Food and Mood: Just-in-Time Support for Emotional Eating

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***Abstract*—Behavior modification in health is difficult, as habitual behaviors are extremely well-learned, by definition. This research is focused on building a persuasive system for behavior modification around emotional eating. In this paper, we make strides towards building a just-in-time support system for emotional eating in three user studies. The first two studies involved participants using a custom mobile phone application for tracking emotions, food, and receiving interventions. We found lots of individual differences in emotional eating behaviors and that most participants wanted personalized interventions, rather than a pre-determined intervention. Finally, we also designed a novel, wearable sensor system for detecting emotions using a machine learning approach. This system consisted of physiological sensors which were placed into women's brassieres. We tested the sensing system and found positive results for emotion detection in this mobile, wearable system.**

I. Introduction

We eat not just because we are hungry and craving nutrients but also for a host of emotional and habitual reasons. There is no single term that encompasses the combination of lifestyle, hedonic, emotional, or habitual over-eating that leads to obesity. For this paper, we will use the term "emotional eating" as a placeholder for non-homeostatic eating (i.e., eating that is not physiologically required). Persuasive technologies have been used within the health space to assist people in developing new habits around health, from making better eating choices to encouraging a more active lifestyle. These systems have, for the most part, relied on fixed contexts to offer support: alarms at particular times of the day; showing performance updates when one glances at their mobile phones [1]; and user-activated support [2,3]. However, one cannot rely solely upon fixed solutions for persuasive technology to effect long-term behavioral change. An alternative approach is to intervene proactively to prevent the behavior from happening. In the case of emotional eating, our goal is to provide an intervention before the person turns to food for emotional support.

We begin to investigate just-in-time interventions to support behavior modification for emotional eating. Designing such a system is an ambitious endeavor: it involves exploring the emotional triggers of eating, developing elaborate technology for automatically detecting emotions, and investigating intervention approaches for emotional eating. In this paper, we present three user studies that move us towards the goal of developing a just-in-time support system for emotional eating. The purpose of the first study was to gather data about emotional eating patterns. The second study investigated the feasibility and benefits of emotional eating interventions. Finally, the third study focused on emotion detection with machine learning and custom-built wearable sensors.

II. Related Work

A. *Persuasive Health Technologies*

Persuasive technologies for health and weight management have become ubiquituous over the past few years with several off-the-shelf fitness technologies like FitBit[1] and BodyBugg[2] helping to make the logging of activity and physiological state more accessible. These fitness gadgets are designed to help people measure physical activity and sleep quality and to motivate increased movement. Amft and Troster [4] built sensors for monitoring chewing and swallowing, and they proposed how these sensors could be included in an elaborate, (yet uncreated) persuasive system for health. Purpura et al. also proposed a similar, uncreative persuasive system [5]. The technology in their system included, to name a few parts: an earpiece for monitoring chewing and swallowing; augmented reality glasses for capturing foods consumed; and heart rate recording for sensing exercise. This proposed system also connected through a mobile phone application in order to process the data and for the person to receive feedback. The hypothetical feedback, whether from a social network, a close friend, or pre-recorded messages, served as a health intervention to encourage the person to be more active or consume less food.

Not at all persuasive systems need to be as elaborate as those discussed above. A persuasive system with peer support alone can help people be more successful in weight loss. Mutsaddi et al. [6] utilized text messages as a form of social support for encouraging more physical activity. They found that even after the novelty of text messages wore off, the text messages were still beneficial because they served as reminders to participants to be more active.

B. *Eating for Non-Homeostatic Reasons*

There are many theories around why we eat. One is largely homeostatic: we eat because we need fuel to survive; we crave certain foods because we require certain nutrients to function [7]. Other reasons are more nuanced, though these too are intertwined in physiological responses. For instance, many people reach for calorically dense foods, like donuts, when stressed. Gilhooly et. al characterized these responses as "instinctive" in that at some point these behaviors may have served a survival function [8]. Stress releases hormones, which trigger a fight or flight response; thus, grabbing high-energy, available foods (like the sugary donut) would be effective

[1]FitBit: http://www.fitbit.com
[2]BodyBugg: http://www.bodybugg.com

for energy production. Likewise, when confronted with the variety of a buffet, it seems a food scarcity mentality kicks in, and more food is taken in than necessary. The challenge in a food abundant culture is that these instinctive responses are no longer helpful. An important insight around over-eating behavior is that non-homeostatic eating patterns can be re-educated [8]. In other words, both our physiological responses (the release of ghrelin to cue stomach grumbling at particular times [7]) and psychosocial responses (eat in the presence of food or in response to stress) are malleable. Therefore, technology that is used to intervene before the maladaptive behavior happens could provide some assistance towards long-term, behavioral change.

C. Supporting Behavior Change

An increasingly well-regarded approach to support eating behavior change is Cognitive Behavioral Therapy (CBT) [9]. The focus of CBT is to help a person become aware of their "maladaptive behaviors" and then replace these with adaptive ones "by modifying their antecedents and consequences and by behavioral practices that result in new learning" [10]. A common approach to supporting discovery of these antecedents to maladaptive behaviors, such as one's cues for emotional eating, is to have participants in CBT do work to identify triggers. Typical approaches include keeping daily food and mood logs or journals. In some cases, the goals of the logs are to highlight particularly positive states ("benefit finding") to enhance success with new, adaptive behaviors [11]. One particularly relevant process has been called "real-time self-monitoring" around eating, related behaviors, and feelings [12]. The rationale for the criticality of monitoring is that "it helps patients to be more aware of what is happening in the moment so that they can begin to make changes to behavior that may have seemed automatic or beyond their control" [12]. An important aspect of CBT is bringing the automatic or thoughtless actions into consciousness for deliberate engagement/change.

D. Implicit Emotion Detection

Emotion detection with sensor data has been carried out in the past. McDuff et al. used a variety of signals (i.e., electrodermal activity, posture, facial expressions, etc.) to detect emotions using a machine learning approach with self-reported ratings of emotion serving as the ground truth in their emotion classifiers [13]. They found that the electrodermal activity (EDA) signal was the most beneficial, which is a measure of the eccrine sweat glands [14,15]. McDuffs et al.'s detection system involved sensors that required users to be tethered to their desk (e.g., Kinect, web cam, etc.).

The goal of our system was to perform emotion detection in a mobile, wearable system, which allows us to collect data as users move about their day. Chang et al. created a mobile system for detecting user emotion but this was done via activity modeling and speech prosody tracking [16]. In contrast, the goal of our system was to use on-body sensors with EDA and electrocardiogram (EKG), since these sensors have been shown to be reliable for emotion detection [14,17,18].

III. Research Approach

Designing a system to provide just-in-time interventions for emotional eating is an ambitious endeavor. Consider the following hypothetical scenario:

Sally has been home from work for a few hours, and she finds herself rather bored. An application on Sally's mobile phone has also detected that she is bored by reading her physiological state through wearable sensors. Since this mobile application has previously learned that Sally is most susceptible to emotional eating when she is bored, the application provides an intervention to distract Sally and hopefully prevent her from eating at that moment.

From this scenario, we see three key requirements for a just-in-time support system for emotional eating. First, the application has to be *aware of the user's emotional eating patterns*. Does Sally emotionally eat only when she is bored? Second, the system needs to be able to *implicitly detect emotions*. This involves wearable physiological sensors that are connected to the mobile phone. Implicit detection of emotions would then be possible through machine learning classification, which requires training on large amounts of users' data. Finally, it is critical (and perhaps the most challenging) to *determine how to intervene*. What type of intervention do we design? How often do we intervene? How do we prevent it from becoming an annoyance to the user?

Our approach to researching a just-in-time support system for emotional eating was to make strides towards addressing these three requirements. We studied these requirements across three user studies, which have been summarized below.

- **Study 1: Gather Emotional Eating Patterns.** We investigated eating behaviors and corresponding emotions of participants by having them self-report their emotions and log their eating patterns using a custom built application called EmoTree. The goal was to understand their emotions associated with eating.
- **Study 2: Investigate An Intervention Technique.** The purpose of Study 2 was to learn about a particular intervention technique for emotional eating. We prototyped implicit intervention by triggering an intervention based on self-reported ratings of emotions. This allowed us to gather early feedback about interventions before implementing an automatic system. Are users aided by the intervention? Was the intervention sent at the appropriate time? What other types of interventions would interest users?
- **Study 3: Emotion Detection with Wearables.** This work was a first step in building an automatic system. We investigated the feasibility of using physiological sensor data, combined with machine learning, to automatically detect emotions in a mobile system. We also present the design of our wearable system.

IV. EmoTree: Mobile Phone Application

EmoTree is a custom designed Windows 7 mobile phone application, consisting of four screens. The default screen provides an overview of the user's logging activity and overall sentiment (Figure 1A). The tree on this screen eventually populates its leaves over time, as the user interacts with the app. Each circle represents a day's worth of activity and the color green is used to indicate positive decisions based on food intake. The user's sentiment is aggregated as the background sky color to indicate positive or negative valence of affect.

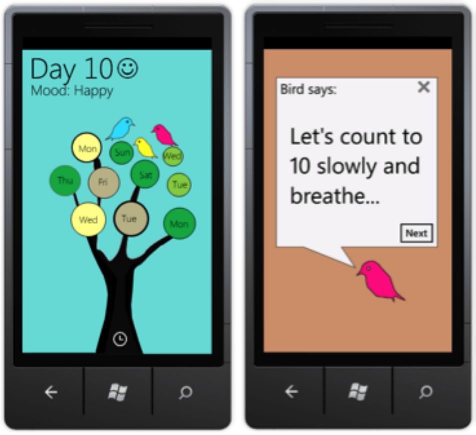

Fig. 1. EmoTree Mobile Phone Application. Main Page (A) and Intervention Page (B)

Fig. 2. EmoTree Mobile Phone Application. Nutrition Log (A) and Self-Report Tool (B)

As usage continues, the user may assess overall progress or history by selecting the history icon at the bottom of the tree. Inspiration for the interface design came from the notion of tending a garden and using that as a metaphor to visually guide users to make better choices [1]. Since the application was designed for long-term use, the idea of a tree that gradually grows based on your daily health decisions served best as a visual guidance system that could invoke encouragement: the healthier your choices, the healthier the tree.

To start using the application, the user goes to the main screen (Figure 1A) and glances at their current mood. By swiping to the left, the user is taken to a screen that asks: “How do you feel?” (Figure 2B) Self-reporting of emotion was based on the Russell’s Circumplex model [15], widely used across the affective computing community [13,19], in which emotion is represented two-dimensionally; valence on the x-axis and arousal on the y-axis. Figure 1A shows the emotion self-report tool that participants used. In our user interface, we used the terminology of “Negative” to “Positive” to describe valence, and “Pumped” to “Relaxed” to describe arousal, as in McDuff et. al [13]. After indicating their current emotional state, the users also indicated how engaged they were with their current task, on the same screen. Reminders to self-report emotions were sent to the users’ mobile phones every hour, on the hour.

Users were also instructed to swipe right from the main screen to log any food that had been consumed (see Figure 2A) for what they were asked to log. Logging food populated the leaves on the main screen. After logging food, the user was immediately sent to the self-report page to indicate their emotions prior to eating. The task engagement question was not asked after logging food.

Lastly, we introduce the intervention screen (Figure 1B). which consisted of a deep breathing exercise. Users were instructed to tap on the screen for each breath that they took for 10 seconds (or 10 taps). The intervention was employed in Study 2 and will be discussed further in Section VI.

V. Study 1: Gather Emotional Eating Patterns

In Study 1, we conducted a user study (N=12, 2 males) to investigate emotional eating patterns using EmoTree. In recruitment, all participants self-identified as emotional eaters. Prior to the study, users filled out a pre-experiment survey that asked about their emotional eating patterns, called the Emotional Eating Scale [20]. All participants were given a demonstration of the EmoTree app, and they were given instructions on how and when to use the software. This study took place over a period of four days (Tues-Fri). Participants were asked to use EmoTree to self-report emotions every hour, on the hour, in addition to reporting food. We collected at least 10 self-reports of emotion per day from participants.

A. *Analysis and Results*

Our pre-survey results on the Emotional Eating Scale showed that the emotions marked as causing a moderate to strong urge to eat included: on edge, nervous, upset, worried, nothing to do, bored, irritated, restless, and discouraged. These findings support research on emotional eating as reported elsewhere [21].

From the four days of data collection, we created two scatterplots for each person (2 plots x 12 participants). The first scatterplot was of a person’s emotional ratings, which visualized their emotional state over the duration of the study. The second scatterplot was of a person’s emotional ratings that were associated with food, showing us their emotional state just before eating. It was not surprising to find that there were a lot of individual differences and that people ate when they were experiencing a variety of emotional states. In fact, most users had eating events that occurred in all four quadrants of the Circumplex model (Figure 2B). However, we did find that six participants tended to eat when they were predominantly stressed with the majority of eating events occurring in the upper-left quadrant (i.e., negative & pumped). We also observed across all participants that few eating events happened when the users were in a calm/serene state, so very few eating events were in the lower-right quadrant (i.e., positive & relaxed).

B. *Intervention Technique*

We decided to intervene based on when users provided self-reports occuring in the upper-left quadrant of the Circumplex model (i.e., negative & pumped). Our goal was to explore if our intervention could help move participants from a stressful state to a calmer state. Therefore, we developed a deep breathing activity (Figure 1B), where a little bird is displayed that counts users' breaths with each tap on the screen. Several components are at work in our design decisions. First, stress has been identified as a contributor to obesity and to emotional eating [7,21]. Second, we found in the analysis of EmoTree's emotional eating data that 6 out of 12 participants were primarily stress eaters, and the Pre-Survey results also show that participants primarily eat in response to feelings that were associated with stress (e.g., on edge, upset, worried). Finally, we leverage a CBT strategy for reducing emotional eating, as described in Section II-C: by targeting stressful moments that *may* be precursors to an emotional eating episode, the breathing exercise may break the focus on stress, allowing for further cognitive processing of what one may be about to do, thus offering the opportunity to choose a different, and more positive, action.

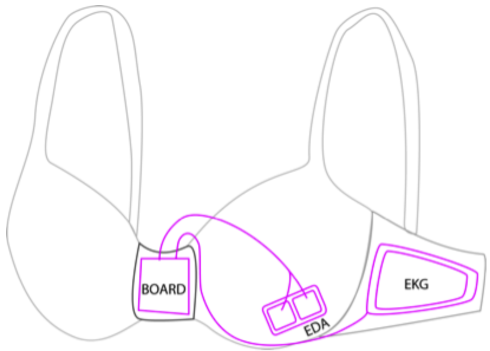

Fig. 3. Sensor placement outline, showing where EKG and EDA was collected and connected to the custom board.

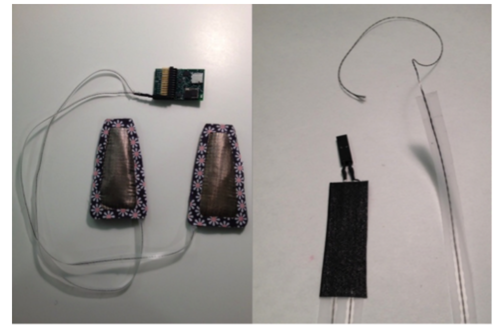

Fig. 4. EKG sensor pads, connected to a GRASP board (A); Conductive thread insulated by scotch tape (B)

A. *Emotion Sensing System*

1) Sensors: We used custom boards called GRASP (Generic Remote Access Sensing Platform) which is a real-time system and is comprised of a physical sensor board, corresponding firmware, software libraries, and an API. The GRASP board has an MSP-430 microprocessor and is powered by a Lithium-Ion polymer (3.7V) battery. GRASP can sample up to eight bio-signal channels (TI80S1298) simultaneously. The GRASP boards in this study were configured to capture heart rate and respiration with an electrocardiogram (EKG) sensor; skin conductance with an electrodermal activity (EDA) sensor; and movement with a 3-axis accelerometer and a 2-axis gyroscope. The board transmitted the sensor stream data to a mobile phone application using Bluetooth, which was then stored remotely into a Microsoft Azure Cloud.

2) Design of Wearables: The design motivation for the bra sensing system (Figure 3) was driven by a few key factors. First, we needed a form factor that would be comfortable when worn for long durations. We also needed a way to gather both EKG and EDA signals; so ideally, we wanted to collect those signals from the same wearable. The bra form-factor was ideal because it allowed us to collect EKG near the heart. Ultimately, we chose to leverage the functionality and wearability of a bra, but had to consider that each participant's chest and rib size would vary greatly. Rather than build each participant their own embedded sensor bra, we aimed for a much more modest solution: conductive pads that could be inserted or removed. This provided us flexibility in recruiting participants, in addition to resolving the wash-ability aspect. Three pads for each participant were required in order to capture both EKG and EDA (Figure 3). For EKG, two pads were designed to fit snug against each side of the ribs. These pads were designed with more surface space to help reduce noise in the signal. The EDA pad was initially designed to fit on the backside of the bra; however, we were unable to gather sufficient signal due to low sweat levels in the back. We therefore had participants relocate the EDA pad into the bra cup, just under the breast. It is worth nothing that collecting EDA from this part of the body is non-standard; however, EDA was still a useful signal.

The board sits at the center of the user's sternum (Figure 3), encased in a fabric pouch that was stitched to the outside of the bra. Each sensor pad is comprised of 2.5mm of laser cut neoprene sandwiched with batting and laser cut conductive silver ripstop fabric (Figure 4). A laser cut outline of cotton was top stitched by a sewing machine to enclose all the material. The insulated wire turned out to be inflexible and obstructive to the wear, so we explored ways in which we could make an electrical connection using conductive thread. For insulation, we sandwiched the thread with two pieces of scotch tape. This method worked remarkably well in that it retained the soft and flexible nature of the thread but was also not noticed when worn. One end of the conductive thread was sewn into the pad and then covered by a top stitch, while the other end was tied to thin wire, heat wrapped, and crimped to a connector on the GRASP board. The average conductivity between the sensor and connector was approximately 12 ohms.

3) Methodology: We conducted a user study to see if emotion detection through physiological sensing was possible in a mobile system. To this end, we had four women from our research lab participate in this study. The study involved these women wearing the three conductive fabric pads inside their bras, as previously described. They also used the mobile application, EmoTree, in order to self-report their emotions, which was used as labeled data in our machine learning classifier (ground truth).

Participants wore the bra sensing system and reported their emotions for about 4-6 hours a day over a period of approximately four days. It was very tedious for participants to wear our prototyped sensing system, as the boards had to be recharged every 3-4 hours, which resulted in participants having to finagle with their wardrobe throughout the day.

4) Analysis and Results: Similar to McDuff et. al [13], we took a machine learning approach for predicting emotions. The sensor data went through several pre-processing stages before we could perform classification. First, we applied two different filters to the raw EKG signal: a 2Hz low-pass filter to get respiration and a 2Hz high-pass filter to get heart rate. Next, we normalized all 8 signals (heart rate, respiration, EDA, 3-axis accelerometer, 2-axis gyroscope) between 0-1. Finally, we extracted features from the signal by creating 5 bands that fell within our normalized values. These bands were: 0 to <0.2, 0.2 to <0.4, 0.4 to <0.6, 0.6 to <0.8, and >0.8. We used these bands to determine within a 10-minute time period the proportion of data that occurred within each band. This feature extraction process resulted in 40 features (8 signals x 5 bands) for each person. The labeled data for classification was self-reported ratings of emotion (x-valence and y-arousal), and the attributes were the 40 extracted features.

We used a classification framework based on Gaussian Process Regression (GPR) [22], which has been shown to be very effective for multimodal affect recognition [23] and fits well into the context of our classification task. In particular, we define a similarity (a kernel) function between two observations x_i and x_j using a Radial Basis Function: $k(x_i, x_j) = exp \parallel x_i - x_j \parallel^2 /2\alpha^2$. GPR considers this similarity when classifying points and assigns labels to test cases such that similar labels are assigned to similar points. We refer readers to Kapoor et. al [23] for further details on affect classification using Gaussian Processes. For testing the classifiers, we used a leave-one-example-out methodology. Specifically, we consider data recorded from all but one data point as the training corpus and then tested the algorithm on the left-out observation. This process was repeated for all points.

We were able to classify arousal at 75.00% and valence at 72.62% accuracy. We observe that for both arousal and valence the recognition accuracy is significantly better than chance. Furthermore, we would like to highlight that the recognition accuracy achieved here is at par with other affect recognition systems [13]. Based on these results, we conclude that building a wearable, physiological system is feasible. However, we will continue to explore how to build a robust, real-world system that stands up to every day challenges with regards to battery life, comfortability, and being suitable for both men and women. Since these classification results were based on log files, rather than real-time sensor data, our next iteration will also run using real-time sensor data that is able to predict emotions and show an appropriately time, personalized intervention.

VIII. Contributions and Future Work

In this paper, we began to investigate just-in-time intervention to support behavioral modification in emotional eating. Designing a just-in-time support system for emotional eating is an ambitious endeavor, and to this end, we presented three user studies that moved us towards the goal of developing a fully integrated system. We found in Study 1 from user logging that 6 out of 12 participants primarily ate when they were stressed. In Study 2, we found that participants were enthusiastic about interventions for emotional eating, but that most wanted personalized interventions, rather than the single, pre-determined deep breathing interventions. Finally, in Study 3, we investigated using wearable sensors to implicitly detect emotions while participants were mobile. Using log files, we were able to detect arousal at 75.00% and valence at 72.62%.

There are several future research directions that are essential to building an integrated system for just-in-time support. First, we have already expanded our implicit emotion detection system to work using real-time sensor data, opposed to log files. While the wearable sensors in the brassiere form factor only allowed women to participate in Study 3, we have now moved towards using the Affectiva Q[3] sensor bracelets for this collection. Our pilot results have been quite promising for men and women. Finally, we are currently exploring the just-in-time intervention space in which we test different intervention approaches in longitudinal studies. We consider research in intervention design to be critical in future iterations, including personalized methods of responding to the user, in addition to investigating formal theories of behavior change [24].

[3] Affectiva Q: http://www.affectiva.com

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