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. We review the literature in section 2, and introduce the pilot study in section 3. The procedure for extracting positive events and identifying its impact interval is presented in section 4.1. The connection between positive events and adolescents' stress-buffering from microblogs are discussed and modeled in section 4.2. In section **??**, we extend the study to integrating stress-buffering patterns into future stress prediction. We present the experimental results in section 5, and discuss the future work in section 6.

2. Literature Review

2.1. Stress-buffering Function of Positive Events

Positive events have been verified as protective factors against daily stress (Ong et al., 2006; Bono et al., 2013), loneliness (Chang et al., 2015), suicide (Kleiman et al., 2014) and depression (Santos et al., 2013). 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

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

life are listed shown in Table 1. There were 2-3 stressor events and 1-2 positive event scheduled per month in current study. Figure 1 shows three examples of a student's stress fluctuation during three mid-term exams, where the positive event *campus art festival* was scheduled ahead of the first exam (*example a*), the positive event *holiday* happened after the second exam (*example b*), and no scheduled positive event was found nearby the third exam (*example c*).

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

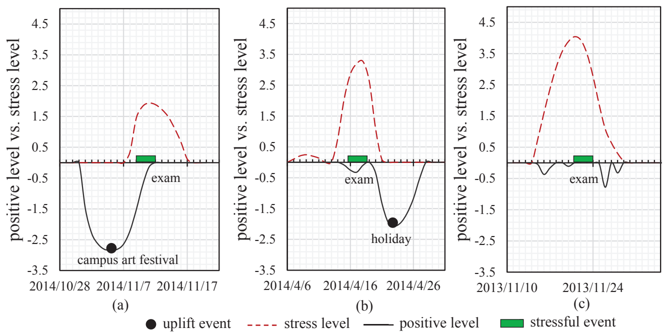


Figure 1: Examples of school scheduled positive events, stressor events, and a student's stress fluctuation

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

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.

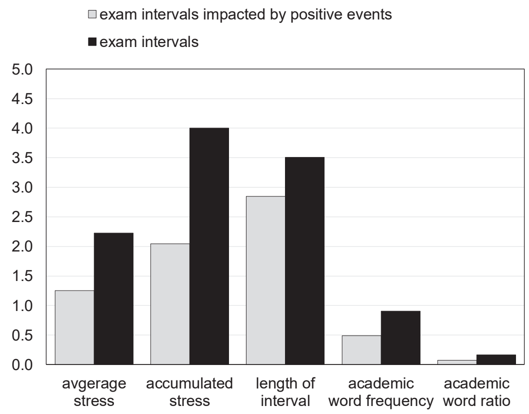


Figure 2: Comparing students' stress during exam intervals in two situations: 1) intervals affected by neighboring positive events (U-SI), 2) no positive events occurred nearby (SI)

4. Framework

We first introduce the procedure to extract positive event and its intervals from microblogs, Based on this, we present a statistical model to depict the connection 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* 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 (expectation, joy, love, 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.

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*)

4.1.1. 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

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

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 interval. 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 from Microblogs

4.2.1. Measures

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.

Positive and Stressful Emotions.

Posting behaviors. Stress could lead to abnormal posting behaviors, reflecting user's changes in social engagement activity (Liang et al., 2015). In this study, we considered four measures of posting behaviors in each time unit (day), and presented each measure as a corresponding series. The first measure was *posting frequency*, representing the total number of posts per day.

Research in Li et al. (2017a) indicated that overwhelmed adolescents tended to post more to express their stress for releasing and seeking comfort from friends. The second measure *stressful posting frequency* per day was based on existing stress detection result and highlights the stressful posts among all posts. The third measure was the *positive posting frequency*, indicating the number of positive posts per day. The forth measure *original frequency* was the number of original posts, which filters out re-tweet and shared posts. Compared to forwarded posts, original posts indicated higher probability that users were talking about themselves. Thus in each interval, user's posting behavior was represented as a four-dimension vector.

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

4.2.2. Statistical Model of Stress-buffering Effects

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 **??**.

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

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

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

$$\begin{aligned}
PNN_r(\ell_x, A) &= \{y|min\{||\mathbf{D}_p^x - \mathbf{D}_p^y||_2\}, y \in (A/\ell_x)\} \\
SNN_r(\ell_x, A) &= \{z|min\{||\mathbf{D}_s^x - \mathbf{D}_s^z||_2\}, z \in (A/\ell_x)\} \\
LNN_r(\ell_x, A) &= \{w|min\{||\mathbf{D}_l^x - \mathbf{D}_l^w||_2\}, w \in (A/\ell_x)\}
\end{aligned} \tag{3}$$

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

$$NN_r(\ell_x, A) = \{v|min\{a \times ||\mathbf{D}_p^x - \mathbf{D}_p^v||_2 + \tag{4}$$

$$b \times ||\mathbf{D}_s^x - \mathbf{D}_s^v||_2 + c \times ||\mathbf{D}_l^x - \mathbf{D}_l^v||_2\}, v \in (A/\ell_x)\} \tag{5}$$

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

$$I_r(\ell_x, A_1, A_2) = \begin{cases} 1, & if \ell_x \in A_i \&\& NN_r(\ell_x, A) \in A_i, \\ 0, & otherwise \end{cases} \tag{6}$$

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:

$$T_{k,n} = \frac{1}{n \times k} \sum_{i=1}^{n} \sum_{j=1}^{k} I_j(x, A_1, A_2) \tag{7}$$

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

$$Z = (nr)^{1/2}(T_{r,n} - \mu_r)/\sigma_r \tag{8}$$

$$\mu_r = (\lambda_1)^2 + (\lambda_2)^2 \tag{9}$$

$$\sigma_r{}^2 = \lambda_1\lambda_2 + 4\lambda_1{}^2\lambda_2{}^2 \tag{10}$$

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

Thus we judge whether the positive events have conducted significant restoring impact on the teen's stress series as follows: if $f(SI, USI) = (nr)^{1/2}(T_{r,n} - \mu_r)/\mu_r{}^2 > \alpha$ ($\alpha = 1.96$ for $P = 0.025$), then the hypothesis H_1 is true.

4.2.3. Monotonous Model of Stress-buffering

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

For a stressful interval $I =< t_i, t_{i+1}, \cdots, t_j >$, let $I^{front} =< t_m, \cdots, t_{i-1} >$ be the adjacent interval before I, and $I^{rear} =< t_{j+1}, \cdots, t_n >$ be the rear adjacent interval of I. The length of I^{front} and I^{rear} are set to $|I|$. For the set of stressful intervals SI composed of $< I_1, I_2, \cdots, I_N >$, the corresponding sets of adjacent front and rear intervals are denoted as SI^{front} and SI^{rear}. Similarly, for the set of stressful intervals $USI = < UI_1, UI_2, \cdots, UI_M >$ impacted by positive events, the corresponding sets of adjacent front and rear intervals are denoted as USI^{front} and USI^{rear}. We compare the intensity of stress changes in following four situations, where $g(.)$ is the function comparing two sets:

1) $g(SI, SI^{front})$ returns if intensive change happens when stressful intervals begin.
2) $g(SI, SI^{rear})$ returns if stress changes intensively after the stressful intervals end.
3) $g(USI, USI^{front})$ returns if intensive change happens when stressful intervals affected by positive events appears.
4) $g(USI, USI^{rear})$ returns if stress changes intensively after stressful intervals affected by positive events end.

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

$$g(SI, SI^{rear}) = \frac{\mu_{SI} - \mu_{SI^{rear}}}{\sqrt{\frac{(n_1-1)\sigma_{SI}^2 + (n_2-1)\sigma_{SI^{rear}}^2}{n_1+n_2-2}(\frac{1}{n_1} - \frac{1}{n_2})}} \tag{11}$$

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

5. Experiment and Evaluation

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 6 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

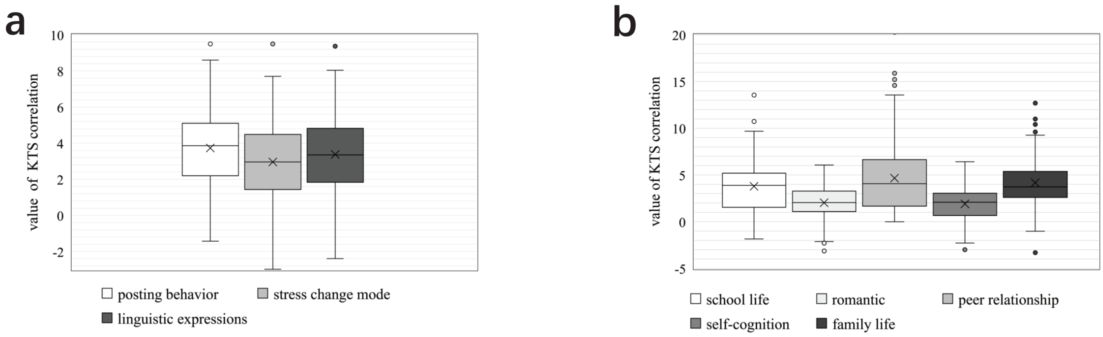


Figure 3: Stress-buffering pattern of positive events. Figure a) shows correlation of each microblog measure, and figure b) shows stress-buffering effect on five dimensions of stress. 'KTS' means KNN-based correlation method.

Table 5: 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%

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%.

Table 6: 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%

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.

Further more, to verify the monotonous stress changes when an positive event impacts a stressful interval, for each stressful interval in SI and U-SI, we quantify its stress intensity by comparing with the front and rear adjacent intervals, respectively. Here four situations were considered and compared, as shown in table 5. The *ratio of intervals* detected with monotonous increase from the *front interval* to *stressful interval* (denoted as *front*→ *I*), and monotonous decrease from the *stressful interval* to the *rear interval* (denoted as *I* → *rear*) were listed. Under the effect of positive events, the ratio of intensive stress in-

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

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

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

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

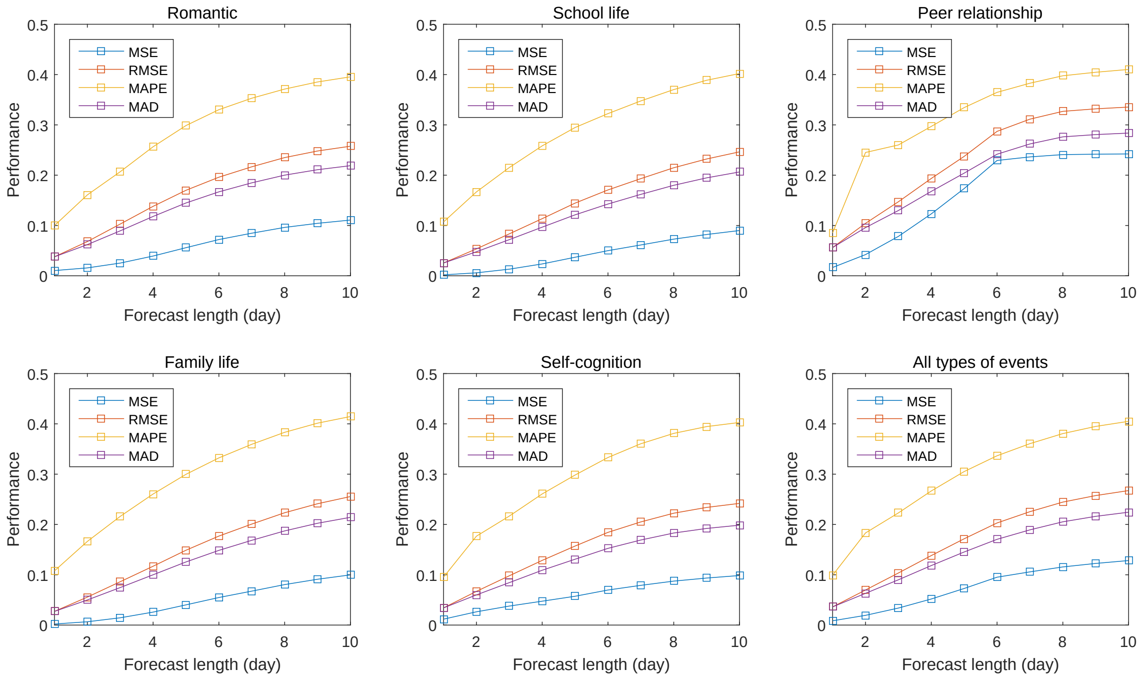
crease in *front*→ I was decreased from 78.51% to 70.17%; and the ratio of intensive stress decrease in $I \rightarrow rear$ was decreased from 79.55% to 75.13%. The most obvious monotonous decrease in *front*→ I were conducted by positive events in family life dimension (12.89% reduction); and the most obvious monotonous decrease in *front*→ I were also conducted by positive events in family life dimension (6.65% reduction). The experimental results indicated the effectiveness of the two sample method for quantifying the effect of positive events, and the rationality of the assumption that positive events could help ease stress of overwhelmed teens.

5.1. Stress Prediction Under Stress-buffering Effects

1) Stress prediction model. To measure the effectiveness of our method for quantifying the restoring impact of positive events, we integrate the impact of positive events into traditional stress series prediction problem, and verify whether the restoring pattern of positive events could help improve the prediction performance. Here we choose the SVARIMA (Seasonal Autoregressive Integrated Moving Average) algorithm, which is proved to be suitable for teens' linear stress prediction problem (Shumway and Stoffer, 2006; Li et al., 2015c), due to the seasonality and non-stationarity of teens' stress series. The basic stress prediction is conducted using SVARIMA approach, in the set of stressful intervals impacted by positive events (U-SI). Since stressor events cause the fluctuation of stress series from normal states, to eliminate the interference, we simply consider the prediction problem in those stressful intervals rather than randomly picked out stress series. The impact of positive events are utilized as adjust values to modify the stress prediction result. Four metrics are adopted to measure the stress forecasting problem, where *MSE*, *RMSE* and *MAD* measure absolute errors and *MAPE* measures relative errors. For all real stress value $\overline{s_i}$ and predicted stress value s_i in predicting sequence $< s_1, \cdots, s_n >$, $MSE = \frac{1}{n}\sum_{i\in[1,n]}(s_i - \overline{s_i})^2$, $RMSE = \frac{1}{n}\sqrt{\sum_{i\in[1,n]}(s_i - \overline{s_i})^2}$, $MAD = \frac{1}{n}\sum_{i\in[1,n]}|s_i - \overline{s_i}|$, and $MAPE = \frac{1}{n}\sum_{i\in[1,n]}|s_i - \overline{s_i}|/s_i$.

We integrate the impact of positive events into stress prediction. The experimental set contains 1,914 stressful intervals under the impact of positive events (U-SI). As shown in Table 7, the original prediction result using only SVARIMA method achieves 0.1281 MSE, 0.3579 RMSE, 0.3604 MAPE and 0.1482 MAD ($L = 7$, $\alpha = 0.5$). Then we integrate the impact of each type of positive events into stress prediction. Specifically, for positive with obvious restoring impact (under the L&S&P pattern), the average stress level during historical restoring intervals are integrated to modify the result, with adjusting the parameter α (details see **??**). After the modification, the prediction performance achieves 0.0649 MSE, 0.2548 RMSE, 0.2638 MAPE and 0.0858 MAD, reducing the prediction errors efficiently (with MSE, RMSE, MAPE and MAD re-

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



duced by 49.34%, 28.81%, 26.80% and 42.11%, respectively).

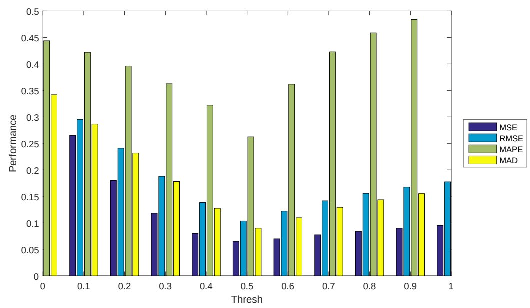
2) Predicting stress under different windows. We present the prediction result under the impact of positive events under different lengths of prediction windows, ranging from 1 to 10 days, as shown in 4. With the window length increasing, the prediction error shows decreasing trend in all metrics. The reason is that longer prediction window takes more previous predicted results, and the error accumulates with more predicted values taken into the next step prediction. Among the five dimensions of events, the prediction for school life stress achieves the best performance. On one side, more positive events and stressors about school life events are detected from teens microblogs, providing sufficient data in prediction. On the other side, stress coming from school life is the most common stress in the student group, with relative stable periodicity and high frequency.

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

4) Parameter settings. The parameter α is adjusted when integrate the impact of positive events into stress prediction. For each of the four groups of restoring patterns, we adjust α in the effect of $\alpha \times L$. We calculate the corresponding prediction result for each teen respectively, and show the result of the whole testing group using the averaging performance. Figure 5 shows the changing trend under the L&S&P pattern. The prediction error decreases first and then increases, and the best performance is achieved when α is nearby 0.52, with 0.0649 MSE, 0.2548

RMSE, 0.2638 MAPE and 0.0858 MAD as the average performance of the whole experimental data set. Multiple methods for integrating the impact of positive event into stress prediction could be adopted. In this paper we adopt the simple one to verify the effectiveness of our model in quantifying the impact of positive events, and the setting of parameter α could be changed due to different individuals and data sets.

Figure 5: Stress forecast performance under the L&S&P pattern of positive events.



6. Discussion

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

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

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

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

7. Limitations and future work

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

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

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

8. Reference

Alden, L.E., Taylor, C.T., Mellings, T.M., Laposa, J.M.. Social anxiety and the interpretation of positive social events. Journal of Anxiety Disorders 2008;22(4):577–90.

APA, . Stress in america: Generation z 2018;:1–11.

Blachnio, A., Przepiorka, A., Balakier, E., Boruch, W.. Who discloses the most on facebook? Computers in Human Behavior 2016;55:664 – 667.

Bono, J.E., Glomb, T.M., Shen, W., Kim, E., Koch, A.J.. Building positive resources: Effects of positive events and positive reflection on work stress and health. Academy of Management Journal 2013;56(6):1601–1627.

Caputo, J.L., Rudolph, D.L., Morgan, D.W.. Influence of positive life events on blood pressure in adolescents. Journal of Behavioral Medicine 1998;21(2):115–129.

Chang, E.C., Muyan, M., Hirsch, J.K.. Loneliness, positive life events, and psychological maladjustment: When good things happen, even lonely people feel better! ☆. Personality and Individual Differences 2015;86:150–155.

Che, W., Li, Z., Liu, T.. Ltp: A chinese language technology platform. In: Proc. of ACL. 2010. p. 13–16.

Cohen, J., Cohen, J., Cohen, D., Cohen, J., Cohen, J., Adad, J., Cohen, J., Cohen, J., Cohen, J., Cohen, J.. Statistical power analysis for the behavioral science. Technometrics 1988;84(334):19 – 74.

Cohen, L.H., Mcgowan, J., Fooskas, S., Rose, S.. Positive life events and social support and the relationship between life stress and psychological disorder. American Journal of Community Psychology 1984;12(5):567–87.

Cohen, S., Hoberman, H.M.. Positive events and social supports as buffers of life change stress. Journal of Applied Social Psychology 2010;13(2):99–125.

Coolidge, F.L.. A comparison of positive versus negative emotional expression in a written disclosure study among distressed students. Journal of Aggression Maltreatment and Trauma 2009;18(4):367–381.

Doyle, K.W., Wolchik, S.A., Dawsonmcclure, S.R., Sandler, I.N.. Positive events as a stress buffer for children and adolescents in families in transition. Journal of Clinical Child and Adolescent Psychology 2003;32(4):536–545.

Folkman, S., Moskowitz, J.T.. Stress, positive emotion, and coping. Current Directions in Psychological Science 2010;9(4):115–118.

Jain, S., Mills, P.J., Von, R., Hong, S., Dimsdale, J.E.. Effects of perceived stress and uplifts on inflammation and coagulability. Psychophysiology 2010;44(1):154–160.

Jin, L., Xue, Y., Li, Q., Feng, L.. Integrating human mobility and social media for adolescent psychological stress detection. In: Database Systems for Advanced Applications. 2016. p. 367–382.

Johnson, R.A., Wichern, D.W.. Applied multivariate statistical analysis third ed. Technometrics 2012;25(4):385–386.

Jun-Sheng, H.U.. Influence of life events and coping style on mental health in normal college students. Chinese Journal of Clinical Psychology 2008;.

Kanner, A., Coyne, J., Schaefer, C., Lazants, R.. Comparison of two modes of stress measurement: Daily hassles and uplifts versus major life events. Journal of Behavioral Medicine 1981a;4:1–39. doi:10.1177/089443939201000402.

Kanner, A.D., Coyne, J.C., Schaefer, C., Lazarus, R.S.. Comparison of two modes of stress measurement: Daily hassles and uplifts versus major life events. Journal of Behavioral Medicine 1981b;4(1):1.

Kleiman, E.M., Riskind, J.H., Schaefer, K.E.. Social support and positive events as suicide resiliency factors: Examination of synergistic buffering effects. Archives of Suicide Research 2014;18(2):144–155.

L Bevan, J., B Cummings, M., Kubiniec, A., Mogannam, M., Price, M., Todd, R.. How are important life events disclosed on facebook? relationships with likelihood of sharing and privacy. Cyberpsychology, behavior and social networking 2015;18:8–12. doi:10.1089/cyber.2014.0373.

L. Bevan, J., Gomez, R., Sparks, L.. Disclosures about important life events on facebook: Relationships with stress and quality of life. Computers in Human Behavior 2014;39:246–253. doi:10.1016/j.chb.2014.07.021.

Li, J., Ritter, A., Cardie, C., Hovy, E.. Major life event extraction from twitter based on congratulations/condolences speech acts. In: Conference on Empirical Methods in Natural Language Processing. 2014. .

Li, Q., Xue, Y., Zhao, L., Jia, J., Feng, L.. Analyzing and identifying teens stressful periods and stressor events from a microblog. IEEE Journal of Biomedical and Health Informatics 2017a;21(5):1434–1448.

Li, Q., Zhao, L., Xue, Y., Jin, L., Alli, M., Feng, L.. Correlating stressor events for social network based adolescent stress prediction 2017b;.

Li, Q., Zhao, L., Xue, Y., Jin, L., Feng, L.. Exploring the impact of co-experiencing stressor events for teens stress forecasting. In: International Conference on Web Information Systems Engineering. 2017c. p. 313–328.

Li, Y., Feng, Z., Feng, L.. Using candlestick charts to predict adolescent stress trend on micro-blog ? Procedia Computer Science 2015a;63:221–228.

Li, Y., Feng, Z., Feng, L.. When a teen's stress level comes to the top/bottom: A fuzzy candlestick line based approach on micro-blog. In: Revised Selected Papers of the International Conference on Smart Health. 2015b. p. 241–253.

Li, Y., Huang, J., Wang, H., Feng, L.. Predicting teenager's future stress level from micro-blog. In: IEEE International Symposium on Computer-Based Medical Systems. 2015c. p. 208–213.

Liang, Z., Jia, J., Ling, F.. Teenagers' Stress Detection Based on Time-Sensitive Micro-blog Comment/Response Actions, 2015.

Lin, H., Jia, J., Guo, Q., Xue, Y., Li, Q., Huang, J., Cai, L., Feng, L.. User-level psychological stress detection from social media using deep neural network 2014;:507–516.

Mcleod, A.I.. Kendall: Kendall rank correlation and mann-kendall trend test 2011;.

Mcmillen, J.C., Fisher, R.H.. The perceived benefit scales: Measuring perceived positive life changes after negative events. Social Work Research 1998;22(3):173–187.

Nabi, R., Prestin, A., So, J.. Facebook friends with (health) benefits? exploring social network site use and perceptions of social support, stress, and well-being. Cyberpsychology, behavior and social networking 2013;16. doi:10.1089/cyber.2012.0521.

Needles, D.J., Abramson, L.Y.. Positive life events, attributional style, and hopefulness: Testing a model of recovery from depression. Journal of Abnormal Psychology 1990;99(2):156.

Nock, M.K., Borges, G., Bromet, E.J., Cha, C.B., Kessler, R.C., Lee, S.. Suicide and suicidal behavior. Epidemiologic Reviews 2008;30(1):133–154.

Ong, A.D., Bergeman, C.S., Bisconti, T.L., Wallace, K.A.. Psychological resilience, positive emotions, and successful adaptation to stress in later life. Journal of Personality and Social Psychology 2006;91(4):730–49.

Santos, V., Paes, F., Pereira, V., Ariascarrión, O., Silva, A.C., Carta, M.G., Nardi, A.E., Machado, S.. The role of positive emotion and contributions of positive psychology in depression treatment: systematic review. Clinical Practice and Epidemiology in Mental Health Cp and Emh 2013;9(1):221.

Schilling, M.. Multivariate two-sample tests based on nearest neighbors. Publications of the American Statistical Association 1986;81(395):799–806.

Scholkopf, B., Platt, J., Hofmann, T.. A kernel method for the two-sample-problem 2006;abs/0805.2368(2007):513 – 520.

Shahar, G., Priel, B.. Positive life events and adolescent emotional distress: In search of protective-interactive processes. Journal of Social and Clinical Psychology 2002;21(6):645–668.

Shchebetenko, S.. Do personality characteristics explain the associations between self-esteem and online social networking behaviour? Computers in Human Behavior 2019;91:17–23.

Shumway, B., Stoffer, D.. Time Series Analysis and Its Applications. Springer New York, 2006.

Spearman, C.. The proof and measurement of association between two things. The American journal of psychology 1987;100(3-4):441.

Tausczik, Y.R., Pennebaker, J.W.. The psychological meaning of words: Liwc and computerized text analysis methods. Proc of JLSP ;29(1):24–54.

Twomey, C., O' Reilly, G.. Associations of self-presentation on facebook with mental health and personality variables: A systematic review. Cyberpsychology, Behavior, and Social Networking 2017;20:587–595. doi:10.1089/cyber.2017.0247.

Vitelli, R.. Hassles, uplifts and growing older. https://www.psychologytoday.com/blog/media-spotlight/201406/hassles-uplifts-and-growing-older; 2014.

Xue, Y., Li, Q., Feng, L., Clifford, G., Clifton, D.. Towards a micro-blog platform for sensing and easing adolescent psychological pressures. In: Proc. of Ubicomp. poster; 2013. .

Xue, Y., Li, Q., Jin, L., Feng, L., Clifton, D.A., Clifford, G.D.. Detecting Adolescent Psychological Pressures from Micro-Blog, 2014.

Youth, C., Center, C.R.. Adolescent mental health alarm: nearly 30% have a risk of depression. China Youth News 2019;:1–2.

Zhao, L., Wang, H., Xue, Y., Li, Q., Feng, L.. Psychological stress detection from online shopping. In: Web Technologies and Applications. 2016. p. 431–443.