# Assessing the Stress-Buffering Effects of Positive Events on Adolescents from 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. In addition, previous research relied on static, one-time measurements, while the dynamic process of stress-buffering was difficult to track due to the lack of effective scientific methods. 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. Based on the data set of 500 high school students, we tested the potential relationship between positive events and stressed individual's microblogging behaviors, and proposed an automatical analysis framework instead of self-reporting methods. The stress-buffering process was 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.

*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 based on social network data.

### 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 measures in three aspects, 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.

Since previous scholars were conducted in a self-report method, to utilize the abundant self-exposures in adolescents' microblogs, the present study propose to work in a non-invasion way. Therefore, 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.

Based on the measures proposed in H2, to further examine the the dynamic process of stress-buffering, the present study propose to assess the mitigation effect of positive events in different phases under hypothesis H3, accompanied with research questions RQ2:

***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.

***RQ2***. How to (a)quantify the impact of positive events, and (b) identify the temporal order between positive event occurring and the monotonous stress changes.

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 verify the stress-buffering effect of positive events on overwhelmed adolescents from social network. In study 1, a case study is firstly conducted on the microblog dataset of 124 high school students associated with the school's scheduled positive and stressor event list. After observing the posting behaviours and contents of stressful teens under the influence of positive events, several hypothesis are conducted to guide the next step research. In study 2, we present the procedure to automatically extract positive events and the corresponding impacted interval from microblogs. 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. In study 3, to quantify the restoring impact of uplift events, we describe a teen's stressful behaviours in three groups of measures (stress intensity, posting behaviour, linguistic), and model the impact of positive events as the statistical difference in comparative situations. Last but not least, In study 4, the present study explores how to predict future stress changes integrating the buffering impact of positive events. 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.

## 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

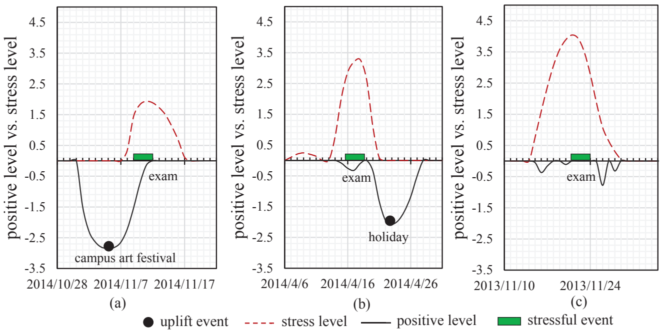
*School-scheduled positive events*. The list of weekly scheduled school events (from February 1st, 2012 to August 1st 2017) are collected from the school's official website [1], with detailed event description and grade involved in the event. There are 122 stressor events and 75 uplift events in total.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

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




### 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, uplift 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

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

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* (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 uplift events (SI), and 2) stressful intervals impacted by uplift events (U-SI). Multiple microblogging behavioral-level measures are tested to describe the correlation between SI and U-SI, based on the hypothesis H1.

Table 4: Structured extraction of positive events from microblogs.

| |
|---|
| I am really looking forward to the spring outing on Sunday now.<br>(Doer:*I*, Act:*looking forward*, Object:*spring outing*) |
| My holiday is finally coming [smile].<br>(Doer:*My holiday*, Act:*coming*, Object:*[smile]*) |
| First place in my lovely math exam!!! In memory of it.<br>Object:*first place, math, exam, memory*) |
| You are always here for me like sunshine.<br>(Doer:*You*, Object:*sunshine*) |
| Thanks all my dear friends taking the party for me.<br>Happiest birthday!!!<br>(Doer:*friends*, Act:*thanks*, Object:*party, birthday*) |
| I know my mom is the one who support me forever, no matter<br>when and where. (Doer:*mom*, Act:*support*) |
| Expecting Tomorrow' Adult Ceremony[Smile][Smile]<br>(act: *expecting*, object:*Adult Ceremony*) |

### 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 uplift 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' uplift stressors 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 uplift event, let $e = [type, \{role, act, descriptions\}]$

Table 3: Examples of topic words for uplift 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 |

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 uplift 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 uplift 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 uplift 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 uplift 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 uplift event 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 uplift event related lexicons, we identify the existence and type of any uplift 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 uplift 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 uplift 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 uplift 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 uplift events. The details are present as Algorithm Appendix D of the appendix.

The examples of teens' microblogs describing uplift 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'*.

To check the performance of uplift event extraction and the validation of our assumption, we first identify uplift 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 uplift 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 uplift 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 *uplift event topic words* in six dimensions, reflecting the existence of uplift 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 uplift-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 uplift 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 uplift events and stressful intervals impacted by uplift 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

Table 5: Quantify the impact of scheduled uplift school events using KTS and baseline method.

| | *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% |

[1]KTS denotes the knn-based two sample method adopted in this research.

hypothesis is denoted as:

$$H_0 : F^{(1)} = F^{(2)} \quad versus \quad H_1 : F^{(1)} \neq F^{(2)}. \qquad (1)$$

Under such hypothesis, $H_0$ indicates points in SI and U-SI are under similar distribution, while $H_1$ means points in SI and U-SI are under statistically different distributions, namely uplift 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 uplift 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 $\ell_x$ in the two sets $A_1$ and $A_2$, we expect its nearest neighbors (*the most similar points*) belonging to the same set of $\ell_x$, 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

*Restoring Impact of scheduled uplift 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 uplift events for *linguistic expression*, *stress intensity* and *post behaviors* towards five types of stressor events are shown in Figure 2, among which the uplift 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

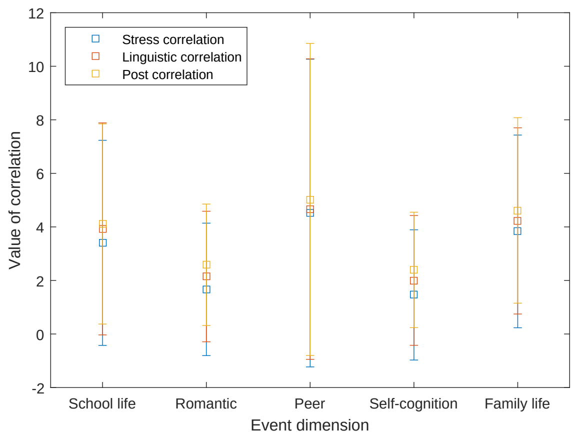
### 6.1. Method

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 uplift events relieve the monotonic negative effect and the monotonic positive effect. Details are presents in part Appendix E of the appendix. The overall pipeline for identifying the restoring impact of uplift events is presented in algorithm **??**.

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 |

Figure 2: Correlation towards each types of stressor events




### 6.2. Result

*Monotonous stress changes caused by uplift events.* Furthermore, to verify the monotonous stress changes when an uplift event impacts a stressful interval, we collected 1,914 stressful intervals in U-SI, and 2,582 stressful intervals impacted by uplift 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* → *rear*) are listed. Under the impact of uplift events, both the ratio of intensive stress increase in *front*→ *I* and the ratio of intensive stress decrease in *I* → *rear* are decreased, showing the effectiveness of the two sample method for quantifying the impact of uplift events, and the rationality of the assumption that uplift 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 uplift events, we integrate the impact of uplift events into traditional stress series prediction problem, and verify whether the restoring pattern of uplift 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 uplift 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 uplift 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 uplift events into stress prediction. The experimental set contains 1,914 stressful intervals under the impact of uplift 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 uplift events into stress prediction. Specifically, for uplifts 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 $\alpha$ (details see 7). After the modification, the prediction performance achieves 0.0649 MSE, 0.2548 RMSE, 0.2638

Table 7: Compare the stress forecast performance under three restoring patterns of uplift events.

| | None | | | | Uplift (L) | | | | Uplift (S) | | | | Uplift (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 |

| | Uplift (L&S) | | | | Uplift (L&P) | | | | Uplift (S&P) | | | | Uplift (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*.

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 uplift 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 uplift 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.

*Contribution of each restoring measure.* We conduct experiments with different restoring patterns included respectively to show its contribution to the impact of uplift 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 uplift events under the four situations into stress prediction using the parameter $\alpha$, as overlapping $\alpha \times S_{historical}$, where $S_{historical}$ is the average stress level in historical restoring intervals. The detailed adjust process of $\alpha$ 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 $\alpha$ is adjusted when integrate the impact of uplift events into stress prediction. For each of the four groups of restoring patterns, we adjust $\alpha$ 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 3: Teens' stress forecast performance under different lengths of predicting windows.

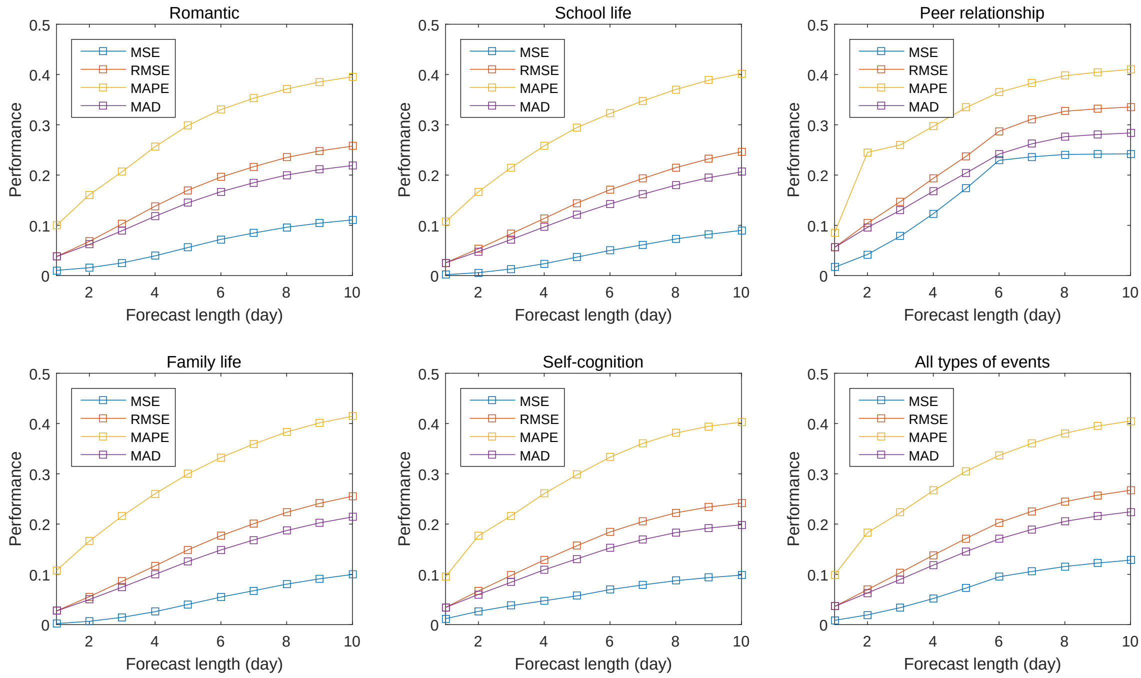
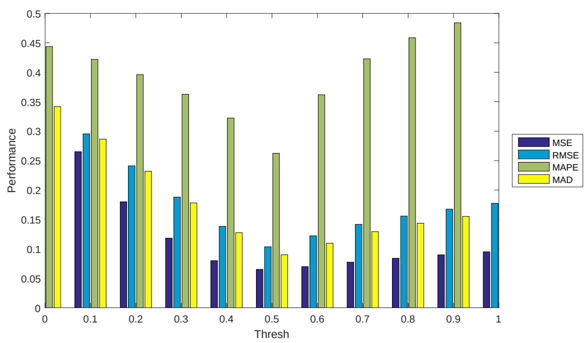



Figure 4: Stress forecast performance under the L&S&P pattern of uplift events.




The prediction error decreases first and then increases, and the best performance is achieved when $\alpha$ 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 uplift 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 uplift events, and the setting of parameter $\alpha$ 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., uplift 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.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## Appendix A. Observe the impact of scheduled positive events: students' stress during exam intervals in two situations

To further observe the influence of uplift 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 uplift 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 $s'_a \le s'_{a+1} \le \cdots \le s'_p \le s'_{p+1} \le \cdots \le s'_b$.

## 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 ($\lambda_1$) and normal conditions ($\lambda_0$) 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

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., $w_k \in < w_i, \cdots, w_m >$, $peak(w_{k+1}) <= peak(w_k)$, $vally(w_{k+1}) <= peak(w_k)$.

$N_1, N_0$ are the number of stressful posts, and $T_1, T_0$ are time duration corresponding to $\lambda_1$ and $\lambda_0$. Without loss of generality, we assume a Jeffreys non-informative prior on $\lambda_1$ and $\lambda_0$, 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 uplift events (SI), and stressful intervals under the impact of uplift events (U-SI). For a detected stressful interval $I =< t_1, \cdots, t_n >$, we consider the temporal order between $I$ and any detected uplift event $u$ happened at time point $t_u$:

- If the uplift event $u$ happens during the stressful interval, i.e., $t_u \in [t_1, t_n]$, the uplift interval $I$ is judged as $I \in SI$.
- For the uplift 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 $\xi$, 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 uplift 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 $\ell_x$. 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 $\ell_x$ 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 $\ell_x$ in each measure is denoted as:

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

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

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

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

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 $\ell_x$:

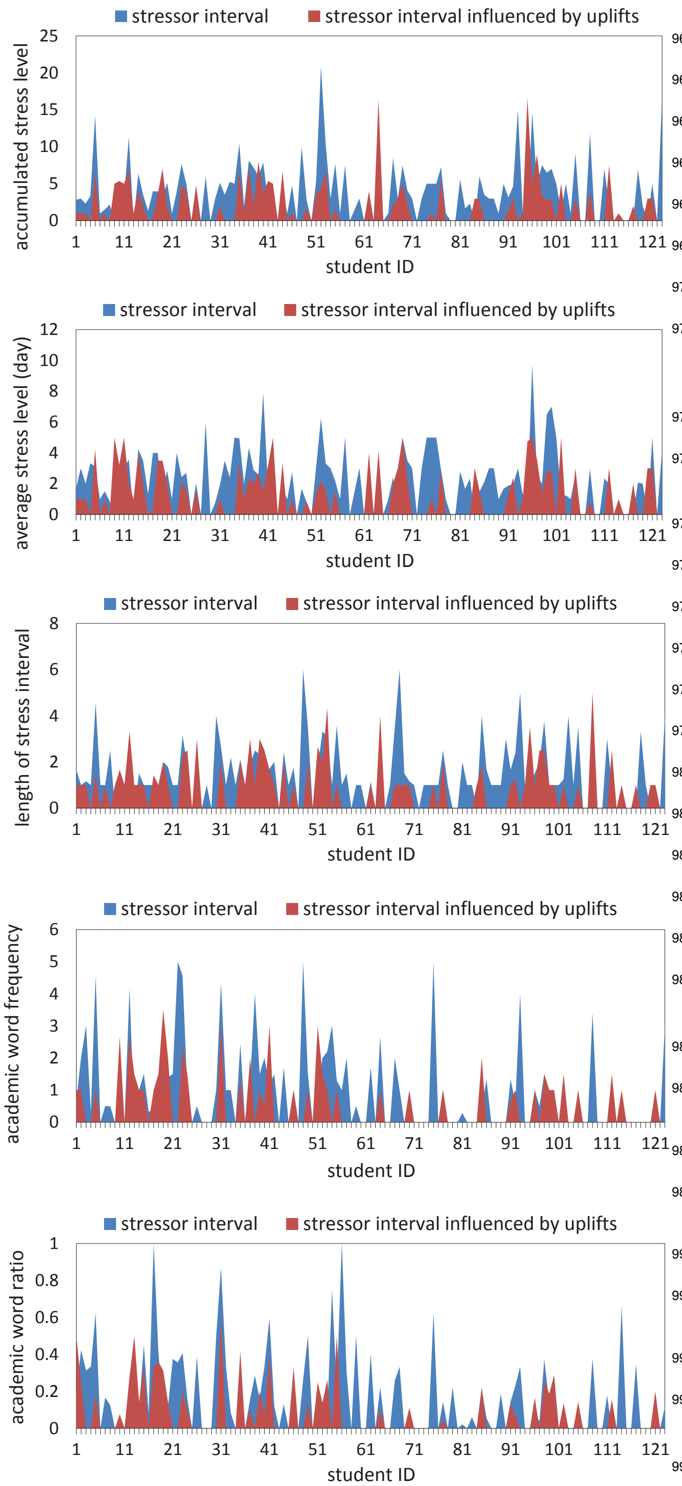
$$I_r(\ell_x, A_1, A_2) = \begin{cases} 1, & if \ell_x \in A_i \&\& NN_r(\ell_x, A) \in A_i, \\ 0, & otherwise \end{cases} \tag{D.4}$$

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:

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

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 uplift events conduct obvious restoring impact on the teens' stress series. Let $\lambda_1 = |A_1|$

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




and $\lambda_2 = |A_2|$, the statistic value $Z$ is denoted as:

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

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

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

where $\mu_r$ 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 ($\lambda_1$ and $\lambda_2$) are large enough, $Z$ obeys a standard Gaussian distribution.

Thus we judge whether the uplift 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 uplift 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 uplift events appears.

④ $g(USI, USI^{rear})$ returns if stress change intensively after stressful intervals affected by uplift 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 $\mu_{SI}$ and $\mu_{SI^{rear}}$ are the mean stress values of intervals in sets $SI$ and $SI^{rear}$, and $\sigma_{SI}$ 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 uplift events relieve the monotonic negative effect of $g(SI, SI^{rear})$ and the monotonic positive effect of $g(SI^{front}, SI)$.