

Change of Heart: Emotion Tracking to Promote Behavior Change

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ABSTRACT

Preventable behaviors contribute to many life threatening health problems. Behavior-change technologies have been deployed to modify these, but such systems typically draw on traditional behavioral theories that overlook affect. We examine the importance of *emotion tracking* for behavior change. First, we conducted interviews to explore how emotions influence unwanted behaviors. Next, we deployed a system intervention, in which 35 participants logged information for a self-selected, unwanted behavior (e.g., smoking or overeating) over 21 days. 16 participants engaged in standard behavior tracking using a *Fact-Focused* system to record objective information about goals. 19 participants used an *Emotion-Focused* system to record emotional consequences of behaviors. Emotion-Focused logging promoted more successful behavior change and analysis of logfiles revealed mechanisms for success: greater engagement of negative affect for unsuccessful days and increased insight were key to motivating change. We present design implications to improve behavior-change technologies with emotion tracking.

Author Keywords

Behavior change, emotions, lifestyle, user studies, everyday life, field experiment.

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous. J.4 Social and Behavioral Sciences: Psychology

INTRODUCTION

Preventable behaviors account for over half of all deaths in high-income countries [21]. Though smoking, alcohol abuse and overeating are controllable through intervention, they continue to be life-threatening problems. One response

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has been the emergence of personal applications to assist self-led interventions. As of 2014, the Google Play and iTunes Application store return over 100,000 results for “Health & Fitness” including apps for diet, exercise, smoking cessation and sleep. This paper takes a novel approach to address preventable behaviors by using an emotion tracking system that encourages participants to reflect on the emotional consequences of that behavior.

While behavior-change technologies have been successfully deployed [30] these systems commonly suffer from low compliance and often fail to maintain long-term change [13]. When systems do draw on theory, they generally emphasize *cognitive* aspects of behavior (Theory of Planned Behavior [3]; Transtheoretical Model [27], Social Cognitive Theory [5] and Goal-Setting Theory [20]). For example, traditional cognitive approaches typically encourage participants to monitor everyday behaviors for the purpose of tracking relevant information (e.g., step count or social comparison) and objective consequences for behavior change goals (e.g., daily weight).

However recent research identifies the critical role that emotions play in motivating behavior. In particular this work shows the importance of *affective forecasting* [6] where behavior change is motivated by a desire to achieve a future affective state. This involves participants thinking about *how they will feel* if they engage in a behavior. Affective forecasting has been successfully applied to body weight regulation, safe sex, time management and









Date	Frequency	Before	Current	Description
5/08	0			I stop and think about it, which makes me aware!
5/07	1			Im glad im being more aware and attempting to make a change!
5/02	0			Yeah! im glad I've done good today!
4/30	6			Damn im pissed I messed up so bad!

Fig. 1: Emotion Tracking UI: Confirmation page showing 4 past entries with date, habit frequency, emotion ratings and user entry for that day.

improved financial behavior [1, 25].

Relatively little of this focus on emotions has found its way into current behavior-change technologies. Although some systems allow participants to log emotions [10], behavior change is typically not the primary focus. Other systems specifically support emotion tracking, but with the goal of regulating emotions [17]. In this paper, we therefore explore new designs that incorporate emotion tracking to determine whether engaging participants' emotions can specifically help reduce preventable behaviors. We address impulse control and refer to the target preventable behavior as a *bad habit*. We use the colloquial definition of "habit" to reference a daily, problematic behavior (e.g., a "smoking habit") that references either consciously (e.g., drinking) or unconsciously triggered activities (e.g., nail biting). To explore benefits of emotion tracking, we first carried out exploratory interviews to better understand how emotions are involved in behavior change. We next conducted a system intervention (see Fig. 1) to explore aspects of emotion tracking for preventing habit engagement and contrasted this with a traditional cognitive approach. Our goal was to encourage reflection on the *emotional consequences* of engaging in a bad habit, so as to discourage habits that induce emotional distress.

We present qualitative and quantitative data to address the following questions:

- What is the *role* of emotion in behavior change?
- What are the *benefits* of emotion-tracking compared with more traditional cognitive approaches? Does engaging emotions reduce bad habits?
- *How* does emotion tracking change behavior? What are the underlying psychological mechanisms?
- *What types* of emotional engagement (positive vs. negative) are most effective at reducing a bad habit?

Our contribution is to show that emotion tracking promotes more successful behavior change than purely cognitive methods. We also identify mechanisms for success: greater engagement of negative affect for unsuccessful days and increased insight were key to motivating change. We present design implications to improve behavior-change technologies with emotion tracking.

RELATED WORK

Behavior-Change Technologies

A common criticism of early behavior-change technology was lack of theoretical foundation. However, this concern is steadily being addressed with the increased use of theory to intelligently scaffold system design [12, 15, 18]. Of these theoretically-driven systems, many are influenced by cognitive behavioral therapy (CBT) approaches, focused on detailed record-keeping to promote *self-awareness* about the relationship between everyday behaviors and consequences for behavior change goals. Self-reflection

within behavior change technologies has also gained recognition as an important component to promote self-awareness and positive change [19]. Many of these technologies have also leverage models, such as Theory of Planned Behavior (TPB) [3], Transtheoretical Model [27], Social Cognitive Theory [5] and Goal-Setting Theory [20], to address factors that can affect behavior transformations (e.g., self-efficacy or social pressure).

While early behavior-change technologies capitalized on the benefits of self-monitoring alone [9, 23], many of these technologies now include more refined features to increase success rates. Popular commercial systems have features motivated by psychological theory such as social pressure (either as competition or cooperation) [5], goal-setting principles [20] and motivational style [11].

One key gap in major behavior change theories and smaller-scale models, such as goal-setting theory, is that little work has focused on how *emotional* factors impact motivation and this oversight has translated to how many designers approach behavior-change technologies today.

Within psychology, empirical studies have made significant progress in identifying the role of emotions in decision-making. Pennebaker & Chung (2007) outlined extensive research documenting the benefits of expressive, emotional writing to improve well-being and health. In addition, contemporary research examines bidirectional relationships between emotions and behavior. In contrast to the traditional view that emotions strictly serve as predispositions to behavior, recent work demonstrates how emotions serve as *target* affective outcomes which influence the likelihood of engaging in a specific behavior. For example, understanding that one feels better *after* exercise serves to promote this habit. This causality is supported by a meta-analysis by Baumeister et al. (2007) which found that of approximately 400 tests focused on emotions as predictors of behavior, only 17% of results were significant. However, for studies aimed at predicting behavior by judgments of anticipated emotional outcomes, 90% of results were significant. In line with this, mental forecasts of future affective states dramatically alter decision making, substantially changing perceived utilities for outcomes and in turn increase the consistency between a person's voiced intentions and actual behavior [1, 25].

Emotion-Oriented Technologies

Our focus here is on the relationship between *emotions* and behavior change, where there is much less system exploration. Nevertheless, a handful of commercial systems have incorporated emotion tracking. For example, the *Runtastic* app [28] includes mood entry post-jogging to record emotional states and provides snapshots for users to view moods after exercise. Similarly, the Mood Runner [16] and Moodkit [29] apps allow mood tracking in conjunction with physiological data such as exercise, sleep or sex drive to help users draw connections between health choices and emotional well-being. The Jawbone UP fitness

tracker allows users to associate days with mood type. However, when displaying “UP Trends” to display correlational data between different categories, such as food intake and step count, mood-tracking information is omitted. In the realm of addiction, the *Quit Pro - Smoking Cessation* application [8] allows users to identify potential triggers to smoking and replays information related to the most successfully resisted or succumbed triggers. Of these possible options, emotional factors (e.g., stress) are included as one of many possible precursors to smoking relapse. In conclusion, although behavior-change technologies are beginning to include emotion-tracking features, most are included as a peripheral characteristic.

Within academic contexts there has also been interest in emotional aspects of behavior change. For example, Health Mashups includes mood tracking alongside other parameters such as food intake, weather and step count [7]. Mood tracking was well-received by participants and provided important information on the relationship between emotional states and health-related behaviors. However, again the system incorporated emotion-tracking as a peripheral characteristic rather than exploring its central motivating role and the paper did not directly test how mood tracking affected behavior change.

Closer to our research objective is the EmoTree app, an ECG system which applies passive emotion detection to raise user awareness about emotional triggers for overeating [10]. The aim is to immediately signal high-risk emotional states to users for just-in-time motivation to reduce binge eating episodes. EmoTree identified a wide range of emotional precursors for overeating episodes and participant feedback indicated that customization for emotional triggers was useful though still ineffective at eliciting substantial change. Carroll et al., [10] reported that while 87.5% of participants became more aware of emotional triggers, only 37.5% communicated changing as a result of immediate warnings. While we are also interested in promoting user awareness of the effects of emotional triggers on behavior, we extend this approach by focusing on conscious reflection and anticipation of *emotional consequences*.

In summary, much prior work has focused on cognitive aspects of behavior change. Although a handful of newer systems have begun to explore the relationship between emotions and behavior, many do not follow our approach of using emotion tracking as the core method to *explicitly reduce a behavior*. We therefore examine the impact of a system that encourages people to track emotions to record emotional consequences when attempting to control bad habits. To inform our intervention we first conducted exploratory interviews to assess how emotions are involved in behavior change.

EXPLORATORY INTERVIEWS TO EVALUATE THE ROLE OF EMOTIONS IN BEHAVIOR CHANGE

Participants

We conducted semi-structured interviews with 12 participant aged 18-21 (9 women) recruited through a university participant pool to satisfy a psychology course requirement. Before the interview, participants were instructed to prepare a topic of discussion for a personally important behavior change goal that was either currently or recently pursued. Interviews were conducted in-person, ranged from approximately 30-60 minutes and transcribed verbatim. Interview transcriptions were independently coded for behavior category and themes of emotional content. Participants’ goals for behavior change ranged from practical lifestyle changes such as improved sleep habits, to reduced aggressive outbursts with family members. From these interviews, we explored what *types* of behaviors people saw as problematic, *why* that behavior was viewed as problematic and most critically the role of *emotions* in affecting those behaviors.

Target Behaviors for Change and the Critical Role of Emotions

Unsurprisingly academic performance was a common concern and many participants specified a main goal of improving study skills (N = 4). In relation to this goal, several participants identified procrastination habits that evoked strong negative affective consequences. One participant described emotional hardship resulting from schoolwork consuming more time than expected, leading to feelings of frustration or working under extreme stress. She specifically discussed her fear of failure, describing how this encouraged procrastination:

(BC3): “...I’m *really afraid* of failure so I put [schoolwork] off because *I’m afraid I’m not going to do a good job on something and then suddenly its time to do the thing and I get really worried...I procrastinate, [then] I think I’m gonna fail, so I procrastinate that longer...*”

Other participants also conveyed a complex relationship between study habits and emotions. Participant [BC13] explained how successful time management promoted better grades, and how the positive emotions associated with that “...encouraged [her] into studying more” with the expectation of continued success. In contrast, school semesters that began with poor time management precipitated the opposite train of events, leaving her to feel discouraged and demotivated. Similarly, participant BC10 acknowledged that poor study habits and resulting bad grades could also affect other life aspects, leading him to “...feel down or depressed or maybe really anxious” and become socially withdrawn.

Many of the participants were lucid about the *emotional consequences* of engaging in certain behaviors. The following participant [BC1] explores her complex relationship to her smoking habit, including the social stressors that precipitate her desire to smoke, (“*being*

attacked by people”, “unappreciated”, “not valued”). She understands the immediate relief of smoking and enjoyment of a nicotine rush. However, she is also aware of the long-term health consequences of indulging her habit and describes it in very strong terms (“I wanna just hurt myself”). She has also considered other ways of reducing stress levels by exercising but notes this alternative requires more effort and planning:

[BC1]: “I know I would *feel so much better* if I had a nicotine rush to de-stress, because when I don’t have time to exercise this is the big issue...I don’t have a way to relieve that stress so when I’m stressed out instantly I’m like “I want a cigarette”... when I have social stressors...when I feel attacked by other people or unappreciated... well **I wanna just hurt myself**, hurt yourself with a cigarette, you don’t really think of it...”

BC1 was also aware of the long term health consequences of smoking but chose to overlook these for short term catharsis: “I just have this weird justification for it...I don’t really care if I die younger, ‘cause **you’re so stressed out and you don’t look at the long picture**, like instant gratification.”

These interviews were informative in revealing to us the types of habits that people want to moderate. More importantly, they revealed the critical role that emotions had in moderating these habits. Participants are attuned to the negative emotional *consequences* of engaging in their habits and the positive emotions that follow from resisting them. Being attuned to emotional consequences was sometimes sufficient to elicit adaptive behaviors. However on other occasions, participants were unable to resist maladaptive behaviors because other alternatives were not easily achieved. These observations along with prior research motivated us to explore whether technological interventions for increased emotional awareness might moderate bad habits.

INTERVENTION: EMOTION VS. FACT FOCUSED TRACKING

We built a mobile web-based system to explore the effects of emotion tracking on behavior change, which we compared with a more traditional, objective monitoring system. We compared the two systems in a field trial where participants aimed to change a bad habit. Consistent with much current work taking a cognitive approach to behavior change, half our participants were randomized into a Fact-Focused condition to track *objective* information (e.g., time, location) related to their habits. The remaining participants were allocated to an Emotion-Focused condition to examine the *emotional consequences* of habit engagement, with the purpose of increasing awareness about emotions as delayed consequences. Both sets of participants reported daily behavior frequency, which should prompt all participants to evaluate success against change goals. Prior work suggests that simple factual description and monitoring of behaviors has benefits [9, 23]. Nevertheless, we anticipated greater

success in the Emotion-Focused condition given that awareness of later emotional consequences of a decision has strong effects on behavior [1, 6, 25]. We also expected this additional emotional processing to reveal itself in participants’ daily reports of their behaviors in system logs: with emotion focused participants showing enhanced insight into behaviors and differences in expressed emotion, depending on success.

Study Design

The intervention involved pre- and post-intervention surveys and 21 days of daily logging information using two different web-based systems. All participation was conducted online. Prior to the intervention, participants identified a single bad habit that they wanted to completely stop or reduce over a 3-week period. We evaluated success by: (a) examining daily reports of habit frequency, and (b) comparing pre- and post-test surveys assessing the habit.

All participants created a *daily record* of an event in which their bad habit was engaged or avoided. In the *Emotion-Focused* tracking condition, participants recorded emotional content about the event and specifically rated their emotional state at the time they engaged in, or avoided, that bad habit. Emotion-Focused participants then also recorded their current feelings about the event in hindsight. In the *Fact-Focused* condition, participants recorded emotionally neutral information (e.g., time, location) about the event. Participants in both conditions recorded the total number of times the bad habit was engaged for a given day. After submitting a new entry, participants were instructed to review the summary page with past entries.

Success in reducing the bad habit was measured through an overall subjective goal progress rating, referred to as *self-perceived success* [26]. We also dynamically assessed success from reported daily *Habit Frequency (HF)*, derived from participant logs. *Success Rate* was computed from logs, as the number of days when the participant entirely avoided engaging in the bad habit ($HF = 0$), expressed as a percentage of total daily entries.

Participants also submitted pre-test responses to rank feelings of *Goal Commitment* and *Goal Self-Efficacy*. Prior work [4, 20] has shown that both goal commitment and self-efficacy affect the outcomes of behavior change interventions and we wanted to eliminate these as possible confounds.

Participants

Participants were recruited from an undergraduate psychology course for the opportunity to receive extra credit. They were randomized into the Emotion- or Fact-focused conditions (using <http://www.randomizer.org>) and equalized across gender. The final sample consisted of 19 participants in the Emotion-Focused condition (11 women, mean = 21 years) and 16 participants in the Fact-Focused condition (9 women, mean = 22 years). Participants were blind to which group they were in and were not informed

that there were different groups. Participant ages ranged from 19 to 26 years ($M = 21.43$).

Procedure

All participants were told that the research goal was to track a bad habit that the participant would like to improve. After completion of the online pretest, we emailed participants a web-link to a secure personal online logging template with login information. To maintain compliance, researchers individually contacted participants by phone once a week to confirm that they were consistently submitting entries and to address any technical errors with the online template. We also scanned server logs to determine that participants were indeed making daily entries and correctly following our instructions. Three weeks after the start date, participants were contacted to answer the post-test survey, they were debriefed and given the opportunity to delete or modify any data that they wish to keep private before data analysis.

Instructions and Measures

Pre-test Materials

Participants completed pre-post intervention surveys and a consent form online. The pre-test included a *Goal Characteristics* survey for identifying one specific bad habit to stop or reduce over the study period [26]. Following prior work on intervention methods [22], we asked participants to set specific goals (e.g. reduce smoking to 0 cigarettes per day) that they personally had sole control over and that could be achieved within a 3-week period. We checked that each participant's goal complied before they began the intervention. The pre-intervention survey also included a 9-item Likert scale for *Goal Commitment* ("How committed do you feel to this goal") and *Goal Self-Efficacy* ("The extent to which you feel you have the skills and resources necessary to attain this goal."), following previous goal-pursuit research [4, 20]. After completion of the study, participants submitted a post-intervention survey response to a 9-item Likert scale for *Goal Progress* ("Please rate how much progress you have made toward your goal").

Web-Based Log Templates

Participants submitted daily templates about their targeted habit. The template was hosted on the lead researcher's private website which was SSL-encrypted and password-protected with a 10-digit alphanumeric code. Participants were allowed to edit or delete entries at any time. However an entry timestamp tracked modified or deleted entries allowing us to monitor participants' compliance and consistency of daily entries throughout the study. After submitting a new entry, a confirmation page would immediately display a summary of all previous records. Participants in the Emotion-Rating condition could additionally see emoticons associated with their entries.

Instructions

Participant instructions were embedded within the Fact-Focused and Emotion-Focused logging templates to ensure correct usage. Participants manually logged the total

number of times the habit was engaged each day (*habit frequency*) and described a single event in which they engaged or resisted the habit.

Following classic behavior change approaches, the *Fact-Focused Template* prompted participants for *objective* information related to an event involving the habit (habit frequency, time, location, social context and optional miscellaneous information). Participants were required to provide the following information:

Overall, how many times did you engage in your specified bad habit today?

Now think back to one specific instance when you engaged in that behavior.

- Enter the **time** of the event:
- Enter the **location** where this event occurred:
- Enter **who** you were with at the time:
- (Optional) Record other **miscellaneous** information:

Below is an example of a Fact-Focused Entry for a participant who wanted to reduce smoking. Despite his intentions, he smoked 9 cigarettes overall that day. The log also shows that at 11:30am while at a corporate event he smoked a cigarette in lieu of interacting with coworkers:

Participant #82

Frequency: 9

Time: 11:30am

Location: Company BBQ

Social Company: By myself

(Optional) Miscellaneous: Went to smoke a cigarette by myself because I could not find anyone interesting to talk to

The *Emotion-Focused Template* directed participants to evaluate habit frequency but also to write about the *emotional* content of an event with a brief textual description and rating of mood using a 5-point emoticon scale, ranging from 1 ("miserable") to 5 ("extremely positive"). We are aware that there are more nuanced ways to register emotions but wanted a logging method that was not onerous. Participants were also asked to rate both how they felt at the time of the event, as well as current feelings about the incident at the time of recording. Participants were required to provide the following information:

Overall, how many times did you engage in your specified bad habit today?

Now think back to one specific instance when you engaged in that behavior.

- Write a few sentences describing **how you felt at the time**:
- **Rate how you felt prior to this event**:
- Reflecting on this situation, **write a brief description about your feelings** toward this memory:
- **Rate your current feelings** about this event:

Below is an example of an Emotion-Focused Entry. Participant #25 who wanted to stop eating outside normal meal times, reports a day when she indulged in 8 instances

of snacking. The entry below describes a specific event when she snacked despite her target goal to reduce overeating and describes her feelings about the event both at the time ('neutral') and currently ('negative'):

Participant #25

Frequency: 8

Prior Emotion Rating: 3 (neutral) *I couldn't control myself around the tater tots at work. Every time they came out of the fryer. I had to have one. I feel disappointed in myself because I know tater tots are bad for you.*

Current Emotion Rating: 2 (negative) *Dissatisfied*

On some days, participants successfully abstained from their habit. If a participant abstained (indicated by them entering "0" for Habit Frequency), the template questions changed to record information associated with success. For example, the prompt "Now think back to one specific instance when you engaged a behavior" would modify to "Now think back to one specific instance when you successfully resisted that behavior". This was done to preserve the habit of daily logging even for successful days.

Quantitative Analysis - Behavior Change Metrics

We analyzed pre- and post-intervention survey responses and participant logfiles to quantitatively assess differences between conditions. Six participants did not provide responses to the post-test survey. However, the logfile data for these 6 participants were retained for the analysis of daily *Habit Frequency* and *Success Rate*. We tested for differences between conditions for 3 dependent variables:

Self-Perceived Success: Differences in post-test responses for an overall assessment of goal progress ("Please rate how much progress you have made toward your goal").

Habit Frequency: Differences in *Habit Frequency* (HF) as calculated from daily logs.

Success Rate: For each participant, we calculated the percentage of entries with a zero habit frequency count (*successful days*) out of total participant entries. For example, if a participant logged 5 days with 0 HF counts out of 20 days logged, their success rate is 25%. Days with a non-zero habit frequency are referred to as *unsuccessful days*.

Self-Perceived Success: Emotion-Focused Logging Is Associated with Greater Perceived Progress Towards Goals

We first analyzed post-test responses to the goal progress question ("Please rate how much progress you have made toward your goal") with responses given on a 9-point Likert scale. We wanted to know whether Emotion-Focus promoted greater perceived progress. Levene's test showed heterogeneity of variances ($p > .05$), so the data was analyzed with Welch's t-test. As expected, mean goal progress for the Emotion-Focused (Mean = 5.82, SD = 1.47) was significantly greater than the Fact-Focused condition (Mean=4.08, SD=2.47, *Welch's* $t(16.479)=2.186$, $p = .044$).

Habit Frequency

Habit frequencies (HF) scores were extracted from logfile entries. Again we wanted to know whether Emotion-Focus reduced habit frequency. HF scores were not similarly distributed between conditions and HF scores for Fact-Focused participants were positively skewed. A logarithmic transformation was applied to the data to normalize distribution. Participants in the Emotion-Focused condition had a lower average daily HF count (Mean = -1.7, SD = 1.45) than Fact-Focused participants, though this fell short of statistical significance (Mean = 3.6, SD = 3.84) ($t(33)=-1.631$, $p = .112$).

Success Rate: Emotion-Focused Condition Promoted a Greater Proportion of Successful Days

A Mann-Whitney U test was conducted to determine differences in success rate between Emotion-Focused and Fact-Focused participants. We used a non-parametric test as both distributions were non-normal. Median success rate was statistically significantly higher for Emotion-Focused participants (Median=27.78%) than for Fact-Focused participants (Median=6.25%), $U = 84$, $z = -2.265$, $p = .024$.

Emotion Ratings: Participants who experienced most difficulties were happiest when they succeeded

Nineteen participants in the Emotion-focused condition provided emotion ratings. Participants retrospectively reported emotional state at the time they engaged their habit (*prior emotion*) and at time of recording (*current emotion*).

We explored the relation between emotion ratings and habit success. The difference between current emotions for unsuccessful vs. successful days was significant, with successful days having a more positive mean current emotion rating (Mean = 4.13 SD .53; CI 3.87 – 4.39) than unsuccessful days (Mean = 2.977, SD = .68, CI 2.65 – 3.31, $t(18)=33.801$ $p < .0005$). Prior feelings were similarly influenced by success; successful days had a more positive average prior emotion rating of 3.83 (SD = .659, CI = 3.51-4.15) vs. unsuccessful days (Mean = 3.09, SD = .404, CI 2.89-3.29, $t(18)=25.33$ $p < .0005$).

There was also a significant correlation between emotion ratings on successful days and overall *daily habit frequency*. This was true for both current and prior emotions (both $r_s(17) > .456$, $ps < .050$). This indicates that participants who engaged their bad behavior more frequently expressed heightened positive reactions when they achieved a successful day; perhaps their rare successes made them more prone to celebrate.

We next conducted checks to rule out various confounding factors that might otherwise explain our results.

Goal Intensity: One possible explanation for our results is that participants in the two conditions set differently challenging goals. From the pre-intervention survey, participant goals were independently coded as either stop goals ("I will smoke 0 cigarettes per day.") or reduction

goals (“I will cut down to 3 cigarettes per day.”). To assess whether differences were attributable to initial goal intensity, we ran a t-test finding no difference in stop or reduction goals across conditions ($t(33)=.151, p=.739$). A Pearson correlation showed a trending relationship between goal intensity and *self-perceived success* with reduction goals corresponding to higher self-perceived success ($r(29)=.384, p=.04$), though no correlation was found between goal intensity and any other dependent variables (all $ps>.651$). However intensity alone cannot explain our results; when we controlled for goal intensity by including it as a covariate in an ANCOVA, there was still a strong significant relationship between condition and *self-perceived success* ($F(26,29)=3.246, p=.019$).

Conscious vs. Unconscious Habits: Participants chose habits that include both consciously and unconsciously triggered behaviors. A minority of participants ($n=6$) targeted habits that were automatic, unconscious behaviors such as instances of nail biting or hair pulling. We coded conscious versus unconscious behaviors as *habit type* and ran a series of two-way ANOVAS with Condition to account for any interaction effects. We found no effects of *habit type* on *success rate*, *habit frequency* or *self-perceived success* (p -values ranging from .287 to .796).

Compliance & Engagement: Compliance was measured by two usage parameters: number of entries and word count per participant. A t-test showed no significant difference in number of participant entries between conditions ($t(33)=.527, p=.602$). However, there was a significant difference in average word count per entry with Emotion-Focused participants having an average of 54.56 ($SD = 20.38$) words per entry and Fact-Focused participants having an average of 18.09 ($SD = 8.22$) words per entry, $t(24.528)=7.144, p<.0005$. Again, however word count cannot explain our results. Controlling for condition, word count did not have a significant correlation with *daily habit frequency*, *success rate*, *self-perceived success* or *percent change* (p -values ranging from .248 to .820).

Goals Differences: To ensure successful randomization between conditions, we conducted t-tests to assess whether pretests of *Goal-Commitment* or *Goal Self-Efficacy* were disproportionately allocated between conditions. The t-tests showed no differences between conditions (both $ts<1.2, ps>.2$). We also examined *Goal type* finding it was not equally distributed across conditions. However a series of t-tests showed that *Goal Type* did not affect any of the dependent variables. Again goal differences cannot explain our results.

Linguistic Analysis: Emotions Promote Insight Especially Experiences of Failure

We used the Linguistic Inquiry & Word Count tool (LIWC) to characterize differences between Emotion- and Fact-Focused conditions. Using LIWC, we confirmed that the experimental manipulation was successful: entries from the Emotion-Focused condition had a significantly higher

percentage of affective language (e.g. “angry”, “cheerful”, “sad”), $M = 4.45\%$ greater, $SE = 0.84\%$, $t(33)=5.301, p<.0005$.

We then went on to explore underlying *mechanisms* for behavior change. We entered this analysis with the expectation that emotion-focused participants would have greater insight into behaviors and differences in the type of emotional language used depending on success. However, we also explored additional mechanisms that were subject to Bonferroni corrections. For these analyses the cutoff p -value for significance is 0.0083 (adjusted for 6 additional post-hoc tests).

Greater Use of Insightful Language in Emotion-Focused Condition

As expected, Emotion-Focused entries had a significantly greater number of words describing complex mental processes (e.g., “analyzed”, “evaluate”, “infer”, “know”), $M = 10.55\%$ greater, $SE = 1.16\%$ ($t(33)=9.062, p<.0005$, particularly insight terms (e.g. “accept”, “admit”, “realize”, “solve”, “think”), $M = 2.96\%$ greater, $SE = 0.3\%$, $t(26.980)=9.906, p<.0005$.

For all participants, the use of such complex mental process language was associated with higher *success rates* ($r_s(33)=.383, p=.023$) and higher *self-perceived success* ($r(27)=.40, p=.031$). Of the mental process subcategories, insight terms were most influential, corresponding to a higher *success rate* ($r_s(33)=.463, p=.005$) and *self-perceived success* ($r(27)=.418, p=.024$). These differences confirm that encouraging participants to engage Emotions led them to reflect more deeply and better understand the consequences of their bad habits, which in turn reduced those habits. Here we see an example of such reflection helping reduce a snacking habit.

Participant #35

Frequency: 0

I *think* to myself *is it worth it, and that helps me resist* to not snacking if I'm not hungry!

Prior Emotion Rating: 4 I stop and *think* about it, which makes me *aware*!

Current Emotion Rating: 5 That's going to be my challenge of the day!

The participant explores the future emotional impact of her snacking habit (“*is it worth it?*”). Thinking about consequences helps her resist indulging (“*and that helps me resist to not snacking if I'm not hungry*”). This improves her feelings both at the time, and when she makes her log.

Reflection Behavior for Successful and Unsuccessful Days

Failure: Past Reflection and Sadness about Failure

Promote Change: Entries for unsuccessful days that featured strong negative emotions (e.g. “crushed”, “distressed”, “grief”) had a significant relationship with *success rate* ($r_s(33)=.433, p=.009$) and higher *self-perceived success* ($r(27)=.415, p=.025$). This suggests that

participants especially benefitted from engaging negative affect or regret about failures.

For example, Participant #29 displayed extremely negative responses to unsuccessful days when he would uncontrollably nap, yet concluded the study with a higher than average *success rate* (52.83%) and *self-perceived success* (7). In one log entry, Participant #29 notes: “*I’m disappointed in myself. I was tired from the last few days and it looks like it culminated into me just giving in with a nap. So stupid of me.*” His emotion ratings were also highly remorseful and self critical:

Prior Emotion Rating: 2 (negative) RGH HHHHHHHH. Frustrated. So. SO. SO. FRUSTRATED.

Current Emotion Rating: 1 (miserable) I didn’t resist. I hate everything right now.

Interestingly, post hoc analyses showed greater use of inhibition terms (“stop”, “deny”, “avoid”) trended to a lower *success rate* ($r_s(33)=-.419, p=.012$) and significant increase in *habit frequency* ($r_s(33)=.572, p<.0005$). This finding relates to previous work showing that planning focused on negating a behavior (e.g., “If my friend offers me a cigarette, I will **not** smoke it.”) causes an ironic rebound effect to actually increase habit frequency [2]. Our participants who emphasized the need to stop a behavior without identifying a substitute response or alternative recourse may have strengthened the bad habit, resulting in worse performance.

Qualitative Analysis: Follow-up Interviews

Two weeks after the study, all participants were contacted to participate in a voluntary follow-up interview. A total of 12 (Emotion-Focused: 10, Fact-Focused: 2) volunteered to discuss their experiences and provide design suggestions. All interviews were conducted individually over Skype and were audio recorded and transcribed.

Perceived Relationship Between Emotions and Target Behavior

Participants in the Emotion-Focused condition were questioned about the relationship, or lack thereof, between emotions and habit engagement. Participants generally acknowledged that affect played a key role in the days they engaged in their bad habits, as well as larger consequences.

EF#29: “*I’m looking at a couple of days worth of entries with kind of like “Oh, I’ve had a lot of naps in the course of the first week of entries”... I kind of realized... “What am I doing with my life?” I thought about how to do something about it and I do actually see myself kind of happier when I’m not taking naps...*”

Some participants did not view affect as a significant factor in their habits. Participant EF#32 stated that he “doesn’t really feel anything” and doesn’t feel guilt for his behavior because he does not view his habit (excessive video gaming) as an important problem. Though this was a minority opinion (N=3 interviews), it suggests that not all

will benefit from this type of intervention and that the effectiveness of emotion-tracking may be dependent on the perceived importance of changing the behavior.

Emotion-Tracking for Raised Awareness:

A majority of participants in the Emotion-Focused condition (7 of 10) had highly positive responses to emotion-tracking and believed that it played a key role in modifying their behaviors. Many discussed the importance of raised awareness as a result of logging emotional states.

EF#29: “*...it just helped contextualize it a little bit...for why I’m doing it... more than kind of what I’m doing, but how I feel when I’m doing it and how the feelings connect to what I’m doing... it helps provide a fuller picture of things as opposed to just being about the bad habit.*”

Participant (EF#27) noted that emotion-tracking made affect “*more salient*” and helped to make it “*more obvious what was happening*”. While this was considered “*eerie to recognize*” she found it helpful “*to make the connection with [a] bad habit--that it’s happening when you’re in a bad mood...It became easier to be aware of it, which was important in the first part, because usually I wasn’t aware of it. And then, being aware of it could, or would, make me stop doing it.*” Participant EF#37 also specifically found the reflection format easier for analyzing his behavior because he was not “*blinded*” by his emotions at the time of the event. Similarly, all interviewees reported a preference for making event entries after the fact because it allowed them to assess their habit behaviors more holistically.

Participants in the Fact-Focused condition were not asked specific questions about Emotion-Tracking features. Strikingly, however, a Fact-Focused participant spontaneously responded to a question about system design improvements by suggesting we add emotion tracking:

(FF#22): “*There should have included...Maybe how it made us feel...probably not open-ended about how it made me feel, but choose how from four: bad, good, okay...You know, to see how people feel about the bad habit.*”

Failure vs. Success Entries

Participants were also questioned on whether they found success or failure entries more important at promoting change. Despite our quantitative results showing that reflecting on unsuccessful entries played an important role in reducing habits, a majority of participants who were interviewed (N=5) communicated a preference to record successful entries only. In total, 3 participants prioritized unsuccessful entries as more important for change and 4 participants thought both types of entries were equally important.

DISCUSSION AND CONCLUSIONS

Our goal was to evaluate a system that encourages users to associate a bad habit with long-term emotional consequences, rather than the generally positive association of immediate relief. Our results suggest a promising new direction for behavior-change technologies. We deployed a

novel system intervention to evaluate the impact of Emotion-Focused vs. Fact-Focused logging of a bad habit for 3-weeks. Raised emotional awareness reduced the persistence of bad habits and improved goal pursuit for a wide range of target goals.

We also learned more about *why* this happened. Emotion tracking promotes deeper insight into problematic behaviors. It encourages users to think beyond *what*, *when* and *where* a behavior occurred but also *why*, drawing broader lessons for the future, and increased awareness of the emotional consequences of detrimental behavior. Failures seem to be particularly motivating. Reflection on past failures induced sadness or regret which was strongly associated with greater self-perceived success and number of days with absolutely no habit engagement. For successful days, the relationship between behavior and habit change was less consistent. This suggests that remorse may be a more powerful motivator to reduce a bad habit, confirming previous literature [6]. Interestingly, these quantitative results partially conflict with our user interviews where a slight majority of participants expressed a preference for seeing successful records. This discrepancy suggests that despite user preference, behavior-change technologies may benefit by encouraging active reflection on failures.

Our results suggest a number of design implications to extend current approaches to behavior change. The success of emotion tracking indicates that this should be included in future systems. However future work will be necessary to determine whether this benefit arose from emotion-tracking or simply because Emotion-Focused participants also engaged in more extensive self-reflection. In addition (and contrary to the opinions of some of our study participants), it seems critical to expose users to failures, as these promote greater motivation and insight than successes. System defaults might therefore direct users to focus on failures not successes. In addition, consistent with other quantified-self systems [7, 10], our users expressed a desire for computational tools enabling them to better analyze relations between emotions and behavior. Users wanted to be able to sort entries based on emotion, as well as to explore behaviors that promoted extreme emotions. Our results also speak to automatic logging of emotions using physiological measures. While these emerging technologies apparently address some of the problems with our application by reducing demands on users to deliberately log emotions, we would caution against them being directly adopted. Our results indicate that active, conscious reflection on events may be an important facilitator of behavior change that automatic logging may not provide. This need for deliberate reflection is supported by prior work highlighting the need for conscious logging in the expression and analysis of emotions for affect regulation [17].

As advocated by other HCI researchers [18] we designed a study to systematically evaluate one component of behavior-change technology. Future systems may benefit by integrating this single component into a more holistic intervention for various targeted behavior change interventions.

Limitations: Participants in each condition were prompted to engage in different degrees of free writing and self-reflection. While participants in the Emotion-Focused condition were required to free write their feelings and thoughts, participants in the Fact-Focused condition were presented a “Miscellaneous” field as an optional place to free write. We need to tease apart the separate contributions of self-reflection formats and emotional tracking. In addition, we need to further explore different goal types. Participants’ goals and habits varied considerably, although we did not find objective differences when we analyzed different goal types. Bad habits vary significantly in their automaticity, and susceptibility to our conscious plan based approach. For example, past work has found bad habits with strong physiological addictive qualities (e.g., smoking or overeating) are more resistant to conventional behavioral interventions [14]. Our intervention was also short term. We need to explore whether improvements can be maintained long term as well as whether participants will comply longer term with the logging we asked from them.

In conclusion, our results suggest a highly promising direction for behavior-change technologies. We can promote successful behavior change by moving from predominantly cognitive views to better engage users’ emotions, in particular by having users reflect on the consequences of their bad habits, and their past failures to abstain from those habits.

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REFERENCES

1. Abraham, C., & Sheeran, P. (2003). Acting on intentions: The role of anticipated regret. *British Journal of Social Psychology*, 42(4), 495-511.
2. Adriaanse, M. A., et al. (2011). Planning what not to eat: Ironic effects of implementation intentions negating unhealthy habits. *Personality and Social Psychology Bulletin*, 37(1), 69-81.
3. Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2), 179-211.
4. Bandura, A. (1994). *Self-efficacy*. Wiley, New York.

5. Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual review of psychology*, 52(1), 1-26.
6. Baumeister, R. F., et al. (2007). How emotion shapes behavior: Feedback, anticipation, and reflection, rather than direct causation. *Personality and Social Psychology Review*, 11(2), 167-203.
7. Bentley, F., et al. (2013). Health Mashups: Presenting statistical patterns between wellbeing data and context in natural language to promote behavior change. *TOCHI*, 20(5), 30.
8. Bitsmedia (2014) Quit Pro (Version 2.2.1) [Mobile app.] Retrieved from <https://itunes.apple.com/us/app/quit-pro-your-smoking-cessation/id336786774?mt=8>
9. Burke, L. E., et al. (2011). Self-monitoring in weight loss: a systematic review of the literature. *Journal of the American Dietetic Association*, 111(1), 92-102.
10. Carroll, E. A. et al., (2013). Food and Mood: Just-in-Time Support for Emotional Eating. In *Proceedings of ACII'13*. (pp. 252-257). IEEE.
11. Carver, C. S., et al. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: the BIS/BAS scales. *Journal of personality and social psychology*, 67(2), 319.
12. Consolvo, S. et al., (2009). Theory-driven design strategies for technologies that support behavior change in everyday life. In *Proceedings of CHI'09*.
13. Eysenbach, G. (2005). The law of attrition. *Journal of medical Internet research*, 7(1).
14. Gould, R. A., et al. (1993). A meta-analysis of self-help treatment approaches. *Clinical psychology review*, 13(2), 169-186.
15. He, H. A. et al., (2010). One size does not fit all: applying the transtheoretical model to energy feedback technology design. In *Proceedings of CHI'10*. (pp. 927-936). ACM.
16. inSight One, Inc. (2012) Mood Runner (Version 1.03) [Mobile app. software.] Retrieved from <https://itunes.apple.com/us/app/mood-runner/id404822869?mt=8>
17. Isaacs, E., et al. (2013). Echoes from the past: how technology mediated reflection improves well-being. In *Proceedings of CHI'13*. (pp. 1071-1080). ACM.
18. Klasnja, P. et al., (2011). How to evaluate technologies for health behavior change in HCI research. In *Proceedings of CHI'11*.
19. Li, I. (2012). Personal informatics & context: Using context to reveal factors that affect behavior. *Journal of Ambient Intelligence and Smart Environments*, 4(1), 71-72.
20. Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American psychologist*, 57(9), 705.
21. Lopez et al., (2006). Global and regional burden of disease and risk factors, 2001: systematic analysis of population health data. *The Lancet*, 367(9524), 1747-1757.
22. Martin, G. L., & Pear, J. (1992). Behavior Modification: What It Is and How To Do It, 9/E.
23. McFall, R. M. (1970). Effects of self-monitoring on normal smoking behavior. *Journal of Consulting and Clinical Psychology*, 35(2), 135.
24. Pennebaker, J.W., et al. (2007). The development and psychometric properties of LIWC2007. [Software manual]. Austin, TX (www.liwc.net)
25. Perugini, M., & Bagozzi, R. P. (2001). The role of desires and anticipated emotions in goal-directed behaviours: Broadening and deepening the theory of planned behaviour. *British Journal of Social Psychology*, 40(1), 79-98.
26. Powers, T. A., et al. (2005). Implementation intentions, perfectionism, and goal progress: Perhaps the road to hell is paved with good intentions. *Personality and Social Psychology Bulletin*, 31(7), 902-912.
27. Prochaska, J., et al. (1997). The transtheoretical model of health behavior change. *Am. J. Health Promot.* 12, 1, 38-48.
28. Runtastic. (2014) Runtastic (Version 5.3) [Mobile app.] Retrieved from <http://itunes.apple.com/us/app/runtastic-gps-running-walking/id336599882?mt=8>
29. Thriveport (2013) MoodKit (Version 2.2) [Mobile app.] Retrieved from <https://itunes.apple.com/us/app/moodkit-mood-improvement-tools/id427064987?mt=8>
30. Webb, T., et al. (2010). Using the internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. *Journal of medical Internet research*, 12(1), e4.