-Sheng, 2008) investigated in 282 college students using the Adolescent Self-Rating Life Events Checklist, and found that the training of positive coping style was of great benefit to improve the mental health of students. The above explorations based on self-report investigations were 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 relied on a limited number of measurements, thus continuous measurements of 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 through social networks (e.g., micro-blog, Twitter, Facebook), researchers explored to apply psychological theories into social network based data mining techniques, thus to better understand user' psychological status from the self-expressed public data source. Multiple content and user behavioral measures have been proven effective in user mental health analysis, including time series curve analysis of stress (Li et al., 2015b,a), topic words (Xue et al., 2013), abnormal posting time (Xue et al., 2014), online shopping behaviors (Zhao et al., 2016), human mobility features (Jin et al., 2016), comment/response actions (Liang et al., 2015) and high dimensional multimedia features (Lin et al., 2014). For example, (Xue et al., 2013, 2014) proposed to detect adolescent stress from single post utilizing machine learning methods by extracting stressful topic words, abnormal posting time, and interactions with friends. (Lin et al., 2014) constructed a deep neural network to combine the high-dimensional picture semantic information into stress detecting. Based on the stress detecting result, (Li et al., 2015c)Li et al. (2015a)Li et al. (2015b) adopted a series of multi-variant time series prediction techniques (i.e., Candlestick Charts, fuzzy Candlestick line, Seasonal Autoregressive Integrated Moving Average model) to predict future stress trend. Taking the linguistic information into consideration, (Li et al., 2017c) employed a Nonlinear autoregressive with External Input Neural Network to predict a teen's future stress level referred to the impact of co-experiencing stressor events of similar companions. (Li et al., 2017a) proposed to detect stressor events from microblog content and analyze stressful intervals based on posting rate. All above studies focused on the discussion of stress detection on 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. Thus we push forward the study from how to find stress to the next more meaningful stage: how to cope with stress.

2.3. *Correlation Analysis Models for Multivariate Time Series*

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

For multivariate time series analysis, two-sample based models were widely adopted. Such kind of models were deduced to check whether two samples come from the same underlying distribution, which was assumed to be statistically unknown. Correspondingly, various kernel (Scholkopf et al., 2006) and distance-based models (Schilling, 1986) were proposed. (Scholkopf et al., 2006) proposed to transform the distance between two variables and nearest neighbors into a reproducing kernel hilbert pace, and solve the problem using Maximum Mean Discrepancy. (Schilling, 1986) adopted the r-nearest neighbor based model to partition two set of event driven time series data. The global proportion of the right divided neighbors were calculated to estimate whether there existed statistically difference between the two sets. This paper adopted the r-nearest neighbor based two-sample model in our problem, thus to measure the distance and correlation between two multi-dimension variables depict the stress-buffering patterns of positive events.

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

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

Scheduled events. The list of weekly scheduled school events, with detailed description involved in the event (grade, exact start and end time), were collected from the school's official website[1] from February 1st, 2014 to August 1st 2017. There were 126 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*),

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

the positive event *holiday* happened after the second exam (*example b*), and no scheduled positive event was found nearby 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 mid-term exam	grade1,2
positive event	2016/11/5	campus art festival	grade1,2,3

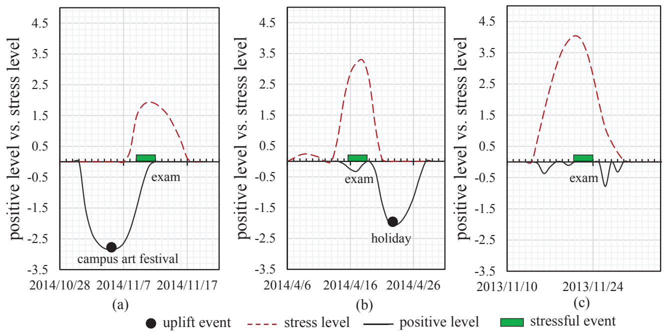

Figure 1: Examples of school scheduled positive events, stressor events, and a student's stress fluctuation

To further observe the effect of positive events on stressed students, we collected all stressful intervals surround the scheduled exams over the 121 students during their high school career applying the interval detection method in (Li et al., 2017a). For each student, we divided all 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 in 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*. 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 value per day was aggregated by calculating the average stress of all posts. The positive level of each post was identified based on the frequency of positive emotional words based on four categories (surprise, joy, expectation, love) of C-LICW lexicons (Tausczik and Pennebaker). Examples of academic related keywords were listed in table 2. The average value of each measure over all eligible slides was calculated.

Table 2: Examples of academic related keywords.

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

3.1. 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). 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, 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 discussed.

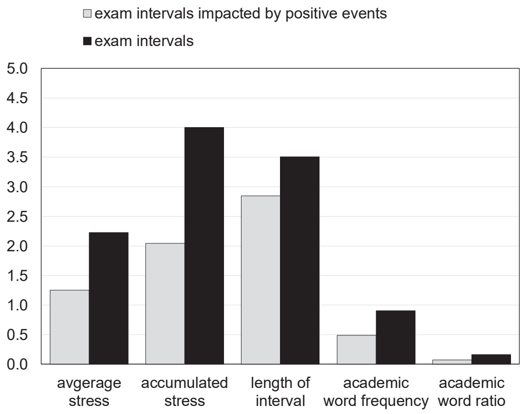

Figure 2: Comparing students' stress during exam intervals in two situations: 1) intervals affected by neighboring positive events (U-SI), 2) no positive events occurred nearby (SI)

Table 4: Extracted 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*)

4. Framework

4.1. Discovery of Positive Events from Microblogs

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. 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 (Jun-Sheng, 2008; Kanner et al., 1981a), adolescent positive events mainly focus on six dimensions, as $\mathbb{U} = \{$ 'entertainment', 'school life', 'romantic', '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 (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 positive lexicons.

4.1.1. Linguistic Parser Model

Positive events were identified through Chinese natural language processing platform (Che et al., 2010). For each post, after word segmentation, we parsed each sentence to find its linguistic structure, and then matched the main linguistic components with positive topic lexicons in each dimension. The linguistic parser model was applied to identify the central verb of 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 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 adolescents' microblogs are listed in table 4. For the post 'Thanks all my dear friends 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 (Li et al., 2017a) to identify the impact interval of each positive event 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.

Step1: Extracted positive events, stressor events and filtered out candidate intervals. For each candidate interval, we set its length to more than 3 days and a maximum gap of 1 day between two neighboured stressed days. Since the stress series detected from microblogs were discrete points, loess method was adopted to highlight characteristics of the stress curve.

Step2: Judged stressful intervals through hypothesis testing. A Poisson based probability model was adopted to measure how confidently the current interval was a stressful inter-

Table 3: Topic words of six-dimensional 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

val. Here the stressful posting rates under stress λ_1 and normal conditions λ_0 were modeled as two independent poisson process:

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

where $i \in \{0, 1\}, n = 0, 1, \cdots, \infty$. 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 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 inferred the posterior distribution $P(\lambda_1|N_1)$ and $P(\lambda_0|N_0)$ according to Bayes Rule. Thus for current interval I_1 and historical normal interval I_0, the quantified probability $\beta = P(\lambda_1 > \lambda_0|I_1, I_0) \in (0, 1)$ indicated the confidence whether I_1 was a stressful interval.

Step 3: Divided stressful intervals into SI set and U-SI set in temporal order. 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 at time point t_u in three cases: 1) If the positive event u happened 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 a stressful interval, considering the probability that it conducted impact on current 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. 3) Other stressful intervals were divided into U-SI set.

4.2. Relationship Between Positive Events and Adolescents' Stress-buffering Behaviors from Microblogs

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

4.2.1. Topic

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.

4.2.2. Positive and Stressful Emotions

4.2.3. 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.

4.2.4. 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.

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 **??**. 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:

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

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 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 **??**.

4.4. Modeling the Stress-buffering Impact of Positive Events

4.5. Integrating the Stress-buffering Impact into Stress Prediction

5. Experiment and Evaluation

5.1. Setup and Metrics

5.2. Stress Buffering

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%

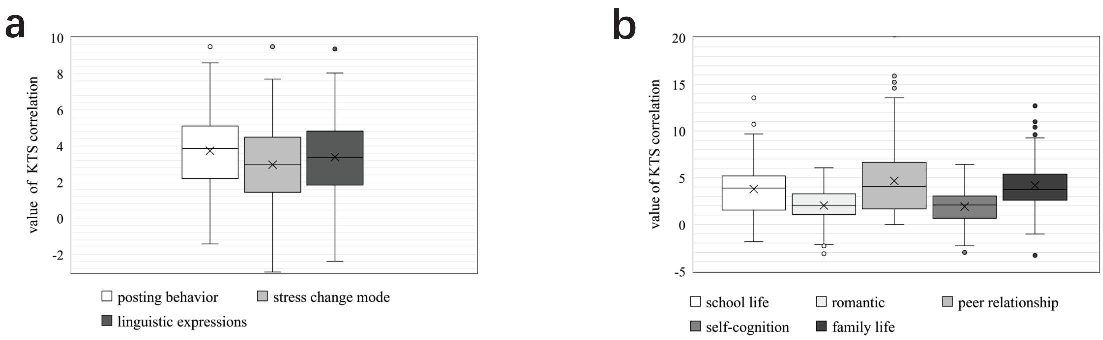

Figure 3: Stress-buffering pattern of positive events. Figure a) shows correlation of each microblog measure, and figure b) shows stress-buffering effect on five dimensions of stress. 'KTS' means KNN-based correlation method.

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.

5.3. Stress Prediction

6. Reference

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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%

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