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

Abstract

Stress is viewed as the leading cause of public mental health issues. Positive events, however, could act as a buffer against stress. Since the stress-buffering effect of positive events in previous studies was mainly examined by subjective self-reporting, continuous tracking research at individual behavioral levels still remains to be explored. In this study, We collected microblogs (n=29,232) from a high school student group (n=500) to examine the relationship between positive events and stress-buffering pattern based on microblog content and behavioral characteristics. Through a pilot study we found that the stress-buffering pattern of school scheduled positive events (n=259) was manifested in both the reduction of stress intensity, the shorter duration of stress intervals, and talking less about academic words on micro-blog. The hypothetical tests for stress-buffering pattern and monotonic effect of stress changes were further conducted based on automatical extracted positive events (n=1,914) from microblogs. The stress-buffering pattern of positive events was closely correlated with posting behavior (80.65%, SD=1.96), stress change mode (67.74%, SD=2.04) and microblog linguistic expressions (74.19%, SD=2.07). Positive events conduct most intensive stress-buffering impact in 'family life' (83.87%,SD=2.72), followed by 'peer relationships' (71.77%, SD=4.04) and 'school life' (67.74%, SD=2.71) dimensions. Positive events buffered monotonous stress changes at both the early (11.88% reduction) and late stages (5.88% reduction). This study could inform the use of social network to reach and track the mental status transition of adolescents under stress. The theoretical and practical implications, limitations of this study and future work were discussed.

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

1. Introduction

Life is always full of ups and downs. Accumulated stress could drain inner resources, leading to psychological maladjustment, depression and even suicidal behaviours (Nock et al., 2008). According to the latest report released by American Psychological Association in 2018, 91% of youngest adults had experienced physical or emotional symptoms due to stress in the past month compared to 74% of adults (APA, 2018). More than 30 million Chinese adolescents are suffering from psychological stress, and nearly 30% of them have a risk of depression (Youth and Center, 2019). Stress-induced mental health problems are becoming an important social issue worldwide.

Studies have found that the occurrence of positive events could exert protective effects on emotional distress, that is, *stress-buffering* (Cohen et al., 1984; Needles and Abramson, 1990; Folkman and Moskowitz, 2010; Shahar and Priel, 2002; Folkman, 1997). 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, tracking the state of stress-buffering is important for understanding the mental status of stressed individuals.

However, the dynamic process of stress-buffering was difficult to track due to the lack of effective scientific methods. Previous studies have been based on static perspective, focusing on one-time measurement of positive events and stress-buffering state after events (Kleiman et al., 2014; Santos et al., 2013; Chang et al., 2015). In addition, the subjective self-reporting was susceptible to many factors, such as social appreciation and pressure from measurement scenarios (Kanner et al., 1981b; Alden et al., 2008; Mcmillen and Fisher, 1998; Jun-Sheng, 2008). There is a lack of research on the stress-buffering characteristics that individuals actually exhibit at the behavioral level.

As social networks have penetrated into people' lives, new opportunities are emerging for timely, content-rich and non-invasive detection of users' mental states. Scholars have shown the feasibility to sense users' stress and stressor events (Xue et al., 2014; Lin et al., 2014; Li et al., 2017a), and predict future stress through social networks (Li et al., 2015, 2017c). The current study aims to contribute to this growing area of interdisciplinary research by examining the potential relationship between positive events and stress-buffering pattern from adolescents' microblog content and behavioral characteristics.

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) and depression (Santos et al., 2013). The protective effect of positive events was hypothesized to operate in both directly (i.e., the more positive events people experienced, the less stress they perceived) and indirectly ways by *'buffering'* the effect of stressors (Cohen and Hoberman, 2010; Shahar and Priel, 2002), with respect to physiological, psychological, and social coping resources (Cohen et al., 1984; Needles and Abramson, 1990).

Due to the immature inner status and lack of experience, adolescents exhibit more sensitive to stressors (i.e., exams, heavy homework, isolated by classmates, family transitions), living with frequent, long-term stress (Vitelli, 2014). In this situation, positive events could help reinforce adolescents' sense of well-being (Coolidge, 2009), restore the capacity for dealing with stress (Doyle et al., 2003), and also have been linked to medical benefits, such as improving mood, serum cortisol levels, and lower levels of inflammation and hyper coagulability (Jain et al., 2010; Caputo et al., 1998). The present study will be based on the consensus conclusions from the above studies that positive events could conduct stress-buffering effect on stressed adolescents.

2.2. *Assessing the stress-buffering effect of positive events*

To assess the stress-buffering effect of positive events, scholars have conducted many studies based on self-support methods, including Hassles and Uplifts Scales (Kanner et al., 1981b), Interpretation of Positive Events Scale (*IPES*) (Alden et al., 2008), Perceived Benefit Scales (Mcmillen and Fisher, 1998), Adolescent Self-Rating Life Events Checklist (Jun-Sheng, 2008). For example, (Mcmillen and Fisher, 1998) proposed the *Perceived Benefit Scales* as a new measure of self-reported positive life changes after traumatic stressors (i.e., lifestyle changes, family closeness, community closeness). (Jun-Sheng, 2008) investigated 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. However, the above explorations based on self-report investigations are difficult to exclude interference from external factors (i.e., social appreciation, pressure from measurement scenarios). Meanwhile, due to the lack of manpower and effective scientific methods, most scholars relies on a limited number of measurements, thus continuous measurements of stress-buffering process was difficult to carry out.

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. (2015)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.

2.4. *Current study*

Given the limitations in the existing literature, this study proposes a complete solution to test the relationship between stress-buffering characteristics of positive events and adolescents' microblogging behaviors in three groups of measures under hypothesis H1, and further automatically track the dynamic process of stress-buffering under hypothesis H2:

H1. The stress-buffering function of positive events is correlated with a)posting behavior, b)stress intensity and c)microblog linguistic expressions.

H2. 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 response to the theoretical hypothesis, we propose new measurement methods in a non-invasion way based on social network data. 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.

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

To answer above questions, 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.

3. Study1: A pilot study on the stress-buffering function of school scheduled positive events

3.1. 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.

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

3.2. Measures

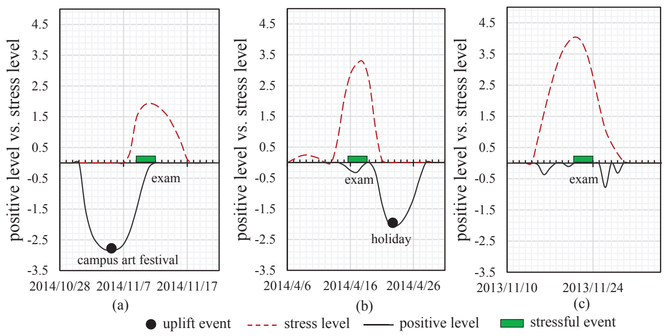
School-scheduled positive events. The list of weekly scheduled school events (from February 1st, 2012 to August 1st 2017) are collected from the school's official website [1], with detailed event description and grade involved in the event. There are 122 stressor events and 75 positive events in total. 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.

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

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

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, positive events and a student's stress fluctuation



3.3. 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 **USI**. 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 (USI) (in Table 5) from the students' microblogs.

3.4. Results

Figure 2 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 (USI) or 2) no neighbouring scheduled positive events (SI), we found that students during exams with neighbouring positive events exhibited less average stress intensity (78.13% reduction in average stress, 95.58% reduction in cumulative stress) and shorter duration of stress intervals (23.30% reduction).

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

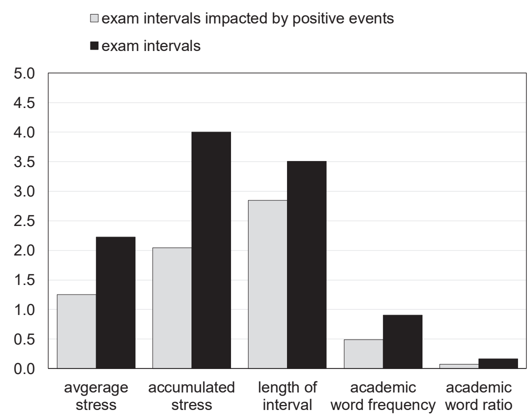


Table 2: Examples of academic topic words from microblogs.

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 2 shows that most students talked less about the upcoming or just-finished exams when positive events happened nearby, with lower frequency (84.65% reduction) and lower ratio (89.53% reduction).

The statistic result shows clues about the stress-buffering 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 satis-

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

fy 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.

4. Study2: 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.

4.1. 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.

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.

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'*}, $\forall e$, $e_{.type} \in \mathbb{S}$.

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 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

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*)

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.

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'*. 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.

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 A.1 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 A.2 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 ?? of the appendix.

4.2. 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.

4.3. 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 4.2. 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:

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

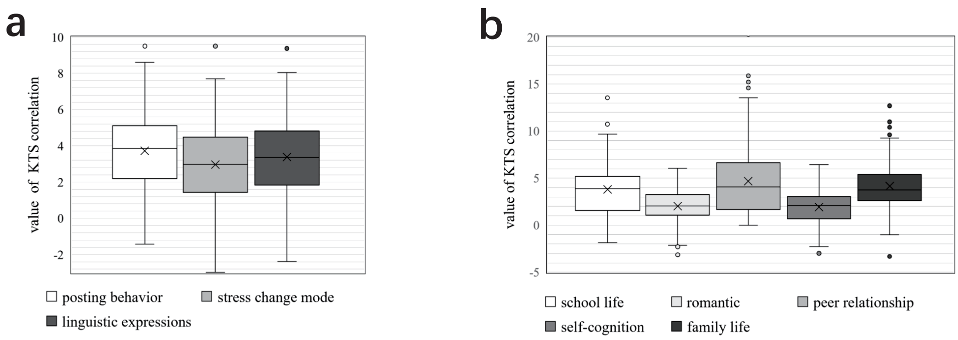
Under such hypothesis, H_1 indicates points in SI and U-SI are under similar distribution, while $\widetilde{H_1}$ means points in SI and U-SI are under statistically different distributions, namely positive events have conducted obvious restoring impact on current stressed teen. Next, we handle this 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 B part of the appendix.

4.4. Results

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

Figure 3: Correlation towards each types of stressor events



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%. We adopt the commonly used Pearson correlation algorithms to compare with the two sample statistical method in this study. The Euclidean metric is used to calculate the distance between two n dimension points X and Y. Experimental results show that our knn-based two sample method (denoted as *KTS*) outperforms the baseline method with the best improvement in *new year party* to 10.94%, and total improvement to 6%.

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

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

The correlation of positive events towards five types of stressor events are shown using box-plot in Figure 3. The stress-buffering pattern of positive events was closely correlated with posting behavior (80.65%, n=100, SD=1.96), stress change mode (67.74%, n=84, SD=2.04) and microblog linguistic expressions (74.19%, n=92, SD=2.07). Positive events conduct most intensive stress-buffering impact in 'family life' (83.87%, n=104, SD=2.72), followed by 'peer relationships' (71.77%, n=89, SD=4.04) and 'school life' (67.74%, n=84, SD=2.71) dimensions. In addition, the correlation between the stress-buffering of positive events and adolescents' stress in 'family life' exhibits concentrated trend, with a higher 25th percentile and 75th percentile. While the correlation values in 'peer relation' exhibit the highest 75th percentile and the lowest 25th percentile, showing a relatively random and unstable stress-buffering impact.

5. Study3: Test the dynamic process of stress-buffering function from adolescents' microblogs

5.1. 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 C of the appendix.

5.2. 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 5.1, as shown in Table 6, where the *ratio of intervals* detected with monotonous increase from the *front interval* to *stressful interval* (denoted as *front*$\rightarrow$ *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

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

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 positive events, and the rationality of the assumption that positive events could help ease stress of overwhelmed teens.

6. 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 three 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.

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.

7. 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.

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Table A.7: 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., $w_k \in < w_i, \cdots, w_m >$, $peak(w_{k+1}) <= peak(w_k)$, $vally(w_{k+1}) <= peak(w_k)$.

Appendix A. Identifying stressful intervals impacted by positive events

Appendix A.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 A.2. Divide intervals into USI collection or SI collection

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:

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

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.

Next, 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). 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:

1). 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 $I \in SI$.

2). 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 B. Modeling the 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 $\boldsymbol{< D_p, D_s, D_l >}$, 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 $\boldsymbol{D_p^x}$, stress intensity matrix $\boldsymbol{D_s^x}$, and linguistic expression matrix $\boldsymbol{D_l^x}$, the r-th nearest neighbor of ℓ_x in each measure is denoted as:

$$\begin{aligned} PNN_r(\ell_x, A) &= \{y|min\{\|\mathbf{D}_p^x - \mathbf{D}_p^y\|_2\}, y \in (A/\ell_x)\} \\ SNN_r(\ell_x, A) &= \{z|min\{\|\mathbf{D}_s^x - \mathbf{D}_s^z\|_2\}, z \in (A/\ell_x)\} \\ LNN_r(\ell_x, A) &= \{w|min\{\|\mathbf{D}_l^x - \mathbf{D}_l^w\|_2\}, w \in (A/\ell_x)\} \end{aligned} \tag{B.1}$$

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

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

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

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:

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

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:

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

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:

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

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

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

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 C. Identifying the temporal order of stress-buffering impact conducted by positive events

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:

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

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 $g(SI^{front}, SI)$.