Assessing Stress-Buffering Effects of Positive Events from Adolescents' Microblogs

Abstract

Studies have shown that the occurrence of positive events could conduct stress-buffering effects. The characteristics and process of stress-buffering play key roles in understanding the mental health status of stressed individuals. Scholars conducted assessments of stress-buffering mainly through subjective self-reporting. However, the stress-buffering characteristics at individual behavioral level remains to be explored. The dynamic process of stress-buffering was also difficult to track through static, one-time survey-based measurements. As social networks penetrate into people' s lives, users tend to reveal various emotional and behavioral characteristics in microblogs. So, how to automatically observe user's behavioral characteristics of stress-buffering and capture the dynamic process of stress-buffering through microblogs? The current study provided solutions to the above problems. We tested the relationship between positive events and stressed individual's microblogging behaviors, and proposed an automatical analysis framework instead of self-reporting methods based on the microblog data set of 500 high school students. The stress-buffering process was further quantified from a dynamic perspective. Our exploration provides guidance for school and parents that which kind of positive events could help relieve adolescent' stress in both stress prevention and stress early stopping situations. The theoretical and practical implications, limitations of this study and future work are discussed.

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

1. Introduction

Life is always full of ups and downs. Accumulated stress comes from daily hassles, major stressful events and environmental stressors could drain inner resources, leading to psychological maladjustment, such as depression and suicidal behaviours (Nock et al., 2008). According to the newest report of American Psychological Association, 91 percent of youngest adults say they have experienced physical or emotional symptom due to stress in the past month compared to 74 percent of adults overall (APA, 2018). More than 30 million Chinese teenagers are suffering from psychological stress, and nearly 30% of them have a risk of depression (Youth and Center, 2019). Stress-induced mental health problems are becoming an important social issue worldwide.

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

Assessing people's stress-buffering status was not a trivial task. Previous assessments of stress-buffering were mainly conducted through subjective self-reporting (Kanner et al., 1981b; Alden et al., 2008; Mcmillen and Fisher, 1998; Jun-Sheng, 2008), which was influenced by many factors, such as social appreciation and pressure from measurement scenarios. However, there is a lack of research on the stress-buffering characteristics that individuals actually exhibit at the behavioral level. At the same time, previous studies has been based on static perspectives, focusing on single measurements of positive events and psychological state after events (Chang et al., 2015; Kleiman et al., 2014; Santos et al., 2013), while the dynamic process of stress-buffering was difficult to track due to the lack of effective scientific methods.

As the social media is becoming deeply woven into our daily life, an increasing number of natural self-disclosures are taking place, thus providing a new channel for timely, content-rich and non-invasive exploration of adolescents' mental health status. Previous studies have shown the feasibility and reliability to sense user's psychological stress and stressor events, and predict future development of stress through social network (Li et al., 2015c; Xue et al., 2014; Lin et al., 2014; Li et al., 2017a). The current study aims to contribute to this growing area of interdisciplinary research by examining the potential relationship between positive events and adolescent's microblogging behaviors, and track the stress-buffering process in a dynamic perspective from microblogs.

2. Literature review

2.1. *Stress-buffering function of positive life events.*

Positive events have been verified as protective factors against daily stress (Ong et al., 2006; Bono et al., 2013), loneliness (Chang et al., 2015), suicide (Kleiman et al., 2014), depression (Santos et al., 2013). The protective effect of positive events was hypothesized to operate in both directly (i.e., more positive events people experienced, the less distress they experience) and indirectly ways by *'buffering'* the effects 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, 1997; Folkman and Moskowitz, 2010) identified three classes of coping mechanisms that are associated with positive events 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). Meanwhile, positive events 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). Thus, in view of the above mentioned literature, the present study will be based on the following hypothesize:

H1. Positive events could conduct stress-buffering impact on overwhelmed adolescents.

2.2. *Assessing stress-buffering function of positive events*

Accurately assessing the process of stress-buffering is important for judging the mental health trends of overwhelmed adolescents. To assess the stress-buffering effect of positive events, scholars have proposed much studies based on self-support methods. Doyle *et al.* Kanner et al. (1981b) conducted *Hassles and 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. Silva *et al.* Silva et al. (2008) presented the *Hassles & Uplifts Scale* to assess the reaction to minor every-day events in order to detect subtle mood swings and predict psychological symptoms. To measure negative interpretations of positive social events, Alden *et al.* Alden et al. (2008) proposed the interpretation of positive events scale (*IPES*), and analyzed the relationship between social interaction anxiety and the tendency to interpret positive social events in a threat-maintaining manner. Mcmillen *et al.* 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 selfefficacy, family closeness, community closeness, faith in people, compassion, and spirituality. Specific for college students, Jun-Sheng *et al.* 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 is of great benefit to improve the mental health of students.

The above explorations are mostly conducted on self-report investigations, which might be influenced by social appreciation and pressure from measurement scenarios. Meanwhile, most scholars focused on single measurement limited by manpower and methods, while the dynamic process of stress-buffering was difficult to track. In response to this problem, the present study will propose new measurement methods in a non-invasion way based on social network data. Here two research questions are proposed:

RQ1. How to (a) automatically sense the positive events experienced by adolescents in a timely manner, and (b) identify the time interval impacted by a particular positive event.

2.3. *Measures and stress analysis based on social network*

As billions of adolescents are recording their life, share multi-media content, and communicate with friends through social networks (e.g., Tencent Microblog, Twitter, Facebook), researchers explored to apply psychological theories into social network based stress mining from the self-expressed public data source. Multiple content and user behavioral measures in social networks have been proven effective in user mental state analysis. Xue *et al.* Xue et al. (2014) proposed to detect adolescent stress from single microblog utilizing machine learning methods by extracting stressful topic words, abnormal posting time, and interactions with friends. Lin *et al.* Lin et al. (2014) construct a deep neural network to combine the high-dimensional picture semantic information into stress detecting. Based on the stress detecting result, Li *et al.* Li et al. (2015c)adopted a series of multi-variant time series prediction techniques (i.e., Candlestick Charts, fuzzy Candlestick line and SVARIMA model) to predict the future stress trend and wave. Taking the linguistic information into consideration, Li *et al.* Li et al. (2017c) employed a NARX neural network to predict a teen's future stress level referred to the impact of co-experiencing stressor events of similar companions. To find the source of teens' stress, previous work Li et al. (2017a) developed a frame work to extract stressor events from post content and filter out stressful intervals based on teens' stressful posting rate. Previous scholars focused on stress analysis, while measures depicting stress-buffering and positive event lack of sufficient verification. In present study, we propose to depict the stress-buffering characteristics in three groups of measures, and tested the relationships as:

H2. The stress-buffering function of positive events is correlated with a)posting behavior, b)stress intensity and c)microblog linguistic expressions.

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

To further examine the the dynamic process of stress-buffering, the present study propose to identify the temporal order between positive event occurring and the monotonous stress changes under hypothesis:

H3. positive events cause monotonous stress changes in two cases: a) slowing down the increase of stress at the beginning, and b) promoting the reduction of stress after stressful events.

In addition, previous scholars have proposed to predict stress according to historic stress changing series (Li et al., 2015c) (Li et al., 2015a) (Li et al., 2015b), considering the occurrence of stressors (Li et al., 2017b), and the occurrence of positive events haven't been taken into consideration. In this study, automatically assessing the stress-buffering effect of positive events will help to predict the future stress changes more accurately. This will benefit schools and parents in arranging positive events at appropriate times to ease and intervene the psychological stress of students. Thus we push forward the research from how to find stress to the next stage: how to deal with stress. From this perspective, a exploration is conducted at the end of the study:

RQ3. how to predict adolescents' future stress under the mitigation effect of positive events from microblogs? Specifically, (a)which stress-buffering pattern contributes the most in stress prediction, and (b)influence of different window lengths on stress prediction accuracy will be taken into consideration.

3. Current study

Given the limitations in the existing literature, this study proposes a complete solution to test the relationship between positive events and adolescents' microblogging characteristics and automatically track the dynamic process of stress-buffering. A pilot study is firstly conducted on the microblog dataset of 500 high school students associated with the school's scheduled positive and stressor event list. After observing the posting behaviours and contents of stressed students under the influence of positive events, several hypothesis are conducted to guide the next step research. In study 1, we test the relationship between the stress-buffering effects of automatically extracted positive events and student's microblogging characteristics. A Chinese linguistic parser model is applied to extract structural positive events from microblogging content based on a six-dimensional positive event scale and LIWC lexicons. We depict a students's stressful behaviours in three groups of measures (stress intensity, posting behaviour, linguistic), and model the stress-buffering effect as the statistical difference in two comparative situations. In study 2, we track the dynamic process of stress-buffering function, and quantify the stress-buffering impact of positive events in temporal order. In the exploratory study , the present study explores how to predict future stress changes integrating the stress-buffering impact of positive events.

4. Pilot study: Observation on the stress-buffering function of school scheduled positive events

4.1. Participants

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

4.2. Measures

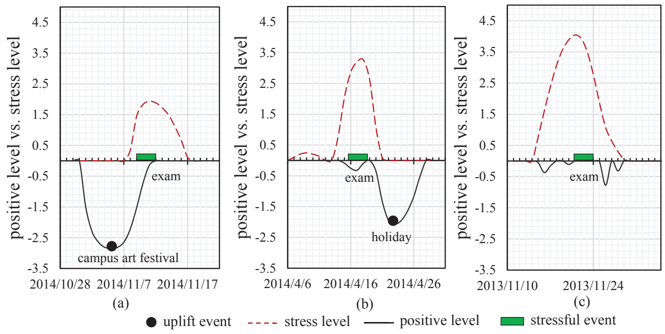
School-scheduled positive events. The list of weekly scheduled school events (from February 1st, 2012 to August 1st 2017) are collected from the school's official website [1], with detailed event description and grade involved in the event. There are 122 stressor events and 75 positive events in total. Here we give the examples of scheduled positive and stressor events in high school life, as shown in Table 1. Comparing the stress curves *a), b)* with *c)*, when an positive event (*campus art festival, holiday* here) happens, the overall stress intensity during the stressful period is reduced. An positive event might happen before a teen's stress caused by scheduled stressor events (*example a*), conducting lasting easing impact; Meanwhile, an positive event might also happen during (*example b*) or at the end of the stressful period, which might promote the teen out of current stressful status more quickly. There are 2-3 stressor events and 1-2 positive event scheduled per month in current study.

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

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

Stress detected from microblogs. Since our target is to observe the restoring impact of positive events for teenagers under stress, based on previous research Xue et al. (2013), we detected the stress level (ranging from 0 to 5) for each post; and for each student, we aggregated the stress during each day by calculating the average stress of all posts. To protect the privacy, all usernames are anonymized during the experiment The positive level (0-5) of each post is identified based on the frequency of positive words (see Section 5 for details). Figure 1 shows three examples of a student's stress fluctuation during three mid-term

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



exams, where the positive event *campus art festival* was scheduled ahead of the first exam, the positive event *holiday* happened after the second exam, and no scheduled positive event was found nearby the third exam. The current student exhibited differently in above three situations, with the stress lasting for different length and with different intensity.

4.3. Method

To further observe the influence of positive events for students facing stressor events, we statistic all the stressful intervals Li et al. (2017a) detected surround the scheduled examinations over the 124 students during their high school career. For each student, we divide all the stressful intervals into two sets: 1) In the original sets, stress is caused by a stressor event, lasting for a period, and no other intervention (namely, positive event) occurs. We call the set of such stressful intervals as **SI**; 2) In the other comparative sets, the teen's stressful interval is impacted by a positive event *x*, we call the set of such stressful intervals as **U-SI**. Thus the difference under the two situations could be seen as the restoring impact conducted by the positive event of type *x*. Based on the scheduled time of stressor and positive events, we identified 518 scheduled academic related stressful intervals (SI) and 259 academic stressful intervals impacted by four typical scheduled positive events (U-SI) (in Table 5) from the students' microblogs. Further observations are conducted on the two sets to verify the impact of positive events from multi perspectives.

4.4. Results

Figure A.5 shows five measures of each teen during the above two conditions: the *accumulated stress*, the *average stress*

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

(per day), the *length of stressful intervals*, the *frequency of academic topic words*, and the *ratio of academic stress among all types of stress*. For each measure, we calculate the average value over all eligible slides for each student. Comparing each measure in scheduled exam slides under the two situations: 1) existing neighbouring positive events or 2) no neighbouring scheduled positive events, we find that students during exams with neighbouring positive events exhibit less average stress intensity (both on accumulated stress and average stress), and the length of stress slides are relatively shorter.

Table 2: Examples of academic topic words from microblogs.

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

Further, we statistic the frequency of academic related topic words for each exam slide (as listed in Table 2), and look into the ratio of academic stress among all five types of stress. Results in Figure A.5 shows that most students talked less about the upcoming or just-finished exams when positive events happened nearby, with lower frequency and lower ratio.

The statistic result shows clues about the stress-buffering function of scheduled positive events, which are 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 our need for automatic, timely, and continuous perception of stress-buffering. Therefore, in study 1, we will propose a framework to automatically detect positive events and its impact interval. Based on this, in study 2, we will examine whether the stress-buffering function of the automatically extracted positive events is related to the microblogging measures (posting behavior, stress intensity, linguistic expressions), and explore its function mode.

5. Study1: The relationship between the stress-buffering effects of automatically extracted positive events and the characters of microblogs

In this section, we propose to model the impact as the teen's behavioral differences in two cases: 1) stressful intervals unaffected by positive events (SI), and 2) stressful intervals impacted by positive events (U-SI). Multiple microblogging behavioral-level measures are tested to describe the correlation between SI and U-SI, based on the hypothesis H1.

5.1. Positive events automatically extracted from microblogs

Because of the scheduled school events in study 1 are limited to our study, next we first introduce the procedure to extract positive events and its intervals from teens' microblogs, thus to extend our study to all types of positive events exposed in microblogs. Our automatically extraction accuracy are verified in part xx, by comparing extracted academic positive events with the scheduled school events in coincident time intervals.

Linguistic structure. Let $u = [type, \{role, act, descriptions\}]$ be an positive event, where the element *role* is the subject who performs the *act*, and *descriptions* are the key words related to u. According to psychological scales Kanner et al. (1981a); Jun-Sheng (2008), teens' positive events mainly focus on six aspects, as $\mathbb{U}$ = { *entertainment', 'school life', 'family life', 'pear relation', 'self-cognition', 'romantic'*}, $\forall u$, $u._{type} \in \mathbb{U}$. Similar to positive event, let $e = [type, \{role, act, descriptions\}]$ be a stressor event. According to psychological questionnaires Jiang (2000); Baoyong and Ying (2002); Kanner et al. (1981b); Yan et al. (2010), we classify stressor events into five types, as $\mathbb{S}$ = { *'school life', 'family life', 'pear relation', 'self-cognition', 'romantic'*}, $\forall e$, $e._{type} \in \mathbb{S}$.

Lexicon. We construct our lexicon for six-dimensional positive events from two sources. The basic positive affect words are selected from the psychological lexicon SC-LIWC (e.g., *expectation*, *joy*, *love* and *surprise*)Tausczik and Pennebaker. Then we build six positive event related lexicons by expanding the basic positive words from the data set of teens' microblogs, and divide all candidate words into six dimensions corresponding to six types of positive events, containing 452 phrases in *entertainment*, 184 phrases in *family life*, 91 phrases in *friends*, 138 phrases in *romantic*, 299 phrases in *self-recognition* and 273 phrases in *school life*, with totally 2,606 words, as shown in Table 3. Additionally, we label *role* words (i.e., *teacher*, *mother*, *I*, *we*) in the positive lexicon.

Parser relationship. For each post, after word segmentation, we parser current sentence to find its linguistic structure, and then match the main linguistic components with positive event

Table 3: Examples of topic words for positive events.

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

related lexicons in each dimension. The parser model in Chinese natural language processing platform Che et al. (2010); Zhang et al. (2008) is adopted in this part, which identifies the central verb of current sentence first, namely the *act*, and constructs the relationship between the central verb and corresponding *role* and *objects* components. By searching these main elements in positive event related lexicons, we identify the existence and type of any positive event. Due to the sparsity of posts, the *act* might be empty. The *descriptions* are collected by searching all nouns, adjectives and adverbs in current post. In such way, we extract structured positive events from teens' microblogs.

Impact Interval of Current Positive Event. We identify stressful intervals from time line thus to support further quantifying the influence of an positive event. Splitting interval is a common time series problem, and various solutions could be referred. Here we identify the teen's stressful intervals in three steps.

In the first step, we extract positive events, stressor events and filter out candidate intervals after a smoothing process. Since a teen's stress series detected from microblogs are discrete points, the loess method Cleveland and Devlin (1988) is adopted to highlight characteristics of the stress curve. The settings of parameter *span* will be discussed in the experiment section, which represents the percentage of the selected data points in the whole data set and determines the degree of smoothing. The details are present as Algorithm Appendix B of the appendix. In the second step, applying the Poisson based statistical method proposed in Li et al. (2017a), we judge whether each candidate interval is a confidential stressful interval. The details are present as Algorithm Appendix C of the appendix. Finally, we divide the stressful intervals into two sets: the SI set and the U-SI set, according to its temporal order with neighboring positive events. The details are present as Algorithm Appendix D of the appendix.

The examples of teens' microblogs describing positive events are listed in Table 4. For the post '*Expecting Tomorrow' Adult Ceremony[Smile][Smile]* ', we translate it into *act* = *'expecting'*, *object* = *'Adult Ceremony'*, and *type* = *'self-cognition'*.

Table 4: Structured extraction of positive events from microblogs.

I am really looking forward to the spring outing on Sunday now. (Doer:*I*, Act:*looking forward*, Object:*spring outing*)
My holiday is finally coming [smile]. (Doer:*My holiday*, Act:*coming*, Object:*[smile]*)
First place in my lovely math exam!!! In memory of it. Object:*first place, math, exam, memory*)
You are always here for me like sunshine. (Doer:*You*, Object:*sunshine*)
Thanks all my dear friends taking the party for me. Happiest birthday!!! (Doer:*friends*, Act:*thanks*, Object:*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*, object:*Adult Ceremony*)

To check the performance of positive event extraction and the validation of our assumption, we first identify positive events and corresponding restoring performance from microblogs, and compare the results with scheduled positive events collected from the school's official web site.

5.2. Measures

To extract the restoring patterns $\boldsymbol{A}$ for each type of positive events, we describe a teen's positive and stressful behavioral measures in SI and U-SI sets from three aspects: posting behavior, stress intensity, and linguistic expressions.

Posting behavior. Stress could lead to a teen's abnormal posting behaviors, reflecting the teen's changes in social engagement activity. For each stressful interval, we consider four measures of posting behaviors in each time unit (day), and present each measure as a corresponding series. The first measure is *posting frequency*, representing the total number of posts per day. Research in Li et al. (2017a) indicates that overwhelmed teens usually tend to post more to express their stress for releasing and seeking comfort from friends. Further, the second measure *stressful posting frequency* per day is based on previous stress detection result and highlights the stressful posts among all posts. Similarly, the third measure is the *positive posting frequency*, indicating the number of positive posts per day. The forth measure *original frequency* is the number of original posts, which filters out re-tweet and shared posts. Compared to forwarded posts, original posts indicate higher probability that teens are talking about themselves. Thus for each day in current interval, the teen's posting behavior is represented as a four-dimension vector.

Stress intensity. We describe the global stress intensity during a stressful interval through four measures: *sequential stress level, length, RMS,* and *peak*. Basically, *stress level* per day constructs a sequential measure during a stressful interval, recording stress values and fluctuation on each time point. The *length* measures the lasting time of current stressful interval. As positive events might conduct impact on overwhelmed teens, and postpone the beginning or promote the end of the stressful interval, we take the *length* as a factor representing the interval stress intensity. To quantify the intensity of fluctuations for stress values, we adopt the *RMS* (root mean square) of stress values through the interval as the third measure. In addition, the *peak* stress value is also a measure to show the maximal stress value in current interval.

Linguistic expressions. We extract the teen's positive and stressful expressions from the content of posts in SI and U-SI sets, respectively. The first linguistic measure is the frequency of *positive word*, which represents the positive emotion in current interval. The second measure is the frequency of *positive event topic words* in six dimensions, reflecting the existence of positive events. Another important factor is wether existing *self-mentioned words* (i.e., *'I','we','my'*). Self-mentioned words show high probability that the current stressor event and stressful emotion is related to the author, rather than the opinion about a public event or life events about others.

Except positive-related linguistic descriptions, we also take stressful linguistic characters as measures, which is opposite with positive measures, while also offers information from the complementary perspective. The first stressful linguistic measure is the frequency of *stressor event topic words* in five dimensions, which represents how many times the teen mentioned a stressor event, indicating the degree of attention for each type of stressor event. The frequency of *pressure words* is the second stressful linguistic measure, reflecting the degree of general stress emotion during the interval. We adopt this measure specifically because in some cases teens post very short tweets with only stressful emotional words, where topic-related words are omitted.

Next, based on the posting behavior, stress intensity and linguistic measures from both the stressful and positive views, we quantify the difference between SI and U-SI sets, thus to measure the impact of positive events.

5.3. Method

In our problem, there are two sets of stressful intervals to compare: the SI set and the U-SI set, containing stressful intervals unaffected by positive events and stressful intervals impacted by positive events, respectively. The basic elements in each set are stressful intervals, i.e., the sequential stress values in time line, which are modeled as multi-dimensional points according to the three groups of measures in section 5.2. Thus we formulate this comparison problem as finding the correlation between the two sets of multi-dimension points. Specifically, we adopt 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 are under different statistical distribution. Assuming the data points in SI and U-SI are randomly sampled from distribution $F^{(1)}$ and $F^{(2)}$, respectively, then the hypothesis is denoted as:

$$H_1 : F^{(1)} = F^{(2)} \quad versus \quad \widetilde{H_1} : F^{(1)} \neq F^{(2)}. \tag{1}$$

Under such hypothesis, H_1 indicates points in SI and U-SI are under similar distribution, while $\widetilde{H_1}$ means points in SI and U-SI are under statistically different distributions, namely positive events have conducted obvious restoring impact on current stressed teen. Next, we handle this two-sample hypothesis test problem based on both positive and stressful behavioral measures (i.e., *posting behavior*, *stress intensity* and *linguisitc expressions*), thus to quantify the restoring patterns of positive events from multi perspectives.

As a classic statistical topic, various algorithms have been proposed to solve the two-sample hypothesis testing problem. Since each point in the two sets (SI and U-SI) is depicted in multi-dimensions, here we take the KNN (k nearest neighbors) Schilling (1986) based method to judge the existence of significant difference between SI and U-SI. For simplify, we use the symbol A_1 to represent set SI, and A_2 represent set U-SI, namely A_1 and A_2 are two sets composed of stressful intervals. In the KNN algorithm, for each point ℓ_x in the two sets A_1 and A_2, we expect its nearest neighbors (*the most similar points*) belonging to the same set of ℓ_x, which indicates the difference between the points in the two cases. The model derivation process is described in detail in the Appendix D.1 part of the appendix.

5.4. Results

Table 5: Quantify the impact of scheduled positive school events using KTS and baseline method ([1]KTS denotes the knn-based two sample method adopted in this research.).

	Practical activity	*Holiday*	*New year party*	*Sports meeting*	*All*
Size of U-SI	219	339	235	226	1,019
Pearson	54.52%	78.39%	63.39%	58.74%	69.52%
KTS[1]	55.65%	70.97%	56.45%	54.84%	65.32%

Restoring Impact of scheduled positive events. Basically, we focused on four kinds of scheduled positive events: *practical activity*, *holiday*, *new year party* and *sports meeting*. For each of the four scheduled positive events, we quantify the restoring impact and temporal order based on corresponding SI and U-SI interval sets of the 124 students. Table 5 shows the experimental results, where 54.52%, 78.39%, 63.39%, 58.74% significant restoring impact are detected for the four specific scheduled positive events, respectively, with the total accuracy to 69.52%.

Baseline methods. We adopt the commonly used Pearson correlation algorithms to compare with the two sample statistical method in this study. As a widely adopted measure of the linear correlation between two variables, the Pearson correlation method computes a value in the range $(-1, 1)$, where 1 denotes total positive linear correlation, 0 denotes no linear correlation, and -1 is total negative linear correlation. In our two sample statistical procedure, to calculate the distance between two n dimension points X and Y, we adopt the Euclidean metric.

For comparison, our knn-based two sample method (denoted as *KTS*) outperforms the baseline method with the best improvement in *new year party* to 10.94%, and total improvement to 6%. The correlation of positive events for *linguistic expression*, *stress intensity* and *post behaviors* towards five types of stressor events are shown in Figure 2, among which the positive events conduct most intensive restoring impact in 'school life' and 'peer relationship' dimensions.

6. Study2: Test the dynamic process of stress-buffering function from adolescents' microblogs

6.1. Method

To measure the temporal order of stress changes in the two sets of intervals (SI and U-SI) , we further compare each interval with the front and rear adjacent intervals, respectively. Here we adopt the t-test method as the intensity computation function, to observe whether the occurrence of positive events relieve the monotonic negative effect and the monotonic positive effect. Details are presents in part Appendix E of the appendix.

Figure 2: Correlation towards each types of stressor events

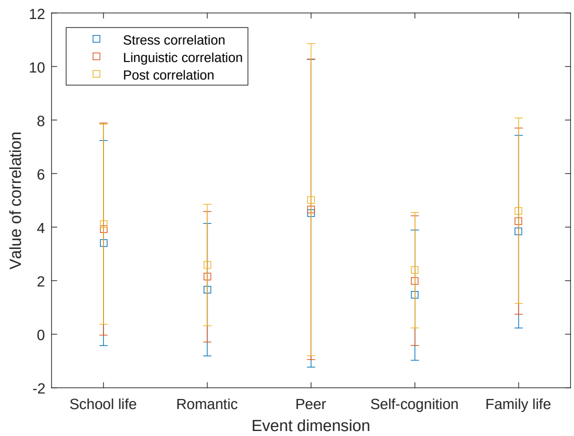


Table 6: Monotonous stress intensity changes in U-SI and SI intervals compared with adjacent intervals.

	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	0.7260	0.7879	0.6903	0.7751	0.7422	0.8159	0.7004	0.7767	0.6791	0.7796	0.7017	0.7851
I → rear	0.7589	0.7840	0.7463	0.7905	0.7813	0.8261	0.7500	0.7915	0.7414	0.7942	0.7513	0.7955

6.2. Result

Monotonous stress changes caused by positive events. Furthermore, to verify the monotonous stress changes when an positive event impacts a stressful interval, we collected 1,914 stressful intervals in U-SI, and 2,582 stressful intervals impacted by positive events in SI. 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 are considered and compared according to the temporal order in Section 6.1, as shown in Table 6, where 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 $I \rightarrow rear$) are listed. Under the impact of positive events, both the ratio of intensive stress increase in *front*→ *I* and the ratio of intensive stress decrease in $I \rightarrow rear$ are decreased, showing the effectiveness of the two sample method for quantifying the impact of positive events, and the rationality of the assumption that positive events could help ease stress of overwhelmed teens.

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

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

We integrate the impact of positive events into stress prediction. The experimental set contains 1,914 stressful intervals under the impact of positive events (U-SI). As shown in Table 7, the original prediction result using only SVARIMA method achieves 0.1281 MSE, 0.3579 RMSE, 0.3604 MAPE and 0.1482 MAD ($L = 7$, $\alpha = 0.5$). Then we integrate the impact of each type of positive events into stress prediction. Specifically, for positive with obvious restoring impact (under the L&S&P pattern), the average stress level during historical restoring intervals are integrated to modify the result, with adjusting the parameter α (details see 7). After the modification, the prediction performance achieves 0.0649 MSE, 0.2548 RMSE, 0.2638 MAPE and 0.0858 MAD, reducing the prediction errors efficiently (with MSE, RMSE, MAPE and MAD reduced by 49.34%, 28.81%, 26.80% and 42.11%, respectively).

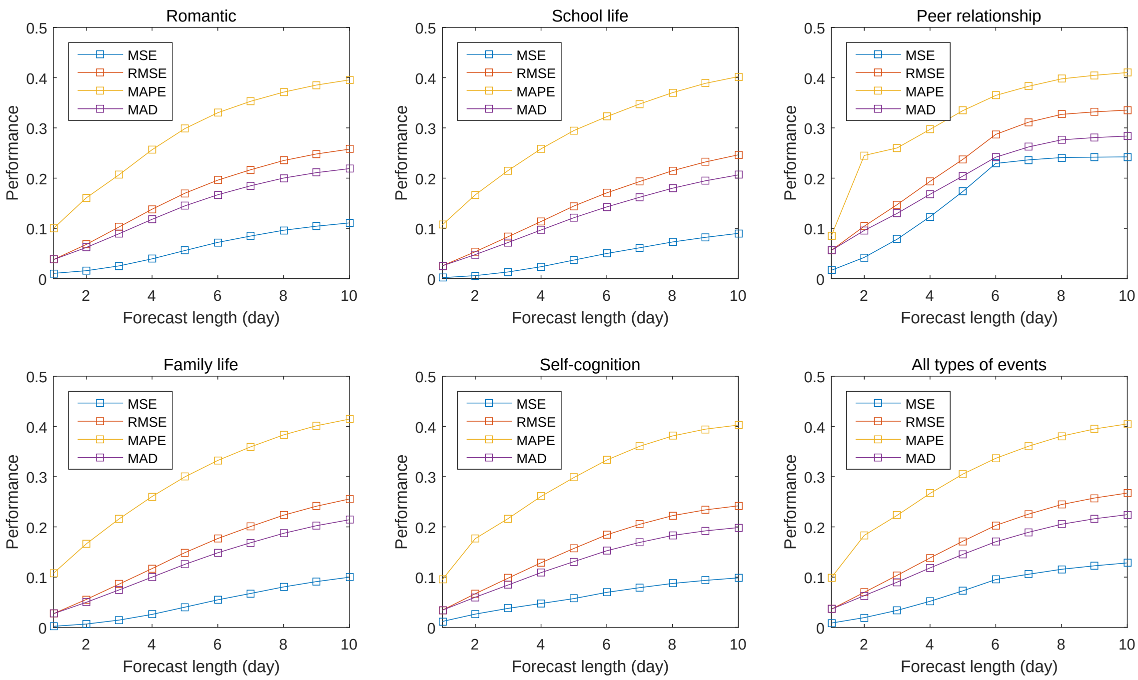
Predicting stress under different windows. We present the prediction result under the impact of positive events under different lengths of prediction windows, ranging from 1 to 10 days, as shown in 3. With the window length increasing, the prediction error shows decreasing trend in all metrics. The reason is that longer prediction window takes more previous predicted results, and the error accumulates with more predicted values taken into the next step prediction. Among the five dimensions of events, the prediction for school life stress achieves the best performance. On one side, more positive events and stressors about school life events are detected from teens mi-

Table 7: Compare the stress forecast performance under three restoring patterns 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 restoring pattern measures: 'L' represents *linguistic expression*, 'S' represents *stress intensity*, and 'P' represents *posting behavior*.

Figure 3: Teens' stress forecast performance under different lengths of predicting windows.

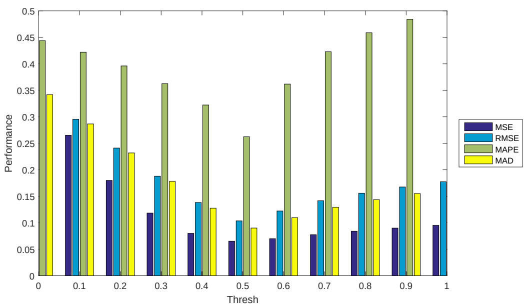


croblogs, providing sufficient data in prediction. On the other side, stress coming from school life is the most common stress in the student group, with relative stable periodicity and high frequency.

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

Parameter settings. The parameter α is adjusted when integrate the impact of positive events into stress prediction. For each of the four groups of restoring patterns, we adjust α in the effect of $\alpha \times L$. We calculate the corresponding prediction result for each teen respectively, and show the result of the whole testing group using the averaging performance. Figure 4 shows the changing trend under the L&S&P pattern.

Figure 4: Stress forecast performance under the L&S&P pattern of positive events.



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.

8. Discussion and conclusion

The main contributions 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 are not only manifested in self-reported subjective feelings, but also in behavioral level in social network. We examined the potential relationship between the occurrence of positive events and the posting behaviors, microblog contents and stress changing patterns on over whelmed adolescents, and verified that the stress-buffering effects of positive events are reflected in both slowing down stress increase at early stage, and prompting the stress reduction at the later stage. Second, this study implements the innovation of methods. Through building a complete technical framework, we realized 1) automatic extraction of positive events and user behavior measures from microblogs, 2) quantification of relationships between stress-buffering of positive events and microblogging measures, and 3) real-time model monitoring the stress-buffering process in adolescents. Third, this article shows great practical significance. On the one hand, it realized timely and continuous monitoring of the stress-buffering process of adolescents based on public social network data sources, which can be used to assess the stress resistance of adolescents; on the other hand, it can provide supplementary advice to schools and parents about 'When to arrange positive events to ease stress of adolescents'.

There were four groups of results in this work. The first group of findings relates to the Hypothesis 1, which assumes positive events can conduct stress-buffering effects on adolescents. In study 1, the scheduled school events with exact time intervals and the microblogs posted by 124 students are collected and statistically analyzed. Results showed that when positive events are scheduled neighboring stressful events, students exhibits less stress intensity and shorter stressful time intervals from their microblogs. In response to the stressor event of exam, the study 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 are presented in study 2, displaying the structural extracting results of positive events from adolescents' microblogs. This study applied positive event topic lexicons into a well developed Chinese parser models for short text Che et al. (2010), and allowed the existence of partially missing semantics during the process of structurally extracting. Further, inspired by the poisson-based abnormal interval detection method Li et al. (2017a), we considered various situations when positive events occurred at different times in or nearby a stressful interval. This study provided a complete solution for automatically detecting positive events based on microblog semantics, which are totally different from traditional questionnaire methods, enabling timely, fraud-proof and continuous detection.

The third groups of results in study 3 directly relates to the stress-buffering patterns of positive events. In order to eliminate the possible errors in the previous positive event detection and avoid false overlays, we first used four scheduled positive events to verify significant stress-buffering effects. Results showed the event *holiday* exhibits the highest proportion of significant stress-buffering. However, this conclusion is questionable because the frequency of the above four events is different and may affect the experimental results. Next, the correlation between three stress-buffering patterns and five types of stress events are test. The most intensive stress-buffering impacts are shown in 'school life' and 'peer relationship' dimensions. *Posting behavior* exhibits most significant correlations among three patterns. This resonated with the study Blachnio et al. (2016); L. Bevan et al. (2014) suggesting that users who shared important, bad health news on Facebook had a higher level of stress.

The fourth groups of results should be considered as exploratory and application. In study4, this study integrated the impact of positive events into traditional stress prediction problem, and verified whether the stress-buffering patterns of positive events could help improve the prediction performance. Results showed the effectiveness our solution in quantifying the stress-buffering function of positive events during the process of dealing with stress.

This article proposed a novel perspective for stress prevention and easing, and demonstrated how to predict adolescents' future stress buffered by different types of positive events. Since more complex situations are simplified in our first step exploration, the goals are still salient in stress-buffering researches from social network.

9. Limitations and future work

This study has a number of limitations. First, it used the microblog data set collected from the social network of high school students, and choose the scheduled positive/stressor school events as the ground truth in the case study. This could be seen as a relative rude verification method, because individual events (i.e., 'lost love', or 'received a birthday present') may also have an impact, except for events planned by the school. Therefore, the data observation in the first study are not 100% rigorous and need further verification.

Second, this paper validate the stress-buffering impact of positive events according to the improved stress prediction accuracy indirectly. At best, it conducts some self-validation in various perspectives of algorithm. We need to conduct more convincing experiments through inviting the participants to complete related scales (e.g., positive and stressor scales), thus to find the direct verification for such findings.

Finally, this study treats positive events as independent existence and studies the impact of each event separately, which ignores the additive and collective effects of multiple positive events at the same time. Thus, our future research may investigate the overlap effects of multiple positive events, as well as the frequent co-appearing patterns of different types of positive events and stressor events, thus to provide more accurate stress-buffering and restoring guidance for individual adolescents.

Based on current research implications, more factors could help analyze the stress restoring patterns among adolescents more comprehensively in future research. Specifically, one factor is how personality impacts the stress-buffing of positive events (Twomey and O' Reilly, 2017; Shchebetenko, 2019), 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. (Nabi et al., 2013) showed number of

Facebook friends associated with stronger perceptions of social support, which in turn associated with reduced stress, and in turn less physical illness and greater well-being. (L Bevan et al., 2015) indicated that experiencing important life events can have a long term deleterious impact on subjective well-being, which could be partially abated by receiving social support from Facebook friends. The corresponding experimental design, and the online-offline complementary verification methods will be the key challenges in the future work.

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.

Baoyong, L., Ying, H.. The development of the life stress rating scale for middle school students. Chinese Mental Health Journal 2002;16(5):313–316.

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.

Cleveland, W., Devlin, S.. Locally weighted regression: An approach to regression analysis by local fitting. Publications of the American Statistical Association 1988;83(403):596–610.

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.. Positive psychological states and coping with severe stress. Social Science and Medicine 1997;45(8):1207–21.

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

Jiang, G.. The development of the chinese adolescent life events checklist. Chinese Journal of Clinical Psychology 2000;8(1):10–14.

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, 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.

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.

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.

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.

Silva, M.T.A., Manriquesaade, E.A., Carvalhal, L.G., Kameyama, M.. The hassles and uplifts scale. Estudpsicol 2008;25(1):91–100.

Susan, F.P.D.. Stress: Appraisal and coping 1984;:1–460.

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.

Wheeler, R.J., Frank, M.A.. Identification of stress buffers. Behavioral Medicine 1988;14(2):78–89.

Xue, Y., Li, Q., Feng, L., Clifford, G., Clifton, D.. Towards a microblog 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.

Yan, H.U., Tao, F.B., Pu-Yu, S.U.. Compilation and reliability and validity assessment of multidimensional life events rating questionnaire for middle school students. Chinese Journal of School Health 2010;February 31(2):146–159.

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

Zhang, M., Che, W., Zhou, G., Aw, A., et al., . Semantic role labeling using a grammar-driven convolution tree kernel. Audio Speech and Language Processing IEEE Transactions 2008;16(7):1315 – 1329.

Appendix A. Observe the impact of scheduled positive events: students' stress during exam intervals in two situations

To further observe the influence of positive events for students facing stressor events, we statistic all the stressful intervals Li et al. (2017a) detected surround the scheduled examinations over the 124 students during their high school career. For each student, we divide all his/her stressful intervals into two sets: 1) stressful intervals under the influence of neighbouring positive events (e.g., *Halloween activity*), and 2) independent stressful intervals. Figure A.5 shows five measures of each student during the above two conditions: 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*. For each measure, we calculate the average value over all eligible slides for each student.

Appendix B. Algorithm 1: Select candidate intervals impacted by positive events

Let the sub-series $w_{<a,b>} = [s'_a, \cdots, s'_b]$ as a *wave*, where $s'_v = vally(w_{<a,b>})$ is the minimum stress value, $s'_p = peak(w_{<a,b>})$ is the maximal stress value during $\{s'_a, \cdots, s'_b\}$, and $s'_a \leq s'_{a+1} \leq \cdots \leq s'_p \leq s'_{p+1} \leq \cdots \leq s'_b$.

Appendix C. Algorithm2: Identify stressful intervals impacted by positive events.

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

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

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

Appendix D. Algorithm3: judge stressful intervals into SI or U-SI

In this part, we filter out two sets of stressful intervals: stressful intervals without the impact of positive events (SI), and stressful intervals under the impact of positive events (U-SI).

Table A.8: Algorithm 1: Select candidate stress intervals impacted by positive events.

A candidate interval $I =< w_1, \cdots, w_i, \cdots, w_m >$ is identified with following rules:

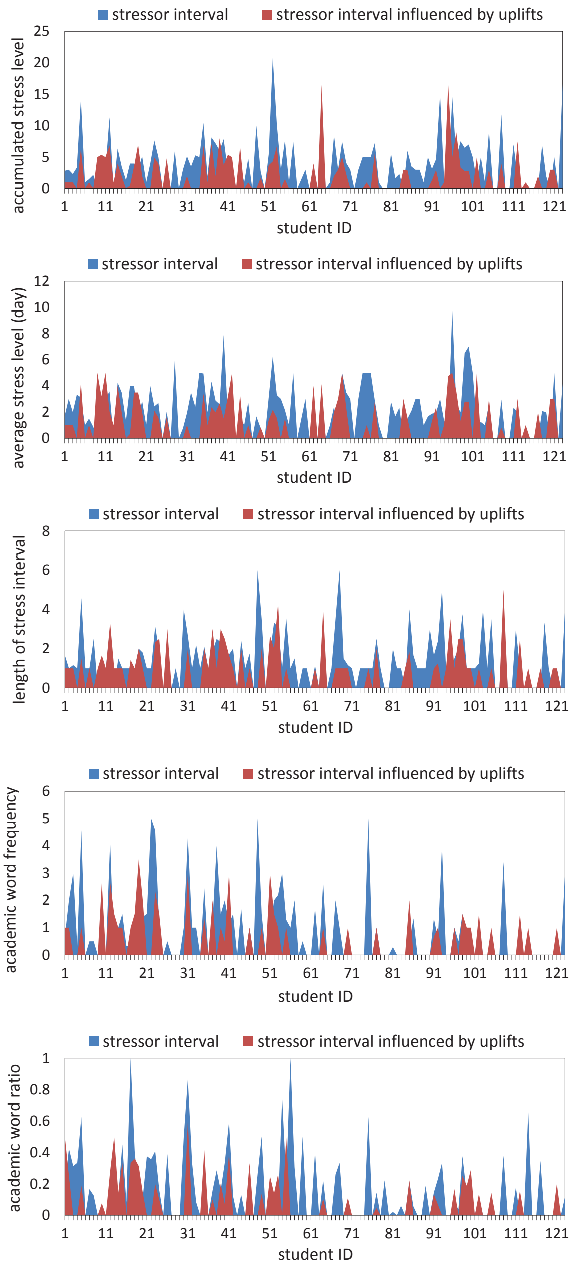
① $s'_1 = 0$, $s'_m = 0$. $\forall s'_j \in \{s'_2, \cdots, s'_{m-1}\}$, $s'_j > 0$.

② Let w_i be the biggest wave in current candidate interval, with $peak(w_i) = \omega$, $\forall$ wave $w_j \in I$, $peak(w_j) <= peak(w_i)$.

③ For w_k before the interval biggest wave w_i , i.e., $\forall w_k \in < w_1, \cdots, w_{i-1} >$, $peak(w_{k+1}) >= peak(w_k)$, $vally(w_{k+1}) >= peak(w_k)$.

④ For w_k behind the interval biggest wave w_i, i.e., $w_k \in < w_i, \cdots, w_m >$, $peak(w_{k+1}) <= peak(w_k)$, $vally(w_{k+1}) <= peak(w_k)$.

Figure A.5: Compare students' stress during exam intervals in two situations: 1) affected by neighboring positive events (U-SI), 2) no positive events occurred nearby (SI)



For a detected stressful interval $I =< t_1, \cdots, t_n >$, we consider the temporal order between I and any detected positive event u happened at time point t_u:

- If the positive event u happens during the stressful interval, i.e., $t_u \in [t_1, t_n]$, the positive interval I is judged as $I \in SI$.
- For the positive event happening nearby a stressful interval, we also consider the probability that it conducts impact on the teen's stressful interval. Here the gap between t_u and I is limited to ξ, i.e., if $t_u \in [t_1 - \xi, t_1) \cup (t_n, t_n + \xi]$, then $I \in SI$.

If a stressful interval satisfies none of the above conditions, we classify it into the U-SI set.

Appendix D.1. Model 1: quantify significant restoring impact conducted by positive events

For each teen, three groups of behavioral measures are considered: *posting behavior*, *stress intensity* and *linguistic expressions*, indicated as $< \boldsymbol{D_p}, \boldsymbol{D_s}, \boldsymbol{D_l} >$, respectively. To measure the correlation for each group of positive and stressful behavioral 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, according to the three group of measures, three sub-functions of $NN_r(.)$ are defined as $PNN_r(.)$, $SNN_r(.)$ and $LNN_r(.)$, corresponding to the teen's posting behaviors, stress intensity and linguistic expressions in each stressful interval, respectively.

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

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

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

$$NN_r(\ell_x, A) = \{v | min\{a \times \|\mathbf{D}_p^x - \mathbf{D}_p^v\|_2 + \quad \text{(D.2)}$$

$$b \times \|\mathbf{D}_s^x - \mathbf{D}_s^v\|_2 + c \times \|\mathbf{D}_l^x - \mathbf{D}_l^v\|_2\}, v \in (A/\ell_x)\} \quad \text{(D.3)}$$

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

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

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

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

The value of $T_{k,n}$ shows how differently the points in the two testing sets (SI and U-SI) perform in three groups of measures. If the value of $T_{r,n}$ is close to 1, it can be shown that the two underlying distributions $F^{(1)}$ and $F^{(2)}$ 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:

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

$$\mu_r = (\lambda_1)^2 + (\lambda_2)^2 \quad \text{(D.7)}$$

$${\sigma_r}^2 = \lambda_1 \lambda_2 + 4{\lambda_1}^2{\lambda_2}^2 \quad \text{(D.8)}$$

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

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

Appendix E. Model2: identify the temporal order of stress-restoring impact

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 $U - SI = < UI_1, UI_2, \cdots, UI_M >$ 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 the teen's stress change 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 change 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 t-test algorithm measures if intensive positive or negative monotonous correlation exists between two sample sets. The function $g(.) = t_{score} \in$ (-1,1) is represented as:

$$g(SI, SI^{rear}) = \frac{\mu_{SI} - \mu_{SI^{rear}}}{\sqrt{\frac{(n_1-1)\sigma_{SI}^2 + (n_2-1)\sigma_{SI^{rear}}^2}{n_1+n_2-2}(\frac{1}{n_1} - \frac{1}{n_2})}} \quad \text{(E.1)}$$

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