eat2pic: Food-tech Design as a Healthy Nudge with Smart Chopsticks and Canvas

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***Abstract*—In this paper, we introduce a food-tech design as a healthy nudge called eat2pic that encourages people to slow down their eating pace and encourage healthier eating habits. The eat2pic system is composed of a sensor-equipped chopstick (one of a pair) and components that use context-aware digital canvases. The eat2pic system achieves (1) automatic tracking of what and how fast the user consumed each mouthful of food, (2) real-time visual feedback that indicates good or bad eating behavior. The key concept of eat2pic involves extending the relationship between humans and paintings in order to establish a closed-loop in which daily eating behavior is reflected in pictures on the canvas near us and feedback from the canvas leads our lifestyles towards healthier diets. The eat2pic system provides a novel experience in which users can come to see eating as a playful task that involves coloring landscape pictures, and not simply taking nutrition into their bodies.**

***Index Terms*—Nudge, Eating activity recognition, Persuasive technology, Internet of things, Food technology**

I. Introduction

Recently, the World Health Organization (WHO) have highlighted the importance of healthy diets in relation to maintaining strong immune systems and avoiding or minimizing chronic diseases and infections [1]. In particular, eating too fast is a bad habit that should be discouraged since it can cause both indigestion and overeating. In contrast, eating slowly improves both digestion and hydration, facilitates weight loss and maintenance, and increases food satisfaction. However, establishing healthy eating habits is not easy for many people, which means that formulating solutions that encourage healthy eating habits such as eating slower and choosing a balanced diet is essential.

To address these issues, various approaches have been proposed in the research areas of pervasive computing (PerCom), ubiquitous computing (UbiComp), and human-computer interactions (HCI). Currently, the most common approach involves eating activity recognition using wearable or environmental sensors and visualizing the results through smartphone applications. However, existing detailed diet monitoring methods require users to wear special devices on their heads, necks, or chests, which may interfere with their eating behaviors [2]–[5]. Separately, there are prior works [6]–[8] that focus on smart table and mat, but none of those have been able to detailed diet monitoring that recognizes both what and how each bite was consumed. Other studies have found that quantitative visualization methods centered on charts, graphs, and statistical reports tend to reduce user motivation levels [9]–[12].

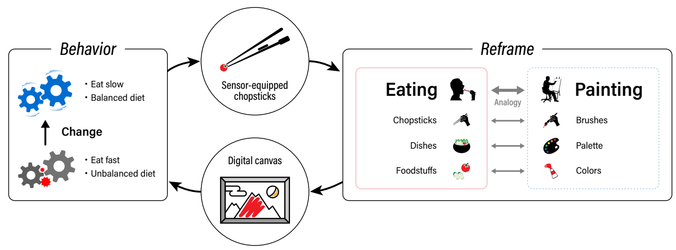

Fig. 1. An overview of the eat2pic concept.

In this paper, we introduce a food-tech design as a healthy nudge called *eat2pic* that aimed to help people to slow down their eating pace and encourage healthier eating habits. The eat2pic system is composed of a sensing component in the form of a sensor-equipped chopstick and intervention components that use context-aware digital canvases as shown in Fig. 1. The eat2pic system provides (1) automatic tracking of what and how fast the user consumed each mouthful, (2) real-time visual feedback that indicates good or bad eating behavior. The key concept behind our eat2pic system involves extending the relationship between humans and paintings, establishing a closed-loop in which daily eating behaviors are reflected in those paintings, and permitting those reflected behaviors to "nudge" our lifestyles towards healthier diets.

II. Overview of eat2pic

A. Approach

We considered the best approach for establishing healthy human eating habits based on the Fogg behavior model [13], [14], in which three elements must meet at the same moment for the desired behavior to occur. These elements are motivation, ability, and prompts. When an intended behavior does not occur, the model states that at least one of those three elements is missing. We also presume that most people already have the ability to establish healthy eating habits because the task of preparing a balanced diet and eating it slowly is not particularly onerous. Therefore, we hypothesize that the lack of healthy eating habits displayed by most people may be due to a shortfall of personal motivation and/or insufficient prompts within their personal living space. For these reasons, we adopted an approach that influences user motivation levels by reframing eating tasks into other playful tasks and draw users' attention to behavior at appropriate times (e.g., when

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detected speed eating) to encourage healthy eating behaviors. Specifically, we employed two types of nudge mechanisms called just-in-time prompts and ambient feedback [15].

B. System Design

Based on the above consideration, we designed a nudging system that monitors their "eating" behaviors in the physical world and reflecting them in a digital "painting" world, i.e., *"eat" to "pic" (eat2pic)*. The Fig. 1 shows an overview of the eat2pic concept design, in which we focused on an analogy between eating and painting behaviors as a means to nudge users toward improved eating habits. The root of our concept is based on the realization that both eating and painting behaviors possess similar elements; in this case, chopsticks and paintbrushes, dishes and palettes, and food types and colors.

To design a technology that integrates smoothly into the dining setting, we decided to use chopsticks (which are typically used during meals) as our sensor and employ pictures (which typically adorn living spaces) as actuators. The sensor-equipped chopstick recognizes the eating speed of the user, the type (color) of food selected, and the amount of food consumed simultaneously using a time-series signal processing and deep learning approach. The eat2pic system encourages the user's healthy diet by representing the progress of a healthy diet with gradually coloring to a landscape picture depending on the user how to eat rather than showing quantitative visualizations such as graphs.

C. Implementation

The architecture of the eat2pic system is shown in Fig. 2, where it can be seen that the system consists of a sensor-equipped chopstick (one of a pair), a gateway device, and the digital canvases. The sensor-equipped chopstick is equipped with IMU sensors (MetaMotionR+*: sensors — 100 Hz quaternion three-axis accelerometer/gyroscope; dimensions — L29×W18×H6 mm; weight — 5.7 g) for eating behavior sensing, and a small camera (endoscope inspection camera†: resolution — 640×480 px; frame rate — 4–5 fps) to capture food imagery before eating, as shown in Fig. 3-A.

The IMU sensor signals and camera data (image sequences) are streamed to the gateway device via Bluetooth Low Energy (BLE) and cable links, respectively. The gateway device then analyzes the IMU sensor signal and camera data simultaneously in order to track the user's eating speed, the type (color) of the foods eaten, and the amount consumed in one bite. More specifically, the gateway device performs the eating activity recognition pipeline that consists of a time-series signal processing part and an image recognition part based on deep learning.

In the time-series signal processing part, the posture angle of the chopsticks is first calculated from the acceleration and gyroscope signals obtained from the IMU sensor, and the amount of rotation during eating. Then, the pipeline applies peak detection processing to this data to identify the user's

*MbientLabs: https://mbientlab.com/metamotionr/

†KKmoon: https://www.kkmoon.com/

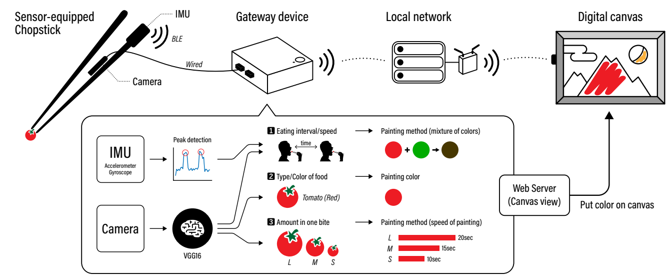

Fig. 2. System overview of eat2pic.

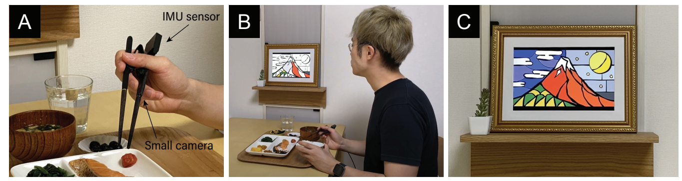

Fig. 3. Real setup of eat2pic system.

food eating behavior. In addition, the pipeline applies a deep-learning-based image recognition process. This process is performed on every frame of the imagery from the camera (4-5 fps). For each frame, the object recognition model used in this process (which we developed based on the VGG16 [16] model from ImageNet [17] and YOLO v3 [18] recognizes the type and color of food, the size of the portion (small, medium, or large), and whether or not the food portion has been placed in the user's mouth.

The pipeline determines the point at which the user consumed the food when a peak is detected in the time-series signal processing part and when the food and mouth are recognized simultaneously in the image recognition part. The user's eating interval and speed are calculated from the detected intake timing. In addition, the pipeline recognizes the type of food and the size of the portion in the view angle of the frame before the detected timing. As a result, the pipeline outputs (1) eating interval/speed, (2) type/color of food, and (3) amount consumed in one bite.

The gateway device also has a web server that controls modifications to the landscape picture (canvas view) displayed on the digital canvas based on the recognized user's eating behavior. In the canvas view, the color of the food consumed is reflected by the color of the applied paint, while eating speed is reflected in the color mixture, and the amount in each bite is reflected in the painting speed.

III. EAT2PIC DEMONSTRATION

In the demonstration, we present examples of scenarios that show how eat2pic helps people to slow down their eating pace and encourage healthier eating habits.

Fig. 4, 5 shows an example of how real-time visual feedback of the eat2pic system works. In our scenario, the digital canvas of eat2pic is mounted on the wall next to the dining table, and users can enjoy their mealtime while looking at a landscape painting as shown in Fig. 3-B,C. In the eat2pic system, the colors of the foodstuffs eaten by the user are reflected as parts

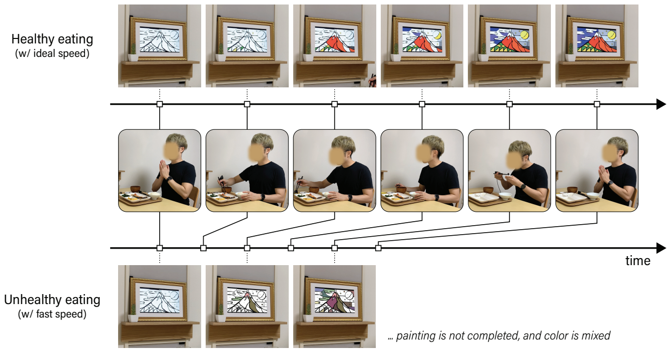

Fig. 4. Example of coloring applied based on eating speed. If the user eats too quickly, multiple colors will be mixed and applied, resulting in a poor visual appearance.

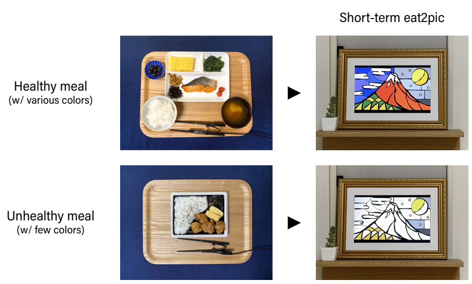

Fig. 5. Examples of coloring results on the canvas after different meal types. If the user chooses a healthy (balanced) meal, the canvas will be filled with beautiful colors. In contrast, there will be many unfilled places on the canvas after an unhealthy (unbalanced) meal.

of the landscape paintings on the digital canvas. At this point, the way the colors are applied will change depending on the way the user eats. For example, if a user rushes to eat a meal, multiple colors will mix on one piece and the appearance of the landscape will degrade, as shown in Fig. 4. In order to paint clean colors, the user will need to take sufficient time (from 10 to 30 seconds) for each bite, which will motivate him or her to eat slowly. The eat2pic system determines the waiting time per intake based on the amount of food brought to the mouth at one time. These interactions also encourage users to eat more slowly.

In the eat2pic system, completing landscape picture par one meal is designed as goals for a healthy diet. Since a landscape picture is composed of a variety of colors, the user is required to eat meals that contain various foods in order to fill the color of all pieces. Fig. 5 shows examples of painting results on the canvas after different meal types. If the user chooses a healthy (balanced) meal, the canvas will be filled with beautiful colors. In contrast, there will be many unfilled places on the canvas after the meal if the user chooses an unhealthy (unbalanced) meal. Herein, we intend that seeing unfinished landscape paintings placed in the living space on a daily basis will motivate the user to color in the missing pieces. For example, if a user looks at a picture with unfilled green areas and notices that low intake of green foods he or she can choose to add a salad to his or her dinner.

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