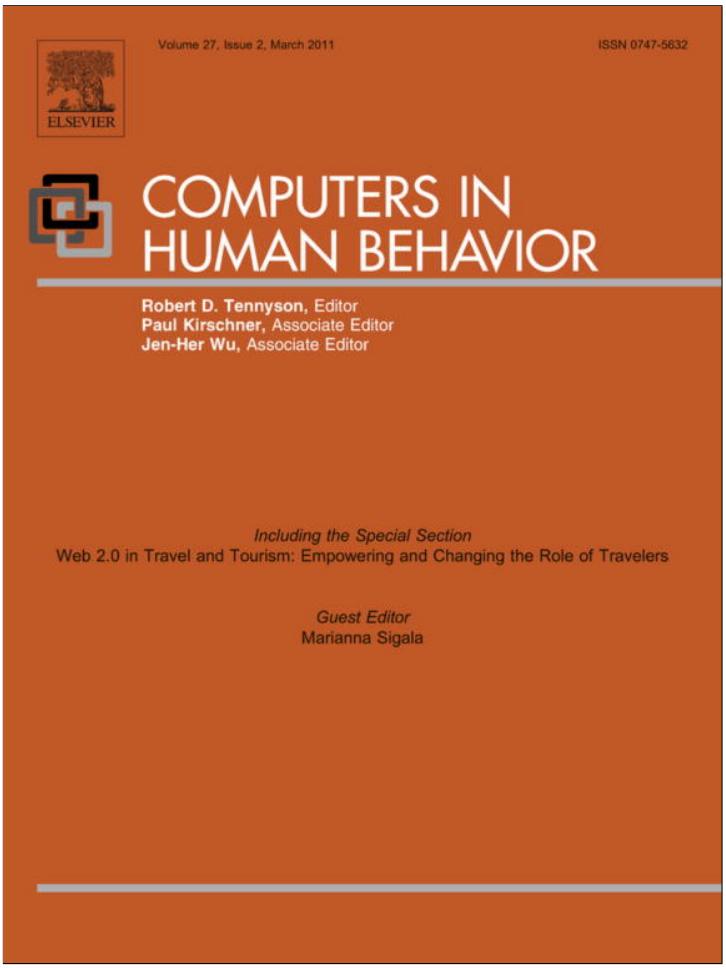

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Linguistically-tailored video feedback increases total and positive emotional expression in a structured writing task

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ABSTRACT

A strength of computer-based interventions is the capacity to tailor to individual differences, but most studies have tailored to self-report, rather than linguistic, data. The purpose of the present study was to develop and evaluate the effects of linguistically-tailored feedback on an Internet-based expressive writing intervention. Two hundred eighty-one participants were asked to engage in 3 days of expressive writing and were randomly assigned to one of 3 feedback conditions: control (no feedback), simple (feedback about levels of emotional expression), and directive (simple feedback + suggestions for emotional processing). A Perl-based implementation of Linguistic Inquiry and Word Count (LIWC) was developed in order to provide dynamic feedback to participants based on levels of emotional expression identified in their writing. This implementation provided near-perfect correlations with standard LIWC output, *r*'s = .98–1.00. Positive and total, but not negative, emotional expression increased over time for those who received simple or directive feedback. These findings suggest that linguistically-tailored feedback has the potential to alter patterns of engagement in computer-based interventions. However, additional research is needed to identify the most effective types of feedback in order to enhance immediate effects on writing and longitudinal effects on relevant outcomes.

1. Introduction

Computer-delivered and self-guided treatment interventions for those with mild to moderate mental health needs have been shown to have promise as an adjunct to more traditional forms of treatment or for those who would otherwise be unable or unwilling to use traditional treatments (Graham et al., 2000; Proudfoot et al., 2004). In the United Kingdom, computer-based interventions are a recommended component of a stepped-care approach to managing depression and anxiety (NICE, 2006). By virtue of the fact that such therapies are typically patient-directed with minimal or no direct consultation with a mental health professional, these treatments have generally used static or only minimally-tailored content that is not necessarily specific to important individual differences that might influence the efficacy of the treatment (e.g., degree of engagement/adherence to the treatment, etc.; Andersson et al., 2005; Cukrowicz et al., 2009; Newman et al., 1997). In other areas of literature, notably health behaviors, tailored interventions have been shown to markedly improve health-related outcomes, including smoking cessation (Lancaster et al., 2000), fruit and vegetable consumption (Campbell et al., 2009; Neville, O'Hara, & Milat, 2009), and physical activity (van Stralen et al., 2009). Because no previous studies have attempted to use tailoring to improve self-guided treatments, we sought to test the effects of real-time, linguistically-tailored emotional feedback on subsequent emotional processing using a longitudinal expressive-writing paradigm. If effective, linguistically-tailored feedback has the potential to improve the efficacy of computer-based treatments for mental health needs.

One unique advantage to using computer-based treatments is that they provide rich behavioral data to supplement self-report surveys (Owen et al., 2005). Chief among these are linguistic data, which have been widely used to identify markers of psychological processing of specific events or stimuli (e.g., Chung & Pennebaker, 2007; Cohn, Mehl, & Pennebaker, 2004; Pennebaker, Mayne, & Francis, 1997). Psychological studies of linguistic data have primarily emerged from the literature on expressive writing. In studies that have employed a standard expressive-writing paradigm, beneficial emotional and physical health outcomes have been linked with specific linguistic markers of emotional processing (Pennebaker & Francis, 1996; Pennebaker et al., 1997), and Linguistic Inquiry and Word Count (LIWC) has been shown to be a valid instrument for identifying emotional expression in linguistic data

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(Bantum & Owen, 2009). LIWC operates by comparing each word of a text file to several dozen categories of psychologically-relevant words (e.g., affect, cognitive processes, social processes, etc.). Other text analysis programs, such as Psychiatric Content Analysis and Diagnosis (PCAD) are available, but LIWC has been shown to have superior signal detection indices, at least for the identification of emotional expression in text (Bantum & Owen, 2009). However, a limitation of LIWC is that it requires manual processing of text files and interpretation of the resulting output. As a result, LIWC is typically used only after study procedures have been completed, during the data analysis phase of a research study. The Perl (Wall & Loukides, 2000) programming language, which can be used in the development and delivery of websites, is also extremely well-suited for text manipulation and linguistic analyses similar to those used by LIWC. Thus, a major benefit of implementing LIWC procedures using a programming language such as Perl is that participants who engage in online expressive writing could be provided with feedback derived from LIWC while a study is still ongoing. We hypothesized that the provision of near real-time, linguistically-tailored feedback would enhance emotional processing in otherwise self-directed expressive writing.

A number of studies have suggested that expressing thoughts and feelings surrounding a traumatic event is valuable (e.g., Everly & Mitchell, 1999; Frattaroli, 2006; Wortman & Boerner, 2007. Putative mechanisms of action for the positive benefits of emotional approach coping include the clarification of personally-relevant concerns and goals, habituation to negative emotions, and facilitation of social support (Stanton et al., 2000). Emotional processing theory (Foa & Kozak, 1986) has contributed to the development of several clinically-effective treatments. This theory suggests that successful interventions to reduce trauma symptoms need to focus on two inaccurate ways of looking at a given experience: the world is extremely dangerous and the belief that the individual experiencing trauma symptoms is incompetent. In attempting to impact both of these dysfunctional thoughts, prolonged exposure, involves asking a participant to repeatedly, yet gradually, recount a traumatic experience in as much vivid detail as possible (Foa & Rothbaum, 1998); this is thought to activate cognitive representations of the trauma, including emotional responses to the trauma, and to then modify these cognitive representations by helping the client incorporate information that helps reframe either trauma or reaction to trauma (e.g., empowerment, sense of security and safety, etc.; Foa & Kozak, 1986). Emotion-focused treatments have also been successfully applied to cancer survivors (Giese-Davis et al., 2002) and treatment of depression (Ellison et al., 2009; Pos, Greenberg, & Warwar, 2009).

A body of evidence now suggests that expressive writing and emotional processing of stressful events in particular, may be associated with improvements in mental and physical health outcomes (Greenberg, 2008; Low, Stanton, & Bower, 2008; Pennebaker, 1997). The expressive-writing paradigm has been tested in over 250 studies (per comprehensive meta-analysis; Frattaroli, 2006), and nearly all of these studies deliver at least three expressive writing sessions spread out over time (e.g., Low, Stanton, & Danoff-Burg, 2006; Pennebaker, 1997; Pennebaker, 2004). While the mechanisms of action have not been fully identified, use of emotion words has been linked with positive outcomes (Pennebaker & Francis, 1996; Pennebaker et al., 1997). It is important to note that emotional expression can be thought of as one of the aspects that can help lead to emotional processing of a given experience. However, it is worth noting that no known studies have evaluated tailored approaches to expressive writing procedures (e.g., modifying subsequent instructions based on the content of what was previously written) in order to modify or enhance the effects of the intervention. Recent successes in using computers to identify emotional expression in text is now possible and provide a platform to use linguistic data as a way of delivering tailored instructions and perhaps increasing the efficacy of this procedure.

Use of computer-tailored treatment recommendations and interventions have been successfully used with other treatment paradigms (Porter, 2009). In nearly all studies that employ computer-based tailoring, tailoring is determined based on self-report responses from a survey. Such tailoring works by either scoring a standardized instrument to provide a participant with information about how they compare to others or by directing participants to specific types of information based on their responses to the survey. Depending on the level of sophistication, the computerized feedback can be delivered in a number of ways, from personalized letters to direct feedback via the computer screen (Brug, Campbell, & van Assema, 1999). The aim of tailoring is to increase the effectiveness of the information given to the individual (Dijkstra & De Vries, 1999).

Computer-tailored feedback has been most heavily studied with respect to changing health behaviors. Basic computer tailoring interventions have been successfully implemented for alcohol abuse treatment (e.g., Matano et al., 2007), smoking cessation (e.g., Buller et al., 2008), as well as improving nutrition, diet, and exercise (e.g., Frenn et al., 2005). Furthermore, it allows for custom health messages, customized assessments, and provides an individual with additional tools for improving their health (Lustria et al., 2009). While tailored messages have repeatedly been shown in the literature to be superior to no message, only a small number of studies have actually compared them against generic messages. These studies have generally found tailored messages to be preferable over a generic or general message (Noar, Benac, & Harris, 2007).

In a systematic review, Kroeze, Werkman, and Brug (2006) identified three of 11 published studies on computer-tailoring for physical activity and 20 of 26 dietary changes that resulted in significant improvements. In those studies that showed tailoring to be efficacious, computer-tailoring was provided immediately after completion of a battery of self-report instruments (e.g., Marcus et al., 1998; Vandelanotte et al., 2005). Those interventions that have provided some degree of interactivity primarily did so by providing profile results generated from completion of self-report surveys on the study website (e.g., Christensen, Griffiths, & Jorm, 2004; Clarke et al., 2002; Osgood-Hynes et al., 1998), and this type of interactivity does not generally change the way the remainder of the intervention is delivered. Self-report responses can be easily categorized by a computer (e.g., check boxes, likert-type ratings, etc.), but short answer or essay formats are not easily deciphered by computers. As a result, existing tailored interventions are unable to encourage participants to engage in exercises that require generative self-disclosure (e.g., expressive writing). However, tools such as LIWC allow investigators to process linguistic data and therefore have the potential to be used to inform linguistically-derived tailoring strategies.

Given our previous efforts to validate LIWC for the identification of emotional expression in text (Bantum & Owen, 2009; Owen et al., 2005; Owen et al., 2006), the present study sought to evaluate whether linguistically-tailored feedback related to emotional expression could be used to modify emotional processing in the context of an expressive-writing paradigm. There were two primary aims of the study. The first aim was to create a valid implementation of LIWC using Perl, an open source computer language adaptable for linguistic analysis and manipulation of text files. By implementing LIWC via Perl, it would then be possible to provide dynamic, linguistically-tailored feedback in real time. The second aim of the study was to experimentally test whether linguistically-tailored feedback could alter emotional processing during expressive writing. We hypothesized that participants who received tailored feedback would engage in greater levels of

emotional processing and experience greater reductions in mood symptoms than those who did not receive such feedback.

2. Methods

2.1. Participants

After obtaining approval from our Institutional Review Board, four hundred forty-eight undergraduates were recruited from the psychology department at an ethnically-diverse academic institution in Southern California. A brief description of the study (i.e., a study that would involve three days of writing over the Internet) was provided on a sign-up sheet, and potential participants provided their names and e-mail address to obtain more information about the study. Participants were then enrolled by a research assistant using a website developed by the investigators. Automatically-generated emails were sent to each participant with a confidential username, password, and instructions for accessing the study website. Once logged-into the study website, participants were provided with an overview of the study, guided through the consent process, and given a visual display of the steps necessary to complete the study (i.e. completing brief baseline and post-test surveys online and writing about their "deepest thoughts and feelings for 20 min each day" for three successive days). Participants were able to start the study on a day convenient for them over the course of the academic term. Of the 448 potential participants, 283 (62.9%) consented to participate in the study, and 277 completed the baseline survey (97.9%).

2.2. Procedure

An overview of study-related procedures is provided in Fig. 1. Upon completing the electronic informed consent, participants were asked to complete a set of baseline self-report measures. We then provided a set of general instructions about writing for three days, writing continuously for 20 min on each day, and protections of anonymity and confidentiality. Participants who indicated they were ready to begin writing were then given a standard set of expressive writing instructions recommended by Pennebaker (1997):

> Now, what I would like to have you write about for the next three days is the most traumatic, upsetting experience of your entire life. In your writing, I want you to really let go and explore your very deepest emotions and thoughts. You can write about the same experience on all three days or about different experiences each day. In addition to a traumatic experience, you can also write about major conflicts or problems that you have experienced or are experiencing now. Whatever you choose to write, however, it is critical that you really delve into your deepest emotions and thoughts. Ideally, we would also like you to write about significant experiences or conflicts that you have not discussed in great detail with others. Remember that you have three days to write. You might tie your personal experiences to other parts of your life. How is it related to your childhood, your parents, people you love, who you are, or who you want to be? Again, in your writing, examine your deepest emotions and thoughts.

All instructions and feedback were presented in both text and video format in order to maximize the likelihood that participants would be adequately exposed to the intended stimuli.

During each expressive writing exercise, participants were able to see a digital stopwatch that indicated how much of the 20 min remained. Participants were unable to submit their writing until 20 min had elapsed. Immediately after submitting writing sessions 1 and 2, those assigned to the simple or directive feedback conditions received text-based and video feedback regarding the level of emotional expression in their writing sample and were asked to complete a brief post-writing survey about their writing and the accuracy of the feedback. No feedback was provided after writing session 3. After writing sessions 1 and 2, all participants were encouraged to return the following day for the next writing session. At the end of the third writing session, all participants completed the follow-up survey.

2.3. Self-report measures

2.3.1. Demographics and frequency of Internet use

At baseline, all participants were asked to describe their age, gender, and ethnicity and to characterize the frequency of their use of the Internet (i.e., almost never, once every few weeks, 1–2 days per week, 3–5 days per week, once a day, or several times a day).

2.3.2. Profile of mood states (POMS)

Mood disturbance was measured using the full POMS. The instrument was administered at baseline and follow-up (i.e., after completing the three days of writing). Participants were asked to rate the extent to which they had felt each of 65 mood descriptors (e.g., "unhappy" or "on edge") in the previous 24 hours. Items were measured using a 5-point Likert scale with anchors at 1 ("not at all") and 5 ("extremely"). After reverse-scoring two items, items for each subscale were summed. A total mood disturbance (TMD) score was generated by adding subscales for Depression, Tension, Anger, Fatigue, and Confusion and then subtracting the subscale score for Vigour. TMD scores ranged from 2 to 292 (cronbach's alpha = 0.939).

2.3.3. Accuracy of feedback and attitudes about written emotional expression

As a validity check after each feedback message, participants assigned to either simple or directive feedback were asked to rate the accuracy of the feedback they received about their level of positive and negative emotional expression (i.e., 2 separate items). Similarly, participants' receptiveness to the feedback messages was assessed by asking them to rate how important they believed it was to try to express more positive or more negative emotional expression (i.e., 1 item for each type of emotion) in their next written essay. Each item was measured using a 5-point Likert scale ranging from "not at all" to "a great deal." At the conclusion of the study, participants were asked to report the degree to which the study had been difficult for them, how much they had thought about the study outside of the experiment, and how valuable or meaningful the study was to them. These items were each evaluated using a 7-point Likert scale using items previously described by (Pennebaker, Colder, & Sharp 1990).

2.4. Objective linguistic markers

Linguistic Inquiry and Word Count (LIWC; Pennebaker, Francis, & Booth, 2003) was used as the basis for the linguistic tailoring and identification of linguistic markers of emotional expression. LIWC has been previously validated for the identification of emotional expression in written text, exhibits good signal detection properties when compared with trained human coders, and has been shown to be superior to other comparable text analysis programs for identification of emotion (Bantum & Owen, 2009). LIWC systematically compares each word in a given text sample to each of three separate libraries of emotion words (overall affect, positive emotion, and negative emotion) to determine whether the word from the text sample matches any of the words or word fragments

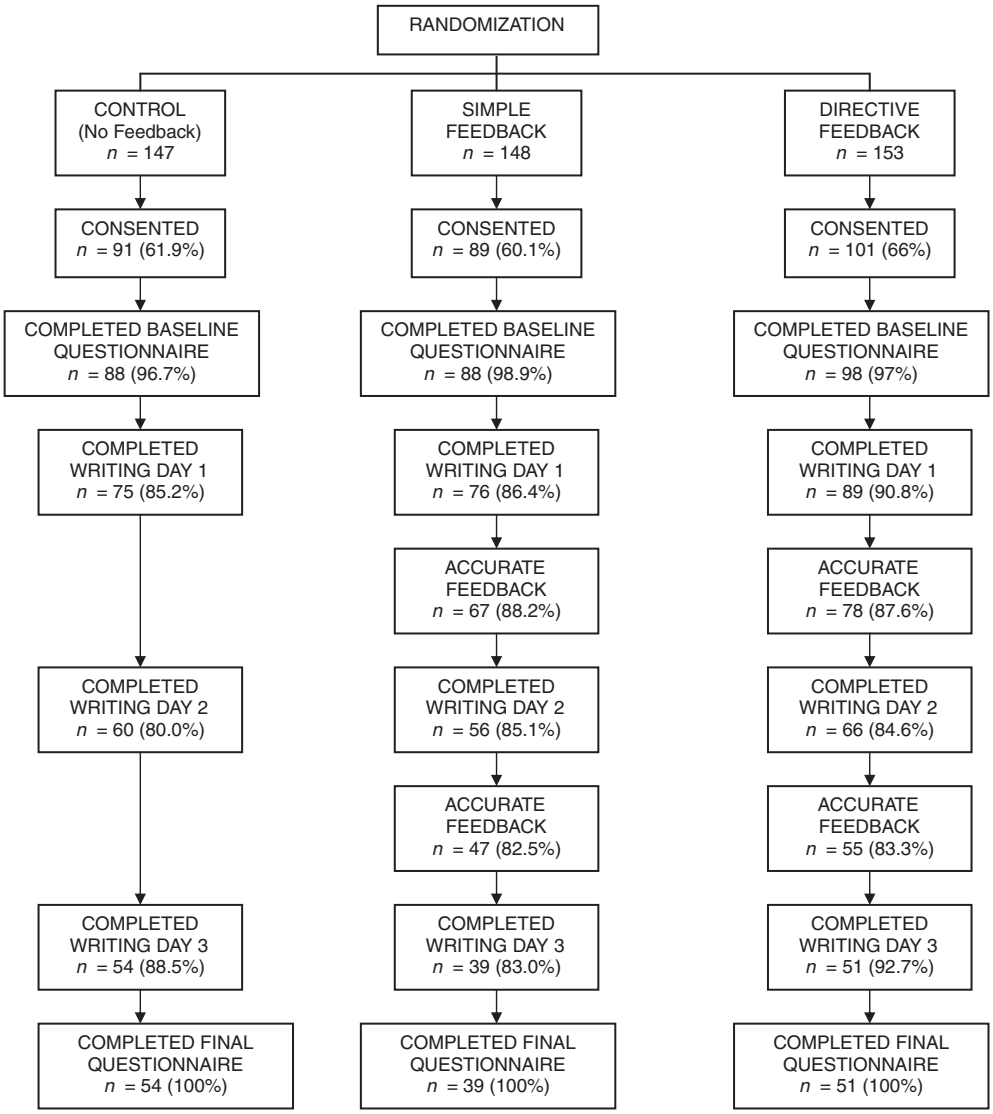

Fig. 1. Flow diagram of participants' study-related activities and attrition over time. *Note.* All percentages reflect the proportion of those progressing from the previous study-related activity.

contained by the LIWC libraries. If a word from the text sample is found to exist in one of the emotion libraries, LIWC iterates the value for that word library by one point. This procedure generates a word count based on the number of words in a submitted text sample that matched words contained in the LIWC emotion dictionaries for overall emotion, positive emotion, or negative emotion. The standard LIWC scoring system divides the number of emotion words identified by the number of total words in the text sample in order to obtain a percentage of total words that are represented by emotion words or specific types of emotion words (e.g., negative emotion, positive emotion; Pennebaker, Francis, & Booth, 2001). The Perl program developed for the current study was designed to replicate the LIWC scoring procedure, with once exception: we elected to use word count (i.e., number of emotion words expressed) instead of the percentage of total words. Percentage of total words has the potential to underestimate emotional expression. Demonstration examples of the word count and word percentage procedures are provided in Table 1. For the present study, hypothesis tests involving linguistic markers of emotional expression were evaluated using the number of emotion words

Table 1
Comparison of scoring strategies for identifying emotional expression in text.

Example text	Number of total words	Number of emotion words	Emotion words as % of total words
A. **Losing** my mother was the most **painful** experience of my life, and it still brings **tears** to my eyes	19	3	15.8
B. **Losing** my mother was the most **painful** experience of my life, and it still brings **tears** to my eyes. Every August, on the anniversary, I think of her all the time. She is always on my mind	37	3	8.1
C. **Losing** my mother was the most **painful** experience of my life, and it still brings **tears** to my eyes. Every August, on the anniversary, I think of her all the time. She is always on my mind. How could you forget an experience like that? It will always be with me	51	3	5.9

Note. Words in bold indicate words identified by LIWC as emotion words.

(i.e., word count) while including total word count as a covariate in these analyses.

2.5. Feedback conditions

At the time of enrollment, participants were randomized to three different feedback conditions: No Feedback (control group), Simple Feedback (feedback linguistically-tailored to level of emotional expression), and Directive Feedback (linguistically-tailored to level of emotional expression plus cognitive cues for processing emotion). Feedback groups did not differ with respect to age, F (2, 274) = 2.6, p = .08, ethnicity, χ^2 (8) = 4.4, p = .82, gender, χ^2 (2) = .3, p = .85, or frequency of Internet use, χ^2 (8) = 4.4, p = .82. The three Feedback conditions were as follows:

2.5.1. No Feedback (Control) Group

Participants who were randomized to the no feedback (control) group were simply thanked after they completed the writing task each day and invited to return 24 hours later to continue participating.

2.5.2. Simple Feedback Group

In the simple feedback group, participants were told (using both text and video) whether they expressed a low, average, or high level of emotional expression on both negative and positive emotion.

2.5.3. Directive Feedback Group

Directive feedback participants received feedback identical to those in the simple feedback group. Additionally, participants were either encouraged to "keep it up" if they expressed a given emotional expression that equated to the "high" category of expression for either positive or negative emotion or to "increase" positive or negative emotion if they fell into the "average" range of emotion, and to "greatly increase" their expression of positive and/or negative emotion if they fell into the "low" level of emotional expression. In addition to emphasizing the importance of exploring emotional experiences, participants were encouraged to identify specific positive or negative emotions they experienced during or after the events they wrote about and to explore how those emotions influenced the way they managed that particular situation.

2.6. Dynamic-implementation of LIWC and linguistically-tailored feedback

Using means and standard deviations previously reported for expressive writing conditions across 43 studies (Pennebaker et al., 2001), each subjects' percentages of positive and negative affect were converted to a standard score. Cut-offs of $z = \pm 1.285$ were used to classify both negative ($\bar{x}$ = 2.6, sd = 1.7) and positive ($\bar{x}$ = 2.7, sd = 1.6) emotional expression as "low", "average", or "high". For the individuals who completed the baseline writing and received accurate feedback, 147 (66.8%) showed low levels of emotional expression, 70 (31.8%) showed average and 3 (1.4%) showed high positive emotional expression. For negative emotional expression, 98 (44.5%) were classified as low, 114 (51.9%) were classified as average, and 8 (3.5%) were classified as high.

2.7. Data analysis

Correlations were used to compare the relationships between the implemented perl scoring system and the LIWC scoring system. To evaluate the effect of feedback on psychological processing of traumatic events over time; we employed three repeated-measures ANCOVAs. Three separate dependent variables were tested: number of overall emotion words, positive emotion words, and negative emotion words. In each model, the effects of time (writing day 1, 2, 3), feedback condition (No Feedback, Simple Feedback or "Simple", and Directive Feedback or "Directive"), and the Time × Feedback Condition interaction were entered as predictors, but only the interaction was evaluated. Significant Time × Feedback interactions would suggest that changes in the dependent variable over time were altered differently across the feedback conditions. All models adjusted for variation in number of words used across participants by including each participant's total number of words written as a covariate in the analysis. Where significant Time × Condition interactions were observed, *a priori* planned comparisons were tested using two orthogonal contrasts of the effects of condition over time: (1) a comparison of those who received any type of feedback (simple or directive) and those who received no feedback, and (2) a comparison of the simple and directive feedback groups. To correct for sphericity in the repeated measures analyses, the Greenhouse–Geisser correction to the F statistic was employed, and epsilon (δ_{G-G}) values are provided for each test.

3. Results

3.1. Participants

The 277 subjects who completed the baseline survey represented a diverse group of young adults. Participants averaged 25.4 years of age. With respect to ethnic identification, 41.9% (n = 116) were Latino, 30.3% (n = 84) were non-Hispanic White, 14.4% (n = 40) were African-American, 6.9% (n = 19) were Asian-American, and 6.5% (n = 18) described themselves as "Other." Participants were largely female (86.3%) and were fairly active Internet users. When asked to describe the frequency of their Internet use, 59.9% (n = 166) reporting using the Internet many times throughout the day, 22.4% (n = 62) used the Internet at least once a day, 15.1% (n = 42) used the Internet several times per week, and 3.2% (n = 7) used the Internet at least once a week. Average word count per writing session across the three feedback conditions was 665.0 words (over twice as high as other expressive-writing studies; Pennebaker et al., 2003).

3.2. Validity of dynamic implementation of LIWC

Correlations between perl-generated scores and LIWC-generated scores were very strong and statistically significant (r's = 0.91–1.00, p's < 0.0001, see Table 2). In an effort to identify unexpected differences between perl-generated and LIWC scores, follow-up evaluations were conducted on the perl-implementation of LIWC. To do so, perl- and LIWC-generated scores were examined closely for randomly-identified text files. In this process, a minor flaw in the scoring algorithm of the perl-implementation of LIWC was identified. Although this flaw was easily corrected, yielding substantially stronger correlations with LIWC (r's = 0.98–1.00, p's < 0.0001, see Table 2), inaccuracies in the scoring led to inaccurate feedback for some participants (n = 20, 8.3% of the 240 subjects who wrote on Day 1, and n = 21, or 11.4% of the 184 subjects who wrote on Day 2). Inaccuracies were randomly distributed between the feedback conditions, $\chi^2(1) = 0.3$, p = .6.

3.3. Effects of feedback on attitudes about emotional expression

As a validity check for the strength of the feedback manipulation, we then evaluated whether those who received Directive Feedback had more positive attitudes about emotional expression than did those who received Simple Feedback. There were significant differences between the two feedback conditions for perceived importance of both positive, F (1163) = 15.2, p < 0.0001, and negative emotional expression, F (1163) = 16.4, p < 0.0001.

Table 2
Pearson product–moment correlations between perl-generated and LIWC-generated indices of emotional expression ($n = 240$).

LIWC Category	perl-Generated values (r)	Corrected perl-generated values[a] (r)
Total word count (# words)	1.00***	1.00***
Linguistic markers of overall emotional expression (% of total words)	.92***	.99***
Linguistic markers of positive emotional expression	.91***	.98***
Linguistic markers of negative emotional expression	.91***	.99***

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
[a] *Note*. These are the correlations with LIWC after the perl program was corrected to appropriately iterate through word fragments in the LIWC dictionary.

Level of agreement that positive emotional expression was important for processing a traumatic event was higher in those who received Directive Feedback ($\bar{x} = 3.7$, sd = 1.2) than those who received Simple Feedback ($\bar{x} = 3.0$, sd = 1.3). Similarly, level of agreement that negative emotional expression was important for processing a traumatic event was higher in those who received Directive Feedback ($\bar{x} = 3.6$, sd = 1.1) than those receiving Simple Feedback ($\bar{x} = 2.9$, sd = 1.3).

3.4. Post-hoc evidence for the validity for LIWC-informed dynamic feedback

Although unexpected, having a sample that received inaccurate feedback about positive and negative emotional expression provided an opportunity to further evaluate the validity of the dynamic implementation of LIWC. It was reasoned that if the feedback was working as intended, those who received accurate feedback, compared with those receiving some degree of inaccurate feedback would describe the feedback they received about their level of emotional expression as being more accurate. Inaccurate feedback was defined as being told either to (a) maintain, rather than increase, a low to moderate levels of either positive or negative emotional expression or to (b) increase, rather than maintain, already high levels of either positive or negative emotional expression.

Those receiving some degree of inaccurate feedback (for either positive or negative emotional expression) after the first writing session were compared with those who received accurate feedback (for both positive and negative emotional expression). After viewing the video feedback message, those who received accurate feedback ($\bar{x} = 3.7$, sd = 1.1) described the message as being significantly more accurate, F (1, 163) = 7.4, $p = .007$, with respect to positive emotional expression than those who received inaccurate feedback ($\bar{x} = 2.9$, sd = 1.4). Those receiving accurate feedback did not differ from those receiving inaccurate feedback on perceived accuracy of negative emotional expression, $F(1, 163) = 0.2$, $p = .66$. Only subjects who received accurate feedback at both Time 1 and Time 2 were included in the remaining analyses.

3.5. Pre-writing differences between feedback conditions

Baseline characteristics of those who completed the first writing session and were given accurate feedback are shown in Table 3. No significant differences between Feedback groups were found for any of the demographic, self-report, or linguistic variables. There were no differences associated with ethnicity, χ^2 (8) = 2.48, $p = .96$, gender, χ^2 (2) = 0.60, $p = 0.76$, or age, F (2, 159) = 2.34, $p = .10$. Baseline mood disturbance also did not differ across Feedback groups, $F(2, 159) = 1.89$, $p = .15$. Similarly, there were no differences in linguistic characteristics of the first writing session (i.e., total word count, $p = .32$, emotion words, $p = .21$, positive emotion words, $p = .24$ or negative emotion words, $p = .35$). Further, there were no differences in total time spent writing ($p = .82$).

3.6. Effects of feedback group on linguistic markers of emotional processing

The Time × Condition interaction was significant for use of total emotion words, F (4, 280) = 2.59, $p = .04$, $\delta_{G-G} = .90$. The Time × Contrast interaction was also significant for the first orthogonal contrast, identifying a difference in use of total emotion words

Table 3
Baseline characteristics for subjects who completed at least one day of writing and received accurate feedback.

	No Feedback ($n = 75$) frequency (%)	Simple Feedback ($n = 67$) frequency (%)	Directive Feedback ($n = 78$) frequency (%)	Full Sample ($n = 220$) frequency (%)
Gender				
Female	63 (28.6%)	59 (26.8%)	67 (30.5%)	189 (85.9%)
Male	12 (5.5%)	8 (3.6%)	11 (5.0%)	31 (14.1%)
Ethnicity				
Asian-American	5 (2.3%)	5 (2.3%)	6 (2.7%)	16 (7.3%)
Black	10 (4.5%)	13 (5.9%)	11 (5.0%)	34 (15.5%)
Latino	33 (15.0%)	26 (11.8%)	29 (13.2%)	88 (40.0%)
White	23 (10.5%)	18 (8.2%)	27 (12.3%)	68 (30.9%)
Other	4 (1.8%)	5 (2.3%)	5 (2.3%)	14 (6.4%)
	$\bar{x}$ (**sd**)	$\bar{x}$ (**sd**)	$\bar{x}$ (**sd**)	$\bar{x}$ (**sd**)
Age (years)	25.6 (9.1)	24.5 (8.0)	27.9 (11.2)	26.1 (9.7)
Word count (Day 1)	667.5 (206.9)	695.6 (252.1)	636.4 (246.4)	665.0 (235.7)
Time spent writing (minutes)	22.7 (7.7)	22.1 (3.4)	22.5 (4.4)	22.4 (5.5)
Overall emotional expression (% of total words)	4.6 (1.2)	4.1 (1.4)	4.1 (1.5)	4.3 (1.4)
Positive emotional expression (% of total words)	2.0 (0.8)	1.9 (0.9)	1.8 (1.0)	1.9 (0.9)
Negative emotional expression (% of total words)	2.5 (1.0)	2.2 (1.0)	2.3 (1.0)	2.4 (1.0)
Total mood disturbance (POMS-TMD)	71.4 (33.6)	63.2 (30.1)	73.2 (33.6)	69.6 (32.7)

Note. All means are adjusted for total word count during the baseline writing session.

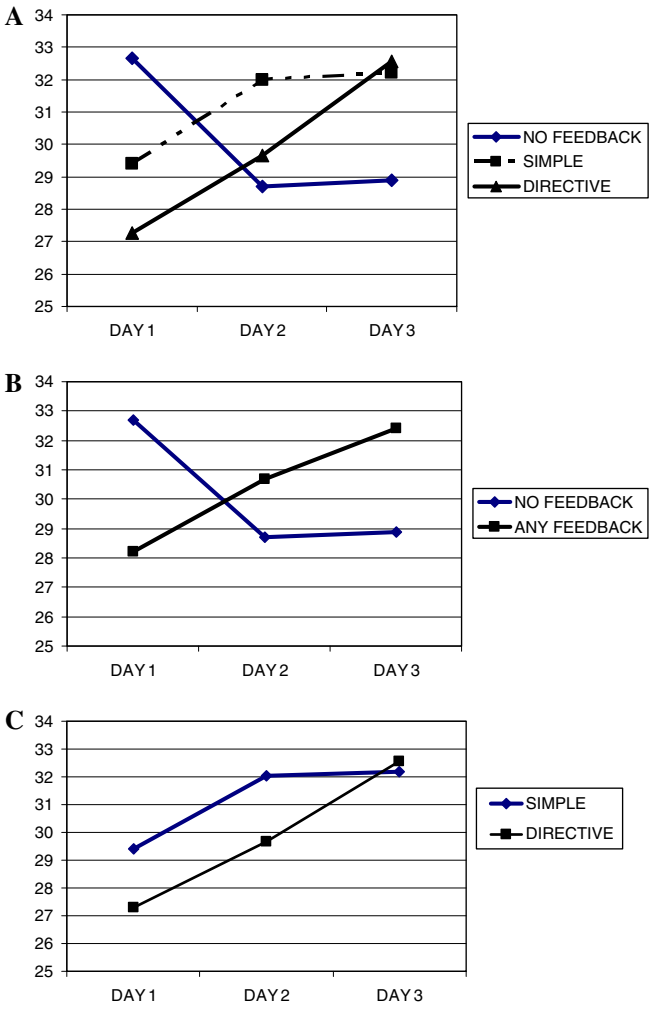

Fig. 2. Omnibus and orthogonal comparisons of condition on use of all emotion words over time. *Note.* (A) Omnibus Time × Condition effects, F (4, 280) = 2.59, p = .04, δ_{G-G} = .90; (B) contrast 1: any feedback vs No Feedback. F (2, 282) = 4.80, p = .01, δ_{G-G} = .90; (C) contrast 2: Simple Feedback vs Directive Feedback, F (2, 174) = 0.5, p = .6, δ_{G-G} = .97.

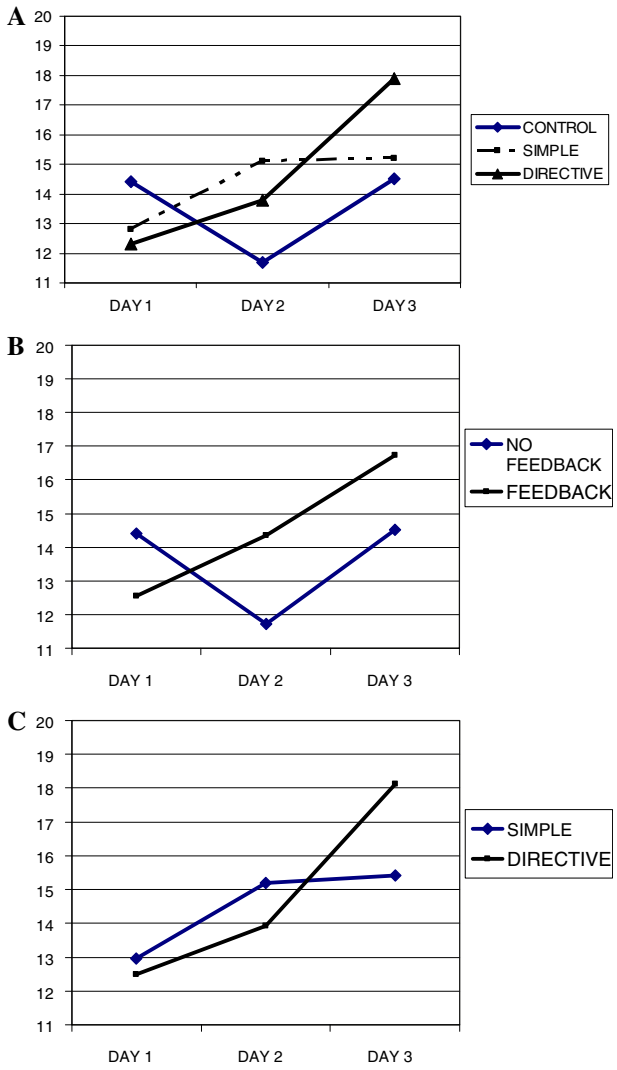

Fig. 3. Omnibus and orthogonal comparisons of condition on use of positive emotion words over time. *Note.* (A) Omnibus Time × Condition effects, F (4, 280) = 3.23, p = .02, δ_{G-G} = .90; (B) contrast 1: Any Feedback vs No Feedback. F (2, 282) = 4.39, p = .016, δ_{G-G} = .90; (C) contrast 2: Simple Feedback vs Directive Feedback, F (4, 280) = 2.59, p = .04, δ_{G-G} = .90.

across time between those who had received any type of feedback and those who received no feedback, F (2, 282) = 4.80, p = .01, δ_{G-G} = .90. As shown in Fig. 2, the control group used fewer emotion words after time 1, whereas those receiving feedback (Simple or Directive) showed an increase in the use of emotion words after time 1. For the second orthogonal contrast, no significant difference between the Simple feedback group and those receiving Directive feedback was obtained, F (2, 174) = 0.5, p = .6, δ_{G-G} = .97.

With respect to use of positive emotion words, there was again a significant Omnibus Time × Condition interaction, F (4, 280) = 3.23, p = .02, δ_{G-G} = .90. Contrast one (Feedback vs Control) was also significant for use of positive emotion words, F (2, 282) = 4.39, p = .016, δ_{G-G} = .90. Results showed an increase over time for those receiving Feedback compared with a flat trajectory for those in the Control group (see Fig. 3). There was no observed difference between those receiving Simple feedback and those receiving Directive feedback, p = .13. For negative emotion words, the Omnibus Time × Condition effect was not significant (p = .28).

There were no differences over time in mood disturbance across the three Feedback groups (p = .69). Similarly, there were no differences in a) how difficult it was for participants to do the writing (p = .31), how much time participants spent thinking about their writing after they completed the writing sessions (p = .94), or the extent to which the study had been meaningful to them (p = .86).

4. Discussion

With a large, ethnically-diverse sample, this study demonstrates the validity of a real-time text analysis procedure for identifying emotional expression in written text. Our perl-based procedure was nearly perfectly correlated with LIWC, allowing us to access and use linguistic data in real-time. This procedure could make it possible to dynamically tailor information or intervention messages specifically to emotional content transmitted via Internet or other communication media.

Instant feedback about emotional expression resulted in increased levels of overall emotional expression and positive emotional expression in particular. These findings demonstrate that tailored feedback, involving no human judgment or interaction, can alter how individuals respond to instructions to engage in expressive writing. Such tailored feedback could be used to enhance treatment effects associated with expressive writing protocols. For example, the effect of instructions on subsequent

writing and outcomes has been shown to be moderated by emotional processing and emotion-focused coping (Austenfeld & Stanton, 2008; Stanton et al., 2002). Identifying real-time emotional expression is a crucial first-step towards creating instruction sets that are dynamically tailored across time to individual differences, such as degree of emotional processing or use of emotion-focused coping skills.

The effect sizes observed in this study (i.e., differences in emotional expression over time) were relatively modest. Only overall emotional expression and positive emotional expression increased with feedback. No effect was observed for negative emotional expression. Because expression of both positive (Pennebaker & Seagal, 1999; Pennebaker et al., 1997; van Middendorp & Geenen, 2008) and negative emotions (Esterling et al., 1994; Low et al., 2006) have been shown to mediate the effects of expressive writing, additional efforts to influence processing of negative emotions is needed. However, it is unknown if increasing emotional expression leads to long-term increases in emotional expression or health benefits. Thus, it is still uncertain if increasing low to high emotional expression through feedback results in the same health and mental health benefits as those who already have high levels of expression.

Additionally, the tailored instructions provided in the current study were fairly simplistic. More elaborate and clinically-focused instructions, provided in response to what participants are writing over time, have potential to strengthen effects of expressive writing. Using emotion focused theory driven tailored instructions may produce greater increases in emotional expression.

Despite the simplicity of the feedback messages provided in the present study, the feedback process itself was very resource-intensive. The study required 108 unique video messages (only three of which were shown to any single participant). Although potentially highly valuable, more extensive tailoring procedures would result in exponential increases in the necessary number of feedback messages. Future investigations should evaluate whether other, less resource-intensive, means of providing tailored feedback are comparable to video feedback, including simple text feedback, computer-generated audio feedback, or animated talking avatars (i.e., realistic, but computer-generated, images of a human face).

There were a number of key limitations of the present study. First and foremost, our feedback procedure yielded incorrect feedback for 20% of our original sample, reducing the total number available for analysis. Second, tailoring was limited to three levels each of positive and negative emotional expression, and feedback about being "low," "average," or "high" was based on norms for expressive-writing studies (Pennebaker et al., 2003). Having reliable estimates of the shapes of distributions for each emotion variable derived from LIWC could allow for more precise tailoring of feedback messages. Finally, narratives written by our participants reflected a considerable degree of trauma in this population, but we did not measure trauma symptoms before or after engaging in the writing studies. Future studies should look specifically at outcomes associated with trauma symptoms or the degree to which individuals have adaptively processed previous trauma experiences.

It is well-established that tailoring information and interventions to individual characteristics can improve effect sizes relative to delivering a standard message or treatment (Kreuter et al., 2000; Neville, O'Hara, & Milat, 2009). While previous studies have relied on self-report methodologies for identifying key individual differences in expressive-writing studies (Gortner, Rude, & Pennebaker, 2006; Sloan et al., 2008), the results of the present study show that it is also possible to tailor messages to computer-identified linguistic behaviors. Real-time and dynamic methods for identifying emotional expression have many potential applications beyond the expressive-writing paradigm and could be applied to transcriptions of interactions between clients and therapists, patients and physicians, or fellow members of a group or community. As natural language processing algorithms increase in complexity (Hripcsak et al., 2009; Mitchell, 1997), the quality and clinical relevance of linguistically-derived feedback messages is also likely to improve over time.

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