

# Can You Smell My Emotion? Exploring Volatile Organic Compounds as Emotional Biomarkers

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## ABSTRACT

This study investigates the potential of volatile organic compounds (VOCs) in human breath as biomarkers for detecting emotional states. Using short film clips as emotional stimuli, the research assessed physiological responses linked to specific emotions. A low-cost detection system was developed employing saliva pH analysis and breathalyzer-based blood alcohol content detection. However, limitations such as low instrument sensitivity, a small sample size ( $n=5$ ), and indirect detection methods constrained the ability to establish definitive associations. The findings indicate that while VOCs show promise as biomarkers for emotional states, the methods used lacked sufficient precision to fully capture these relationships. Future research should utilize advanced detection tools to target and measure specific VOCs with higher sensitivity. This study provides a foundation for advancing research into emotion detection via VOC analysis with potential applications in healthcare, mental health, and human-computer interaction.

## CCS CONCEPTS

• Human-centered computing → Laboratory experiments.

## KEYWORDS

Emotion, Volatile Organic Compound (VOC), human exhaled breath, saliva

## 1 INTRODUCTION

In a social context, the ability to recognize emotions is a crucial skill, as it promotes effective communication and fosters healthy interpersonal relationships [33]. Recently, the study of human emotion detection has gained significant attention due to its growing importance in advancing human-computer interaction (HCI) designs for feedback, analysis, and adaptive system responses [1, 36]. Various sensing and recognition techniques have been explored to achieve this, including electroencephalography (EEG), electrocardiography (ECG), skin resistance or temperature measurements, heart rate variability (HRV), respiration rate analysis, electromyography (EMG), as well as machine learning applications focused on facial expressions and body motion analysis [1, 16].

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However, while methods such as facial expression analysis and physiological signal monitoring are well-established, a lesser-explored modality is the analysis of body odors, including the VOCs (volatile organic compounds) emitted from human breath, sweat, and axilla, which may carry emotional information. This lack of exploration can largely be attributed to the technical challenges involved in detecting trace-level chemical compounds using cost-effective and portable detection technologies. Previous evidence supports that emotions can indeed be communicated through chemosignals or body odor. For instance, studies have shown that humans can perceive fear [20], stress [19], and happiness [5] through olfactory cues.

The human body releases VOCs from various biological processes through breath, sweat, and other excretions, and these compounds can act as biological markers that reflect a person's physical or emotional state [32]. For instance, trained dogs have been shown to detect diseases by sensing these volatile compounds [24]. Among these compounds, key VOCs include isoprene (12–580 ppb), acetone (1.2–1,880 ppb), ethanol (13–1,000 ppb), methanol (160–2,000 ppb), and other related alcohols, which are present in human breath [12].

Traditionally, methods to analyze VOCs in exhaled breath rely on highly specialized analytical technologies such as gas chromatography (GC) and mass spectrometry (MS) [12]. Other established techniques like proton-transfer-reaction time-of-flight mass spectrometry (PTR-TOF-MS) have also been adopted to assess VOCs in ambient air or human breath [10, 29]. However, these methods tend to be expensive, bulky, and not suitable for integration into portable, low-cost applications, particularly for HCI purposes. Portable electronic nose (eNose) systems, which include sensors such as metal-oxide semiconductor (MOS) sensors, piezoelectric sensors (e.g., SAW and QCM), electrochemical sensors, and optical gas sensors, have become increasingly popular as alternatives due to their reduced size and versatility [9]. However, these systems are often expensive, limiting their accessibility for cost-sensitive applications.

To address these limitations, we introduce a novel, low-cost emotion detection system focused on detecting changes in VOCs in exhaled breath and saliva to identify three basic emotions—happiness, fear, and disgust. This proof-of-concept prototype employs a breathalyzer and pH test paper as its primary detection tools. The choice to include saliva in this system stems from its feasibility in experimental contexts. Unlike breath analysis, which requires sophisticated condensation techniques to isolate VOCs, testing saliva for its pH changes offers a simpler and more practical approach. A previous study identified a significant correlation between breath VOC patterns and pH variations in exhaled breath condensate [7], supporting this choice.

Our system represents an innovative step toward creating a simple, low-cost mechanism for detecting emotions by identifying changes in VOC levels and their effects on biological indicators like pH. While the findings from this proof-of-concept did not demonstrate definitive patterns—likely due to limitations in sensitivity of the breathalyzer, variability across participants, and the small sample size in our experiment—the research advances the exploration of emotion detection through human VOC analysis.

The contribution of this work comprise:

- (1) We present a low-cost approach that combines a breathalyzer and saliva pH analysis to explore the detection of biomarkers linked to emotional states such as happiness, fear, and disgust.
- (2) We establish an experimental framework that uses emotion induction via film clips to evaluate the proposed detection mechanism.
- (3) This study investigates the relationship between changes in saliva pH and VOCs, highlighting the complexity and challenges in achieving a consistent and reproducible emotion detection signal.

## 2 RELATED WORK

Several studies have explored the role of human VOC emissions from both breath and skin in relation to emotional responses. One notable study measured the concentrations of carbon dioxide, isoprene, and acetone in a movie theater setting using PTR-ToFMS and a carbon dioxide detector during the screening of 16 films across various genres, including comedy, horror, and romance [10]. The study found that suspense and comedy scene events exhibited the most significant causal linkages to the observed chemical emissions. Additionally, “injury” scenes were correlated with VOCs such as methanol, acetaldehyde, 2-furanone, and butadiene. Bensemann et al. extended this analysis by applying pattern mining techniques to the same cinema dataset, uncovering that changes in VOC concentrations were objectively related to the content of the movies [9].

Turner et al. conducted a pilot study that analyzed breath samples using thermal desorption combined with gas chromatography-mass spectrometry (GC-MS). They identified six biomarkers associated with psychological stress, including indole, 2-hydroxy-1-phenylethanone, benzaldehyde, and 2-ethylhexan-1-ol [11]. Similarly, another investigation into stress through breath analysis employed GC-IMS, identifying stress-sensitive VOCs such as ethanol, 2-propanol, and 1-propanol [30].

In addition to breath-based studies, research has also focused on VOC emissions from the skin. Lucchi et al. identified three key VOCs, including fatty-acyls derived from lipids such as heptadecane and 2-methylpentadecane, emitted from the foreheads of 35 women during exposure to psychological stress. They also observed a decrease in skin pH under stress [8]. Another study identified six stress biomarkers from skin VOCs: 1,2-ethanediol, acetophenone, heptadecane, hexanedioic acid dimethyl ester, benzyl alcohol, and benzothiazole [26]. Further, saliva has also been investigated as a medium for analyzing emotional states. Studies have found that during anxiety states, salivary pH shifts toward acidity compared to the resting state [4, 27]. These findings support the theory that

stress, fear, and anxiety reduce saliva secretion, resulting in an increased concentration of hydrogen ions and, consequently, greater acidity [27].

These studies collectively highlight the association between VOCs in breath, skin, and saliva with emotional responses and stress, emphasizing the potential of VOC analysis and pH measurement as a biomarker-based method for understanding emotional states.

## 3 SYSTEM DESIGN PROTOTYPE

### 3.1 Overview of the Proposed System

The proposed emotion detection system leverages two primary tools: pH test strips and a breathalyzer, to detect physiological changes associated with emotional states. This low-cost and portable prototype focuses on analyzing saliva pH and blood alcohol content (BAC) percentages based on the exhaled breath as biomarkers for emotions, as shown in the experiment setup in Figure 1. The rationale for selecting these components lies in their simplicity, accessibility, and potential correlation with changes in human physiology under varying emotional conditions.



**Figure 1: Illustration of the components of the detection system, which includes pH test paper, a pH indicator, a breathalyzer, mouth pieces for the breathalyzer. The experiment setup also uses an Apple watch for heart rate measurement, and plastic cups to hold saliva samples.**

### 3.2 Components of the Detection System

**3.2.1 Saliva pH Testing.** The detection of saliva pH was carried out using pH test strips capable of measuring a full range of values from 1 to 14. These strips include a colorimetric indicator, which changes color upon exposure to saliva, allowing for comparison against a reference color scale with a resolution interval of 1 pH unit. Saliva pH testing was chosen due to its straightforward application and its established association with emotional states such as stress and anxiety, which are known to increase salivary acidity [27].

**3.2.2 Breathalyzer for BAC Analysis.** The breathalyzer used in this study measures blood alcohol content (BAC) percentages based on the participant's exhaled breath. Though traditionally designed for alcohol detection, the breathalyzer serves as a cost-effective proxy for analyzing volatile organic compounds (VOCs) present in breath, which may vary under different emotional states. Participants exhaled into the device, and the recorded BAC value was used as an indirect indicator of VOC changes.

## 4 USER STUDY

This section provides an overview of the stimuli used in the user study to induce the target emotions—fear, disgust, and happiness—and outlines the experimental procedure.

### 4.1 Stimuli for Emotion Induction

To elicit the target emotions of fear, disgust, and happiness, we selected six short movie clips that have been previously validated for their effectiveness in evoking these emotions. Two clips were chosen for each target emotion:

- **Fear:** *Lights Out* [3] and *Paranormal Activity* [14], both known for their suspenseful and frightening content.
- **Disgust:** *Pink Flamingos* [15] and *Trainspotting* [17] [31], which contain scenes designed to provoke strong feelings of disgust.
- **Happiness:** *Singing in the Rain* [18] and *500 Days of Summer* [18], selected for their uplifting and cheerful narratives.

These clips were chosen to ensure consistency in emotional induction across participants, leveraging their well-studied impact on emotional states.

### 4.2 Experiment Procedure

Five participants (two females and three males) were recruited for the study. Each participant was seated individually in a controlled environment designed to minimize distractions. To ensure consistent physiological baselines, participants were instructed to avoid consuming food or beverages or engaging in activities that might affect their saliva pH and breath alcohol concentration within two hours prior to the session.

Each participant underwent one trial for each of the three target emotions (fear, disgust, and happiness), with two movie clips used to induce each emotion. The order of trials was randomized for each participant to minimize potential order effects. In total, each participant was exposed to six movie clips.

At the start of the session, baseline measurements of participants' saliva pH, blood alcohol content (BAC), and heart rate were taken while they were in a neutral emotional state. To maintain consistency across all trials, participants were asked to rinse their mouths and drink water before each trial. These steps helped ensure that measurements were not influenced by residual factors from previous trials.

After viewing the two clips for a given emotion in the trial, participants provided a saliva sample, which was immediately analyzed using a pH test strip. The color of the test strip was compared against the pH indicator half a second later to determine the pH value. Participants also exhaled into a breathalyzer to measure their BAC. Additionally, their heart rate was measured by an Apple

watch, and recorded as a supplementary physiological response. Figure 2 illustrates the procedure for one trial.

Following these measurements, participants completed a self-rated questionnaire to assess the intensity of the emotion they experienced. The emotions of fear, disgust, and happiness were rated using a 9-point Likert scale ranging from 0 ("not at all") to 8 ("extremely") [28]. This approach ensured precise quantification of emotional intensity while minimizing the likelihood of response bias.

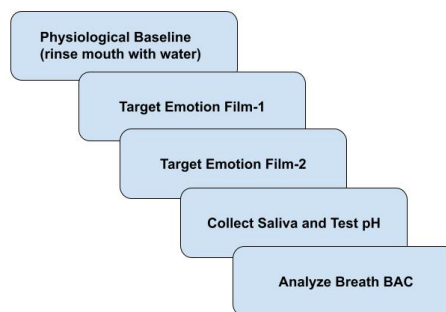


Figure 2: Illustration of a trial in the experimental procedure.

## 5 RESULTS

This section presents the findings from physiological measurements of the detection system and subjective self-assessments of emotion induction. Due to the small sample size, statistical analysis was not performed. Instead, the data were visualized to provide an overview of the results.

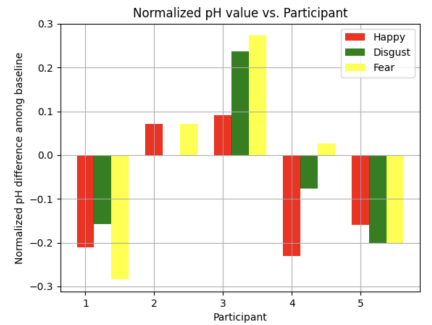
### 5.1 Physiological Measurements

Physiological changes in saliva pH ( $\Delta$  pH) and heart rate ( $\Delta$  HR) were calculated by subtracting the baseline measurements taken during the neutral state from those recorded after emotion induction. The values were then normalized with respect to the neutral state baseline, allowing for a standardized comparison across participants. Figure 3 illustrates these differences across participants for the three target emotions: happiness, fear, and disgust. While variations were observed in saliva pH and heart rate, no measurable changes in blood alcohol content (BAC) were detected, as all recorded BAC values remained at 0.000% throughout the experiment.

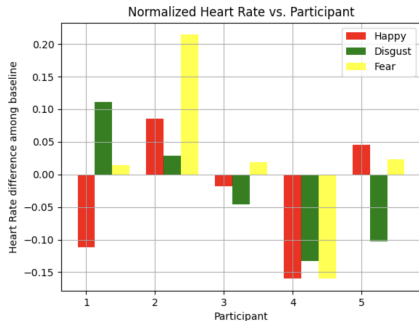
**5.1.1 Saliva pH.** Changes in saliva pH, which were hypothesized to correlate with emotional states, are presented in Figure 3(a). Similar to heart rate, pH changes varied among participants and emotions. For example, several participants exhibited more acidic saliva (negative pH change) during fear induction, while others showed negligible changes.

**5.1.2 Blood Alcohol Content (BAC).** The breathalyzer used to detect BAC levels did not yield any meaningful data, as all recorded values remained at 0.000% throughout the experiment. This limitation may be attributed to the breathalyzer's insufficient sensitivity to detect VOC changes associated with emotional states.

**5.1.3 Heart Rate.** Heart rate changes were observed as a proxy for physiological arousal, which can indicate successful emotion induction [21, 23, 35]. Participants showed varying heart rate differences across emotions, as shown in Figure 3(b). While some participants exhibited increased heart rates for fear and happiness, others demonstrated minimal changes, possibly due to individual differences in emotional responses.



(a) Normalized Saliva pH Change vs. Participant



(b) Normalized Heart Rate Change vs. Participant

Figure 3: Physiological measurements

## 5.2 Self-Assessment of Subjective Experiences

The subjective intensity of emotions was assessed using a 9-point (minimum 0, maximum 8) Likert scale, with successful emotion induction defined as achieving a mean intensity of at least five points for the target emotion [13, 15]. Figure 4 displays self-reported emotion intensities for happiness, fear, and disgust for each participant. Based on the self-reported data, only a few participants successfully experienced intense levels of happiness, disgust, and fear. The mean scores for happiness and disgust inductions were both five, meeting the success threshold, whereas the mean score for fear induction fell short at 4.2.



Figure 4: Self-assessment score on induced emotion intensity across participants

## 6 DISCUSSION

This study aimed to explore the detection of biomarkers linked to emotional states, specifically happiness, fear, and disgust, using a low-cost approach that combines breathalyzer-based BAC analysis and saliva pH measurements. The results indicate no clear correlation between emotional states and changes in saliva pH or BAC values. This absence of obvious correlations could stem from insufficient emotional stimulation during the experiment and individual variability in physiological responses.

### 6.1 Saliva pH Analysis

According to Figure 3 (a), some trends suggest potential relationships between emotional states and changes in saliva pH, although the small dataset makes it difficult to draw definitive conclusions. For instance, participants experiencing fear often exhibited positive pH deviations compared to their baseline values, with Participant 3 showing the largest increase. This may suggest a link between fear and metabolic changes that elevate pH. However, this observation contradicts the findings from [27], which reported increased acidity under extreme emotional states (ie. stress, fear, anxiety). In contrast, disgust was observed to correlate more frequently with negative pH changes, as seen in Participants 1 and 5, potentially indicating a physiological response to lowered pH. Happiness, on the other hand, generally showed smaller deviations, staying closer to the baseline values. An exception was Participant 5, who exhibited a significant negative deviation, suggesting individual variability in physiological responses associated with happiness.

### 6.2 Blood Alcohol Content (BAC) Analysis

The breathalyzer used in this study did not detect any meaningful changes in BAC, as all recorded values remained at 0.000% throughout the experiment. This lack of variation is likely due to the breathalyzer's limited sensitivity in detecting the trace concentrations of volatile organic compounds (VOCs) associated with emotional states. Breath alcohol levels can be influenced by compounds such as ethanol, methanol, 2-propanol, and 1-propanol, which are present in the parts-per-billion (ppb) range under typical emotional conditions [12, 30]. The breathalyzer used is primarily optimized for measuring BAC within a range suited to detect ethanol levels following alcohol consumption. Its limited sensitivity to trace

VOCs under varying emotional arousal suggests that it may not be an appropriate tool for detecting emotional changes.

### 6.3 Heart Rate Deviations

The heart rate changes observed in this study suggest that participants may not have been sufficiently engaged or stimulated by the emotional stimuli. According to prior research, fear induced by emotionally evocative films typically results in a decrease in heart rate due to sympathetic inhibition and reduced arousal during passive coping stages [2, 21, 35]. However, as shown in Figure 3 (b), most participants exhibited positive heart rate changes during fear induction, deviating from these expected patterns.

For happiness, while some participants showed positive deviations in heart rate, others (e.g., Participant 1 and Participant 4) exhibited a drop in heart rate. This aligns with prior findings suggesting that decreases in heart rate during happiness are generally more transient and less pronounced [23]. These mixed responses may suggest that participants were not consistently engaged with the emotional stimuli or that emotional engagement was insufficient to elicit robust physiological responses.

These findings highlight the potential influence of both the small sample size and the variability in individual emotional responses. If the experiment were conducted with more participants and more tailored, emotionally stimulating stimuli, stronger and more consistent physiological trends might emerge. Increased emotional engagement would likely lead to clearer physiological responses, thereby offering more meaningful insights into the proposed emotion detection system.

## 7 LIMITATIONS AND FUTURE WORK

This study faced several limitations that constrained its ability to fully explore the relationship between VOC biomarkers and emotional states. A major limitation was the reliance on indirect methods to detect volatile organic compounds (VOCs) linked to emotions. Saliva pH detection, while cost-effective, has limited evidence supporting its ability to accurately capture VOCs linked to emotions [4, 7, 27]. The pH test strips used could be more precise by measuring changes at intervals of 0.1 rather than just 1 pH unit. Similarly, the breathalyzer, primarily calibrated for detecting high alcohol concentrations, lacked the sensitivity required to detect trace levels of VOCs.

Another key limitation was the small sample size of just five participants, which reduced statistical strength and made it difficult to draw general conclusions. Variability was further introduced by individual differences in emotional responses and baseline VOC levels. While validated emotional stimuli such as film clips were employed to induce emotional states, factors like personal preferences, cultural differences, and varying emotional thresholds contributed to inconsistencies [34]. Although environmental conditions were controlled during testing, they could not fully account for external influences [11, 12, 30].

Despite these limitations, this study lays the groundwork for future research into emotion detection through VOC analysis. To overcome these challenges, future studies should employ advanced detection methods targeting specific VOCs, such as Schiff's reagent for aldehydes [25], chromotropic acid for formaldehyde [22], and

highly sensitive photoionization detectors (PID) [6] for detecting trace alcohols in breath. Expanding the sample size to include a diverse range of participants would enhance statistical reliability and the ability to identify consistent patterns across different populations. Furthermore, the development of low-cost, portable VOC detection technologies could strike a balance between affordability and precision, facilitating real-world applications of emotion detection systems.

Future studies could also diversify emotional stimuli, incorporating personalized content, music, or virtual reality experiences, and standardize pre-experiment protocols, such as minimizing distractions and dietary influences. A multi-modal approach combining VOC analysis with other biomarkers (e.g., cortisol, EEG, galvanic skin response) could provide a more comprehensive understanding of emotional responses.

Finally, exploring practical applications of emotion detection technologies in fields such as mental health monitoring and human-computer interaction could demonstrate real-world utility and scalability. Addressing these limitations in future work could lead to the development of robust, reliable, and accessible emotion detection systems with wide-ranging applications.

## 8 CONCLUSION

This study investigated the detection of biomarkers associated with emotional states—happiness, fear, and disgust—using a low-cost system combining saliva pH analysis and BAC measurements. While the results showed no significant correlations between biomarkers and emotional states, the study highlighted trends in physiological changes and emphasized the challenges of using low-sensitivity tools for VOC analysis.

Despite its limitations, this research provides a foundation for future work in emotion detection. Enhancing instrument sensitivity, increasing sample size, and incorporating advanced analytical tools or multi-modal approaches can improve reliability. These advancements hold potential for applications in healthcare, mental health monitoring, and human-computer interaction, enabling the development of accessible and scalable emotion detection systems.

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