The Effect of Emotion Background on Pathological Internet Users' Comments on Online News: Evidence From Online Text Analysis

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Abstract

The increased use of Internet communication emphasizes the need to explore the characteristics of online comments, which help better understand their impact on individuals' internal emotional states and how the emotional valence of online news impacts online commentaries among Pathological Internet Users (PIUs). Eighteen PIUs and 14 controls commented on online news of two types (positive and negative valence) under two separate elicited emotional states (positive and negative), with commentaries analyzed through TextMind. PIUs and Controls both used more positive words when exposed to positive versus negative news and more negative words when exposed to negative versus positive news regardless of elicited emotions. However, individuals with PIU used more positive words than controls. PIUs and Controls commented similarly under positive or negative emotion elicitation concerning casual, inclusive, and exclusive words. However, the use of discrepancy word varied due to group assignment and the emotion background. Controls used more discrepancy words when commenting on negative news while in a positive emotional state and commenting on positive news while in a negative emotional state, which does not hold for PIUs. The internal emotional state and emotional valence of online news affected the group differently, suggesting that though PIUs can get emotional catharsis on commenting activities, they lack the perceptual consistency of emotional background when conducting online activities and have lower cognitive complexity. This research demonstrates the utility of incorporating a new method for detecting individuals subject to PIU by applying text analysis to their online behavior.

Introduction

As Web services have grown exponentially, so have concerns about the likelihood of individuals increasingly over-indulging in engaging, often unfiltered, online activities and concomitantly devoting less time to exploring what is occurring around the globe. Pathological Internet Use (PIU), one such condition, refers to disturbed patterns of use on the Internet and/or smartphone that is associated with compulsive thinking, increased tolerance, diminished inhibition or control ability, and withdrawal symptoms (El Asam et al., 2019; Morahan-

Martin & Schumacher, 2000; Tian et al., 2017). Many researchers reported the poor cognitive function and poor emotional function of PIU (Choi et al., 2014; Fayazi & Hasani, 2017; Nie et al., 2016; Wang et al., 2017). Due to these two main susceptibility factors, the original online activities gradually develop into PIU, which in turn, worsens the cognitive function defects and aggravate negative emotional experience of real life. Summarizing the existing studies on the psychological characteristics of IPIU, both empirical researches and theoretical ideas basically deduce the relationship model of cognitive, emotion and PIU, which is shown in Fig. 1.

Linguistic function of PIU, reflecting cognitive and emotional processing, has attracted much attention. Several studies revealed disturbing associations between impaired linguistic function and PIU. For example, language fluency was lower among those with Internet Addiction (IA; Nie et al., 2017). Comparisons of individuals with and without PIU have shown the former individuals to possess weaker verbal comprehension, poorer vocabulary skills, lessened expression abilities, and reduced levels of participation in social activities (Oktan, 2011; Park et al., 2011).

Figure 1. *The Relationship Model of Cognitive, Emotion and PIU.*
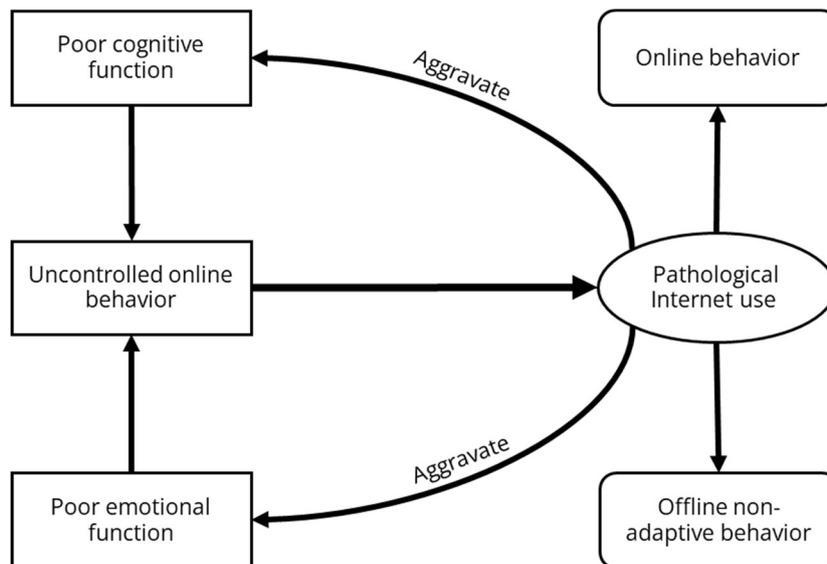
While most investigations of impaired linguistic aspects of PIUs (Pathological Internet Users) have focused exclusively on the features of offline language, few have done so for online language. Online language is a somewhat unique linguistic form that people use to collect, publish and exchange information on the network, within two dimensions. "Language input" or encoding of information takes the network as the carrier and receives it through the visual organ, and "language output" involves processing of internal information in order to ultimately express them in typing on a keyboard (e.g., comments on news, online communication, email editing; Bojic et al., 2013). This two-dimensional process makes individuals more sensitive to visual information, as documented by L. Zhao and Gao (2007). They found individuals with PIU to reveal an attentional preference for visual stimulation related to the network compared to those absent PIU. Moreover, it also leads to a reduced ability of high-frequency Internet users to recognize words compared to low-frequency users (S. Zhao et al., 2017).

Though few studies focus on the content of online comments, Emotional Expression Writing, as a paradigm and a psychological therapeutic process, put forward by Pennebaker, has been much discussed (Pennebaker & Beall, 1986; Smyth & Pennebaker, 2008). The writing disclosure paradigm requires participants to write down their traumatic experiences. Subjects feeling upset and painful at the time of writing also found it meaningful and valuable after a while (Pennebaker & Beall, 1986). Besides writing about personal experiences, there are also some interests in features of online commentary, especially commenting during different emotional states.

Internal emotional states impact individuals' use of emotional words, as highlighted by Mayer et al. (1995). They found a significant correlation between persons' use of emotional words and their mood states. The "happy-mood" group was more likely to use positive words, while the "sadder-mood" group used more negative words. Subsequent research has shown that a person's internal emotional state also impacts the expression of online language. As just one example, people with PTSD are more likely to use negative words, such as "accident" and "shooting," in their online self-statements (Dinakar et al., 2012).

Similarly, the emotional valence of language comments is directly related to the attributes of the subject matter. People use positive emotional words (e.g., love, nice, sweet) when writing about positive events, and conversely more negative emotional words (e.g., hurt, ugly, nasty) when writing about negative events (Kahn et al., 2007). Moreover, PIUs often experience more negative emotions (e.g., depression or anxiety) and reveal specific responses when processing negative stimuli (Fumero et al., 2018; Schimmenti et al., 2018). Zheng (2009) presented stimuli that included three types of words in a Stroop-like task, wherein the first letters were the same for every word triad. However, the meanings of the three words were either positive, neutral, or negative (e.g., gandong, ganjue and ganshang). Subject preference for word attributes was classified according to the number and response time of the subjects' single selection to the three sets of words. Individuals with PIU were significantly slower at selecting positive information yet quicker to orient to negative information while in a negative emotional state. Finally, Oktan (2011; among others) documented that emotional management ability is significantly negatively correlated with Internet addiction.

Most studies of language cognition focus on phonetic perception and acoustic cues, word fluency, and so forth. The few investigations of online language behavior of individuals with PIU have been limited in their approach, in three chief respects: (1) Internet users can easily hide or limit access to records or logs (Shuai et al., 2016), leaving researchers to rely solely on self-report for determining PIU and usage. (2) Questionnaires assessing symptomatic tendencies are often transparent and susceptible to social desirability biases, with social desirability accounting for 10–75% of the variation in such self-reports (Nederhof, 1985). The strong emotive qualities of the term "addiction" (Caplan, 2002) may further lead some respondents to deny problems and refuse to admit that they are addicted to the Internet, leading to underreporting of prevalence. (3) When network language features have been studied, researchers have yet to incorporate online text analysis technology to determine the kind of words generated autonomously.

The proliferation of the Internet as a medium of expression in modern society has continuously generated large amounts of text data, presenting unique opportunities to study PIU with more comprehensive and valid online text analysis technologies to extract and quantify feature items of most interest efficiently. Feature items can be text, symbols, structure, and context, which are then analyzed, identified, and concluded, enabling researchers to infer the deep meaning of a text (Duriau et al., 2007).

Information individuals upload on Internet platforms (e.g., social networking sites) includes active recordings of daily life (e.g., selfies, chatting), as well as comments on others, such as news stories (Glynn et al., 2012; Tenenboim & Cohen, 2014) and "hot news" (Hsueh et al., 2015), which provide a more accurate representation of an individual's online psychology and behavior. In fact, text information in social media is used successfully to identify risk factors and establish risk prognostic models of psychological illnesses. Research of this type, for example, has revealed that the frequency of certain words used on social media can help to predict suicide risk (Won et al., 2013), aid screening of patients with PTSD, and distinguish them from non-patients (Q. He et al., 2012), and identify cyberbullying (Dinakar et al., 2012), emotional contagion (Zhang et al., 2016), and terrorist violence (Meloy & Yakeley, 2014; Sanfilippo et al., 2014). Mining the unique online language characteristics of PIUs allows researchers to directly understand how a person is experiencing "their world" (Tausczik & Pennebaker, 2010).

TextMind lexicon, the program used in our investigation, allows words to be classified within many categories, such as linguistic processes, personal concerns, spoken categories and psychological processes which can be further divided in categories (e.g., social processes, affective processes, perceptual processes, cognitive processes, biological processes and relativity words; Tausczik & Pennebaker, 2010). The study mainly focused on using psychological processes words of subjects based on the research objective. News comments are more involved in emotions, attitudes, and opinions on news than social processes and perceptual processes. To that end, the use of emotional and cognitive words was taken as the dependent variable to help to understand emotions and the psychological aspects of how words are processed and events reinterpreted in different groups and conditions (Tausczik & Pennebaker, 2010).

The present study was designed to provide a more fine-grained analysis of the differences in emotional and cognitive words use between individuals characterized as having PIU specifically and controls by eliciting specific emotional states and simulating online situations, which can bridge the gap of online language research of PIU. Online commentary language characteristics were additionally examined to determine whether PIUs are more susceptible to internal emotional states and the affective valence of news comments.

Based on existing research and theory, the following hypotheses were formulated:

H1: The use of emotional words was consistent with the internal emotional state. Subjects would use more positive words in a positive emotional state and more negative words in a negative state.

H2: The use of emotional words was also consistent with the emotional tendency of the news. For two groups, this study hypothesized the commenting pattern to be different between two groups.

However, the specific hypotheses about these differences were difficult because it was also an exploratory test.

Methods

Participant Screening and Selection

Two hundred and seventy young adults, attending a major campus in China, responded to advertisements posted about our online survey and were screened by the Types of College Students' Internet Addiction (TCSIA) scale (Z. Zhou & Yang, 2006). For our purposes, total scores were computed for each participant and ordered from low to high, assigning 19 students with the high scores (higher than one standard deviation above the mean) to the PIU Group and 15 with low scores (lower than one standard deviation below the mean) to a Control Group. Demographic characteristics and TCSIA scores are shown in Table 1.

Table 1. *Demographics Characteristics of the Final Sample (N = 34).*

	Control Group (N = 15)	PIU Group (N = 19)	t (df = 32)
Age	20.80 ± 2.37	20.21 ± 2.07	0.77
Sex (# of Females & Males)	5/10	9/10	
Internet use history (years)	8.50 ± 3.48	7.89 ± 2.98	0.55
TCSIA scores (# of all items)	38.80 ± 4.68	63.2 ± 8.00	10.47[***]

Note. [***]p < .001 values when comparing mean values for the Controls to the PIU group.

Materials

Material for Screening Participants

The Types of College Students' Internet Addiction (TCSIA), developed by Z. Zhou and Yang (2006) for Chinese-speaking young adults is often used to identify those who use the Internet frequently and have developed psychological dependence but have not reached a clinical diagnostic standard of disorder from a professional. It is comprised of 20 total items, each rated on a 5-point Likert-type scale, where 1 = *strongly disagree* and 5 = *strongly agree*. In this study, the mean score plus or subtracting a standard deviation were taken as the high and low cut-off lines, a more rigorous screening criterion than the standard cut-off (Chen et al., 2003) to ensure these two groups show a difference in pathological Internet use. The internal reliability of the TCSIA and its sub-scales range from .79 to .92.

Materials for Eliciting Specific Emotional States

Film clips for eliciting specific emotional states were evaluated quantitatively through multiple steps. Two graduate assistants first searched video websites to select six film clips that best elicited positive and negative emotional states. These clips were then shown to a random sample of students (9 males, 11 females; age, 20.50 ± 1.00), who rated them independently for their emotional content, where 1 = *so bad* to 10 = *so well*. The two clips receiving the most disparate ratings were selected for inclusion in our investigation: Despicable Me (Length: 255 seconds; Emotion score: 8.05 ± 1.00), for its high positive emotional content, and The Cove (Length: 309 seconds; Emotion score: 2.15 ± 1.09), for its high level of negative emotional content.

Materials Utilized for the Commented News

The micro-blog news for making comments online was selected from the People's Daily Online news, published on the Weibo (a Chinese web media, just like Twitter) from June to August 2016. The news was downloaded and modified by removing corresponding pictures to avoid introducing redundant variables for images also

conveying emotions. The item associated with politics, representing powerful value guidance, was deleted for being hard to estimate emotion type. Social events related to violence and pornography will not be reported in detail. Therefore, items associated with violence and pornography were also deleted. Ninety alternative text-only news stories were shown to another random sample (10 males, 9 females; age, 20.58 ± 1.77) to rate the positive emotional intensity, negative emotional intensity and familiarity from 1 to 10. Every news item selected on each topic should satisfy (taking positive news as an example) (1) Positive emotional intensity score > 5; (2) Negative emotional intensity score < 5; (3) Familiarity score < 5. Twelve (Average length:124 words) ultimately were selected, with 6 being positive and 6 being negative (as shown in Table 2). Each set of 6 text-only news was further divided into two subsets, consisting of three different topics. No significant differences were found in emotional intensity and familiarity when comparing the two sets of positive text-only news and two sets of negative text-only news.

Table 2. *The Evaluation for Four Sets of Micro-Blog News.*

	Topic	Word Count	Emotional Intensity		Familiarity
			Positive	Negative	
Pos-news A	Society	129	8.44 ± 1.65	2.06 ± 2.13	4.78 ± 3.42
	Law	133	7.11 ± 2.70	2.17 ± 1.76	2.83 ± 2.46
	Academics	113	6.28 ± 2.63	2.39 ± 2.52	2.22 ± 2.29
Pos-news B	Society	129	9.22 ± 1.52	2.00 ± 1.41	4.72 ± 3.20
	Law	111	7.78 ± 2.90	2.33 ± 2.45	3.72 ± 3.39
	Academics	131	6.17 ± 2.73	3.22 ± 3.25	2.89 ± 2.25
Neg-news A	Dispute	113	1.56 ± 1.42	8.28 ± 2.14	3.50 ± 2.83
	Accident	128	2.67 ± 2.64	7.67 ± 1.68	3.61 ± 2.91
	Drugs	126	3.28 ± 2.68	8.06 ± 1.73	3.22 ± 3.04
Neg-news B	Dispute	126	2.39 ± 2.25	7.11 ± 2.89	3.83 ± 3.59
	Accident	125	2.61 ± 2.30	8.00 ± 1.72	3.67 ± 2.79
	Drugs	127	2.67 ± 2.20	7.56 ± 1.54	3.61 ± 2.87

Note. Pos-news A, positive-news set A; Pos-news B, positive-news set B; Neg-news A, negative-news set A; Neg-news B, negative-news set B.

Design and Procedure

Participants were invited to take part in the experiment during the September and October 2016. All participants were expected to watch film clips designed to elicit positive as well as negative emotions. One-half of the subsample was exposed to the positive-emotion-elicitation task first and the negative-emotion-elicitation task the following day. The remaining participants received the tasks in the reverse order. Separating tasks by a minimum of 24 hours minimized confounding emotional carry-over effects. Each complete experimental task consisted of two parts: one involving the target emotions, the other focused on making comments online.

At the start of each session, participants listened to relaxing piano music for approximately 2 minutes. They subsequently viewed the film clips designed to elicit positive or negative emotions. Participants' emotional states were measured before and after watching positive film clips by completing the Emotion Rating questionnaire of Xu et al. (2008). This questionnaire, drawing upon Ekman's (1993) emotion theory, is designed to assess the level of 6 distinct states, each rated on a 0–9 Likert scale: happiness, goodness, anger, sadness, fear, and disgust. The following criteria were implemented to determine success at eliciting the desired emotional state (positive versus negative): (1) successfully elicited positive emotion (*happiness* and *goodness* scores > 5, and *anger*, *sadness*, *fear*, and *disgust* scores < 2); and (2) successfully induced negative emotion (*happiness* and *goodness* scores < 2, and *anger*, *sadness*, *fear*, and *disgust* scores > 5). Participants who met these criteria for successfully eliciting the target emotion when exposed to the film clips were asked to make positive and negative comments online (with the order counterbalanced).

During the online commentary phase, participants were instructed to read and comment on every piece of text-only news presented on Qzone, one of the popular social networking sites among Chinese young adults. Participants were positioned approximately 75cm away from a computer screen (Lenovo 13.5-inch, LCD monitor) to type their comments on a standard keyboard, which were then uploaded to the Internet. Participants were

allowed to make comments casually, such as using any emoji or emoticons, and were instructed to use no fewer than 30 characters (to ensure sufficient data for analysis). All participants received a small monetary reward after completing the experiment. The study procedures were carried out in accordance with the Declaration of Helsinki. All study procedures have been approved by the Research Ethics Committee of Central China Normal University and accords with research ethics. The flow chart of the experiment is shown in Fig. 2.

Figure 2. *The Flow Chart of Experiment.*
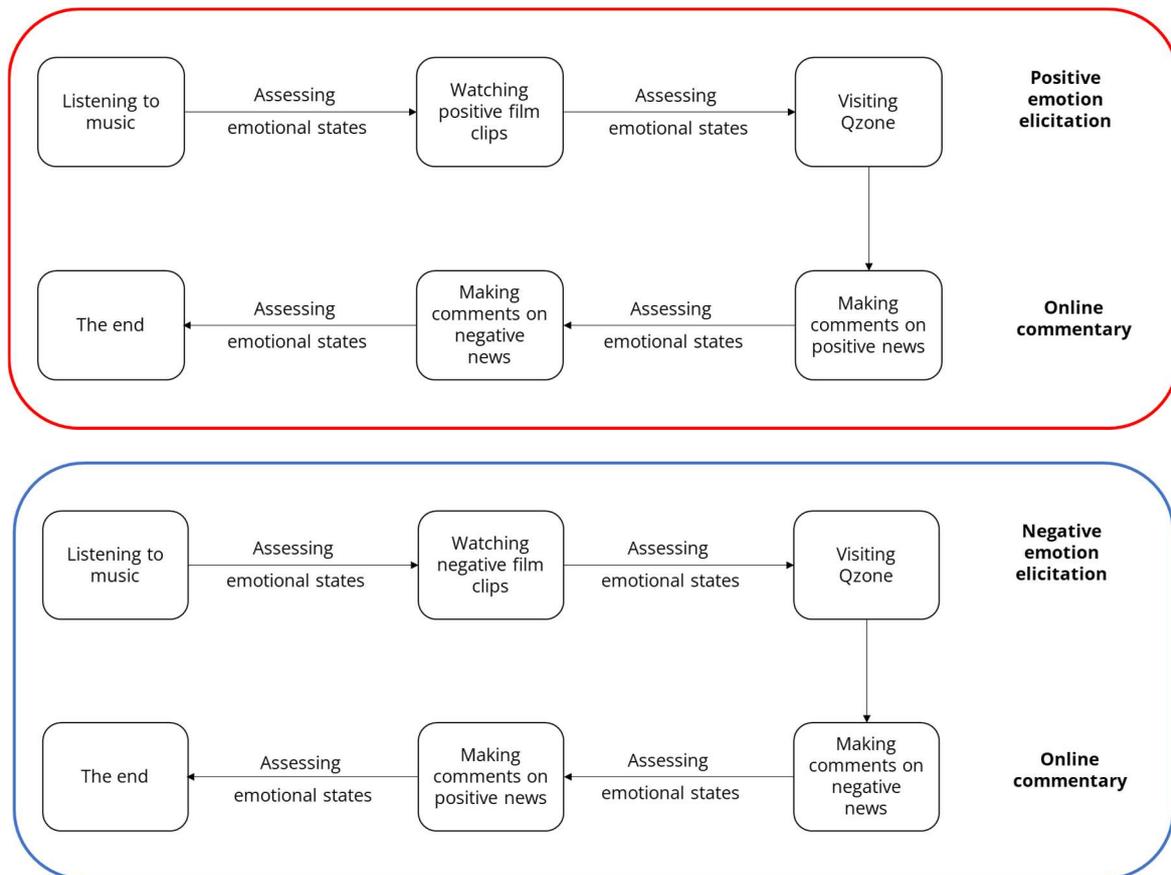
Language and Statistical Analysis

All comments were pre-processed in multiple stages. To ensure between-individual consistency, standardization procedures were used to correct common misspellings and Internet slang.

Following these extensive spelling checks, all resultant online commentaries were subsequently analyzed by TextMind software, a Chinese language psychological analysis system developed by the Computational Cyber-Psychology Lab, Institute of Psychology, Chinese Academy of Sciences, which also was called Simplified Chinese version of Linguistic Inquiry and Word Count (SCLIWC). Although the Linguistic Inquiry and Word Count (LIWC) software supports the expansion and use of the simplified Chinese dictionary, it was originally designed and coded for Western language and cannot process Chinese content appropriately sometimes (Gao et al., 2013). TextMind, based on LIWC, provides easy access to analyze the preferences and degrees of different categories in the text. Through correlation analysis between human ratings and TextMind variables of word count, there were significant correlations with the coefficients of generally the same level in previous studies (N. Zhao et al., 2016), indicating TextMind has good validity (Gao et al., 2013; Lu et al., 2022). Its categories are compatible with LIWC developed by Tausczik and Pennebaker (2010). TextMind analyses the online texts in two categories: emotional Chinese characters and cognitive Chinese characters.

TextMind lexicon is further designed to divide emotional words into positive and negative categories and classify cognitive characteristics into eight concrete subdimensions: insight (e.g., *know*), causation (e.g., *because*), discrepancy (e.g., *should*), tentative (e.g., *maybe*), certainty (e.g., *always*), inhibition (e.g., *constrain*), inclusive (e.g., *and*), and exclusive (e.g., *but*). Separate two-way repeated-measures ANOVAs (Group: PIU vs. Controls) x (News Category: Positive vs. Negative) were used to explore the between-group differences in performance on the positive and negative emotion elicitation tasks, with the latter serving as within-subject variables. The frequency of positive and negative emotional words extracted by the TextMind software was used as a dependent variable.

Statistical analyses were performed using SPSS 24.0 statistical software package, with significance defined at the 0.05 level, two-tailed.

Results

According to the standard of successful emotion elicitation, data were excluded for two participants who failed to elicit a positive or negative emotional state. The emotional evaluation after listening to piano music and after emotion elicitation was shown in Table 3 and Fig. 3. There was no difference between the PIU group and the control group in different emotion scores under different periods ($ps > 0.05$).

Table 3. *The Emotional Score of Two Groups Under Different Periods.*

		Happiness	Goodness	Anger	Sadness	Fear	Disgust
Positive emotion elicitation							
After listening to piano music	PIU group	7.06 ± 1.77	6.78 ± 1.35	0.39 ± 0.61	1.44 ± 1.38	0.56 ± 0.86	0.39 ± 0.78
	Control group	6.86 ± 1.23	6.00 ± 1.57	0.07 ± 0.27	0.93 ± 1.49	0.29 ± 0.61	0.14 ± 0.36
After emotion elicitation	PIU group	8.00 ± 1.02	7.00 ± 1.65	0.28 ± 0.58	0.17 ± 0.38	0.17 ± 0.38	0.06 ± 0.24
	Control group	7.50 ± 1.29	6.57 ± 1.09	0.14 ± 0.36	0.14 ± 0.36	0.14 ± 0.36	0.14 ± 0.36
Negative emotion elicitation							
After listening to piano music	PIU group	5.29 ± 2.66	6.33 ± 1.94	0.33 ± 0.59	3.44 ± 3.00	0.78 ± 1.44	0.50 ± 0.86
	Control group	5.00 ± 2.80	4.57 ± 2.31	0.00 ± 0.00	3.36 ± 2.85	0.36 ± 0.84	0.07 ± 0.27
After emotion elicitation	PIU group	0.28 ±0.58	0.28 ± 0.58	7.17 ± 1.38	7.06 ± 1.63	5.78 ± 1.06	7.33 ± 1.33
	Control group	0.07 ± 0.27	0.00 ± 0.00	7.00 ± 1.75	7.36 ± 1.28	6.00 ± 1.18	7.00 ± 1.24

Figure 3. *The Emotional Score of the Two Groups Under Different Periods.*
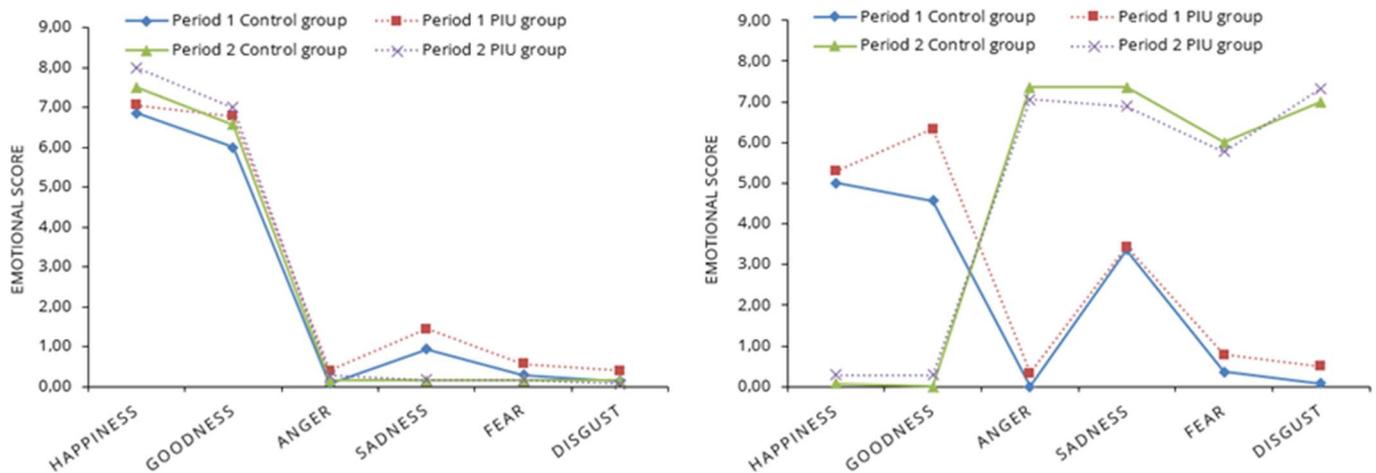
Note. Left: Positive Emotion Elicitation; Right: Negative Emotion Elicitation; Period 1: After Listening to Piano Music; Period 2: After emotion elicitation.

The remaining 384 comments (the control group, 14; the PIU group, 18; age, 20.56 ± 2.23) were entered for further analyses. Although the internal emotional state is a within-subject variable, we analyzed each state separately due to the need to have a washout period between each task elicitation.

Results of the Positive-Emotion-Elicitation Task

Data for positive and negative words use were entered in a 2 (groups: PIU group vs. control group) × 2 (news categories: positive vs. negative) MANOVA with groups and news categories as independent variable. The analyse met the assumptions of MANOVA. Frequency of use of positive and negative words was shown in Fig. 4. Results showed a significant main effect of news categories, Wilks' $F_{(2, 59)} = 40.62$, $p < .001$, $\eta^2_p = .58$. The effect of group, Wilks' $F_{(2, 59)} = 0.59$, $p = .559$, $\eta^2_p = .02$, and interaction effect were not significant, Wilks' $F_{(2, 59)} = 0.71$, $p = .498$, $\eta^2_p = 0.02$. The main effect were found for both positive words, $F_{(1, 60)} = 20.03$, $p < .001$, $\eta^2_p = .25$, and negative words use, $F_{(1, 60)} = 62.70$, $p < .001$, $\eta^2_p = .51$. All subjects used more positive words when commenting on

positive news than commenting on negative news and more negative words when commenting on negative news.

Figure 4. *The Proportion of Positive and Negative Words on the Positive-Emotion-Elicitation Task.*
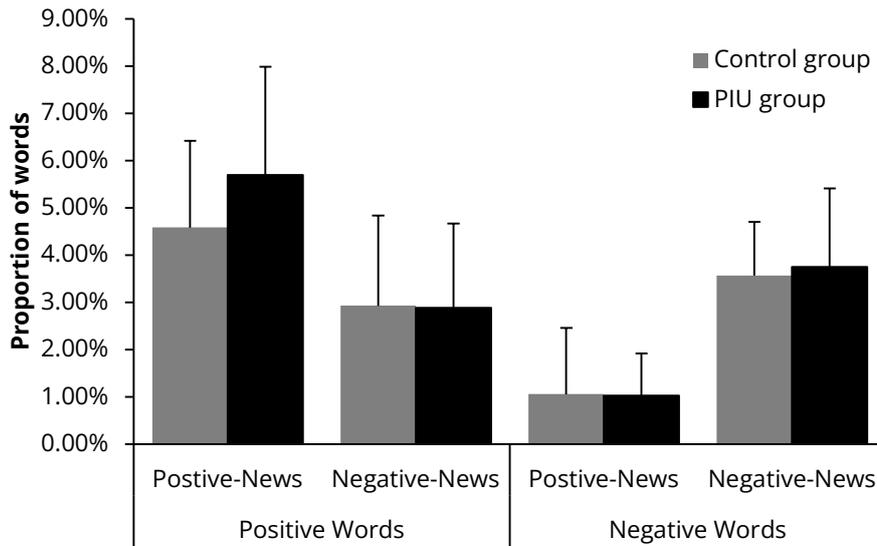
Data for five categories of cognitive words (insight words: know, think; causation: because, effect; discrepancy: lack, should; inclusive: include, and; and exclusive: but, without, exclude; the proportion of other three categories were too small to analysis) were respectively entered in a two-way MANOVA, and the result is shown in Fig. 5. The assumption of homogeneity of variance was not met in MANOVA, Box's M = 86.79, p = .005, where the Pillai's Trace test results were reported.

Results showed main effect on group, Pillai's $F_{(5, 56)}$ = 2.76, p = .027, η^2_p = .20, and news categories, Pillai's $F_{(5, 56)}$ = 6.96, p < .001, η^2_p = .38. The group effect was only found in inclusive words use, $F_{(1, 30)}$ = 11.68, p = .001, η^2_p = .16, where PIU group used more inclusive words than control group. The effect of news categories was found in causation words, $F_{(1, 30)}$ = 5.57, p = .022, η^2_p = .09, inclusive words, $F_{(1, 30)}$ = 5.58, p = .021, η^2_p = .09, and exclusive words use, $F_{(1,30)}$ = 29.83, p < .001, η^2_p = .33. All subjects used more inclusive words when commenting on positive news and more causation exclusive words commenting on negative news.

Figure 5. *The Proportion of Cognitive Words on the Positive-Emotion-Elicitation Task.*
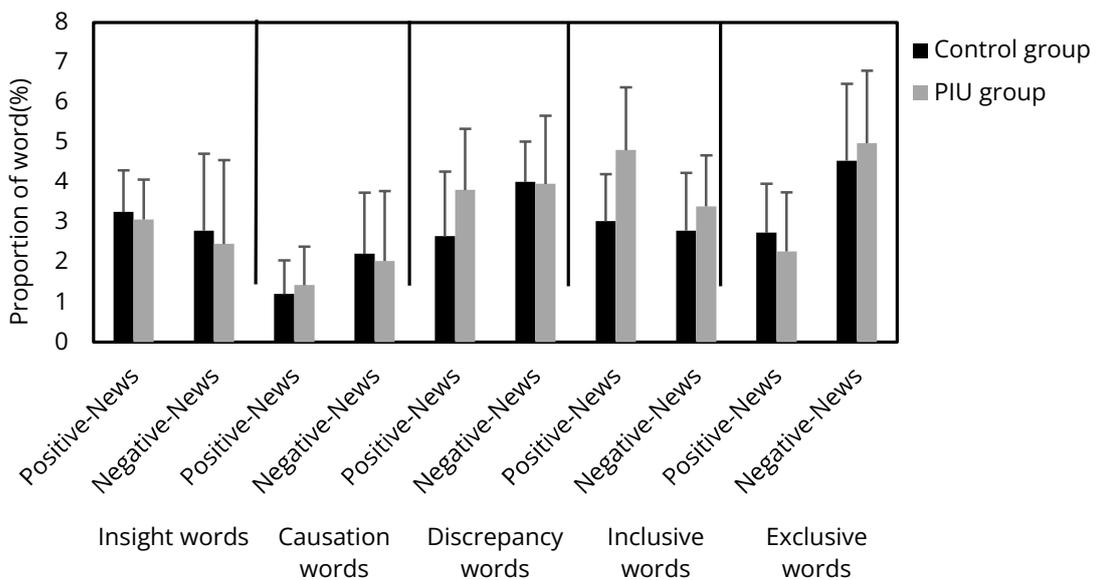
Though the interaction effect was not significant, Pillai's $F_{(5, 56)}$ = 1.17, p = .334, η^2_p = .10. The follow-up analysis on discrepancy words use also didn't show significant interaction effect. However, simple effect analysis found that control group use more discrepancy words when commenting on negative news than commenting on positive news, $F_{(1, 60)}$ = 5.59, p = .021, η^2_p = .09. PIU group use the same frequency of discrepancy words commenting on different emotion news, $F_{(1, 60)}$ = 0.08, p = .773.

In summary, all subjects used more positive words when commenting on positive news and more negative words when commenting on negative news. For cognitive words, in the positive emotional state, all subjects used more inclusive words for commenting on positive news and more causation and exclusive words when commenting on negative news. Individuals in the PIU group were more likely to use inclusive words compared to the control group. They used more discrete words for commenting on negative news than commenting on positive news.

Results of the Negative-Emotion-Elicitation Task

Data for positive and negative word use were respectively entered in a 2 (group) × 2 (news categories) MANOVA (see Fig. 6). The assumption of homogeneity of variance was not approved, where the Pillai's Trace test results were reported. Results showed a significant main effect of news categories, Pillai's $F_{(2, 59)} = 39.36$, $p < .001$, $\eta^2_p = .57$. The main effect were found for both positive words, $F_{(1, 60)} = 25.26$, $p < .001$, $\eta^2_p = 0.30$, and negative words use, $F_{(1, 60)} = 43.91$, $p < .001$, $\eta^2_p = .42$. All subjects used more positive words when commenting on positive news and more negative words when commenting on negative news.

The effect of group, Pillai's $F_{(2, 59)} = 2.55$, $p = .087$, $\eta^2_p = .08$, and interaction effect, Pillai's $F_{(2, 59)} = 2.87$, $p = .065$, $\eta^2_p = .09$, were not significant. However, for positive words use, there were a significant main effect of group, $F_{(1, 60)} = 5.16$, $p = .027$, $\eta^2_p = .08$. PIU group used more positive words than control group.

Figure 6. *The Proportion of Positive and Negative Words on the Negative-Emotion-Elicitation Task.*
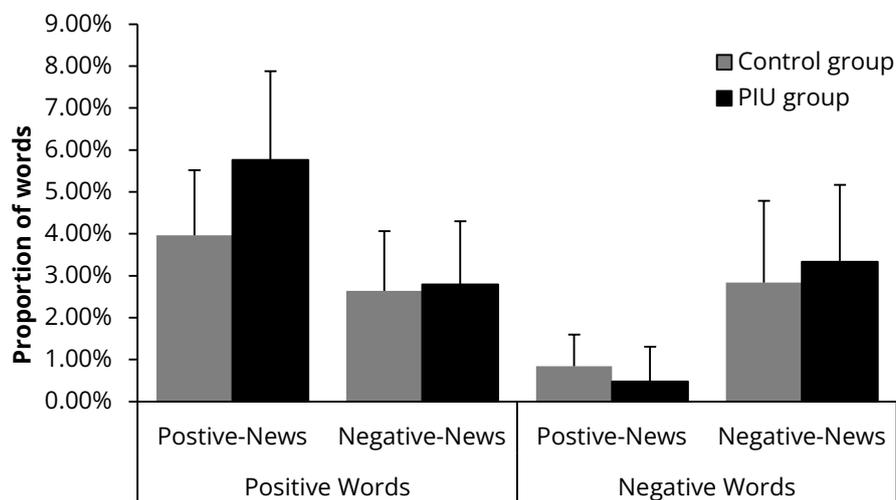
Data for five cognitive word categories were entered in a two-way repeated measures ANOVA (see Fig. 7). The assumption of homogeneity of variance was met, where Wilks' Lambda statistics were reported.

Results showed main effect on news categories, Wilks' $F_{(5, 56)} = 7.28$, $p < .001$, $\eta^2_p = .39$. There were significance between different news categories in causation words, $F_{(1, 60)} = 4.28$, $p = .043$, $\eta^2_p = .07$, inclusive words, $F_{(1, 60)} = 7.50$, $p = .008$, $\eta^2_p = .11$, and exclusive words use, $F_{(1, 60)} = 32.59$, $p < .001$, $\eta^2_p = .35$. All subjects used more inclusive words when commenting on positive news and more causation exclusive words commenting on negative news.

The main effect of group and interaction effect were not significant, Wilks' $F_{(5, 56)} = 2.04$, $p = .087$, $\eta^2_p = .15$. However, for inclusive words use, there were a significant main effect of group, $F_{(1, 60)} = 6.94$, $p = .011$, $\eta^2_p = .10$. PIU group used more inclusive words than control group.

Similarly, for discrepancy words use, results showed a significant interaction effect of group and news categories, $F_{(1, 60)} = 5.10$, $p = .028$, $\eta^2_p = .08$, though the overall interaction effect was not significant, Wilks' $F_{(5, 56)} = 1.35$, $p = .256$, $\eta^2_p = .11$. After simple effect analysis, it was found that in the negative emotional state, the discrepancy words use of the control group for commenting on positive news was significantly higher than commenting on negative news, $F_{(1, 60)} = 4.05$, $p = .049$, $\eta^2_p = .06$, and there was no significant difference of discrepancy words use when commenting on positive and negative news among PIU group, $F_{(1, 60)} = 1.28$, $p = .262$.

Figure 7. *The Proportion of Cognitive Words on the Negative-Emotion-Elicitation Task.*
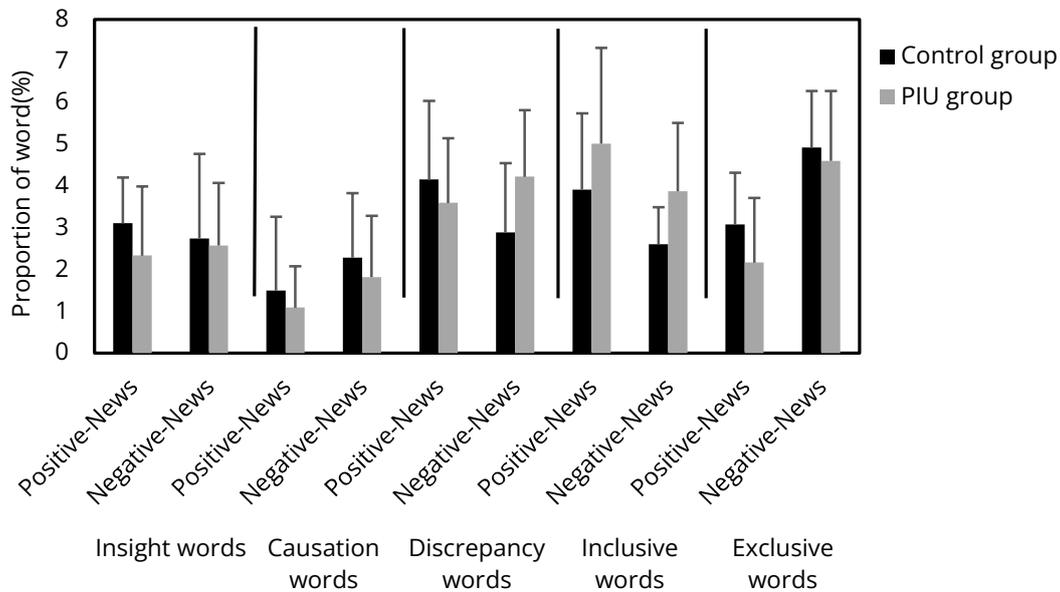
To summarize, for emotional words, all subjects used more positive words when commenting on positive news and more negative words when commenting on negative news. However, PIUs used more positive words than controls. For cognitive words, in the negative emotional state, all subjects used more inclusive words for commenting on positive news and more causation and exclusive words for commenting on negative news. Individuals comprising the PIU group were more likely to use inclusive words compared to those in the control group. They used more discrete words for commenting on positive news than commenting on negative news.

Discussion

The current study investigated the influence of the internal emotional state and the emotional valence of online news on the use of emotional and cognitive words between two groups of Internet users through online text analysis. There were three hypotheses: a. subjects would use more positive words with a positive emotional state and more negative words with a negative emotional state; b. subjects would use more positive words when commenting on positive news and more negative words commenting on negative news; c. the PIU group and control group would have different patterns of positive and cognitive word use.

Our analysis of online commentaries showed that participants used more negative emotional words when commenting on the negative online news regardless of their emotional state, which validated hypothesis b but not hypothesis a.

Several studies have shown that people in general tend to use (a) positive emotion words in positive emotional states and negative emotion words in negative emotional states (e.g., Mayer et al., 1995), and (b) positive emotion words when writing about positive events and more negative emotion words when writing about negative events (Tausczik & Pennebaker, 2010). Our findings further demonstrate the importance of examining the second aspect. The experimental design may explain the non-salient effect of internal emotional state. In the positive emotion elicitation task, subjects first read positive news after emotion elicitation, where the valence of internal emotional state and text were consistent. The effect of two independent variables was mixed and showed the same results. When reading negative news, emotional experience derived from the elicitation task was more fragile than those from current news, diminishing the influence of positive emotion. The same logical phenomenon was also shown in the negative emotion elicitation task.

Though the effect of internal emotional state is hidden under the valence of emotional news, it can be seen from other results among the PIU group. In the negative emotional state, PIUs used more positive words than controls. This finding shows how both the internal emotional state and emotional valence of online news influence the online language process of individuals absent and with PIU, which also validated hypothesis c.

Therefore, both the individual emotional state and the emotional valence of the text impact the use of emotional words. This effect is pronounced in PIUs, more or less related to their impulsiveness. The viewpoint that PIU is an impulse disorder (Mazhari, 2012; Treuer et al., 2001) suggests that individuals with PIU tend to make rapid

and unplanned responses to internal and external stimuli, with their behaviors more likely being affected by internal emotions and external stimuli. Consequently, the behavior of commenting is susceptible to being dominated by the internal emotional state and the emotional valence of online news.

Specifically, Individuals with PIU are inclined to use more positive words than others, which may show the cathartic function of online activities. Online commenting is viewed as a method to express one's true feelings. The network is regarded as a safe harbor that can provide a temporary escape from reality due to its visual anonymity, equalized status, and identity flexibility (Joinson, 2001; Riva & Galimberti, 1997). Surfing the Internet and participating in online activities become a source of pleasure, a way to release, and alleviate negative emotions. This finding, important as mentioned studies, suggested that even commenting on the negative online news can also improve personal mood. However, whether it can enhance the emotional experience to negative news of PIUs requires further study.

For cognitive words use, individuals tend to use more causation words and exclusive words when commenting about negative news regardless of what the internal emotional state, unfolding the association between emotion and cognitive process. It is better remembered or understood when events and text with a negative keynote. (Davidson, 2006) Negative text decreases reading time and improves processing speed, helping detailed inference (Clavel & Cuisinier, 2010; Mouw et al., 2019). The use of causation words, indicating the devotion to internal causal inference, and exclusive words, showing the distinction of whether something is in a given category suggest higher cognitive complexity (Newman et al., 2003). This suggestion validates the finding that information with negative emotion improve exquisite processing (Clavel & Cuisinier, 2010; Mouw et al., 2019). Contrary to the meaning of causation and exclusive words, inclusive words suggest lower cognitive complexity (Pennebaker, 2011), and were used more when commenting on positive news. Interestingly that the percentage of inclusive words used among PIUs was higher than that among control group, providing evidence about poor cognitive ability of PIUs (Brand et al., 2014).

Furthermore, according to the results, there is a bold assumption that individuals with PIU may well lack abilities to perceive the consistency of, and tend to ignore perceptions of the emotional background when engaging in network activities, which is especially evident in using cognitive words. It is known that when the emotional valence of the stimulus is the same as the emotional state of the subject, the phenomenon of emotional consistency is generated (Bland et al., 2016), while emotional conflict occurs when unrelated emotional stimuli interfere with the current task (Etkin et al., 2006). People would experience negative emotions such as anxiety and depression, which are reflected in the use of discrepancy words in writing (Li et al., 2018), an emotional conflict background (Paulhan, 1930). The proportion of discrepancy words used by individuals absent PIU (our control group) decreases when feeling emotional consistency but increases when the emotional background is inconsistent. This relationship does not hold for PIUs, as the proportion of discrepancy words remained the same whether the emotional background was consistent or inconsistent.

Though such an interesting pattern is yet to be discovered with solid evidence, some researchers have suggested the impaired processing ability in both cognition and emotion of PIUs. On the one hand, the overuse of Internet diminished individuals' general cognitive processing ability and brain activity, which is demonstrated in the decrease of P300 amplitude and the prolonged incubation period and decrease of GMD in the left insula, left lingual gyrus and the anterior and posterior left cingulate cortex (J. B. He et al., 2008; Y. Zhou et al., 2011). On the other hand, Liu et al. (2015) found that subjects with more Internet experience had slower responses to emotional words than those with less Internet experience, supporting the notion of poorer overall conceptual processing for PIUs. Concerning meaning processing, there was no difference between high-frequency Internet users in identifying emotional words and non-emotional words, while the difference was found among low-frequency Internet users (S. Zhao et al., 2017). These findings partly revealed the problems in cognition and emotional processing of PIUs, which may serve as the basis of an abnormal mechanism related to emotion background.

When the emotional background was consistent, individuals in the control group used less discrepancy words, and the negative emotional experience induced by emotional conflict increased the proportion of discrepancy words. However, PIUs may lack perception of the emotional background due to impaired cognitive and emotional processing abilities. Even in a state of emotional conflict, individuals with PIU could not significantly perceive differing content, resulting in no significant difference in the proportion of discrepancy words used under the two emotional background conditions. The insensitive emotional perception is adverse to

communication and social activities, further making individuals escape from reality and indulge on the Internet (Oktan, 2011; Park et al., 2011).

Based on the pattern related to the use of positive words, inclusive words, and discrepancy words, the language expression characteristic of PIUs suggests the problem in cognitive and emotional aspects. It suggests the possible reason that Internet is a vital place for emotional catharsis, which keeps them addicted in Internet activity. The study provides a new perspective that both natural language analysis and rigorous experimental paradigm can explore the cognitive and emotional function of PIUs and other groups. At the same time, because of the restrictions on sample and experimental materials, it is not clear whether the results will be extended to other PIUs. This paper modestly provided a new claim that needed more research to pursue.

Implications

The relationship model reveals that both online and offline performance can reflect cognitive and emotional problems. Studies of PIU have rarely collected actual online behavioral data—data that is rich with digital information (such as online time, and textual data, reflecting psychological characteristics) and free from most biasing effects. Direct analysis of behavior online allows one to more effectively evaluate the psychological state of individuals when using the Internet. To bridge this gap, the present research took into account the actual online behavior of Internet users while manipulating the emotional states of individuals and the emotional valence of online news through a controlled experimental design and a language analysis technique to quantify the content of textual comments. In consequence, by comparing online language characteristics between those individuals identified as PIU and those showing no evidence of PIU, similar type applications may provide enhanced ways to increase the understanding of its deleterious effects. This helps to expand and enrich the diagnosis and intervention research on PIU. Researcher should focus the beneficial effect of online expression on PIUs and at the same time pay attention to the problem of inconsistent perception of emotional background reflected in their comments. The potential theoretical implications for the development of Internet psychological counselling should be also taken into consideration.

On practical side, researchers can dynamically monitor online behavior and identify emotional states of PIU based on the style of words use. The establishment of online language feature database and measurement indicators of PIU can be outlined considering the characteristics of language output obtained under different experimental conditions. Finally, the study can provide reference to a promising way to develop online psychological guidance, Internet psychotherapy.

Limitations and Future Directions

As this investigation was one of the first of its kind, we believed it prudent to draw from a convenience sample of young college students, recognizing that this could impact the generalizability of our findings. Thus, further research is needed to determine whether and how the current findings may apply to other, more chronic and severe populations. Further, the method we used to analyse language was limited because focused on certain characteristic information and did not take textual context into account (to make this initial investigation more feasible). In conclusion, we believe that research that uses "big data" technology to critically analyse the current Internet environment may well yield essential important insights. The results of this study thus may be viewed as a supplementary method for guiding and detecting online addictive behavior and its effects in the future.

Conflict of Interest

The authors do not have any conflicts of interest to report.

Authors' Contribution

Wei Zhang: conceptualization, writing—original draft, and funding acquisition. **Wangling Zhu**: formal analysis, writing—original draft, and writing—review & editing. **Jia Nie**: conceptualization, methodology, and formal analysis. **Frank Andrasik**: writing—review & editing. **Xara Naomi Blom**: writing—review & editing.

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