eat2pic: An Eating-Painting Interactive System to Nudge Users into Making Healthier Diet Choices

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Fig. 1. By transforming eating into a task of progressively coloring a landscape projected onto a screen, the eat2pic system encourages users to eat more slowly and maintain a healthy balanced diet. The eat2pic system is composed of a calm sensing component based on a sensor-equipped chopstick (A) and visual feedback components using two types of digital canvases (C, E). The colors of the foods consumed by the user are shown on one part of a landscape displayed on two digital canvases to illustrate a single meal and the food consumed in a week as digital paintings generated by an automated system. The one-meal eat2pic (B, C) guides a user's behavior through a single meal with real-time feedback, whereas the one-week eat2pic (D, E) guides a user's food choices and eating behaviors with longer-term feedback accumulated over a full week.

Given the complexity of human eating behaviors, developing interactions to change the way users eat or their choice of meals is challenging. In this study, we propose an interactive system called eat2pic designed to encourage healthy eating habits such as adopting a balanced diet and eating more slowly, by reframing the task of selecting meals into that of adding color to landscape pictures. The eat2pic system comprises a sensor-equipped chopstick (one of a pair) and two types of digital canvases. It provides fast feedback by recognizing a user's eating behavior in real time and displaying the result on a small canvas called "one-meal eat2pic." Moreover, it also provides slow feedback by displaying the number of colors of foods that the user consumed on a large canvas called "one-week eat2pic." The former was designed and implemented as a guide to help people eat more slowly, and the latter to encourage people to select more balanced menus. Through two user studies, we explored the experience of interaction with eat2pic, in which users' daily eating behavior was reflected in a series of "paintings," that is, images produced by the automated system. The experimental results suggest that eat2pic may provide an opportunity for reflection in meal selection and while eating, as well as assist users in becoming more aware of how they are eating and how balanced their daily meals are. We expect this system to inspire users' curiosity about different diets and ways of eating. This research also contributes to expanding the design space for products and services related to dietary support.

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CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**; **Human computer interaction (HCI)**.

Additional Key Words and Phrases: Behavior change, Digital nudge, Human-food interaction, Dietary monitoring, Well-being, Aesthetic feedback

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1 INTRODUCTION

Our personal eating habits are a significant aspect of our lifestyle and behavior and have a serious impact on our health. Since the COVID-19 pandemic, the World Health Organization (WHO) has highlighted the importance of healthy diets in relation to maintaining strong immune systems and avoiding or minimizing chronic diseases and infections [2]. To obtain sufficient nutrients from one's daily diet, selecting foods from a well-balanced menu of meals that includes a variety of healthy foods is important, as is eating at a healthy pace [19].

However, establishing healthy eating habits is often challenging in practice for many people. The recent COVID-19 pandemic has increased the frequency with which people eat alone at home [68]. Studies have shown that eating alone is associated with several negative health consequences [16, 45, 57]. For example, people who eat alone tend to select unhealthy foods that can be prepared easily, which often do not contain enough vegetables. Moreover, the proliferation of attractive digital content has reduced the amount of attention many people pay to their diet and encouraged unhealthy eating habits, such as eating too rapidly or not eating a healthy balance of different foods [14, 27, 50]. This background highlights that solutions to encourage healthy eating habits, such as choosing healthy, well-balanced meals, and eating at a healthy pace, are essential.

In research on human-computer interactions (HCI) and ubiquitous computing (UbiComp), various dietary support systems with sensing and feedback functions have been proposed to address these issues and support healthy diets. However, most existing diet tracking methods that enable detailed monitoring require users to wear special devices on their heads, necks, or chests, which may interfere with their eating behaviors and comfort while eating. Moreover, the most common feedback approach using quantitative visualization methods may reduce users' levels of motivation [15, 20, 32, 55, 66]. By contrast, the use of stylized representations of behavior on personal displays represented by "ubifit garden" [17] and "ubigreen" [26] provides a good starting point for the design of effective feedback methods to change people's behaviors and eating habits. Recent research [3, 51] has highlighted that design with a visual aesthetic that incorporates ambiguity and creative self-expression is an essential factor in future interactive systems developed to support healthy living.

In this study, we propose an interactive system called *eat2pic* (Figure 1), which is designed to encourage users to pursue a healthier diet while raising awareness of how colorful foods they eat are. The system was developed to influence people to eat more slowly and select foods with a wider variety of colors through an aesthetic interaction, which translates eating into a task of coloring pictures. Our idea is based on the findings in nutrition research: eating more colorful foods has been shown to provide an intuitive way of maintaining a healthy diet [44]. The eat2pic system comprises a chopstick with an integrated sensing component that automatically recognizes how the user consumes each mouthful, as well as two types of digital canvases that provide visual feedback on the user's eating habits. Our approach includes small and large digital canvases called one-meal and one-week eat2pic , respectively, that provide real-time and slower-paced feedback. The one-meal eat2pic provides immediate feedback by mapping a user's eating habits based on a single meal. This feedback is designed to encourage users to slow down and enjoy their meals. The one-week eat2pic provides longer-term feedback that maps the color balance of users' meals over the course of a week. This feedback is designed to raise awareness of color balance in users' daily diets and encourage them to select well-balanced menus.

The contributions of this study are summarized as follows:

- We designed an interactive system called eat2pic to encourage users to eat well-balanced diets more slowly.
- We implemented the eat2pic system to track how users consumed each mouthful and provide aesthetic visual feedback through digital canvases according to users' eating behaviors.
- The results of this work provide insights for the design of dietary support systems that can be smoothly integrated into people's living spaces and provide feedback on daily health.

2 RELATED WORKS

2.1 Automatic Diet Monitoring Technologies

Automatic diet monitoring technologies are an important and challenging topic in research on HCI and UbiComp. The use of audio sensors on smartwatch devices to recognize chewing and swallowing was proposed by Kalantarian and Sarrafzadeh [38], while Sen et al. [62] proposed a system designed to recognize what types of foods users ate and how fast they ate them by integrating data from cameras and motion sensors. However, these approaches require the eater to wear a smartwatch on the hand with which they are eating. Other methods have been developed that use necklace-type [77], earbud-type [10, 49], and glasses-type [9, 63, 76] wearable devices to recognize the pace at which users eat, the types of foods they consume, and their chewing behaviors. Recognition methods have also been proposed that require multiple wearable devices [25, 53]. However, it is widely recognized that eating while wearing unfamiliar wearable devices can impair enjoyment and comfort while dining.

By contrast, DataSpoon [80], HAPIfork [29], and sensing chopsticks [7, 56] have been proposed as "smart" utensils that monitor mealtime behaviors such as intake speeds and movements. In addition, Sensing Fork [37], Smart-U [33], and CogKnife recognize the various types of foods that are touched by the device. Taking a different approach, Zhang et al. [78] developed a smart fork designed to recognize the speed with which a user eats by detecting the actions of picking up food and the weight consumed during each bite. However, although the use of sensor-equipped eating utensils has significant potential, no smart utensils are currently available that can perform diet monitoring that includes recognition of the timing of food intake, food type, and the amount of food consumed during each bite. Therefore, the development of a single device that recognizes detailed dietary behavior while focusing on each bite remains challenging.

In this study, we focused on chopsticks as an interface for daily meal tracking. Chopsticks are a multifunctional eating utensil capable of performing several basic actions such as pinching, supporting, and transporting, as well as more complex activities such as cutting, tearing, unraveling, peeling, and scooping. Currently, more than one-fifth of the world's population uses chopsticks daily [18]. In this work, we designed and implemented sensor-equipped chopsticks to understand the details of the behavior mentioned above, including what users are eating, how quickly they are eating, and how much they consume in a single bite.

2.2 Interactive System for Healthy Diet

Over the last several years, the idea of using computational systems to directly influence user behaviors has attracted considerable attention and is applied in several systems as a promising feedback mechanism for supporting behavior change in research on HCI and UbiComp [11, 12]. Nudging is a concept developed by Thaler and Sunstein [48] within the realm of behavioral economics that is built on the concept of choice architecture. More specifically, a "nudge" is any aspect of a choice architecture that alters people's behavior without forbidding any other options or significantly changing their economic incentives. For example, replacing cakes with fruits in impulse-buying baskets next to cash registers has been found to nudge people to buy more fruits and less cakes [48].

Adams et al. [4] created a plate that uses the Delboeuf illusion [70] to influence an individual's perception of the amount of food on the plate, whereas Lee et al. [47] designed a robot to promote healthy snacking based on knowledge related to cognitive biases. In addition, Barral et al. [8] developed a system in which certain cues were quickly flashed to users to encourage particular food selections based on subliminal priming [69], whereas the EcoMeal system developed by Kim et al. [41] was designed to weigh the food on a user's plate, infer their pace of eating, and alert the user to slow down through light feedback when it considered them to be eating too fast.

Kadomura et al. [36, 37] designed persuasive technology to improve children's eating habits (such as those of picky eaters and/or those easily distracted during mealtimes) using a sensor-equipped fork and games on a smartphone app. Khot et al. designed the Tastybeats [39] system, which enhanced palatable experiences by improving the understanding of physical activities through abstract visualization. It also provided an appetizing drink as an incentive. Meanwhile, the Playful Bottle system designed by Chiu et al. [13] was based on an augmented water bottle designed to encourage drinking water by using water intake as input for a mobile game. In addition to the studies mentioned above, numerous human-food interaction systems that encourage healthy and playful eating behaviors [5, 6, 34, 40, 54, 60] have been proposed.

However, these systems focus on interactions during a meal. To the best of our knowledge, the present work is the first to provide a system designed to encourage slow and healthy eating throughout the day. Because eating habits are complex behaviors involving multiple factors, we argue that designing interactions that occur both during meals and in meal planning is necessary to provide a system to support users in adopting healthier behaviors. Moreover, designing interactions that effectively encourage users to adopt a healthier diet without excessively interrupting their dining experience can be considered a notable challenge. Therefore, we designed interactions incorporating elements of visual aesthetics and creative self-expression to encourage self-reflection about eating habits based on the concepts of calm technology [71] and slow technology [30]. We developed ambient displays in the form of paintings as a display interface that represents the users' eating habits in a way that can be understood at a glance while blending into their daily living space and providing helpful feedback.

3 EAT2PIC

3.1 Behavioral Insights and Approach

In this work, we designed an interactive system to encourage healthy eating habits, such as eating slowly and choosing colorful meals. We considered approaches to discourage users from following the two unhealthy eating habits of "fast eating" and "unbalanced diet" and modify their behavior to make healthier food choices based on the Fogg behavior model [1, 24]. Fogg's behavior model asserts that for a person to follow a target behavior pattern, they must be (1) sufficiently motivated, (2) able to perform the tasks associated with the target behavior pattern, and (3) prompted to perform those tasks. When the intended behavior change does not happen, the model states that at least one of these three elements is missing.

Eating slowly is desirable, as it improves digestion and hydration, facilitates maintaining a healthy weight, and increases the satisfaction derived from eating. We presume that most people can overcome the habit of eating too fast because eating slowly is easy for most people. Thus, we hypothesize that many people fail to develop the habit of eating slowly due to a lack of prompts to reflect on their eating style during mealtime. By contrast, maintaining a balanced diet is a highly complex behavior because it requires planning at mealtime and sometimes days in advance, including shopping for the meals. There is no doubt that a well-balanced diet is beneficial for human health, but the health benefits of changes in diet may not always be experienced immediately. For example, the sense of satisfaction derived from eating healthy foods may naturally tend to fade over time after eating. Therefore, we hypothesized that designing interactions that blend into the living space with playful elements could help users experience a lasting sense of accomplishment for having selected a colorful diet. These elements could also provide positive reinforcement.

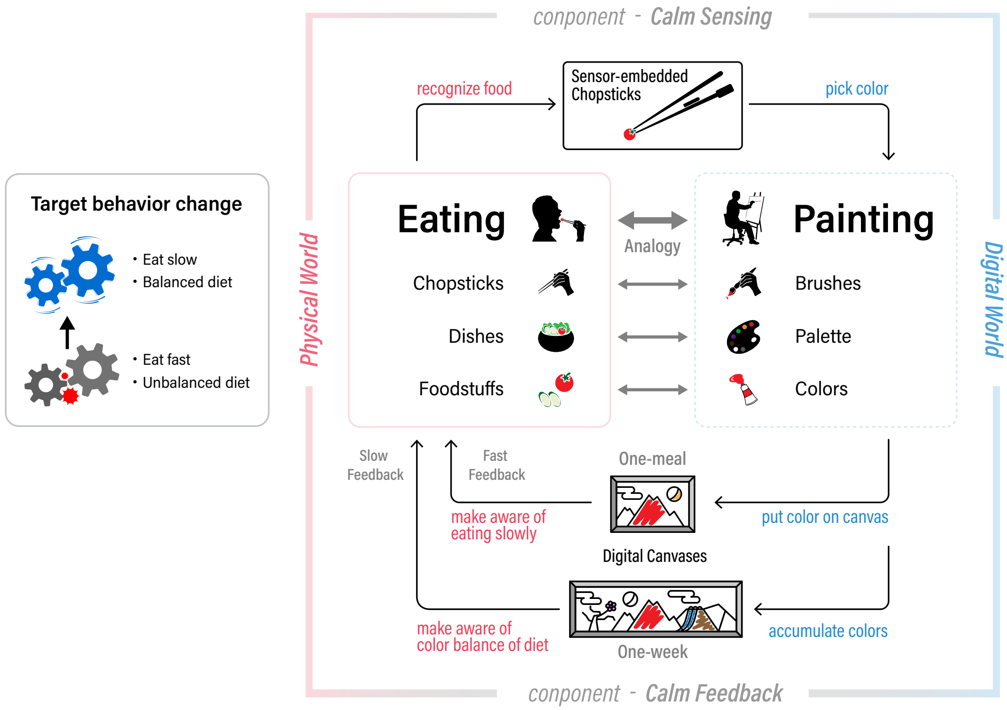


Fig. 2. Overview of the eat2pic concept. Two components, including a calm sensing component to observe the user's eating behavior and a calm feedback component to reflect the user's behavior as a painting, work together to create a closed-loop system between the physical/real and digital/virtual worlds to nudge users toward the intended actions.

In designing the eat2pic system, we focused on two types of nudge mechanisms designed to change users' behaviors: just-in-time prompts and ambient feedback [12]. Just-in-time prompts serve to draw users' attention to their behavior at appropriate times (e.g., when their behavior deviates from the ideal). Ambient feedback reinforces specific behaviors while reducing the potential disruption of users' activity. In eat2pic, the just-in-time mechanism prompts the user to slow down while eating, and the ambient feedback mechanism is used as a guide to raise awareness for eating a more balanced diet with food of widely varying colors.

3.2 Design Concept

Figure 2 shows the design concept of eat2pic. The system is based on an analogy between eating and painting behaviors — in this case, chopsticks and paintbrushes, dishes and palettes, and food types and colors. The eat2pic system is based on the Japanese food culture known as "washoku." We focused on the color of users' meals because the colors of food ingredients are important in washoku culture. In general, washoku culture encourages people to prepare every meal using five or seven colors (red, green, yellow, white, black, purple, and brown). In addition, it is considered polite to bring food slowly to our mouths when eating. The key concept behind the eat2pic system involves extending the meal experience through an interaction between eating and paintings, establishing a closed loop in which daily eating behaviors are reflected in digital paintings. These reflected aesthetic representations are designed to promote engagement in self-reflection and nudge users' diets in a healthier direction in terms of their lifestyle and behavior.

The eat2pic system consists of a calm sensing component in the form of a sensor-equipped chopstick setup and a visual feedback component in the form of digital canvases. To design a system that can be naturally incorporated into a living space, we selected chopsticks as a sensor platform given their widespread usage and employed pictures, which typically adorn living spaces, as a feedback mechanism. The sensor-equipped chopstick setup simultaneously recognizes the eating speed of the user, color (type) of the selected food, and amount of food consumed. Then, the recognition results are reflected in a landscape painting on the digital canvas. The eat2pic system has two types of digital canvases: *one-meal eat2pic* and *one-week eat2pic*. The one-meal eat2pic provides a small canvas that can be filled within a single meal and gives instant feedback that maps a user's way of eating a single meal. By contrast, the one-week eat2pic provides a larger canvas that takes several days to fill and provides slow feedback that maps the color balance of the user's meals during the week. The former is designed as a prompt to encourage a user to maintain a slow eating pace, while the latter is designed to encourage users to choose a more balanced menu.

3.3 Use Case Scenario

We provide realistic use-case scenarios that show how eat2pic can be useful in practice (see Figure 3). For example, one of the participants in this study, Taro, a 20-year-old college student who lives alone, observed a digital canvas (one-week eat2pic) hanging on the wall of his kitchen (Figure 3A). Based on the colors shown on the one-week eat2pic canvas, Taro realized that during the first half of the current week, his meals were biased towards brown and white. Indeed, in the first half of this week, he was so busy with class assignments and homework that he resorted to ready-to-eat meals and frozen foods. Taro reflected on the lack of a balanced diet. With his classwork and homework settled, Taro decided to go shopping at the supermarket to make up for the lack of red-, green-, and purple-colored food items in his diet. At the supermarket, Taro procured ingredients based on the colors missing from his diet the first half of the current: mainly vegetables, such as tomatoes, broccoli, and eggplant (Figure 3B). After returning home, he began to prepare dinner. To make up for his lack of variety in foods, Taro cooked a nutritious meal including a variety of colorful foods (Figure 3C). After cooking, Taro arranged the finished meal on a plate and took it to the dining table. The small digital one-meal eat2pic canvas, which reflects on a single meal, was positioned on the wall above the dining table. Taro was ready to eat, so he started eating his dinner (Figure 3D). Each time he took a bite of food, a color was reflected on one part of the canvas. Suddenly, Taro noticed that the color of a part of the one-meal eat2pic was blotted out in black. In this way, the one-meal eat2pic system informed Taro that he was eating too fast. Taro then slowed down the pace at which he was

Fig. 3. An eat2pic use case scenario.

eating. Taro ate his dinner slowly, enjoying the interaction with the canvas as pieces gradually became colored with each bite. After finishing his meal, Taro was pleased to see that he had been able to color all parts of the one-meal eat2pic canvas, mainly because the menu that evening was well-balanced (Figure 3E). After dinner, Taro took a short break and started cleaning up the dishes (Figure 3F). The one-week eat2pic system in the kitchen also reflected the colors of the food Taro just ate, which gave Taro an added sense of accomplishment. In the kitchen, Taro checked the missing colors in the one-week eat2pic and planned his menu for the next day as he washed the dishes'. Since he started planning his meals using eat2pic, Taro has enjoyed eating a well-balanced diet and found the system fun to use.

3.4 Design and Implementation

Figure 4 shows an overview of the eat2pic system, which comprises a sensor-equipped chopstick (one of a pair) and two types of digital canvases: *one-meal eat2pic* and *one-week eat2pic*.

The sensor-equipped chopstick was equipped with IMU sensors (MetaMotionRL[1]: sensors — 100 Hz quaternion three-axis accelerometer/gyroscope; dimensions — L29×W18×H6 mm; weight — 5.7 g) for eating behavior sensing,

[1]MbientLabs: https://mbientlab.com/metamotionrl/

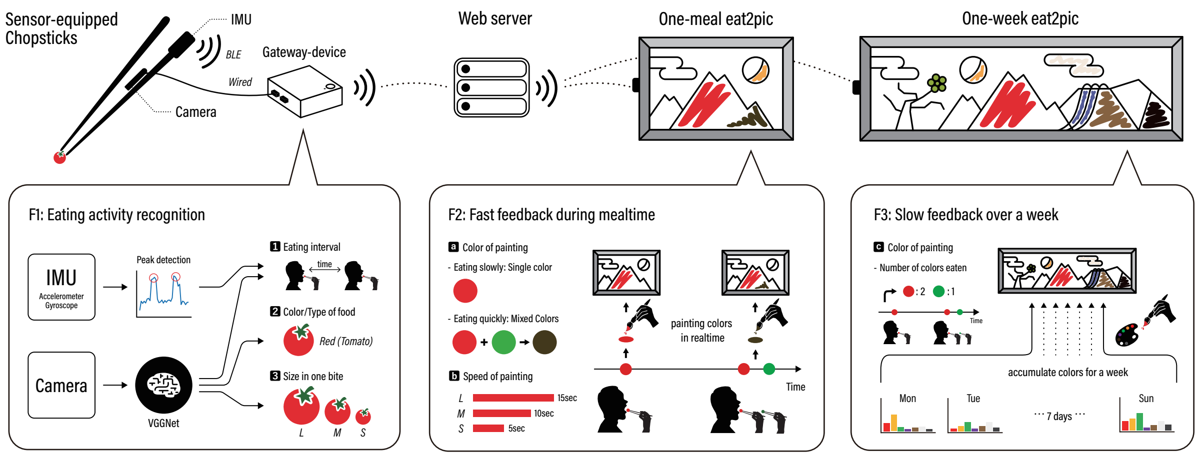
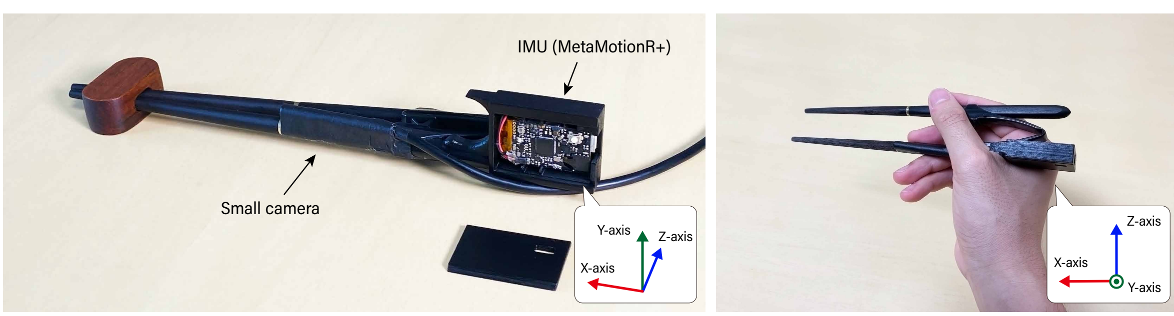


Fig. 4. System overview of eat2pic.



(a) A sensor-equipped chopstick (one of a pair)

(b) Appearance when holding a chopstick

Fig. 5. Sensor-equipped chopstick setup.

(a) one-meal eat2pic

(b) one-week eat2pic

Fig. 6. Two types of eat2pic canvases: (a) One-meal eat2pic canvas placed on the dining table to nudge the user towards improved eating behavior during a single meal with real-time feedback, and (b) one-week eat2pic canvas placed within the kitchen to nudge the user towards choosing healthier meal ingredients on a day-to-day basis with slow feedback.

and a small camera (endoscope inspection camera[2]: resolution — 640×480 px; frame rate — 4–5 fps) to capture images of the user's food before each meal. The exterior of a sensor-equipped chopstick was designed using 3D CAD, and multiple prototypes were produced using a 3D printer. The positions of the sensor and camera were determined by trial and error with a focus on ease of holding and use. The device was implemented as shown in Figure 5 (length: 21 cm, weight: 41 g). The IMU sensor signals and camera data (image sequences) were streamed to the gateway device via Bluetooth low energy (BLE) and cable links, respectively. The gateway device then analyzed the IMU sensor signal and camera data simultaneously to track the user's eating timing, the type (color) of the foods eaten, and the amount of food consumed in a single bite.

The web server changes the landscape picture (canvas view) displayed on the digital canvases based on the user's eating behavior. In the canvas view, the color of the food consumed is reflected by the color of the applied paint, whereas eating speed is reflected in the color mixture, and the amount consumed in each bite is indicated by the speed with which the painting is filled in.

In this study, we used thin tablet devices and a signage terminal for the one-meal and one-week digital canvases, respectively, as shown in Figure 6. The one-meal eat2pic canvas consisted of 49 pieces (7 colors × 7), whereas the one-week eat2pic canvas consisted of 350 pieces (7 colors × 50). Each original picture was created by a human artist based on a Japanese landscape theme. On the one-meal eat2pic canvas, a guideline of 50 or more mouthfuls for each meal was set. The number of one-week eat2pic pieces was tentatively determined based on the requirement that target users would eat balanced meals at home with the sensor-equipped chopstick set at least seven times per week.

3.5 System Functions

The eat2pic system provides two functions: (1) automatic diet tracking of how the user consumed each mouthful of food and (2) ambient visual feedback with stylized painting representations of eating habits describing the user's behavior in terms of each single meal and over a given week. Below, we describe how each function of the eat2pic system is implemented and how they work together.

3.5.1 F1: Diet Tracking Function. An overview of the pipeline is shown in the Figure 7. The inputs comprise the acceleration and gyroscope signals obtained from the IMU sensor and image data collected from the camera

[2]KKmoon: https://www.kkmoon.com/

mounted on the tip of one chopstick. The pipeline outputs comprise (1) eating interval/speed, (2) color/type of food, and (3) size consumed in each bite. The system was controlled by software written in Python.

The pipeline consists of three steps. The system performs the following three steps sequentially on time-series data in 3-second windows, providing a just-in-time description of how the user consumes each mouthful of food. In Step 1, peaks are detected from the time-series signals of the Z-axis Euler angles calculated using the Kalman filter-based sensor fusion function from the accelerometer and gyroscope data to identify when the chopsticks were moved toward the users' mouths. Specifically, the system is designed to detect peaks at which the Euler angle of the Z-axis is tilted upward by 5 degrees or greater. In Step 2, mouth detection with a VGG16-based fine-tuned model is applied to the image data from the camera (4–5 fps) to determine whether the image corresponding to the timing detected in Step 1 is the user's mouth. The pipeline determines the point when the peak detection method used in Step 1 and mouth detection in Step 2 return true as the timing of the moment when the user consumed the food. The system then proceeds to Step 3 in which it determines what the user ate. Here, a VGG16-based fine-tuned model trained to recognize different types (colors) of food as well as small, medium, and large portion sizes is applied to frames in the 1-second period before the point determined as the eating time. The recognition results for each 1-second set of frames are combined into a single result by majority vote. flushright

In creating the image recognition model used in steps 2 and 3, we used a convolutional neural network model based on the VGG16 architecture [64]. The input of the VGG model is a 224 × 224 sized RGB image. We used the original VGG16 model pretrained with the ImageNet dataset [22]. Then, we modified the number of neurons in the fully connected layers to match the number of target classes and fine-tuned the parameters of each model. To train the image recognition network, we collected a dataset of eating behaviors using the sensor-equipped chopstick system. Specifically, with the help of five experimental participants, we collected approximately 100 GB of sensor data about eating behaviors, including movements of grasping food with chopsticks, bringing it to the mouth, and eating it. As shown in Figure 8, the experiment investigated 45 different kinds of normal Japanese food (broken down by seven colors). The collected dataset contained approximately 200 intake behaviors and 36,000 images for each food.

The results of the automatic eating recognition pipeline are shown in Table 1. The window size was set to 3 seconds to detect the timing of eating. We divided the dataset into training data and test data in a ratio of 5:5 and then evaluated each VGG16-based model in the pipeline. As a result, M2, M4, and M5, which were used for feedback from the one-meal eat2pic described below, exceeded 90% accuracy. Although meal timing detection accuracy using IMU sensor data alone was only 85%, we could improve detection accuracy to 95% by combining

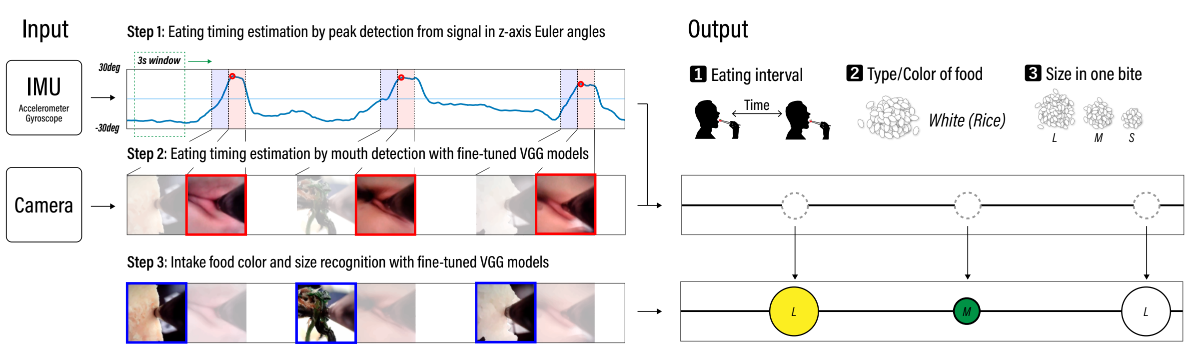


Fig. 7. Overview of diet tracking pipeline using a sensor-equipped chopstick.

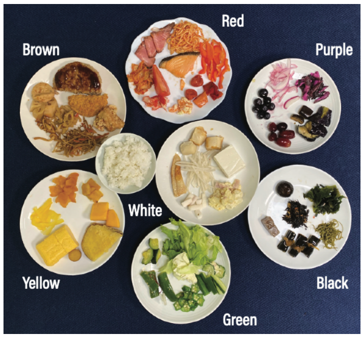


Fig. 8. 45 meals used in the validation.

Table 1. f-score for intake detection/type/color/amount of food classification.

Item	Description	f-score
M1	Intake detection using only IMU signal	0.85
M2	Intake detection using both IMU and image signals	0.95
M3	Type of food: 45 foods included in the dataset	0.89
M4	Color of food: red, green, yellow, white, black, purple, and brown	0.92
M5	Size of food (Small, Medium, Large)	0.93

image processing with time-series sensor data processing. We also confirmed highly accurate recognition results for the types (89%), colors (92%), and sizes (93%) of foods.

3.5.2 F2: Ambient Visual Feedback Function. The eat2pic system provides (a) fast feedback by recognizing the user's eating behavior in real time and reflecting the recognition results in the small canvas of the one-meal eat2pic, and (b) slow feedback by displaying the number of colors of foods that the user consumed on a large canvas called one-week eat2pic.

(a) One-meal eat2pic: fast feedback. Figure 9 shows an example of real-time visual feedback in the one-meal eat2pic. We assume that the one-meal eat2pic is mounted on the wall next to the dining table, and users can enjoy their meal while looking at a landscape painting on the digital canvas. In the one-meal eat2pic, the colors of the foods eaten by the user are reflected as parts of the landscape paintings on the digital canvas. At this point, the way the colors are applied changes depending on how the user eats. If a user rushes through a meal, multiple colors are mixed on one piece (based on subtractive color mixing theory), and the appearance of the

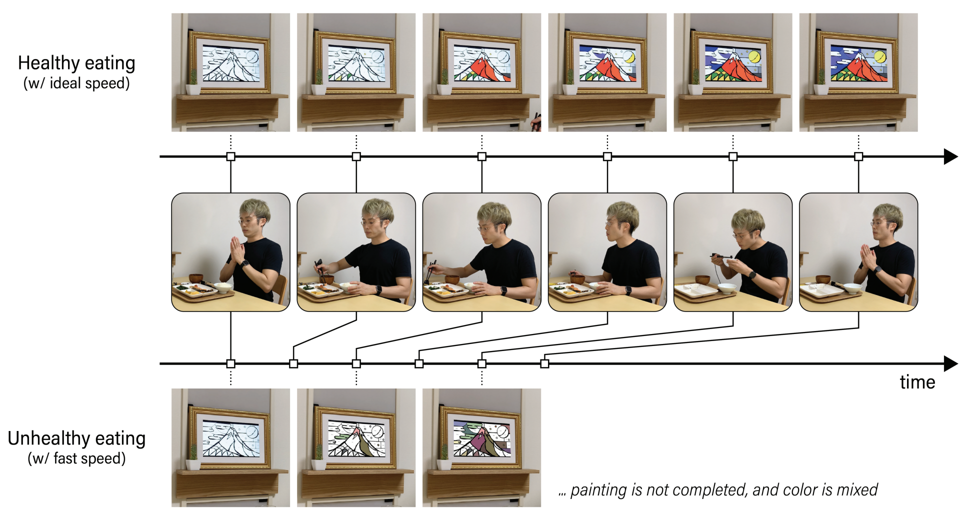


Fig. 9. Example of coloring the canvas based on eating speed. The user's eating behavior is monitored, and the status is reflected as part of the coloring applied to the canvas. The painting is gradually completed as the user eats. If the meal is eaten too quickly, multiple colors are mixed and applied, resulting in a poor visual appearance.

Fig. 10. Picture displayed on the one-week eat2pic

landscape degrades, as shown in the bottom row of Figure 9. This effect was inspired by the fact that colors in a real painting may blur if an artist does not wait for the paint to dry before painting with a different color, and is designed to act as a prompt for the user to notice that they are eating too quickly. The eat2pic system determines the waiting time per intake based on the size of the portion the user brings to their mouth at a time (small: 5 seconds, medium: 10 seconds, large: 15 seconds). Using such a mechanism, the one-meal eat2pic canvas visualizes the user's eating speed as a color-mixing effect.

(b) One-week eat2pic: slow feedback. This component of the system is designed with the idea that the act of looking at an unfinished landscape painting of the one-week eat2pic placed in a daily living space will prompt the users' desire to add color to the missing parts. Moreover, this beautiful landscape painting, which is gradually completed over several days as users maintain a balanced diet, is intended to provide users with the motivation to maintain a healthy diet and a sustained sense of personal accomplishment. The one-week eat2pic canvas is designed to color one part of the canvas picture with the color of each bite the user eats, regardless of how fast it is eaten. Hence, the one-week eat2pic canvas does not reflect the color mixing effect described for the one-meal eat2pic. This role allows the user to see how well they have been eating by looking at the one-meal eat2pic canvas and evaluate the color balance of their daily diet by looking at the one-week eat2pic canvas. As shown in Figure 10, the color painted on each piece is predetermined, and the user can tell which color of food they may not be eating enough of simply by looking at the picture. The right side of Figure 10 shows examples of painting results on the canvas after different meal types. Many unfilled places are left on the canvas after the meal if the user chooses an unhealthy (unbalanced) meal. If the user chooses a healthy (balanced) meal, the canvas will be filled with beautiful colors.

4 HYPOTHESES

In the previous section, we introduced the interaction design of eat2pic to nudge a user toward a healthier diet. Specifically, we designed the one-meal eat2pic to act as a prompt to slow down the pace of eating and the one-week eat2pic as a prompt to encourage the selection of a more balanced menu. Throughout the design process of eat2pic, the hypotheses we imposed were as follows:

H1: The fast feedback from the one-meal eat2pic encourages a more enjoyable and slower eating experience. It is effective in suppressing fast eating.

H2: The slow feedback from the one-week eat2pic raises awareness of the benefits of more colorful diets and encourages a well-balanced diet. It is especially effective for users who are interested in art or games.

To test these hypotheses and gain insight into how feedback from the two types of eat2pics embedded in a living space might change users' awareness and behaviors toward eating, we conducted two user studies.

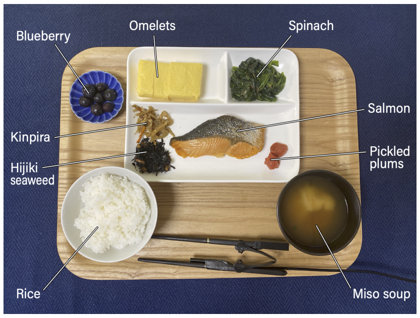
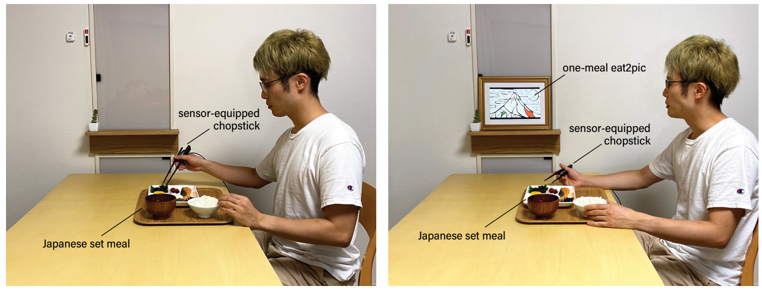


Fig. 11. Japanese set meal used in the study.



(a) NF - No feedback (baseline)

(b) AF - Ambient feedback (one-meal eat2pic)

Fig. 12. Experimental scenery of each condition.

5 USER STUDY1: EVALUATION OF THE ONE-MEAL EAT2PIC (WITHIN-SUBJECTS DESIGN)

In this user study, we aimed to validate hypothesis H1 and gain insight into how feedback from one-meal eat2pic would be experienced. In particular, previous studies [31, 58, 74] have shown that young adults living alone spend less time on meals and are more likely to adopt unhealthy habits. Based on this background, we invited 20 people (19 males and 1 female; mean age = 22.95, standard deviation (SD) = 1.12) through a university's local social media to participate in an experiment. These people were living alone when the experiment was conducted and were usually aware of their fast eating habits. Each participant was among the first to use the one-meal eat2pic system.

5.1 Conditions

We adopted a within-subjects design and observed their experiences under the following two conditions:

NF - No feedback (baseline): In this condition, the participants' eating behavior without feedback was recorded, as shown in Figure 12 (a). The participants ate the provided Japanese set meal (Figure 11) using the sensor-equipped chopstick setup (Figure 5). The participants were free to eat the set meal as usual. We set this condition as our baseline.

AF - Ambient feedback (one-meal eat2pic): In this condition, we recorded the participants' eating behaviors as they received visual feedback from the one-meal eat2pic, as shown in Figure 12 (b). The participants ate the same set meal (Figure 11) as in the NF condition using the sensor-equipped chopsticks. Here, the colors of the meal items consumed by the users were reflected in the landscape painting. If a participant ate too fast, the piece colored in the last bite was overwritten with the color of the next bite (the result being a mixture of two colors). If the participants ate slowly with each bite, no color mixing effect occurred.

5.2 Settings

For the experiment, we rented a one-bedroom home facility, as shown in Figure 12. Each participant consumed two meals under different conditions (NF, AF) on different days in the dining area of this model home. As a baseline, each participant initially ate under NF conditions. Then, they ate under AF conditions. The schedule was assigned according to the convenience of the participants. In all experiments, each subject dined alone while consuming the same set of menu items using sensor-equipped chopsticks. Each participant was provided a well-balanced, typical Japanese meal consisting of salmon, kinpira, pickled plums, scrambled eggs, hijiki seaweed, spinach, miso soup, and rice, as shown in Figure 11. Participants were asked in advance to adjust their appetites to normal levels to minimize physical biases as much as possible. Furthermore, the participants were not informed in advance of the purpose of the eat2pic system. They were only given a basic explanation of how the system worked, such as how the content on the digital canvas would change according to users' eating behaviors. To avoid interference with the content of the study, participants were asked not to talk publicly about the experiment during the experimental period. After obtaining their consent, a single camera was installed in the dining area to observe participant reactions to the system's visual feedback. After all the tasks were completed, we conducted an interview for approximately 10 minutes and asked the participants to answer questions about their impressions of their awareness and experiences while eating with the one-meal eat2pic.

5.3 Results

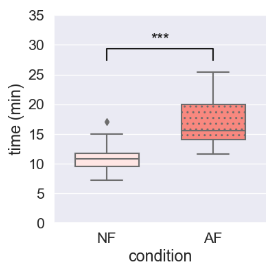


Fig. 13. Meal time.

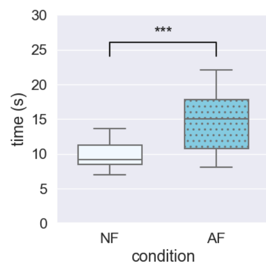
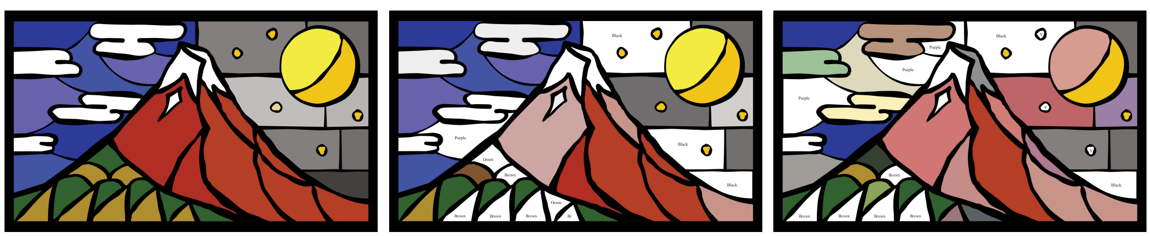


Fig. 14. Intake interval.

Table 2. Summary of results: user study 1.

	All Subjects (N = 20)		
	NF	AF	Diff
Time	Mean (SD)	Mean (SD)	P-value
Meal time (min)	11.08 (2.33)	16.72 (4.01)	**0.000004**
Intake interval (s)	9.71 (1.87)	14.7 (4.12)	**0.000027**



(a) P0's coloring result in PI2 (b) P5's coloring result in PI2 (c) P8's coloring result in PI2

Fig. 15. Example of differences between the coloring results for participants under AF conditions.

The box plots of the time required by participants to finish the set meal and the interval time between each bite are shown in Figure 13 and Figure 14. The average time to finish the set meal was 11.08 minutes (SD = 2.32) for the NF condition and 16.72 minutes (SD = 4.01) for the AF condition. This result confirms that the average time taken to finish a meal increased by 5.64 minutes (+ 50.89%) under the AF condition compared to the baseline under the NF condition. This result is a desirable change, as it is generally considered good practice to take at least 15 minutes to eat. The average interval time after a bite was 9.71 seconds (SD = 1.87) for the NF condition and 14.6 seconds (SD = 4.12) for the AF condition. This result confirmed that the bite interval under the AF condition was 4.95 seconds (+ 50.97%) longer than the baseline under the NF condition. The short interval between each bite indicates insufficient chewing. Therefore, the extended bite interval is a positive trend, indicating better chewing. To analyze significant differences in the NF and AF conditions, we performed a paired sample two-sided Wilcoxon signed rank test [72]. As shown in Table 2, significant differences were observed both for overall meal time ($p = 0.000004$, $p < 0.05$) and intake intervals ($p = 0.000027$, $p < 0.05$). These results suggest that feedback from the one-meal eat2pic has the potential to act as an effective prompt to encourage slower eating.

From the video recorded during the experiment, we observed that most participants watched the changes in the paintings with each bite with interest during the AF conditions. Many participants enjoyed the new experience of coloring paintings by eating, and we received considerable positive feedback, such as *"It felt like I was actually* *painting a picture"*, *"I've found a way to eat in order to paint a nice picture"*, *"The food tasted better because of the increased visual enjoyment during the meal."*, and *"I was able to enjoy the changes in the picture and eat slowly and chew well."*. Figure 15 shows examples of the results of coloring the eat2pic canvas under the AF condition for different participants. As may be observed, even with the same food menu and same conditions, different outcomes were obtained for each participant. Participant P0 was eating slowly, chewing each bite well. As a result, all pieces were painted without any color mixing. Participant P5 tended to eat larger bites than other participants. As a result, certain pieces are not colored. Participant P8 was very interested in the color mixing effect. He enjoyed eating the meal through trial and error, as if he were experimenting with all the color mixing combinations. Thus, the system provides an interesting way to subtly infer how a person ate a meal from the results shown by the one-meal eat2pic canvas. These results support hypothesis H1 by suggesting that feedback from the one-meal eat2pic helped the participants slow down while eating and increased their enjoyment during the meal.

6 USER STUDY2: EVALUATION OF THE ONE-WEEK EAT2PIC (WITHIN-SUBJECTS DESIGN)

In this user study, we aimed to validate hypothesis H2 and identify changes in users' dietary awareness and food choices through the feedback provided by the one-week eat2pic system. To achieve this goal, we conducted an in-the-wild experiment that lasted one month (4 weeks,). However, the prototype sensor-equipped chopsticks were not sufficiently strong to withstand daily usage and retain their functionality, rendering them unsuitable for this experiment. Therefore, for this experiment, we changed the automatic tracking of sensor-equipped chopsticks to an alternative, using manual input from an app to enable users to report their meals, as shown in Figure 16. The counts representing how many bites of each color (red, yellow, green, purple, brown, white, and black) of food the participants ate, which served as input to the one-week eat2pic feedback, were collected through manual input by users, using the meal-reporting app.

Participants were recruited through a dispatch company. At the time of recruitment, participants were asked to complete a brief questionnaire to identify the stage of behavior change, based on the transtheoretical model [59], toward healthy eating habits as well as their daily interest in art and games. Based on the results, 30 participants (22 males and 8 females; mean age = 24.1, SD = 2.12) who fell into the contemplation stage (that is, a stage at which people begin to recognize that their behavior is problematic and begin to consider the pros and cons of continuing their behavior) of behavior change were selected for this experiment. Of the 30 participants, 20 were interested in art and games, while the remaining 10 were not. The participants were students at the same university. We provided a reward of approximately $200 for participating in the experiment.

6.1 Conditions

We adopted a within-subjects design and observed the experiences of the participants under two conditions. In this study, participants were asked to place one-week eat2pic canvases (Figure 6 (b)) in spaces where they would spend time. For this experiment, we provided small digital canvases, approximately 15 cm in width and 6 cm in height, for easy installation at a place selected by the participants in their living space.

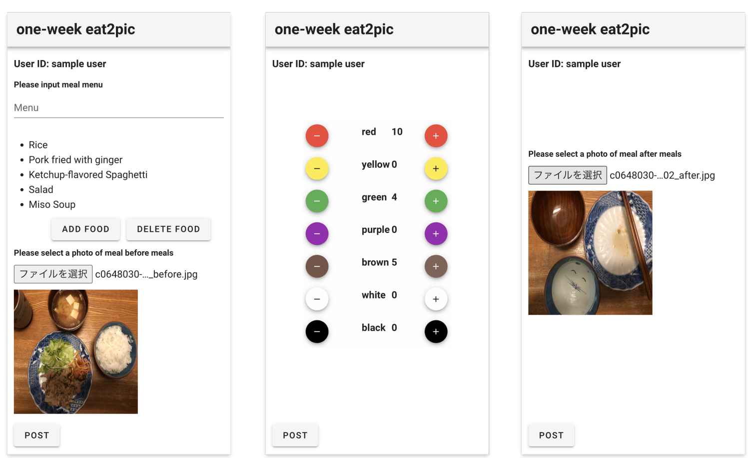
- **NF - No feedback:** In this condition, participants manually recorded their meals through the meal reporting app, but no feedback was provided (the screen of the one-week eat2pic was turned off). Participants were free to eat their usual meals. This condition was set as a baseline to record the participants' usual eating habits.
- **AF - Ambient feedback (one-week eat2pic):** In this condition, the screen of the one-week eat2pic was turned on, and the participants received this ambient feedback. Here, the color per bite information, manually entered by the participant through the application, is reflected in each piece of the painting picture on the one-week eat2pic. Similar to the NF condition, participants were free to eat as they wished.

The one-week eat2pic was designed around the concept of painting colors over a week. The colors painted over the week were reset each Monday.

6.2 Settings

An overview of the experimental procedure is shown in Figure 17. We divided the participants into two groups (considering an even gender and age balance) to counterbalance the two conditions, NF and AF. Group A was then assigned conditions in the order AF, NF, AF, NF, and Group B in the order NF, AF, AF, NF. We collected the participants' dietary logs during the experiment in two ways. The first was manual input by participants using the meal-reporting app (as shown in Figure 16), and the other was a brief-type self-administered diet history questionnaire (BDHQ). The BDHQ is a 58-item fixed-portion–type questionnaire created to evaluate the Japanese diet [42, 43]. These were used to calculate food and nutrient intake for a week. We calculated the average daily intake by food category according to the results of the BDHQ questionnaire. In addition to each week during the experiment, we also took the BDHQ questionnaire one week before and after the experiment to investigate pre- and post-experimental dietary history.

During the experiment (week 1 to week 4), participants were required to take photos of their daily meals (before and after eating) and manually report in through the meal reporting app how many bites of which color foods they ate during their meals. A list of food color correspondences was provided to prevent color confusion among participants. During the experiment, the validity of the number of colors reported by the participants was checked by the experimental assistants by comparison with the submitted images to prevent false reports and cheating. In addition, we used the results of the BDHQ responses to calculate daily intake (in grams) for each of six representative food categories (grain dishes, vegetable dishes, fish and meat dishes, milk and milk products, fruits, and fats and sweets). Participants were required to answer the BDHQ six times: a week before the experiment started, every weekend during the experiment period, and a week after the completion of the experiment. After all the tasks were completed, we collected a questionnaire on the use of the one-week eat2pic



(a) Meal information input screen (b) Color count input screen (c) After meal image input screen

Fig. 16. UI of the meal reporting application used in user study 2. Before eating a meal, participants took a picture of the meal menu shown on the screen (a); during the meal, they manually counted which colors of food they ate using buttons on screen (b); after the meal, they took a picture of the empty plate on the screen (c).

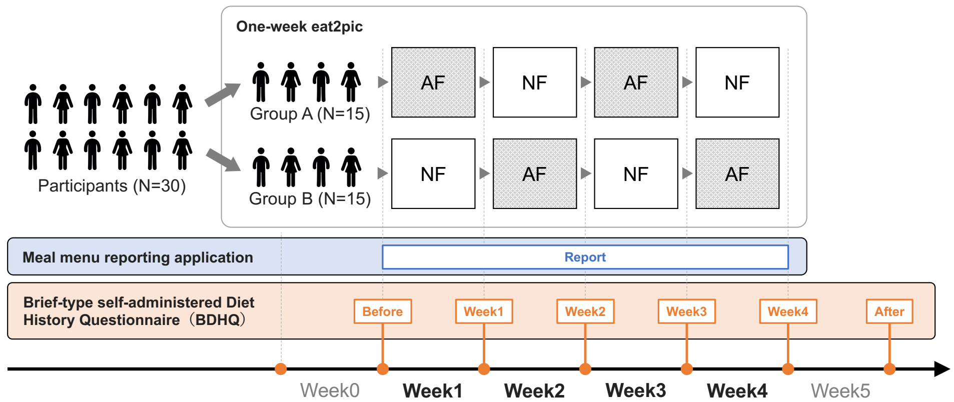


Fig. 17. Overview of experimental procedures.

and conducted 60-minute interviews to evaluate the awareness and changes in consciousness and behavior brought about by the system during the experiment.

6.3 Results

The results of the average counts by color per week under the two conditions as reported through the mobile application are shown in Figure 18. Overall, we can confirm a trend toward inadequate intake of purple and black foods. In addition, a slightly increasing trend was observed for all colors except red. The average daily intake for each of the six dietary categories calculated from the BDHQ results is shown in Figure 19. In addition to the results for the NF and AF conditions, the results for the week before the experiment (BEF) and the week after the experiment (AFT) are also shown. Compared to the BEF, NF, and AFT conditions, we observed a slightly increased trend in the intake of "vegetable dishes" and "fruits" in the AF condition. Conversely, for "milk and milk products" and "fats and sweets," a decreasing trend was observed in the other conditions compared to the BEF condition.

To analyze significant differences between the NF and AF conditions, we conducted a paired sample two-sided Wilcoxon signed rank test (as shown in Table 3 and Table 4). Additionally, to determine the effect of participants' usual interest in art and games on the effect of eat2pic, we divided the 30 subjects (G0) into two groups (G1: interested in art and games, G2: uninterested in art and games) based on the results of a precollected questionnaire and calculated significant differences for each group. The results in Table 3 show that, across subjects (G0), a predominant difference was observed in the consumption of purple, white, and black foods. In addition, group G1 showed a significant difference in the consumption of green, purple, white, and black foods. By contrast, group G2 showed no significant differences in the consumption of foods of any color. The results in Table 4 show no significant difference in intake per food category between the NF and AF conditions for groups G0 and G2. By contrast, in group G1, which consisted of subjects interested in art and games, a significant difference was observed in vegetable intake between the NF and AF conditions. The AF condition increased the intake of vegetables by an average of 20.99 grams (+ 9.16 %) per day compared to the NF condition.

These results suggest that for users who enjoy art and games on a regular basis, the one-week eat2pic may serve as an effective approach to encourage a more balanced and colorful diet. This result partially supports hypothesis H2. However, it was found to be ineffective for users who did not express interest in art, indicating that these issues must be addressed for generalization. Comparing the results in the two tables (Table 3 and Table 4), we can expect that the increase in white, green, purple, and black food counts indicated an increase in the consumption of grain dishes, vegetables (including seaweed), and fruits. Overall, the results confirm that an

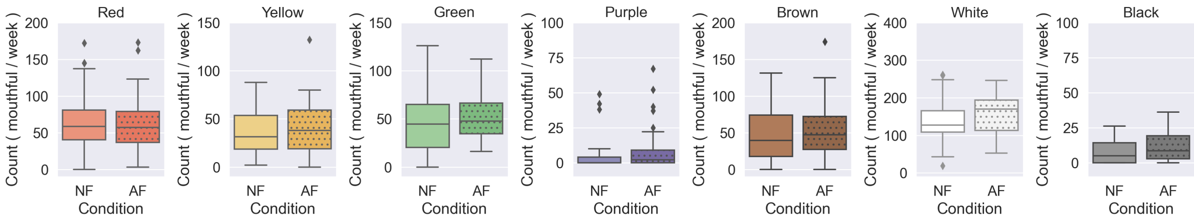


Fig. 18. Average counts by color per week under two conditions.

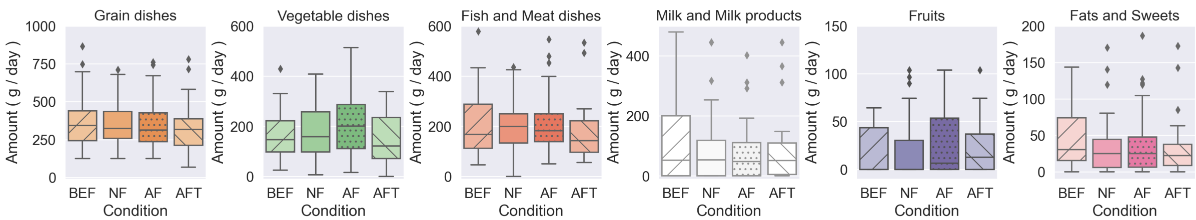


Fig. 19. Average daily intake by food category (BEF: before experiment, AFT: after experiment).

Table 3. Summary of results: the color of the food eaten.

	G0: All Subjects (N = 30)			G1: Interested in art and games (N = 20)			G2: uninterested in art and games (N = 10)		
	NF	AF	Diff	NF	AF	Diff	NF	AF	Diff
Color	Mean (SD)	Mean (SD)	P-value	Mean (SD)	Mean (SD)	P-value	Mean (SD)	Mean (SD)	P-value
Red	64.03 (40.54)	62.63 (39.35)	0.645	63.37 (40.88)	61.70 (35.84)	0.506	65.35 (40.88)	64.50 (46.53)	1.000
Yellow	48.15 (35.29)	48.38 (30.84)	0.421	37.40 (24.50)	40.78 (26.23)	0.143	69.65 (43.65)	63.60 (34.27)	0.621
Green	46.58 (32.15)	51.13 (28.35)	0.155	**44.95 (32.50)**	**52.52 (24.74)**	**0.033**	49.85 (32.02)	48.35 (35.04)	0.903
Purple	**5.75 (14.10)**	**8.68 (15.66)**	**0.006**	**4.83 (11.37)**	**8.87 (15.40)**	**0.005**	7.60 (18.61)	8.30 (16.58)	0.614
Brown	47.98 (36.10)	50.22 (35.72)	0.420	47.75 (37.89)	52.45 (37.05)	0.130	48.45 (33.18)	45.75 (33.34)	0.556
White	**145.80 (73.74)**	**153.93 (64.10)**	**0.049**	**138.70 (60.17)**	**156.45 (52.91)**	**0.007**	160.0 (95.56)	148.9 (83.50)	0.856
Black	**8.57 (12.19)**	**11.03 (13.03)**	**0.013**	**7.85 (8.11)**	**10.95 (10.18)**	**0.027**	10.0 (17.97)	11.2 (17.73)	0.294

Table 4. Summary of results: the category of the food eaten.

	G0: All Subjects (N = 30)			G1: Interested in art and games (N = 20)			G2: uninterested in art and games (N = 10)		
	NF	AF	Diff	NF	AF	Diff	NF	AF	Diff
Food category (g)	Mean (SD)	Mean (SD)	P-value	Mean (SD)	Mean (SD)	P-value	Mean (SD)	Mean (SD)	P-value
Grain dishes	341.25 (128.78)	363.07 (227.94)	0.775	335.80 (135.06)	380.43 (257.76)	0.319	352.14 (117.75)	328.36 (151.82)	0.327
Vegetables	199.00 (155.83)	212.06 (146.14)	0.122	**228.99 (174.95)**	**249.98 (152.01)**	**0.049**	139.03 (83.08)	136.20 (99.00)	0.985
Fishes and Meats	216.26 (130.88)	219.58 (137.81)	0.685	237.32 (144.96)	231.93 (160.77)	0.798	174.11 (85.18)	194.89 (70.43)	0.230
Milk Products	85.78 (116.80)	68.35 (82.84)	0.429	91.06 (112.53)	80.52 (92.92)	0.722	75.21 (127.24)	44.01 (51.50)	0.432
Fruits	20.08 (35.86)	27.20 (37.27)	0.096	20.32 (36.79)	28.52 (39.70)	0.110	19.60 (34.85)	24.55 (32.68)	0.514
Fats and Sweets	41.29 (65.60)	40.17 (62.40)	0.904	40.03 (52.05)	42.59 (73.58)	0.481	43.81 (88.25)	35.32 (30.64)	0.211

improvement in color count leads to an improvement in intake (an increase in calorie intake). The increase in vegetable and fruit intake under AF conditions is a healthy change, as Japanese dietary guidelines [52, 61, 73] recommend maintaining an intake of fruit and vegetables of at least 350 grams and 200 grams per day, respectively, to prevent lifestyle-related health conditions and diseases.

The participants provided interesting positive feedback on the one-week eat2pic in the post-event interviews. In terms of enjoyment and presence of the one-week eat2pic, the following comments were obtained: *"I enjoyed* *coloring with eat2pic as if it were a real-world game.", "I enjoyed spending my weekends checking how many pieces were still unpainted and planning when I would eat the missing color ingredients.", "I was concerned about the appearance of the painting, as it seemed to reflect on my choices, as it is always displayed in my living room.", "I have started to choose products that contain as many different colors as possible at the supermarket.", "I often shared the content of the painting with my friends and used it as a conversation topic.",* Some participants found the experience of coloring through food to be a novelty, with some enjoying the one-week eat2pic coloring experience as a real-world game and others as a form of self-expression. In addition, some participants changed their purchasing behavior after a week of eat2pic, while others used the experience as a conversation starter with friends. This suggests that interaction with the one-week eat2pic may add value to daily meals in the form of game-like entertainment and content that can be shared with others and can motivate people to eat a color-balanced diet. Many participants, however, stated that manually recording their meals (including color counts) using a mobile application each time they ate was cumbersome to them. In fact, most of the negative comments about the one-week eat2pic were related to the perceived hassle and inconvenience of the input methods. This implies a need for automatic diet-tracking systems.

7 DISCUSSION

Our user study allowed us to investigate participants' experiences to show the potential for behavioral change brought about by their interactions with eat2pic, providing a holistic view and rich insights into these experiences. In summary, interaction with one-meal eat2pic provides the opportunity for "reflection-in-mealtime" and interaction with one-week eat2pic provides the opportunity for "reflection-on-mealtime." These interactions have the potential to bring new curiosity to users about their daily diet by urging them to think about the way they eat and the balance of their meals. In particular, the approach of the eat2pic system was perceived as being friendly and favorable to users who were interested in art and games.

7.1 Reflection-in-mealtime

Several participants noted through the user study that the real-time feedback from the one-meal eat2pic helped them become more conscious of how they ate each bite. The increased awareness of each bite seemed to lead them to a better appreciation of the food they ate. As a result, some participants spent more than twice as much time as usual using eat2pic to enjoy their meals. In fact, in the AF condition, they were observed looking at the canvas with interest after each bite. Some participants identified the experience as *"the experience of coloring through food was very fun and refreshing, as it led me to eat new food combinations that I had never tried before"* and *"I liked the fact that I could create original artifacts by using the mixed color effect"*. This suggests that the inclusion of ambiguity and aesthetic elements in the feedback was a major factor in encouraging people to reflect on how they ate as well as increasing their curiosity. The benefits of incorporating aesthetic elements and ambiguity in feedback have been shown in previous studies [3, 28, 51]. We believe that the design of calm feedback, which incorporates these elements and blends naturally into everyday life, will become increasingly important in designing interactive systems to support reflection during meals, given the recent renewed focus on eating styles called mindful eating [23, 35], which emphasize a sense of calmness at mealtimes.

7.2 Reflection-on-mealtime

The participants revealed that the slow feedback from the one-week eat2pic encouraged them to think more often about the colors of the food they ate each day. They also found that they were more likely to think about the color of the foods they should eat to fill in the uncolored pieces. This suggests that the one-week eat2pic implements the Zeigarnik effect [75], according to which the psychological tendency for the desire to complete unfinished tasks increases awareness of goal behavior. In addition, the participants revealed their experience of always being aware of the color balance in their food to fill in all the pieces of the one-week eat2pic. Some participants revealed that while shopping at the supermarket, they began to consider ingredients that they had not previously used. This suggests that interactions reframing daily diet as an aesthetic coloring experience may have caused a change in consciousness, where previously unconsidered ingredients began to fall within the scope of purchase choices based on color. Although the participants noted that when using other diet support apps, they rarely thought about changing their daily diet, eat2pic had inspired them to adopt a more balanced diet. We believe this occurred due to the simple and easy-to-understand task of coloring and the interface design of the art canvas, which fits naturally into one's daily life. To compensate for the issue that a healthy diet takes some time to provide obvious rewards, such as changes in body shape, eat2pic serves as an easy-to-understand positive reinforcement. As one-week eat2pic becomes a visible presence in the living room, it serves to remind people of their dietary efforts and helps maintain a sense of accomplishment. However, our results show that the approach of stylizing a specific, easy-to-understand format, such as coloring pictures in the case of eat2pic, is ineffective for users who are not interested in that format. Therefore, careful design of the format according to the expected target user group is an essential aspect of designing an effective behavior change support system.

7.3 Complementarity with Other Diet Support Systems

Through user studies, we concluded that eat2pic was not a competitor to existing diet support systems but rather could complement them by providing additional enjoyment from an aesthetic perspective. The feedback from state-of-the-art diet-tracking apps is generally quantitative [21], such as caloric and nutritional information. However, existing apps often lack ways of providing motivation to users to ensure sustained use. The eat2pic input is not limited to the data obtained from sensor-equipped chopsticks. Other diet-tracking apps could possibly be integrated with eat2pic, and their data could be presented as painting feedback. Therefore, the aesthetic feedback of eat2pic could serve as an additional reward mechanism to motivate users and encourage them to continue using the diet tracking app. In addition, some participants in User Study 2 who used the mobile app as an alternative to the sensor-equipped chopsticks commented that *"It was a hassle to launch the app every time and enter the food record."*. Considering this opinion, automatically recording diet logs by eating a meal with sensor-equipped chopsticks is an attractive approach that eliminates the need for manual input and thus has the potential to be widely accepted as an input interface that complements existing diet support systems.

7.4 Limitations and Further Research

The results of our experiments show that eat2pic is a promising approach, but it has some limitations.

First, the current prototype of the sensor-equipped chopsticks is limited to the implementation of functions for the proof-of-concept of the one-meal eat2pic in an experimental environment and cannot adequately function outside a controlled environment. Therefore, manual reporting via a smartphone application was used as an alternative by the users in User Study 2 to track their eating habits for one month. In the future, we plan to improve the sensor-equipped chopsticks such that they can automatically record food consumption in ordinary environments. Specifically, we plan to design and implement the base circuit for wireless communication and collect large-scale eating data taken from the special angle of view of the tip of the chopsticks to create comprehensive and robust image recognition models. In this study, we created the interaction design based on Japanese food culture. However, in terms of the transferability of the concept, future research should examine how the eat2pic system can be extended for use with other tableware, such a knife and fork, and food habits from other cultures.

Second, we conducted two preliminary user studies with 20 and 30 participants to investigate their experiences in interacting with eat2pic. The results of the two studies partially supported our two hypotheses. However, we do not claim that the results are generalizable. Our research aimed to provide a proof-of-concept for the proposed eating-painting interactions and provide insights based on our approach to research through design [79]. The research through design of eat2pic will contribute to the field of digital commensality [67] by providing a novel approach to effecting behavior change in the context of food consumption. Such an experimental scale is relatively common in design research that focuses on a detailed, case-by-case examination of personal experiences and meaning-making activities [46, 51, 65].

Finally, although we evaluated interactions with the one-meal eat2pic and the one-week eat2pic separately, we were unable to examine the impact of the system-wide behavior change by integrating the two sets of feedback. As described in the use case scenarios in Section 3.3, the two play a complementary role, with the one-meal eat2pic encouraging slow eating and the one-week eat2pic encouraging a balanced diet. Therefore, conducting a long-term user study to investigate the impact of interaction with a system that integrates the one-meal and one-week eat2pic on people's eating habits remains an important topic for future research. While we encourage eating foods of different colors through the design of eat2pic based on existing research findings [44] that increasing color awareness is a very effective heuristic for healthy eating, simply eating colorful foods is not always healthy. Additional research must be conducted in this regard in collaboration with nutritionists. In addition, identifying the effects of familiarity and ways to overcome boredom with behavior change support systems such as eat2pic is also an interesting research subject. Specifically, we are interested in studying whether periodically changing the theme of the paintings would decrease familiarity and increase effectiveness and are considering additional research on this topic.

8 CONCLUSION

In this study, we proposed an interactive system called eat2pic based on interactions between eating behaviors and a digital painting that encourages healthy eating habits such as slower eating and balanced diets. We designed and implemented the eat2pic system, which consists of sensor-equipped chopsticks that track how the users consume each mouthful and digital canvases that display this information. The system provides rapid feedback during mealtimes and slow feedback during non-mealtimes. Through two user studies, we explored the experience of interaction with eat2pic, where daily eating behavior was reflected in a painting. The experimental results showed that eat2pic provides an opportunity for both "reflection-in-mealtime" and "reflection-on-mealtime" and has the potential to help users become more aware of how they eat and the balance of food varieties in their meals. It also generates new curiosity in them about their daily diet. The design and research of eat2pic contribute to expanding the design space for products and services related to dietary support. Future research will investigate the nutritional aspects of how the long-term use of eat2pic affects users' dietary habits.

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