Vol.2022-HCI-196 No.19
2022/1/12

Acoustic-Based Mood Tracking as a Means of Emotion Regulation

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Abstract:
In this report, we present a computer-mediated mood self-tracking application with a built-in interactive music creation feature called TENOR. Users capture and classify their emotional state through the creative process of generating a song on a simple grid-type interface. The act of cascading their emotions into a subjective and non-invasive format is meant to cultivate a greater self-awareness that may in turn assist in improved emotion regulation. Existing mood tracking tools fall short in providing users with classification methods that move beyond the restrictiveness of labels; TENOR has the goal of subverting this by empowering the user with the ability to define their emotions on their own terms, which in turn encourages them to reappraise their feelings without shame.

Keywords: Human-computer interaction, self-tracking, mental health, mood tracking, emotion regulation

1. Introduction

Researchers in the field of human-computer interaction (HCI) have long been delving into the measurement, tracing, and quantification of emotions for the sake of producing technological interventions for mental health [1], [2], [3]. Electronic and mobile healthcare solutions have been designed for both individuals with psychiatric illnesses [4], [5], [6], [7] and for the general population [8], which is indicative of its value as an avenue for improving wellbeing across a variety of lived experiences.

The Majority of experimentation within the subdomain of HCI for mental health is centered on the self-tracking of emotional states [9]. While these systems have shown promise in assisting in emotion regulation and the facilitation of psychiatric treatment, there are significant issues and concerns hindering its progress. One is the potential harm that self-tracking poses as a result of pushing externally-derived social standards for emotional stability [10], which users may become pressured to conform to. Studies have shown that users of self-tracking technologies may feel worse upon seeing the trends and patterns in their tracking results as it does not always reflect their efforts taken to perform well or to take proper care of themselves [8]. Another point of focus is the unexplored territory of emotion reappraisal and repression, both key aspects of emotion regulation [11], [12], [13]; existing emotion self-tracking technologies fall short in providing opportunities for users to take action to improve their mood or confront their feelings in a productive manner. Such a feature may better incentivize users to track their mood and see the value in the ritual, as greater motivation — even just at the onset of the process — has shown to increase the benefits an individual receives from therapeutic services [14].

To better motivate individuals and maximize their opportunity to improve their emotion regulation habits without imposing normative ideas of wellbeing improvement, we pose the following questions: (1) Could music be a viable alternative for quantifying emotions in a more open-ended manner that goes beyond simply classifying moods as simply "good" or "bad"? Most mood tracking technologies make use of words, colors, and pictures to label emotions, which can be limiting and even restrictive on the user due to its lack of personalization [15]. Another

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potential advantage to using music to track mood lies in its proven usefulness as a therapy tool for mental healthcare clients with low therapy motivation [16]. Users may take joy in the act of creating songs and feel more inspired to track their mood; (2) Could existence of a music prompt assist individuals in recalling their emotions more reliably, therefore increasing the possibility of stirring acts of emotion reappraisal while mitigating repression?

These questions are confronted by the acoustic-based mood-tracking tool, TENOR, which encourages users to create songs as a way to express and annotate their emotional experiences. In this report, we cover the progress that HCI has made in the field of mental health, its many novel contributions to emotion self-tracking, and the gaps that TENOR hopes to fill as a creative-based self-tracking platform that attempts to intervene on the mental health management of users.

2. Literature Review

2.1 HCI and Emotional Health

Emotional health in human-computer interaction has been rapidly gaining traction throughout the years. A 2019 review of the preceding decade of HCI and emotional health research in the ACM Special Interest Group on Computer-Human Interaction (SIGCHI) (https://sigchi.org/) revealed a corpus of 139 papers written on depression, anxiety and bipolar disorder. The majority of these papers focus on automated diagnosis, self-tracking technologies, and assisted therapy for multiple stakeholders ranging from adult sufferers to their respective peers and caregivers [9]. While automated diagnosis is the most prevalent point of focus in this research domain, the second largest proportion of work centers on self-tracking technologies, where a considerable portion deals with emotional states.

2.2 Digital Mood Tracking

There are various dimensional approaches to tracking and mapping emotions. One approach operates on the basis of intensity or activation level (arousal) [17] and pleasurableness (valence) [18], [19]. A third dimension also explored in some models is dominance, which refers to a person's sense of control over their situation [20]. Various studies have designed ways to measure the valence, arousal, and dominance (VAD) of emotions through text mining. Typically a lexicon of words with manually assigned VAD scores is used to calculate a body of text's overall VAD score, such as Warriner et al.'s collection of 13,915 English words [21] or Buechel and Hahn's EmoBank, a corpus of 10,000 English words spanning multiple genres [22]. Experiments utilizing VAD have enabled researchers to provide more context to the productivity levels of users and the emotional factors influencing their efficiency at work [23], [24]. By assessing their valence, arousal, and dominance levels through text found in written issue reports, one study was able to determine what circumstances allow software engineers to thrive and what struggles give them pause [25]. The results, however, were still impacted by the fact that the lexicon employed was for general-purpose use and therefore had a chance of misrepresenting the VAD score of certain words that possessed a different value from a software engineering context.

Other forms of digital mood tracking employ more physiological sensing to determine emotional states through either wearables or GPS tracking. Smartphone GPS data can intimate the emotional state of the user based on their physical activity, movement patterns, and travel frequency, although such factors may not always determine a person's level of social interaction with others [26], [27], [28]. Biosensors that track EEG, heart rate variability (HRV), and skin conductance are another non-invasive form of emotion sensing that allows users to track their emotional fluctuations without having to directly interact with a machine or application [29], [30]. While these can provide real-time data on users' emotional fluctuations, advanced programs and analyses are required to parse them into digestible information and such items may be expensive to create, monitor, and purchase; other issues such as the feasibility of long-term use and the immense granularity of the data are two other matters of concern [31].

2.3 Mobile Mood Tracking

A sweeping issue among the technologies mentioned above is accessibility: Digital mood tracking via VAD, GPS tracking, or biosensing requires enormous amounts of data and analysis to be of use and can be both expensive and taxing on the user over a long-term period. Mobile mood tracking is popular as a result due to the ubiquity of smartphones and its ease of use [32], [33], [34], but little research has been conducted to assess the clinical benefits of the more mainstream applications available on mobile app stores [15]. It is difficult to incentivize users to track their mood or maintain the habit of tracking due to the complexity of commonly-used mood measures [35], and many mood tracking applications make use of emotion annotation methods that can be limiting on the user due to a lack of diversity and personalization options for mood classifiers [15].

A feature analysis surveying the characteristics of 32 mobile mood-tracking applications found that these platforms generally involve four stages: **Preparation**, **Collection**, **Reflection**, and **Action** — Preparation serves as the instructional portion of the process, in which users are given a motivation to track their mood; Collection refers to the method in which the user's mood data is aggregated; Reflection is how the application visualizes and outlines the user's mood data through graphs or charts; and Action is where the user is offered assistance or recommendations on how to improve their mood based on their inputs [15]. Results showed that very few applications had a motivating force for users to track their emotions. Users require more "priming" and engagement in order to build and sustain the habit of mood tracking, most especially considering the struggle those with mood disorders often experience with forming routines [4].

We identified two key issues in existing mood-tracking technologies: (1) The lack of an open-ended and flexible labeling system for emotions, and (2) the absence of sufficient follow-through after the act of self-tracking that prompts users to properly evaluate their mood data. These concerns formed the foundations of our tool, TENOR.

3. Overview of TENOR

TENOR is a mood-tracking application that employs music creation as a means of classifying emotions. Users are encouraged to translate their emotions into songs on a 256-key virtual drum pad (Figure 2), annotate them with the use of an emotional word bank (Figure 3), and then revisit them at a later date as a form of emotion reappraisal as seen in Figure 4 and Figure 5. A 12-item two-dimensional valence and arousal matrix was used to fill the emotional word bank, with each quadrant representing the intensity-to-pleasure scale of each emotion (Figure 1).

Emotions are not confined to binary conceptions of "good" and "bad" [10]. They are highly subjective experiences whose valences alone cannot dictate their benefit or detriment. Positive emotions can be an early warning sign for manic episodes in those with bipolar disorder [36], and the processing of negative emotions has shown to help build resilience and problem-solving skills in individuals [37]. TENOR encourages users to do away with normative ideas of "positive" and "negative" emotions and instead decide for themselves how to best define and interpret them.

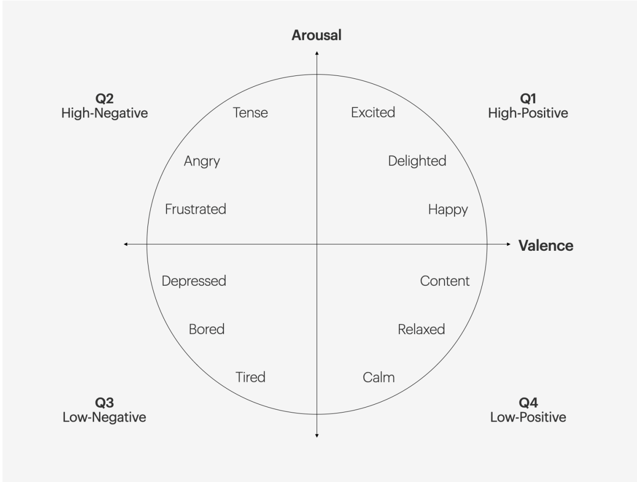

Fig. 1 Two-Dimensional Valence and Arousal Matrix [38].

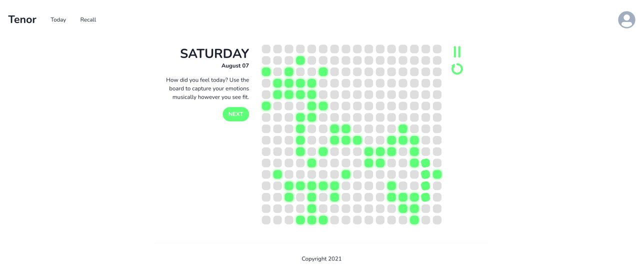

Fig. 2 TENOR Music Grid

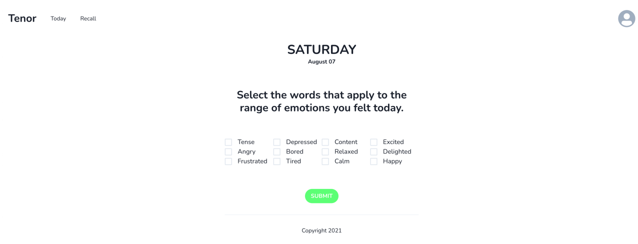

Fig. 3 TENOR Emotional Word Bank

4. Testing and Observations

An experiment was conducted with 19 test subjects over a two week period, 2 of which dropped at the beginning of the study. An untreated setup using only the emotional word bank was measured against a treated setup that included the music creation interface. 9 users were given the treated setup in the first week and the untreated setup in the second week, while the remaining 8 were given the opposite sequence. Each week, users were given Monday

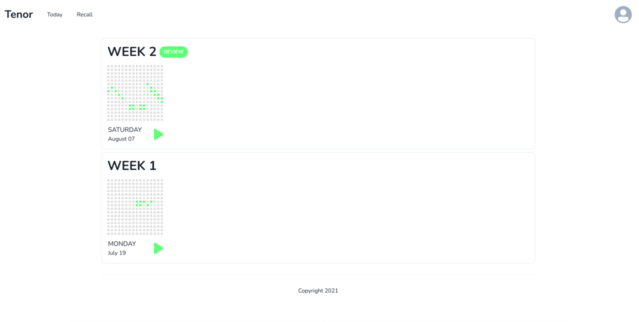

Fig.4 TENOR Song list

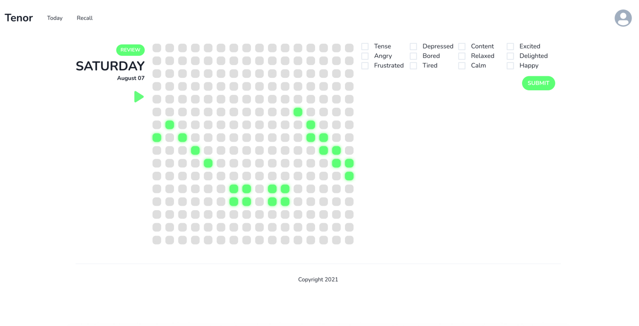

Fig.5 TENOR Recall Test

and Tuesday to warm up to the process of logging their emotions and had Wednesday as the official input day. Users had to recall their Wednesday emotions on Sunday after three days of rest.

In order to investigate the impact of test mode on the recall quality of emotions with respect to their valence quadrant, we constructed a mixed effects model where recall instances were broken up into eight groups: The four valence and arousal quadrants for each testing mode (Table 2). We then fit a mixed-effects model with correctness as binary dependent variable and the eight quadrant/testing scenarios as independent variables. Participants were controlled as a random factor in the model.

To investigate whether valence quadrants affected recall quality, we divided each recall instance into eight groups, the four valence and arousal quadrants for both the treated and untreated setup (Table 2), and constructed a mixed effects model. We fitted the model with correctness as the binary dependent variable and the eight quadrant/testing scenarios as the independent variables. Participants served as a random factor. Results showed that three of the quadrants were significant against the dummy variable (Table 1). Although the psuedo R-squared was rather small at 0.13, it's an understandable result given the narrow participant pool and demonstrates that valence and mode have a potential impact on recall quality of users.

Table 1 Significant Pairwise Test

Results 1	**Estimate**	**p.value**
0-1	-3.42202	0.0037
0-2	-1.56548	0.0432
0-6	-1.68209	0.0296
1-3	2.25845	0.0433
1-4	2.21139	0.0492
1-7	2.29272	0.0414

Table 2 Quadrant and Mode Combinations

No.	**Combination**	**No.**	**Combination**
0	Q1 + Control	**4**	Q1 + Treated
1	Q2 + Control	**5**	Q2 + Treated
2	Q3 + Control	**6**	Q3 + Treated
3	Q4 + Control	**7**	Q4 + Treated

We delved further into the impact of quadrants and testing mode through a pairwise test without adjustment. Due to low sampling power and number of comparisons, we chose not to use a post-hoc adjustment. These results should thus be seen as preliminary and are used to justify future research.

The results of the pairwise test (Figure 6) revealed six significant pairs: Q1 in Control v. Q2 in Control [0,1], Q1 in Control v. Q3 in Control [0,2], Q2 in Control v. Q4 in Control [1,3], Q1 in Control v. Q3 in Experimental [0,6], Q2 in Control v. Q1 in Experimental [1,4], and Q2 in Control v. Q4 in Experimental [1,7].

Users were able to recall their emotions consistently across all valence-quadrants in the treated setup while a high discrimination was detected in the results of the untreated setup. Participants performed best in the treated setup when remembering high-arousal positive emotions and low-arousal positive and negative emotions, but had recalled at a diminished capacity when confronted with past high-negative emotions. This may be due to a possible dampening effect on negative high-arousal states caused by the delight factor attached to creating and listening to music.

Although this dampening effect poses issues in processing and reappraising high arousal negative emotions, the music interface remains superior in its ability to induce recall across the board. Engaging interfaces that prioritize user involvement and agency play a significant part in improving and maximizing user outcomes; this study would benefit from conducting further experiments with larger participant pools in order to probe into this further.

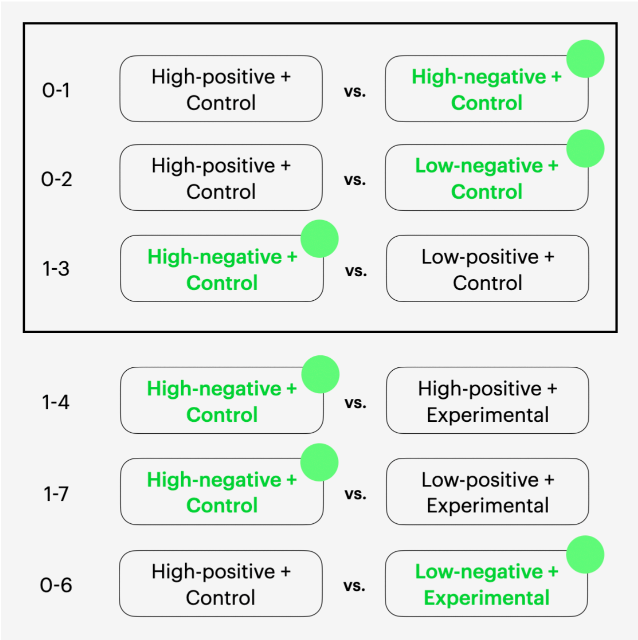

Fig.6 Pairwise Test Results. The green dots refer to the better performing quadrant and mode combination within each pair. The box highlights the discrimination within the control setup.

5. Use Cases and Future Challenges

5.1 Use Cases and Unique Approaches

TENOR is designed to be an alternative mood tracking application that maximizes accessibility while minimizing user fatigue through the simplicity of its system. Its use of a music creation feature to classify emotional states is meant to empower users to generate more subjective labels for their emotions that are best interpreted by them. There are several ways of applying TENOR:

Detecting Trends in Music Creations and Their Mood Prompts. Data from TENOR's validation study can be used to examine if there are typical patterns in the songs created by users when labeling their emotions. This can then be transformed into an algorithm capable of mapping out TENOR songs that were prompted by an emotion. These mapped out songs can later on be fed back into another pool of test subjects to confirm if they can accurately identify the emotion being expressed by the music.

Using Mood Tracking and/or Emotion Induction to Increase Productivity. Valence, arousal, and dominance have shown to influence memory and productivity [23], [24], [25]. It may possible to use TENOR or a similar iteration of the application to induce emotions that assist in learning and skill acquisition.

5.2 Potential Challenges

This tool may best benefit individuals suffering from neurological and psychological conditions, most especially ones that are accompanied by struggles with emotional acuity (e.g. autism spectrum disorder, substance abuse, disordered eating [39], [40], [41]) as many mood tracking tools exist that cater specifically to certain mood disorders [42], [43], [44]. However, receiving ethical clearance to test with such targeted sample would be difficult. Currently, there is a lack of clinical trials and collaborations with medical researchers in the field of HCI and emotional health due to the lengthy process of receiving validation and clearance [9], and mobile mood-tracking applications themselves fall short in providing clinical-based evidence of their design benefits [15].

Another option and subsequent limitation involves TENOR's applicability as a therapy platform for children and adolescents. Adult sufferers and caregivers make up the majority of participant samples in studies on HCI technologies for mental health [9], while children and adolescents are rarely explored in spite of the fact that they also experience illnesses like depression, anxiety, attention-deficit hyperactivity disorder (ADHD), obsessive-compulsive disorder (OCD), and even post-traumatic stress disorder (PTSD). Working with children and adolescents would be a great way to test whether TENOR's non-invasive interventions into emotion tracking could benefit them without compromising their mental and psychological state.

6. Conclusion

Emotions are convoluted and unpredictable, but the brave decision to tackle them often leads to significant returns in one's personal growth and life satisfaction. Addressing difficult feelings includes suppression as a means of self-preservation and regulating behavior [13], [45], [46], [47] but also involves confronting them for the sake of gaining richer perspectives [37]. Ultimately, the practice of emotion regulation and replacing suppression with acceptance can lead to more efficient coping mechanisms against challenges [48]. All of this points towards a well-founded need for mobile health technologies that move beyond mere mood tracking and incorporate ways for users to improve their emotional acuity.

In this report we presented TENOR, which has shown promise in its ability to generate and sustain the interest of users and encourage recall of emotions across valence and arousal states by using music creation instead of simple mood tracking. However, the narrow sample size calls for additional validation studies with a larger participant pool. There is a dampening effect on high-arousal negative emotions that is potentially being caused by the delight factor found in creating music; future studies will endeavor to address this and further investigate what elements of the system's features impact emotion regulation and mental health, if any.

Acknowledgments

This work is supported by JSPS KAKENHI Kiban B (Grant Number: 20H04213).

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