EXPLORING A NOVEL DESIGN TO SUPPORT HEALTHY EATING

by

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ABSTRACT

Seemingly trivial eating habits, such as eating too fast, have been linked to diverse and rather serious health issues. While technology-mediated interventions have leveraged several strategies to promote healthy dietary habits, designing successful pervasive interventions remains challenging. This thesis first offers three contributions with the aim of assisting in the design of eating interventions: 1) a review of 62 studies which focused on interventions targeting eating habits; 2) a generative design framework with multiple design parameters; and, 3) an exploration of the potential efficacy of the developed framework. These contributions will improve designers' comprehension and ability to apply current trends and state of the art technologies in the design space.

Heightened food intake rates (i.e., eating too fast) are linked to several health concerns such as an elevated risk of obesity or gastritis. In this thesis, a novel smart-eating utensil is proposed, which can potentially increase the users' awareness of their eating rate by detecting their food pick-up gesture as well as the weight of the food on the utensil before each bite. A proof-of- concept prototype fork with multiple embedded sensors and a processor to collect the eating data was designed and implemented. Following this, a solution was proposed for the food pick-up gesture detection and food amount estimation in each bite. The accuracy of our solution is assessed through ten successful data collection sessions with participants.

A low fidelity proof-of-concept prototype device has been developed to demonstrate the feasibility of applying a pneumatically actuated shape-changing interface to embed physical interference into an eating utensil. A high fidelity, self-contained prototype smart fork was built with the ability to detect the food pick up gesture and provide the bending fork feedback to the users. When the fork detects the user's attempt to pick up food within a short interval following their last food pick-up, the fork bends itself using its mechanical structure, so as the user cannot efficiently pick up food. However, if the user waits a sufficient time before their next food pick-up the fork will not bend, and the user may consume the bite without interference.

PUBLICATIONS

[1] Zuoyi Zhang, Teng Han, John Swystun, Yumiko Sakamoto, and Pourang Irani. "Design to Eat Smart! A Design Framework for Pervasive Interventions of Eating Habits." In: To appear at PervasiveHealth 2020. 2020.

[2] Zuoyi Zhang, Junhyeok Kim, Yumiko Sakamoto, Teng Han, and Pourang Irani. "Applying a Pneumatic Interface to Intervene with Rapid Eating Behaviour." In: *Studies in health technology and informatics* 257 (2019), 513—519. ISSN: 0926-9630. URL: http://europepmc.org/abstract/MED/30741249.

[3] Zuoyi Zhang, Huizhe Zheng, Sawyer Rempel, Kenny Hong, Teng Han, Yumiko Sakamoto, and Pourang Irani. "A Smart Utensil for Detecting Food Pick-up Gesture and Amount While Eating." In: *Proceedings of the 11th Augmented Human International Conference*. AH '20. Winnipeg, Manitoba, Canada: Association for Computing Machinery, 2020. ISBN: 9781450377287. DOI: 10.1145/3396339.3396361. URL: https://doi.org/10.1145/3396339.3396361.

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ACRONYMS

1 INTRODUCTION

The development of poor eating habits often leads to undesirable and serious health concerns. For instance, researchers have identified strong links between frequent snacking and obesity [13], as well as between fast eating rates (i.e., how much food a person eats within a measured interval of time) and obesity [113]. In contrast, habits such as eating at a slower rate have been linked to positive outcomes such as earlier satiety [82] and prevention of excess energy intake [138]. Although the commonly held belief is that bigger portions and inactivity are two of the primary underlying drivers of obesity epidemics, a strong case has also been made to consider the link between fast eating and obesity [107]. Moreover, Kim *et al.* found that a high eating rate was associated with an increased risk of endoscopic erosive gastritis in Korean adults [74]. Previous research has also suggested that eating too fast as an increased risk factor for health concerns such as metabolic syndrome [162], heart disease, diabetes [133], and choking [85]. Further, reducing one's eating rate is considered a fundamental principle of mindful eating; in order to maintain a healthy weight [109]. Altogether, these studies suggest that a slower eating rate is key to a healthy life.

To tackle poor eating habits in a non-clinical context, numerous technology-mediated interventions have been developed on various platforms, such as websites [121], video games [155], mobile and wearable devices [79], and smart tableware

[55]. These emerging solutions leverage a variety of persuasive technologies [38] as well as strategies to ultimately improve users' eating habits. Nonetheless, designing new interventions is not trivial. Designers face challenges when selecting suitable strategies for inciting behavior changes as well as when attempting to map them onto appropriate technologies. Designers must rely greatly on an understanding of technology platforms, persuasion approaches, and behavior modification theories [116, 126]. Designers also face challenges caused by the lack of well-established design guidelines for practical interventions within the field. Clear investigations of existing interventions are also difficult to perform, partly due to the lack of a standard matrix of existing design factors.

This thesis proposes a novel design framework to assist designers in navigating this design process and making informed, suitable design choices. Employing an iterative bottom-up analysis, design parameters from 62 related academic projects were extracted. Then the design parameters were used to develop a generative design framework containing design dimensions with corresponding design parameters (see Figure 2.1). The interrelationships between parameters were visualized following previous approaches (e.g., [34, 63, 104]) in order to understand the key trends amongst existing works (see Figure 2.2). To investigate the usage of the framework, A design study was also conducted with seven participants, each with a design background. Using the newly developed framework, participants (N = 7) were able to generate a variety of novel ideas (22) for new technology-based eating interventions.

The contributions of Chapter 2 are threefold: (i) a review of research projects aimed at poor eating habit intervention; (ii) a design framework that outlines commonly used persuasive strategies and key design parameters; and, (iii) a validation of the generative nature of the developed framework in assisting designers to produce novel design ideas.

Eating rates have been shown to be linked to health and consequently, the overall well-being of individuals. For instance, Ohkuma *et al.* [113] conducted a systematic review of studies focusing on the relationship between eating rate and obesity. Their study concluded that a fast eating rate was positively correlated with Body Mass Index (BMI) and obesity. Understandably, studies showed that a reduced eating rate is associated with a reduction in calory intake [138] and therefore, minimizes the risk of obesity [113]; a serious health issue effecting North America in recent years [4, 107].

Maintaining healthy eating habits (especially an appropriate eating rate) is important. Numerous interventions have been applied in various settings to improve eating habits [168]. Some studies have manipulated eating rate [138], while others have leveraged digital interventions to help modify eating behaviors [140]. One critical feature to providing such an intervention is the accurate detection of eating, especially eating rates; but, many of these digital interventions are unreasonable to apply in everyday life. For example, some interventions require setting up additional devices and equipment such as a Mandometer[1] or a Smartplate[2]. The requirement for multiple tools and burdensome setup causes a considerable inconvenience, likely lowering any motivation to adopt such interventions. Thus, I propose the development of a smart and easy-to-carry eating utensil that is able to monitor food pick-up gestures and the amount of the food on the utensil.

For this thesis, I identified the critical capabilities and essential functions needed to design a device to detect eating rate. The device, or system, must be able to

1 https://mando.se/en/
2 https://www.getsmartplate.com/index.html

detect the movement of delivering food for consumption, and how much food is consumed by the user in weight or calories. Thus, I focused on a self-contained solution to detect the food pick-up gesture on its rotational movement and food weight on the utensil. An Inertial Measurement Unit (IMU) was used to detect the eating gesture, chosen based on prior projects which examined various modalities to detect eating moments [152]. To measure the food amount estimation, I applied a load cell to predict the weight on the fork prototype.

After investigation of the load cell and the IMU sensor data, a regression model was applied to the load cell data to estimate the weight of the food. After I developed a prototype, using a fork as a base, a study with twelve participants was conducted to collect sensor data on the prototype. Evaluation of the dateset demonstrated that the prototype had the ability to successfully detect the food pick-up gesture and estimate the food weight.

My work outlined in Chapter 3, stands to make three main contributions; specifically encompassed in the area of digital monitoring for eating behavior. First, I created a prototype eating utensil with variable sensors, able to collect types of user data pertinent to the development of detection methods for both food pick-up gestures and food weight estimation. Second, I produced a method of detecting eating gestures and food weight based on the sensor data. Thirdly, I provided an evaluation to study the accuracy of my proposed method with eating data collected from participants.

In order to design a device for eating behavior intervention, critical capabilities and essential functions must first be identified. Specific to eating interventions, these essential functions are two-fold. First, the device or system must be able to detect eating movement, or the moment at which food enters the mouth.

Second, the device must be able to provide feedback in order to intervene with consumption.

Currently, using light and/or vibration signals are two of the most commonly applied methods for delivering eating utensil feedback and interference. These feedback methods have been applied to commercial eating devices such as the 10s Fork [3] and non-commercial eating guide devices such as Slowee [79]. Studies [57][55][56] have shown that feedback methods using light and vibration on the 10s Fork, were not obvious to the participants in a user experience study. Additionally, in a controlled lab study when a slower eating rate was induced by the 10s fork device, the total amount of food consumed in a single sitting remained unchanged. Since the vibration and light feedback on the 10s fork did not change the fast eating behavior significantly [55]. It appears that feedback mechanisms embedded into the smart eating utensils have not yet been effective. Evidently, these feedback mechanisms must be designed to be "unavoidably obvious" to the users in order to effectively influence eating rate and food consumption.

Since vibration and light feedback have not yet been effective, I studied the user experience of physical resistance by altering the stiffness and shape of an eating utensil, creating a prototype able to leverage physical resistance. The proposed utensil design integrates a pneumatic, shape-changing interface to change the stiffness of the device, whereby the handle loses its rigidity and fork bending.

The research in Chapter 4 stands to contribute to the field of digital intervention design for eating behavior, providing a design for a prototype eating utensil with variable stiffness. To my knowledge, this project is the first to apply a pneumatic shape-changing interface in an eating utensil to provide physical resistance in an actual eating environment.

3 http://www.slowcontrol.com/en/

Since the pneumatic structure tends to be unstable, I made improvements to the design using a mechanical structure. In the chapter Chapter 5, a prototype of the novel feedback mechanism is introduced and it was used to provide a demonstration of the bendable fork design. This design contributes to the design space of the novel feedback mechanism for eating intervention and regulation.

Overall, this thesis explores the design of novel digital interventions applied for the improvement of individuals' eating habits. First, I begin with an investigation into the design trends of existing eating interventions. Following this, I developed the prototype and methods to capture users' eating rate. I concluded my work with the design of a novel feedback mechanism for the provided prototypes; the feedback mechanism enabled through the embedded pneumatic and mechanical structure of the prototypes.

2 DESIGN FRAMEWORK

2.1 BACKGROUND

2.1.1 *Design Frameworks*

A design framework (or, design space [10, 100]) usually provides a classification and taxonomy of design dimensions, with corresponding parameters to support design practices. Designers often used design frameworks as conceptual guidelines to support creative exploration [34]. Design frameworks have also shown value in categorizing design factors in emerging fields, such as personal visual analytics [63]; such categorization helps to summarize existing trends and inspire future design decisions. A design framework can also be used to help designers evaluate existing design ideas in a systematic manner and enable the identification of the potential design gaps [10, 100, 104, 161]. A framework allows designers to explore many alternatives conceptually, without risking the full costs of production. For example, a multi-dimensional framework was developed to aid for the design of windshield applications in a car [50]. However, a design framework for interventions on eating habits is still missing.

2.1.2 *Unhealthy Eating Habits*

Unhealthy eating habits are quite common. For instance, children are often distracted during a meal, consequently prolonging their meal time [70, 97]. This, in turn, hinders efficient nutritional intake: eating too slowly can be linked to negative outcomes. On the other hand, eating too rapidly has been shown to lead to obesity [113]. Obesity can then lead to various physical and psychological issues [4, 107]. Slowing eating speed has been shown to reduce energy intake [138], and consequently help prevent obesity. Moreover, eating fast has been shown to lead to other health concerns, such as endoscopic erosive gastritis [74].Proper eating speed seems to be an important contributor for our health. In North America, researchers have found that fruit and vegetable intake among adolescents is decreasing [91], while the consumption of fast-food is highly prevalent [90]. Furthermore, picky eating among children is also capturing the attention of researchers [70]. Research shows that making healthy food choices and eating less high-fat snacks is important for good health [86, 118, 139].

2.1.3 *Digital Technologies for Eating Intervention*

Various solutions have been proposed to reduce unhealthy eating habits (e.g., policy interventions via public campaigns or nutritional labeling [19]). Moreover, school-based interventions have been developed for providing healthier meals [141]. Meanwhile, less complicated digital interventions (e.g., meal journaling on smartphones) have been proposed. This chapter of my thesis focuses not only on

Level	Dimension	Values							
Theoretical	Persuasive Strategies	Feedback	Education	Self-control	Advice & Reminder	Monitoring	Social influence	Food estimation	Goal setting
Practical	Technology Modalities	Gaming	Application	Website	Smart device	Tableware	Multimedia		
	Stage	Single-process	Multiple-process						
	Timing	Before-meal	During-meal	After-meal					
	Frequency	Per-meal	Daily	Weekly					
	Social	Single	Group						
	Personalization	General	Tailored						

Figure 2.1: Design framework elements extracted from a review of key papers (N=62) for eating intervention design.

digital solutions but also persuasive technologies for improving eating habits in the context of Human-Computer Interaction (HCI).

The goal of persuasive technologies is to influence the attitudes and/or behaviors of users [38]. Persuasive technologies have contributed to improving users' health and wellness [51, 116] via diet or physical activities [140]. Designing persuasive systems has been investigated by generations of researchers [114]. However, unlike works that investigated behavior change theories [108, 126, 160] or Behavior Change Techniques (BCT) [1], this chapter of my thesis focuses on providing a design framework which bridges the theories with practical considerations in order to guide eating intervention design. Note, healthy eating is a subjective term and applies differently to each person, such as balanced nutrition, appropriate food amount, or a desire eating speed. Here, we did not split these variances of healthy eating in this chapter.

2.2 GENERATING THE DESIGN FRAMEWORK

A literature search was conducted using the ACM digital library for two keywords; "eat" and "diet" (2018 October). To identify applicable papers, only papers exploring the two specific topics were included; 1) designs for improving eating habits; and 2) interventions on eating habits. However, technical papers focusing solely on eating detection were eliminated (e.g. [154]), since they are not closely related to our goal. Relevant papers were collected using review papers on the topic [51, 116, 140]. When multiple papers targeted similar designs, only the latest one was included to eliminate redundancy. A snowballing search was conducted on the reference lists of articles included. Finally, papers from other prominent domain-based venues such as the journals *Appetite* and *Applied Nursing* were included. These selection steps yielded 62 relevant papers, all of which were published between 2005 and 2018.

Adopting commonly used methods [34, 63, 104], a bottom up approach was employed first. Specifically, this was an open coding process on the design parameters, and generated a set of design factors for eating interventions. Subsequently, a careful refinement of these factors yielded seven dimensions and two categories (see Figure 2.1). Once drafted, the framework was carefully reviewed, revised, and verified by three HCI researchers. Note the goal of this framework was to provide a principal starting point for future intervention design. For this purpose, it was not intended to be exhaustive. Rather, the framework was developed as to be widely applicable across platforms and strategies. Finally, since eating habit intervention technologies represent a growing field, it must be acknowledged that the framework will evolve further.

2.3 DESIGN FRAMEWORK OVERVIEW

2.3.1 *Theoretical Considerations*

Behavior change models and persuasive strategies play a crucial role in the design of digital interventions from a theoretical perspective.

2.3.1.1 *Persuasive Strategy (PS)*

When composing new tactics for intervention, a strong understanding of persuasive strategies is of great benefit when selecting an appropriate design strategy. Persuasive strategies are not limited to a single approach. In some cases, various persuasive strategies are integrated to achieve the desired outcomes.

PS1: FEEDBACK A user's self-awareness is often heightened by providing feedback (or assessment of task performance) when attempting to reduce undesirable habits or increase desirable ones [58, 81] for behavior shaping. Typical feedback approaches include visual (e.g., flashing light on a dinning board [95]), audio (e.g., sound from a fork [71]), tactile (e.g., a smart fork vibrates [55]), or mixed cues (e.g., vibration on a wristband plus light flashing on a table unit [79, 80]). In general, the main purpose of feedback is to provide either positive reinforcement or punishment [70] [124]. A delicately balanced combination of reinforcement and punishment can facilitate the improvement of behaviors (e.g., earning points as positive reinforcement in a game [97]). For instance, smart devices (e.g., smart wristbands [79, 80], smartwatches [77], and smart forks [55]) often provide vibration to disrupt a user (i.e., positive punishment by providing undesirable stimuli).

When applied appropriately, reinforcement and punishment through feedback can gradually increase the frequency of desirable eating habits while also reducing the frequency of undesirable habits.

PS2: EDUCATION According to the Knowledge-Attitude-Behavior model (KAB model), education strategy focuses on facilitating learning experiences [112]. Education strategy has the potential to improve users' attitudes when applied to eating interventions [112]. For example, researchers executed an in-classroom internet/video delivered education program for students to decrease the percentage of dietary fat consumed [41]. Modern technologies also allow for the design of more interactive approaches in education, such as "serious games", which have been used successfully to facilitate the knowledge acquisition process [25]. For example, "Escape from Diab", was designed to teach young players to reduce their risk of Type 2 Diabetes and obesity [155]. The underlying premise of an educational strategy is to facilitate individual information acquisition, which can lead to the heightened awareness of eating habits.

PS3: SELF-CONTROL According to the Dual Process model (i.e., behavior is a result of two processes, either automatic/unintentional or deliberative and conscious), one important determinant of eating unhealthy food is the automatic and impulsive process [61, 92, 148]. Self-control strategy can improve eating habits by training individuals to avoid eating unhealthy food [15]. For instance, researchers leveraged a training task, "go/no-go", which presented users with images of healthy as well as unhealthy food options [158]. Participants were asked to decide "go" or "no-go" to the stimuli, to train their self-control abilities [158]. In another project, researchers developed a chocolate machine which can automatically release chocolate balls and the users could choose to resist the chocolate balls to train their self-control [73]. Another approach to improve self-control focused on directing users' attention to their long-term dieting goals, termed as implementation intentions (i.e. reminding users of their goals to prompt diet improvement) [158]. Implementation intentions can follow an "if-then" structure, which aims to create a strong link between a specific situation and a response that allows users to select the right response to the specific situation [20]. Giving control back to the user and assisting with making appropriate decisions is the goal of the self-control strategy.

PS4: ADVICE AND REMINDER Suggestions and reminders, especially when users are not fully aware of their habits, have been shown to be an effective motivator. For example, nutrition-recommendation systems providing meal alternatives have been designed based on users' health goals and preferences [163]. Recommendation applications have also been created for easy access to health consultation [110]. Researchers have employed reminders about healthy diets through email [130] and short messages [45] to influence eating and snacking [72].

PS5: MONITORING Tracking and monitoring eating also provides an opportunity to boost individuals' awareness of their dietary habits [24]. For example, an eating-journal application called Weight Management Mentor promotes self-reflection by allowing users to log food intake and perform regular eating behavior analysis [42]. In other works, food purchase tracking is proposed to encourage a balanced diet [14]. A monitoring strategy is also applied to a customized scale device, the Mandometer[1], which can assess food consumption in order to guide

1 https://mando.se/en/mandometer-method/the-mandometer-device/

eating rate regulation [39]. To supplement food journaling, these approaches usually provide feedback on monitoring results [157]. In addition, using pictures of food to track consumption was proposed for users' convenience [159]. The pursuit of eating monitoring has been a challenge since the efficacy largely depends on the accuracy of the eating monitoring.

PS6: SOCIAL INFLUENCE Eating behavior is known to be strongly influenced by social contexts [60]. Social-Cognitive Theory (SCT) emphasizes that social factors, combined with existing behaviors and personal cognition, influence behavioral outcomes [144]. From SCT, eating behaviors are influenced by behavioral expectations, environment (including social factors), and factors relating to unique individuals. Social support can be provided with family-level socio-technological interventions for improving healthy eating patterns [99]. This support can also be provided through social media (e.g., comments and liking on food tracking in Instagram) [23]. Competitive awareness has also been implemented through ranking the healthiness of a meal in order to motivate users [32]. One study induced expectation assimilation, which described how others' evaluation of the healthiness of a meal could influence the evaluation of food quality [150]. In that project, researchers developed a social media system which unconsciously improved users' eating habits through covertly increasing the others' evaluation of the healthy food [150]. Overall, social influence is effective in promoting healthy eating habits among groups [96].

PS7: FOOD ESTIMATION Food volume is commonly estimated using cues such as food weight, unit amounts, food type, and energy density [5, 46]. However, without technological support, human perception often produces ambiguous and unreliable results when analyzing food volume. Food estimation strategy manipulates the perception of food quantities to influence food consumption in an unconscious way (termed as Mindless Computing [2]). Several designs have proposed using Augmented Reality (AR) to change the apparent visual amount of food with Head-Mounted Displays (HMDs) [111], or to change the visual perception of the plate or virtual dish to influence human perception of food [2, 142]. A tableware called MindFull has been designed to influence users' sensory perception by using heavy materials to create a sense of density to control portion size [8]. This food estimation strategy extends the design space by allowing users to modify their eating habits without conscious effort. One limitation is that implementations usually rely on additional devices to manipulate perceptions.

PS8: GOAL SETTING According to Goal Setting Theory [98], a suitable goal can motivate individuals to develop better eating habits in a step-by-step manner, regardless the types of goals (e.g., long-term/large goals, or short-term/small goals) [117]. For example, the Crumbs project provides a daily challenge to motivate users to increase eating mindfulness and learn about nutrition [36]. Many projects combine goal settings with other strategies, such as using daily challenges with social influence strategy, to promote healthy eating in a company [21], or with the feedback strategy to review goal achievement.

2.3.2 *Practical Considerations*

To implement the aforementioned behavior change models, various design factors should be considered when developing and deploying a design.

2.3.2.1 *Technology Modalities*

Designers must determine which Technology Modality (TM) is best suited for their intervention design.

TM1: GAMIFICATION A gamification strategy is often applied not only for entertainment but also for educational purposes (i.e., a serious game [27]), when delivering nutritional information [27]. Since video games normally involve complicated visual effects, storylines [125], operations [155], their design, and development can be costly. Games which offer shorter and simpler sessions (i.e., casual games) have been leveraged for healthy eating education [117]. Gaming interventions can be engaging and effective in motivating healthy eating [64], especially for children and adolescents [102]. For example, Grocery Hunter is a children's game in which players look for healthy grocery store items based on clues to help children make healthy food choices [75]. Games can also be designed for multiple players to leverage social influence [9].

TM2: APPLICATIONS Many software applications (or Apps) have been designed to monitor eating patterns [42] and/or to provide feedback [78]. This modality may be deployed on a myriad of hardware including smartwatches [77], head-worn displays [149], and projectors [44]. Designers can develop various digital intervention apps with functionally rich tools to achieve fast prototyping practices.

TM3: WEBSITE Websites are a dominant intervention platform (i.e. online forums [121], online cooking tutorials [37], and eating intervention programs [22]).

A clear benefit of using a website is that its content is deployed in browsers, without requiring the installation of extra software, and can be updated easily with an internet connection.

TM4: SMART DEVICE Smart devices are designed specifically to support eating regulation (i.e., a combination of a wrist band and a table unit to provide feedback [79, 80], a novel belt to provide pressure feedback on the body [124], and a chocolate machine to help users to train self-control [73]). These smart devices helped designers to translate their design concepts in a tangible way.

TM5: TABLEWARE Interventions embedded in tableware could improve awareness of eating patterns throughout the course of a meal. Tableware interventions include smart utensils, trays [76], and mixed gear [65]. However, such intervention is often restricted by the unconventional sizes and shapes of the tableware when being deployed in an eating environment or used over a lengthy period.

TM6: MULTIMEDIA Multimedia tools deliver information to support dietary habit improvement for various audiences, and include various digital media (i.e. online videos [156], short messages [11], and social media [23]). Deliberately generated multimedia content can be conveyed to target users passively, making this digital platform useful in promoting improved comprehension.

2.3.2.2 *Stage*

Eating intervention approaches were classified into single-stage or multi-stage processes. Projects leveraging a single-stage process focus on one aspect of the behavioral change to alter eating habits (e.g., providing real-time feedback while users are eating [55]). In contrast, projects employing a multi-stage process focus on two or more steps. The Transtheoretical Model (TTM) [131], for instance, views behavior change as a multi-stage process, starting with the gaining of awareness of healthy behavior to action of behavior change, followed by maintenance of behavior, and ending with upholding maintenance and avoiding a return to the original behavior. Several projects have been designed [41] and/or evaluated based on TTM [48]. In addition, Playful Tray [97] is a device designed based on a three-stage intervention model (volition, performance, and habituation). In general, the stage dimension can provide designers with a longitudinal perspective of behavioral change and a stage-based approach. Typically, single-stage interventions are simpler and easier to implement than multi-stage interventions, which are usually more complex and require more time.

2.3.2.3 *Timing*

Timing refers to the temporal phases to a meal when considering an intervention (i.e., Before-meal, During-meal, and After-meal). Reminders and/or recommendations [163] are given "before-meal" to produce an inoculation effect to avoid unhealthy eating. During-meal refers to interventions applied while users are eating. For example, a smart eating fork [2] provides real-time light and vibrational feedback during a meal to regulate eating rate [55]. Moreover, an interactive robot and a plate were designed by Randall *et al.*, which can provide feedback during a meal to help improve eating habits in children [135]. Another example is Foodworks, which digitally augments a plate by projecting animations and light on the meal table and plate to encourage eating vegetables in children [44]. During-meal interventions can contribute to an in-situ effect [7, 136]. After-meal refers to

2 http://www.slowcontrol.com/en/

approaches which follow a meal, such as a summary of the food consumption on tracking applications [159]. After-meal approaches are valuable in providing users with a review of their eating habits to encourage reflection.

2.3.2.4 *Frequency*

Frequency describes how often an intervention is administered to target users (i.e., per meal, daily, and weekly). Per meal interventions provide guidance for each meal (i.e., real-time feedback on a tray [97]). Daily interventions often provide a daily reminder to guide users' eating [72, 130]. Weekly refers to interventions that provide guidance on a weekly basis, such as an online website providing a weekly intervention [66]. Daily and weekly are not limited to how many times the approach applies to the user in a given day or week. For example, a weekly-based design sends personal healthy eating messages three times per week [45]. While higher frequency of the intervention could induce heightened awareness more continuously at the beginning of the intervention, it may also annoy the user and lead them to boredom.

2.3.2.5 *Social*

The social dimension focuses on whether solutions were implemented to an individual or to a group. One example of group design is an intervention to encourage healthy eating within a family [99]. The group design leverages social influence to improve eating habits, including updates and overviews from friends, family, and peers via social media [84]. For example, a two-player augmented reality (AR) game [9] was designed for co-diners to engage in proper mastication in an enjoyable way. Without setting up social interactions, deploying the solitary design to a single individual is simple. For example, a nutrition knowledge game

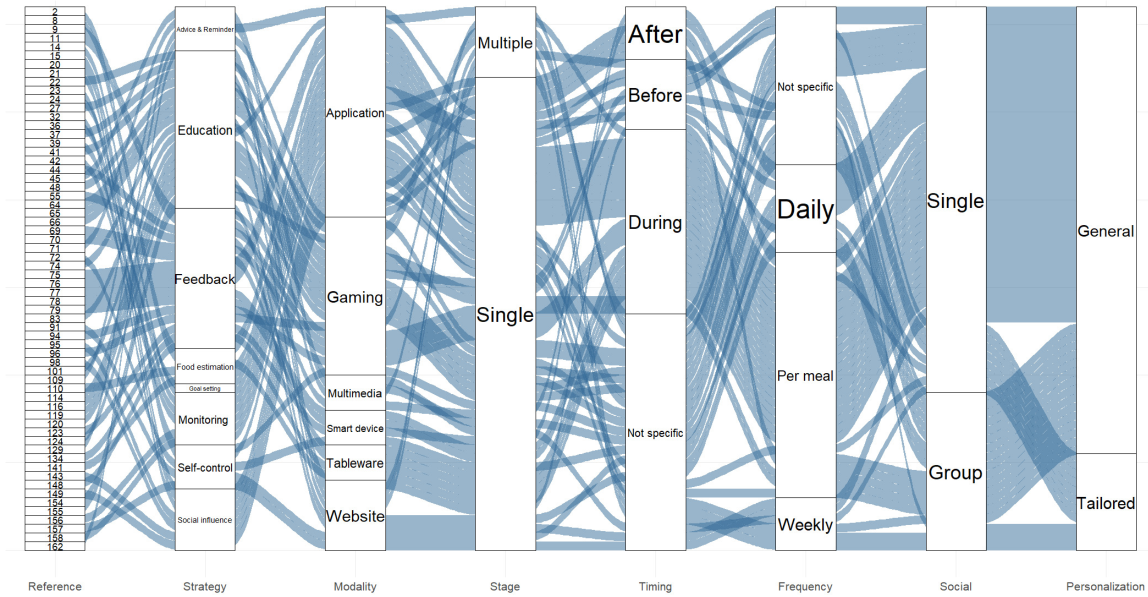

Figure 2.2: Parallel coordinates of the papers surveyed and categorized using design dimensions of the framework (N = 62).

[120] can be played by one user, and the results depend on the user's performance only. In contrast, the group design requires setting up a group and its effects depend on the social interactions of those users.

2.3.2.6 *Personalization*

Nowadays, interventions are customized to a given user's personality and his/her living environment (i.e. a system tailors food recommendations to each individual based on the user's preferences and needs [110]). In contrast, educational videos targeting numerous students are not personalized [41], as they are intended to be presented to the general population. Research indicates that personalization can improve the effectiveness of a game designed to promote healthy eating [115]. Personalized intervention targets users individually, based on their characteristics to improve effectiveness. Naturally, personalization requires more data input to build the user model (e.g., Body Mass Index information).

2.4 EMERGED PATTERNS

Frameworks generally offer a multidimensional matrix that maps out the various projects to identify the gaps in the design space (for examples, see [10, 104]) or by visually plotting the interrelatedness (for example, see [34, 63]). To explore the categories and show potential design directions, I mapped all the reviewed papers using a parallel coordinate view (Figure 2.2). Such a view is extensible and can add new dimensions as the framework evolves over time.

In the plot, each line represents one of the 62 papers we surveyed. Each line traces through the points in the various dimensions as per our synthesis. In a few special cases, projects possess multiple values. This is common in design strategies, because some strategies are non-orthogonal and can be used together (e.g., feedback strategy and education strategy in [70]). In these cases, only the primary strategy applied in the project has been selected as the value to identify major trends. Furthermore, a few projects do not yield any specific values in dimensions such as time and frequency. For example, there is no requirement on when and how often users should play a game [48]. In such cases, the value was set to "not specific" on the time dimension and the frequency dimension.

2.4.1 *Design Trends*

We investigate the parallel plot to see the design patterns from the current projects. Based on parallel coordinates, we discovered that there are no clear trends in the field. Thus, we investigated each dimension independently. To categorize existing designs, we summarize patterns that are reflected in the parallel coordinates (Figure 2.2). Here, patterns reflect multiple projects in one cluster.

2.4.1.1 *Advice and reminder to a single user*

Five projects [45, 72, 110, 130, 163] leveraged an "advice and reminder" strategy, which targets a single stage process and single users. Four of them (80%) used personalization to induce higher persuasiveness. Personalization was particularly common, given that 11 of the 62 projects (18%) employed it.

2.4.1.2 *Real-Time Intake Monitoring*

Five projects were designed to monitor dietary intake (i.e., tracking food consumption) targeted at single users in a single process [24, 39, 42, 72, 159]. Somewhat unexpectedly, only two of the five projects adopted a personalized approach in their design, despite their potential to employ personalization [42, 72]. All of these self-monitoring applications are deployed on mobile devices (e.g., a smartphone), due to their ubiquity and convenience. This eating tracking design has been largely applied to commercial apps such as MyPlate [3] and MyFitnessPal [4] and LoseIt![5] or commercial devices such as the SmartPlate [6] (intervention tools of this sort were excluded from the literature review in favor of focusing on academic outcomes and prototypes).

3 https://www.livestrong.com/myplate/
4 https://www.myfitnesspal.com/
5 https://www.loseit.com/
6 https://www.getsmartplate.com/

2.4.1.3 *Educational gaming and websites*

Eleven out of the 62 reviewed projects applied the education strategy on gaming platforms (i.e., serious games with educational/training purposes). While the goal of education is to provide nutrition information, the gaming modality can transform this experience into a pleasant one while reducing boredom caused by the repetition. Moreover, five of the reviewed projects used websites to educate healthy eating. Interestingly, most of the educational gaming approaches target a single stage (i.e., nine out of eleven projects) rather than multiple stages.

2.4.1.4 *Real-time feedback*

This design delivers, in real-time (during-meal), feedback to the users (14 projects). While real-time feedback can effectively influence eating behaviors, it requires accurate identification of improper eating behavior. Therefore, real-time feedback heavily relies on sophisticated eating recognition systems on tableware (e.g., trays and utensils) or wearable devices (e.g., wrist bands [77, 78]).

2.4.1.5 *Training for healthy eating*

We found designs which train individuals to be cognizant of healthier eating patterns.

SINGLE USER'S FOOD ESTIMATION CONTROL IN REAL-TIME. Four solutions applied the food estimation control strategy from a single process perspective, which fell into the during-meal category in the timing dimension with per-meal frequency; each was designed for single users in the social dimension. These projects leverage and manipulate users' perception of food estimation in a real-time eating setting. Mindless Plate designed by Adams *et al.* [2] is one of such design, in which the plate's color changes according to the color of the food on it so it could create an illusion of more food being there. This perceptual effect aims to influence users' food serving size. Their intuition is that users may serve less, since small portions seem large enough due to the perceptual manipulation.

SELF-CONTROL FACILITATION FOR SINGLE USERS. Five projects employed the self-control strategy from a single process perspective, which targeted single users without limitation in the time dimension (e.g., an online training program with implementation intentions and go/no-go tasks [158]). Designers of such interventions need to be adequately familiar with the training methods which falls in the field of psychology.

2.4.1.6 *Promoting healthy eating behaviors to a group*

Interventions which target a group of users often leverage social interactions to impact eating habits.

SOCIAL INFLUENCE VIA SOCIAL MEDIA APPLICATIONS. Seven projects employed a social influence strategy and leveraged application modalities to a group of users. Social media applications can nudge mobile device users to post pictures of meals, make comments, and interact with other users' eating-related posts. This trend can be further expanded due to the proliferation of social media platforms.

FAMILY-BASED DIGITAL INTERVENTIONS. Of the 62 projects, two induced family-based social support to regulate food intake (one focused on healthy snacking [144], while the other focused on general healthy eating [99]). The results from these two research studies firmly supports that family-based interventions can indeed produce positive changes in eating habits [99, 144] because family members care about each other's well-being, and can influence each other greatly with regards to their eating habits.

2.4.2 *Potential future directions and challenges*

Potential design directions emerged based on the above summary of our analysis from the parallel coordinates plot visualization.

2.4.2.1 *Tailored solutions*

Among the reviewed projects, user-tailored solutions (11 out of the 62) seem to be an area that has not been fully explored. Given that individuals have unique eating habits, personalization could be effective to support their eating regulation. One potential direction is tailored feedback, which is based on each individual's preference and characteristics. Naturally, target users would accept tailored solutions more easily than non-tailored solutions. Personalization could also present challenges, because additional data is required from users to make adjustments. While the tailoring procedure might be complex technologically, it is promising and beneficial for future interventions.

2.4.2.2 *Applied feedback to a group*

One project applied feedback strategies to a group of users [9], using gamification in an engaging way. A potential direction could be providing feedback for a group of people while using other modalities, such as mobile apps.

2.4.2.3 *Multiple-stage design*

Eight projects applied a multi-process approach; seven of them leveraged the education strategy and the other applied the feedback strategy [97]. This significant overlap (7 out of 8) exists presumably because the education strategy includes multiple processes. The infrequent use of the multiple process design could be attributed to difficulties associated with the investigation that are needed over the long-term with various stages. Multiple process designs, or the combination of various, single process designs could help improve eating behaviors at various stages longitudinally. Expanding focus from a single process (e.g., real time eating feedback) into multiple stages for eating habit intervention (e.g., healthy eating education) is promising but relatively complex, and thus requires careful investigation.

2.5 DESIGN STUDY

To see whether our framework can actually contribute in design practice by inspiring novel ideas, I conducted a series of design sessions to explore the framework's generative aspects. I aimed to qualitatively explore the fundamental question: "Can the framework guide designers' idea generation process?"

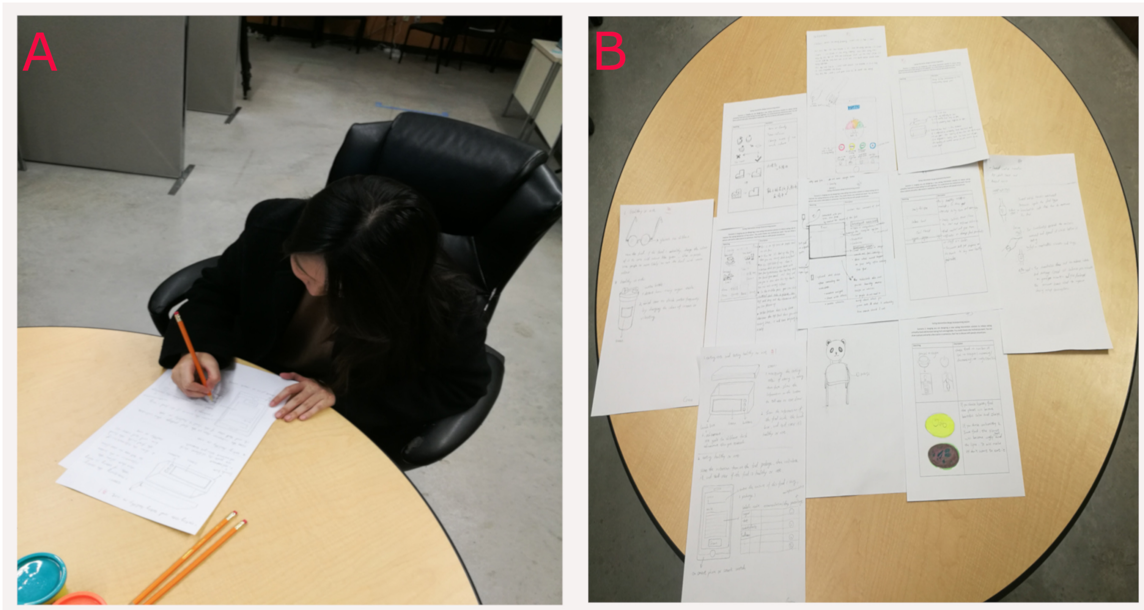

Figure 2.3: A design brainstorming study was conducted to test our framework. A: A participant sketching design ideas during the design brainstorming study. B: The sketches produced during the brainstorming session.

2.5.1 *Design brainstorming sessions*

Two brainstorm sessions were conducted with seven participants (n = 3 in the first and n = 4 in the second session) with a design background. Participants with some design background were recruited to enhance the brainstorming sessions. All of them were recruited through posters at a local university. A 30 CAD gift card was provided to each participant as compensation. This study protocol was reviewed and approved by the local university review board.

The participants' demographic information was collected prior to the design session. Each participant indeed had a design background (F = 5, M = 2; M_{age} = 22.9). Most of the participants were beginner student designers or amateur designers except for one participant who was a professional designer. More specifically, three participants were art school students, while two participants

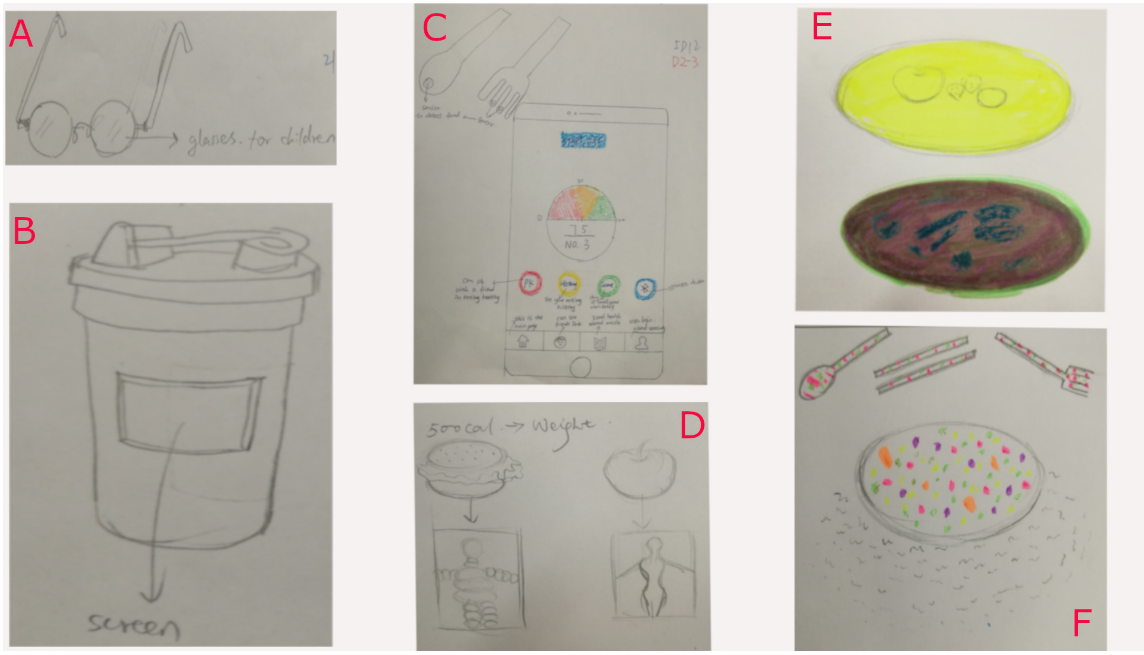

Figure 2.4: Designs were sketched by the participants. A (D1-3) are smart glasses which can adjust lens color to provide feedback. B (D1-4) is a smart water bottle with a display to remind users to drink water and monitor water intake. C (D2-3) is an application to monitor eating. D (D5-1) is an application that can display body images based on the detection of the food. E (D5-2) is a plate which can display various colors and shapes based on the food on it to provide visual feedback. F (D5-4) is a plate with numerous lights which can flash and shake in order to provide visual feedback.

already had a degree from a design-related program (e.g., decorative design and graphic design; note one of them worked as a designer). The other two had experience in graphic design (e.g., posters and tickets). In the first half-hour, the research assistant provided participants our framework Fig 2.1, which was thoroughly explained along with pertinent examples found in the literature. In the next step, participants were asked to collaboratively design and draw solution ideas for the following issues:

- High food intake rate for fast eaters;
- Unhealthy food consumption and low consumption of fruits and vegetables

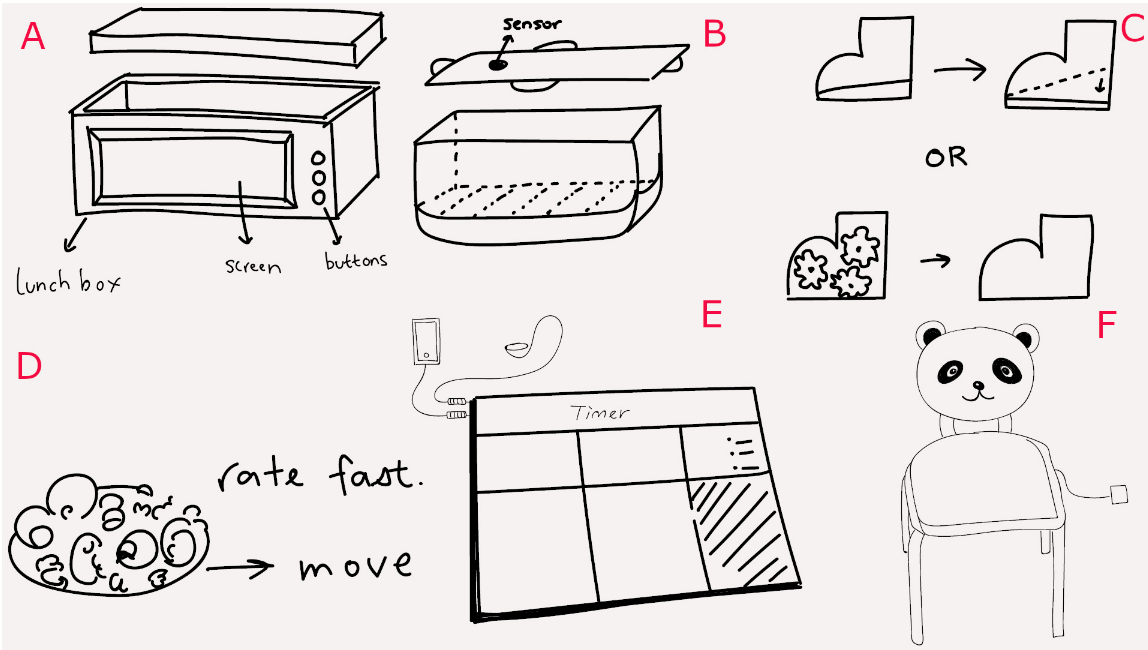

Figure 2.5: Six designs generated from the design brainstorming study. We asked graphic designers to illustrate them. The illustrations are shown: A is a lunchbox with a screen which can show the eating rate and provide feedback according to the healthy eating goal achievement (D1-1). B is a lunchbox with two levels which can lock the second level of food when it detects unhealthy food (D2-2) . C is a pair of smart shoes which can change the height of the sole and shape of the outer layer logo to provide feedback (D3-4). D is a moveable plate that can move away from users to slow down eating rate (D5-3). E is a smart tablecloth which can measure food consumption by connecting tableware, and can show nutrition data and support video chat on its screen (D6-1). F is a chair which can play music in order to influence children's eating rate and food consumption (D7-2).

The participants were informed to assume that any eating detection technologies would be available to achieve their design. Thus, their idea generation is not hindered by the lacking technologies.

The participants had one hour to brainstorm and sketch new designs. Then, participants were asked to explain and discuss each of their designs with other participants. Finally, participants separately answered open ended questions (e.g., "How did the design framework support your design in this study?") on a

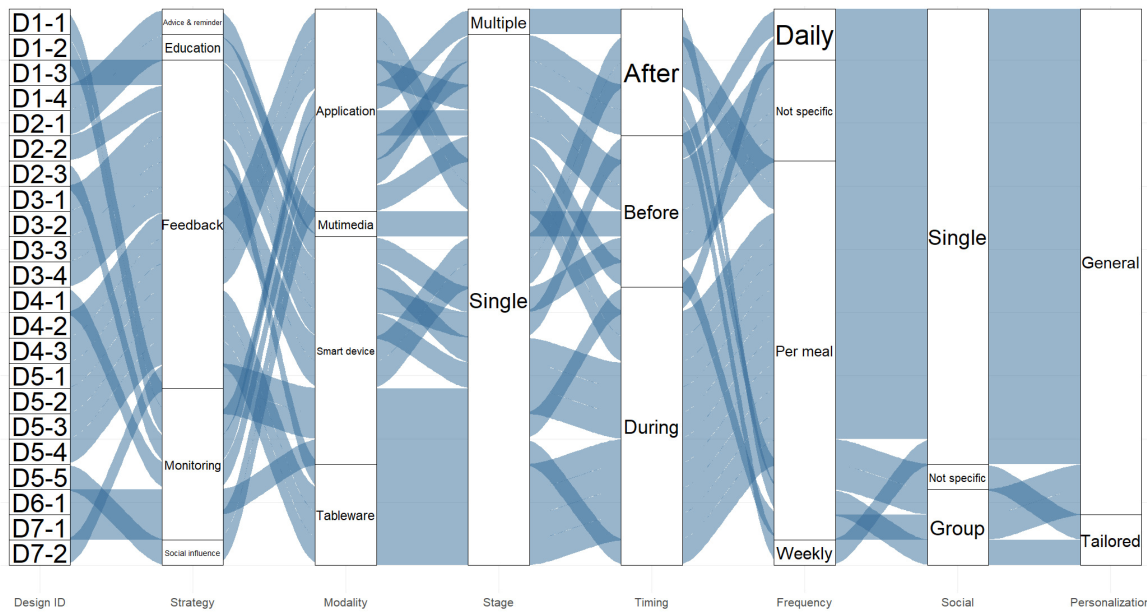

Figure 2.6: Parallel coordinates based on the designs generated by participants in the study using our proposed framework

sheet. Thus, the participants' experience of using the framework was explored qualitatively. Each design session lasted two hours in total.

2.5.2 *Design discussions*

From the design session, 22 design ideas were generated (see Figure 2.4). 21 of them targeted the two design objectives as instructed on the design sheets. One design (D1-4, or the fourth design from participant 1), a smart water bottle, focused on monitoring water intake. This design was included in discussion since healthy liquids intake is indeed related to food intake habits and could be combined with other designs to provide healthy eating regulation (e.g., [71]). After the design session, the generated designs were investigated, which are illustrated in

Figure 2.5. Through another visual analysis (Figure 2.6), I explore and describe how the patterns in these newly generated designs build off our framework.

2.5.2.1 *Leveraging persuasive strategies*

Participants leveraged five types of persuasive strategies in their designs. The most frequently used types were feedback and monitoring, which are commonly applied in commercial fitness and wellness monitoring applications. In contrast, neither the food estimation nor the self-control strategies were employed. This is in line with the limited use of such strategies in existing works (Figure 2.2). These omissions may be due to the participants' lack of knowledge and experiences with such strategies in comparison to feedback and monitoring.

Not surprisingly, the goal setting strategy was jointly implemented with the monitoring strategy. One example is a diet monitoring lunchbox with a goal setting feature, to track food intake based on the goals set by users (D1-1). The lunchbox provides clear goals to allow users to see the tasks needed to be completed. Participants also applied social influence strategy in their designs, such as a diet monitoring tablecloth with a screen which can support video chat (D6-1). The reason social interaction features were included could be related to the fact that participants are continuously exposed to various types of online social interactions (i.e., higher familiarity). Applying social influence strategy into a design benefits target users in gaining support from peers to regulate eating habits. The trend of combining various persuasive strategies to design interventions for eating habits also exists in the related literature.

2.5.2.2 *Implement practical design factors*

Most designs from the brainstorming sessions focused on modalities that included application, smart device, and tableware. One tableware uses lights with various colors, which can flash to provide visual feedback to influence the user's eating rate (D5-4). This design is similar to the Kooijman Dish, a prototype which utilizes a light attached to a dish to influence eating [83]. Note, this Kooijman Dish was not provided as an example to the participants, which indicates our participants were able to generate novel devices with our framework. Additionally, one design was an earphone (D3-1) which can provide auditory intervention; another idea focused on smart shoes (D3-4,C in Figure 2.5) to provide feedback based on the user's eating behavior. These novel designs show that our framework can facilitate participants' design activity, at least partially. Interestingly, gamification and website modalities were not employed by participants. This could be due to the perceived complexity in designing games and websites (hence, not suitable to discuss in a brainstorm session), but also a reflection of the participants' backgrounds, as none of the participants had experience with game or web development.

Most of the designs applied the single-process, within the stage dimension. Furthermore, there were only two designs that emphasized personalization. The lack of the multiple process and tailored approaches shows that incorporating these strategies could be a challenge or simply undesirable, at least for these participants. The multiple-process design is also rarely apparent in the literature (only eight out of 62 applied multiple-process), which reflects how most designers prefer to focus on single process solutions.

2.5.3 *Participants' experiences*

The experiences of participants in using the design framework was explored qualitatively, using the questionnaire.

2.5.3.1 *Efficacy of the framework*

All the participants commented on the framework's usefulness (e.g., P3 or participant 3:"guided me to know more information"; P2: "This framework gave me a lot of ideas"). These responses are encouraging as they also indicate that the framework is comprehensible. Furthermore, participants' responses implied that they explored beyond the boundary of the framework (e.g., P1: "think through each theory and see what you can find"; P2: "use the theory first to determine what kind of strategy would you like to apply"). Moreover, P2 was concerned about the feasibility of implementing design ideas in practice, even though I asked them to disregard the limitations of the technologies.

2.5.3.2 *Amount of information: Providing examples*

The importance of providing examples in design practice has already been investigated in previous studies [59]. Thus, design examples taken from our literature review were provided to facilitate participants' understanding of the framework. As expected, participants valued these examples and noted that these examples guided them in understanding what to design. Further, P3 suggested that adding descriptive images of the examples could be useful when introducing the framework. Making the framework available online, with example images linked to it, could be one approach to offering more detailed information. While providing images of examples may make improve a user's ability to imagine these sample technologies more readily, it may implicitly limit a user's imagination at the same time (i.e., I should design something like the example I saw). Further investigation is needed to understand how much information, especially images, should be provided in order to enhance creativity.

2.5.3.3 *Complexity vs. Simplicity: cost and benefit*

Three participants found the framework somewhat confusing at first. P4 mentioned "it took some time to understand it ... could be simpler". P7 mentioned the necessity to clarify the intent of the framework when introducing it. One reason for this perceived complexity might be due to the multiple dimensions and values of the framework. Furthermore, none of the participants had used this kind of framework for their design activities. The framework may benefit from further simplification, especially if used by designers who have never used a design framework. Although a simplified framework may become easier to understand, it might not provide enough information. Thus, alternatively, the users should have more time to understand the framework with clearer instructions, prior to the design activity, in order to maintain the efficacy of the framework.

2.6 DISCUSSION AND LIMITATION

The review, as expected, does not cover the entire field. The narrowed down literature search strategy did not detect potentially valuable papers such as food journaling [26, 164], improving snacking [62], dietary sharing interventions [47, 122] or design of persuasive technology on user interfaces [93]. Along with developments in the field, more recent works are emerging on topics such as different types of food trackers [101] and photo-based diary meal tracking [16]. The goal of our review was not to provide exhaustive information, but to offer a set of primary design dimensions to aid in the beginning stage of the design process. We believe our review still offers significant coverage in terms of unique attributes.

For practical design practice, the goals and target users are important to consider. Here, healthy eating is a broad term which has various meanings to different target users. In a study with dietitians, Luo *et al.* found each individual has different needs for healthy eating (e.g., increasing or decreasing calorie intake, adding a variety of food, getting more protein, avoiding sugar), depending on their age, gender, health conditions, activity levels, etc [101]. Without understanding who the target users are and what "healthy eating" means to them, it is unlikely to make an impact on target users' eating habits. Here, it is assumed the design goal and target is clear, and we aim to focus on the design parameters for health eating intervention. We believe a target user investigation is another important study area, which is not within the scope of this project.

I acknowledge that the current version of the framework, with multiple dimensions, might appear somewhat complex at a glance. This complexity may be challenging, especially for designers who have never employed a design framework. One solution to this perceived complexity could be to present the design framework in a hierarchical structure (see ordered sequences of the thematic tree in [161]). A hierarchy logic might be needed for the designers to follow. Such a hierarchy might assist in deciding/determining the order in which to consider design factors (e.g., strategy, modality, stage, timing, personalization). For now, such logic was not generated, to avoid misleading and limiting the designers' creativity. Alternatively, specific subgroup frameworks could be developed based on independent design descriptions (e.g., real time feedback eating intervention), possibly simplifying our descriptive framework.

The parallel coordinates attempted to encapsulate the current trends. The visual identification of the trends is challenging, reflecting the lack of major trends in the field. Another explanation could be the sheer number of projects reviewed (since the area is rather new). Attempts to cover as many design considerations (design dimensions in the framework) as possible led to the inclusion of a multitude of dimensions, making the trend identification task in the static visualization more complex. The usability and interpretability problem raised regarding the use of parallel coordinate plots to investigate such a complex framework. Alternatively, it may be possible to instead use a multidimensional matrix to map out various existing designs, to identify the gaps in the design space [10, 104]. However, this alternative can only represent the interrelations between two dimensions at a time. Perhaps interactive features could be added to our parallel coordinates, to represent even minor trends for smoother interpretation [35, 63]. Since the current plot limits each design to a single value within each dimension, a novel visualization is needed to accommodate multiple, jointly designed parameters in each dimension, which would be useful to improve the interpretation of the design patterns.

In the design study, we did not quantitatively investigate the appearance of the framework on the design generation (i.e., can designers benefit from our framework?). A future experiment comparing the quality of generated design ideas may be fruitful (i.e., With Design Framework vs. Without Design Framework while controlling participants' design experience level and capability specifically in the field). Inviting another group of experts to evaluate the designs from participants, with a single standard on the design quality is also necessary to investigate the design ideas [137]. Additionally, most of our participants were beginners and the generalizability of our results to experienced designers is unclear [137]. While beginners appreciated the framework, this may not be the case for more experienced designers. Studies with experts who work in healthy eating design domains will also increase our knowledge of the framework's usability, and support the discussion of the potential pros and cons of different choices within the various design dimensions.

Evaluations of the interventions we reviewed are not included in the current project. A future evaluation matrix is needed to evaluate the quality of the interventions in promoting healthy eating with actual users. Even though the framework presented in this chapter of my thesis prompts valuable design thinking and may inspire useful future designs, lacking the considerations of quality might be a problem for technology design in the health domain, where there are significant concerns around safety and efficacy. Researchers need to evaluate interventions according to efficacy (does a design cause health behavior change in users), usability (can people use it), acceptability and engagement (will people use it), and safety (does a design harm the user or lead to inappropriate behavior change). To establish ways of designing and evaluating health interventions, Mckay *et al.* created a scale to measure the quality of potential behavior change, used in mobile phone applications [103]. Validating the outcomes of the design study with actual users would also be an option if I were to have higher fidelity prototypes. In this project, the design quality was not the focus and instead, I focused on summarizing previous work, to identify under explored areas. I admit the omission of the quality considerations and believe this could be addressed in the future work.

2.7 FUTURE WORK

Although participants recognized the value of our framework in guiding their design activity, a minor complexity issue emerged. In future, interactive features could be implemented into our framework to better facilitate understanding. The development of an interactive web application with animations could highlight relevant aspects of the design framework (i.e., an interactive design framework website[7]). Guidelines for understanding the design framework could also be provided to assist learning and using the framework (as Lundgren *et al.* did in [100]). To tackle eating habit concerns faced by society, new intervention technologies are rapidly emerging. As the field evolves, the addition of new design consideration and dimensions should be considered. Since the goal of the study was to explore the utility of a framework, the generated design ideas were not immediately evaluated. A future study focusing on the evaluation of the generated ideas, based on formalized design criteria could be valuable(see [137] as an example).

7 http://designforlocation.org/

3 EATING DETECTION

3.1 RELATED WORK

3.1.1 *Eating Detection Techniques*

Thomaz and his researcher team first found using the Inertial Measurement Unit (IMU) on the smart watch could help to detect the eating movement [153]. Thomaz *et al.* [153] presented a practical approach that leveraged an inertial sensor from a smartwatch to identify eating moments. They conducted a semi-controlled lab study to train an eating moment classifier based on inertial sensor data, and then they validated the classifier in two in-the-wild studies. Compared with other modalities such as first-person images captured by a camera and acoustic data captured by earbuds, inertial sensing is beneficial because it does not interfere with user privacy [152]. Maintaining user privacy also makes motion tracking more appropriate when applying this modality to detect intake behaviour in research studies. Mirtchouk *et al.* [105] concluded that the combination of multiple sensing modalities and personal free-living data could improve accuracy of eating detection. Furthermore, Dong *et al.* affixed a smartphone on a user's wrist to detect whether or not a user was eating from accelerometer and gyroscope data [30].

3.1.2 *Detecting Eating Gesture and Bite*

Various solutions have been raised to track the eating gesture. Kim *et al.* [79] designed Slowee, which is equipped with elaborate sensors on headphones and a necklace to detect the eating action, which are potentially intrusive to users. The Slowee system applies Electromyography (EMG) and piezo sensors to detect chewing and swallowing, in order to provide eating speed guidance. Kadomura *et al.* [69] designed and implemented a smart fork called Sensing Fork to recognize eating behavior (e.g. poking food and lifting) for children, and the fork can detect the eating gesture as well as the food color.

In contrast, Dong *et al.* proposed a method to detect the bites gesture by monitoring the variation of the roll value caused by rotational movement of the wrist from the inertial sensor worn on the wrist [29]. Dong *et al.* introduced an algorithm that applied the roll velocity of the inertial sensor to track the eating wrist motion [31]. Their method is simple enough to be implemented on an embeddable microcontroller (e.g. Arduino). Following this method [31] Shen *et al.* applied a wrist motion tracker to detect and count bites for eaters in a cafeteria [145].

Zhang *et al.* [166] developed a machine learning model on the IMU sensor data from the wrist band to detect the feeding gesture and recognize bites. They conducted the data preprocessing and model training while comparing various algorithms and parameters for the development of the machine learning model. Zhang *et al.* used a wrist-worn sensor to detect eating episodes on eight participants in the wild and found a high number of false positives were detected caused by hand movements such as texting on the phone [165].

Kyristis *et al.* [88] generated a dataset from an IMU sensor on a wrist band from Microsoft and annotated the data using video data captured by a Gopro. Kyristis *et al.* used Supported Vector Machine(SVM) and Hidden Markov Models(HMM) to train their models to detect the five eating micro-movements including: picking up food, upwards, downwards, feeding and inserting food into mouth, and no movement. Kyristis *et al.* present a solution that combines the SVM with Long Short Term Memory(LSTM) network to improve the gesture detection on the dataset collected with 10 participants using a smartwatch [89]. Papadopoulos also applied the SVM and LSTM to a semi-supervised machine learning method on the eating gesture detection [119]. In the recent project, Kyristis *et al.* proposed an algorithm combining the Convolutional Neural Network (CNN) and LSTM to detect the food intake cycles on a dataset of twenty-one meals with twelve participants [87]. The evaluations of the method showed their proposed method performed sufficiently well [87]. These machine learning based gesture pattern models are accurate but complex with heavy models. It is hard to deploy such a model in an embedded device (e.g. the ATmega328P microcontroller used in our prototype with 32 KB memory and 2KB RAM).

3.1.3 *Food Weight Detection*

To detect the eating rate, the system needs to accurately detect the food weight/ energy intake. Amft *et al.* [6] investigated measuring chewing sound to predict the weight of each bite through linear regression and they verified their approach with three selected foods across eight participants. Mitchouk *et al.* [106] proposed using in-ear audio and motion sensor on the head and wrist to detect the food type and estimate the food amount in weight consumed by people. Besides the food weight, Hamatani *et al.* [52] designed FluidMeter which leverages the IMU sensor data from a smartwatch to detect the human drink activity and estimate the amount of fluid intake in weight by analyzing the motion sensor data.

Several other devices have been used to measure food consumption in weight. One such device, the MandoMeter[1], leverages a smart device with a scale that is put under the food to track food consumption and provides visual feedback on a smartphone application. Another device, SmartPlate[2], includes a weight tracking plate embed with a scale to track weight, and a smartphone application that could take pictures of the food on the plate to provide visual analysis data on the meal. Both the MandoMeter and the SmartPlate require additional equipment in the form of a plate-sized weight scale.

Since the previous work on the eating rate detection mainly rely on the wearable device or addition device, here in this chapter, I would like to design a utensil prototype to achieve the detect of the eating gesture and food amount on itself. I aim to propose a method which is less complex and able to be embedded in the utensil prototype itself.

3.2 DESIGN AND IMPLEMENTATION

3.2.1 *Prototype Design*

The current prototype of the smart fork utensil is shown in Figure 3.1. It is a self-contained device with a controller section for the data collection. The current

1 https://mando.se/en/mandometer-method/the-mandometer-device/
2 https://www.getsmartplate.com/

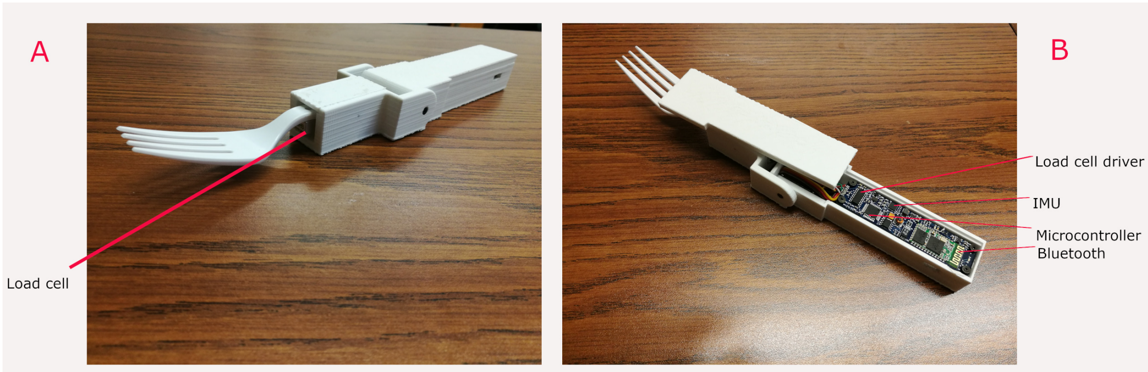

Figure 3.1: The current prototype we built for the data collection sessions and the current prototype circuit structure

prototype contains a custom Printed Circuit Board (PCB) with an ATmega328P micro-controller on it, and a Bluetooth module to support information transmission. A load cell with a capacity of 780g was attached to the prototype and its corresponding driver was embedded on the PCB to extract the load cell sensor data. The load cell could detect the force on the top of the fork (i.e., the weight of the food). There is an Inertial Measurement Unit (IMU; MPU 6050 module) on the board to detect the motion of the utensil. Finally, the prototype is powered by a 3.7V 400 mAh Li-po battery. The current prototype is around 23 cm long, 4 cm wide and 1.7 cm high. The fork tip is a one-time use plastic addition, which is replaceable for hygiene purpose.

3.2.2 *Food Pick-up Detection Implementation*

Kadomura *et al.* [70] categorized the eating motion into four stages: at rest, holding, poking and biting. In another project, the food intake cycle could be categorized into five different micro-movements including picking up food, moving the device upwards and downwards, delivering the food to one's mouth, as well as no

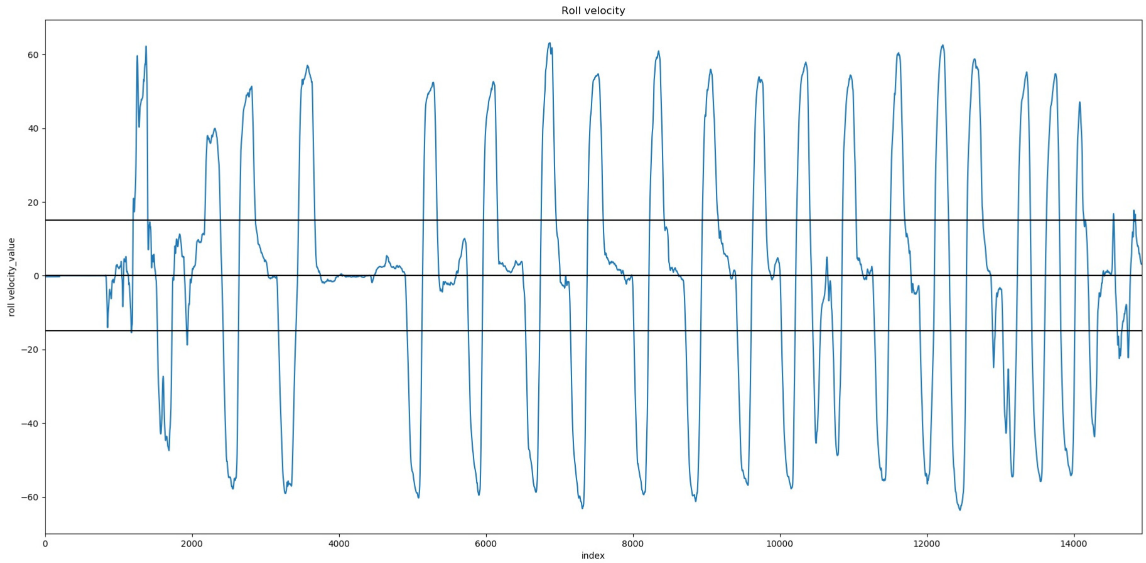

Figure 3.2: The roll velocity data plot from the session data (S1) collected from Participant 1 (P1).

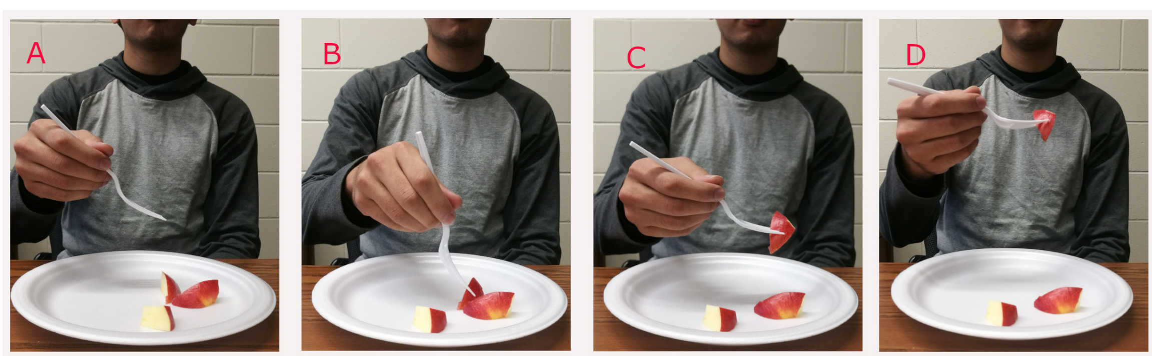

Figure 3.3: The rotational movement while eating with a fork

movement [88]. To make it simple, I first aimed to detect the eating movement in a less complex stage structure. Using Dong's algorithm [31], I found that there is a rotational movement while eating with a utensil, especially when picking up the food and then angling the fork to deliver it to the mouth (see Figure 3.3).

The IMU sensor provides the orientation data of the angular roll, pitch and yaw values. I leveraged the IMU sensor data to track the movement of the fork by computing the roll velocity to detect the rotational gesture. Following Dong's

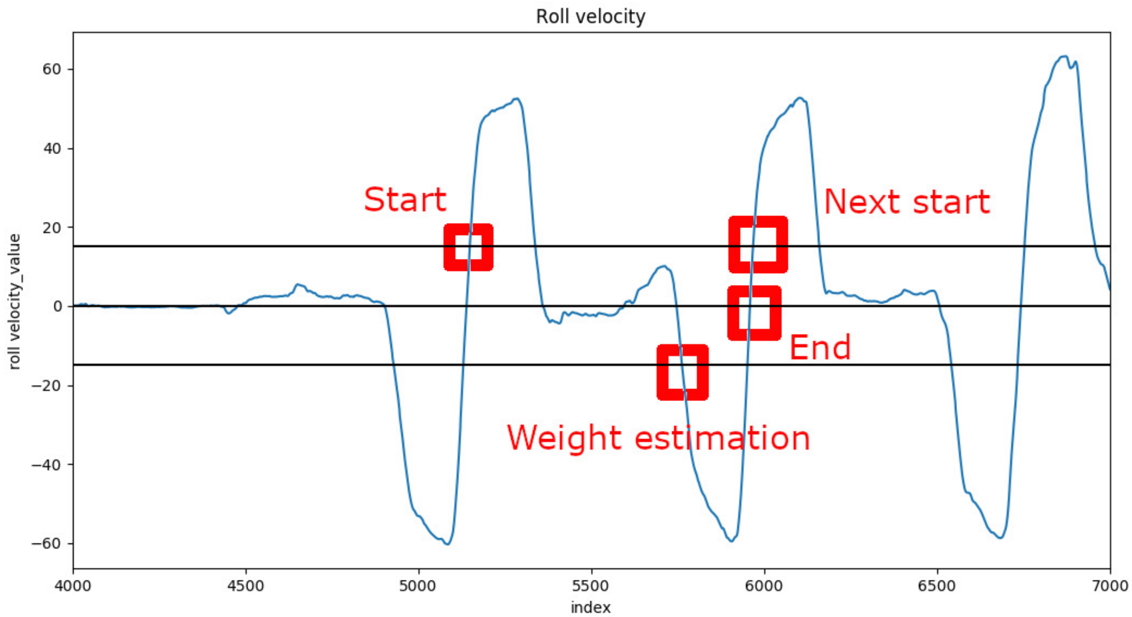

Figure 3.4: The chunk of roll velocity data plot for the cycle of the rotational motion corresponding to a series of pick-up gestures. The data collected from the session data (S1) collected from Participant 1 (P1).

approach [29] I computed the derivative of the roll data as the roll velocity to show the changes of the roll (the roll velocity results from data collection session 1 (S1) with Participant 1 (P1) are shown in Figure 3.2).

I modified Dong's algorithm [29] and developed a threshold value based algorithm, which is shown in Algorithm 1. I added one more threshold value in our algorithm compared with Dong's algorithm. In Dong's algorithm [29], aside from the threshold value on the roll velocity, there is also a time interval threshold value to count the bites and eating gesture. In contrast, I only focused on the food pick-up gesture and I inferred bites upon the pick-up. Thus, I did not set a time interval threshold value for pick-up detection since I believe the pick-up gesture is solely related with the movement rather than the time duration (see Figure 3.4).

Algorithmus 1 : Food Pick-up Gesture Detection

```
Data : rv as the roll velocity at the current time;
Result : Food Pick-Up Detection
bitestart is false;
pickup is false;
while not at end of the dataset do
    if rv is larger than thresholdvalue1 and bitestart is false then
        bitestart is true;
    end
    if rv is less than thresholdvalue2 and bitestart is true then
        pickup is true;
        bitestart is false;
    end
    if rv is larger than thresholdvalue3 and pickup is true then
        pickup is false;
        bite detected;
    end
end
```

3.2.3 *Food Weight Estimation Implementation*

I leveraged the load cell to detect the weight of the food on the fork. As I learned by a previous design, the load cell could be used to develop a scale, especially a spoon-sized scale used to get the weight of food ingredients in the kitchen [146]. One challenge with the spoon scale is that the scale requires users to pick up food and wait for a certain amount of time for the spoon to stabilize before obtaining the weight value. Since eating behavior is a series of actions that are connected (picking up food, and then biting, etc.), the time required to pick up the food and wait for the load cell to compute the result are not reasonable in a real eating scenario.

I computed the food amount value by taking the load cell force value's average (lc) in a time span. Since the sensor data gathered in movement varies at each time, I computed the average of the load cell value to reduce this variability. I then applied a linear regression to compute the Weight (W) with the linear regression parameters (p and I) to compensate for the noise caused by the mechanical structure and the sensor itself.

$$W = \mathrm{lc} * \mathrm{p} + \mathrm{I} \tag{3.1}$$

3.2.4 *Issues in the Implementation*

3.2.4.1 *Potential Left Hand Issues*

Since my algorithm leverages the rotational movement induced by picking up food, the approach (Algorithm 1) is, theoretically, applicable to either left or right hand users as the rotational movement is similar in both. Furthermore, food weight estimation computation is unaffected by handedness.

3.2.4.2 *Noise in Data*

Compared with the previous work [166], I did not apply a smoothing techniques to the raw data since we aim to keep the system simple to deploy on the fork itself. A preliminary study shows that the noise is within control. Small effects of the noise caused by the sensor will not significantly affect the results.

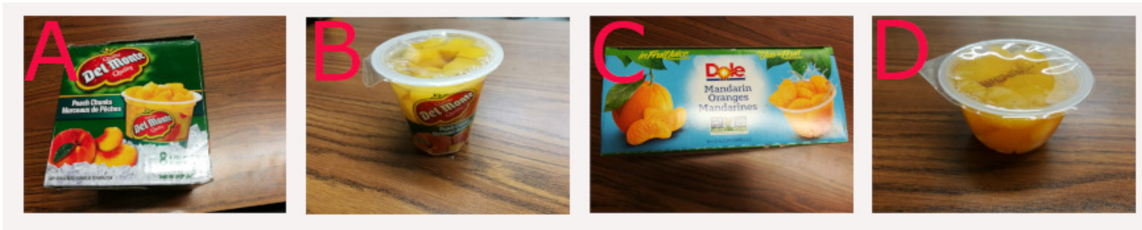

Figure 3.5: Food provided for the data collection session study

3.3 STUDY METHODOLOGY

3.3.1 *Participants*

Twelve participants (Females = 3) were recruited from a local university. The participants were required to be 18 years of age or older, and have no food allergies or food restrictions to the fruit cups we provided for the experiment (see figure 3.5). Data from two participants were excluded due to mechanical errors. Thus, for analysis, I used the remaining ten participants (Females = 2) from this study. All participants were right-handed.

3.3.2 *Study Procedure*

The study was conducted in a lab of a local university. Each participant was asked to eat using the prototype, which would send real-time data to a computer via Bluetooth. Two types of fruit cups were provided; the first half of the participants had mandarins slices while the rest were asked to eat peach slices (see Figure 3.5). The ingredients of the food were shown to participants before they started eating for health purposes and I put the fruit into a one-time use bowl for each participant. The fork prototype was put horizontally, facing upward to initialize

Figure 3.6: Participant 5 (P5) in the data collection session. (Left) The participant's fork is leaning toward the food. (Right) The participant picks up food. Both of these states are distinctly recognized by the detection method.

the load cell and IMU. During each session, I used a scale under the bowl of the fruit to track the weight in the bowl, and a GoPro camera was placed in front of the participants to capture the ground truth of the eating gesture and the food weight showing on the scale screen (see Figure 3.6). The sensor on the fork collected the data and transmitted it to the computer with a frequency at approximately 100 Hz. First, the instructions for the study was provided by the on-site researcher. After they agreed and signed the consent form, the eating activity started: Each session took up to 30 minutes. The participants were asked to eat at their own speed.

Following previous studies [106, 119], I asked participants to perform a quick vertical movement with the fork at the beginning and the end of the session. The purpose of the gesture was to generate a high peak in the data to support the synchronization of the sensor data and the ground truth (see Figure 3.7).

3.3.3 *Ground Truth Annotation*

After the study, the Boris software [43] was used to annotate the video for the ground truth of the gesture and weight on the scale in time span. I chose to use Boris over other softwares (e.g., ChronoViz [40]) or the software developed by researchers for the eating gesture annotation [134] because Boris is convenient to annotate behavior in a more detailed way for video with corresponding timestamps.

I first plotted the raw Z axis acceleration data from the IMU (e.g. Figure 3.7). I found the high peak gesture in the figure and then we found the corresponding data point. I synchronized the moment of high peak in the video with the corresponding moment in the sensor data. I then annotated the start and the end high peak movements and the pick-up gesture. The pick-up gesture started from the moment the fork began to approach the fruit target, and it ended when the food was picked up. During the annotation, I found some events such as food falling down from the fork and the user poking the food multiple times to pick up the food. These actions are natural and happen regularly in real life. I further annotated the weight values on the scale in grams.

Additionally, I processed the annotation data by extracting the weight value and the gesture annotation with the corresponding time and removed the irrelevant observation data created by the Boris software. Then I matched the annotated start and the end time points with the sensor data. After this, I computed the food weight based on the weight scale data recorded. The food weight per pick-up was computed by the weight changes between two consecutive time points on the scale (i.e., before picking up food and after picking up food).

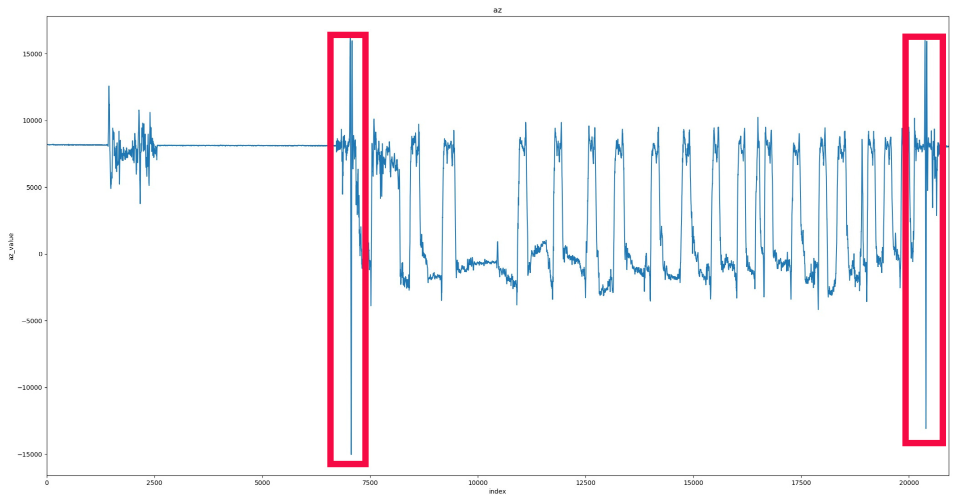

Figure 3.7: The plot of the Z axis of the accelerometer sensor data from participants 1 (P1). The red rectangle was labeled to show the high peak movement sensed by the sensor.

Next, I labeled the raw sensor data with the corresponding synced ground truth data (including start, end, and pick-up food) and the weight record. After I finished processing data for all of the ten participants, I manually cleaned the data to run the algorithm for the detection. The data sets required extra cleaning due to some broken data points caused by Bluetooth data transmission. The final data set was then used to build the detection algorithm to detect the pick-up gesture and weight.

3.4 EVALUATION

I applied our algorithm 1 to perform the gesture detection and compute the accuracy on the pick-up gesture detection. I used the ground truth data with the sensor data to train a linear regression model to predict the food weight estimation.

The evaluation of the utensil design was based on the analysis of the study data collected with the prototype. I analyzed the results from both of the detection of the pick-up gesture and the estimation of the food weight. Following the previous paper [29], I first computed the sensitivity of the food pick-up gesture detection. Then I computed the accuracy of the food weight estimation.

3.4.1 *Gesture Detection Sensitivity*

Based on Dong's method [29], I computed the sensitivity to evaluate the detection of the pick-up gesture. I first computed the frequency of true detections, undetected, and false detections. Following Dong's definition [29], true detections are pick-up gestures that are within the cycle of the pick-up gesture defined by the method. Additional detections within the same cycle were identified as undetected. A pick-up cycle detected with no true pick-up gesture occurring within the cycle are false detection (See Figure 3.8).

The sensitivity is computed following Dong's method [29]:

$$sensitivity = \frac{true\ detections}{true\ detections + undetected\ gestures} \times 100\%$$

3.4.2 *Gesture Detection Results*

The algorithm for gesture detection was tested based on our data, and the accuracy of the eating detection was computed. I conducted trials to tune the parameters

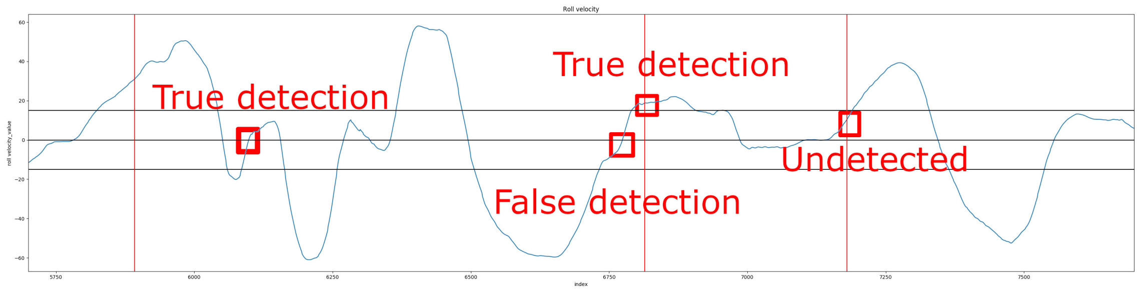

Figure 3.8: The classification of the gesture detection resulting from the cycles of the gestures. The red lines are the ground truth gestures. The chunk of the data from Participant 3 (P3) in Session 3 (S3).

of the algorithm and evaluate the accuracy of our method of detecting the food pick-up gesture.

After the trials of tuning the parameters of the algorithm, we found that if we set the *thresholdvalue1* as 15 and *thresholdvalue2* as -15 and the *thresholdvalue3* as 0 for the cycle of the gesture, I could compute results with higher accuracy. After investigating, I detected 202 pick-up gestures out of 226 food pick-up gestures seen in the video. The sensitivity was computed as mentioned above. The resulting sensitivity of the device and the method is 89.38%. The results are summarized in Table 3.1.

3.4.3 *Weight Estimation Results*

I examined the load cell data of all the 202 true detected pick-up gestures. I found that Participants 3 and 4 's load cell data were outliers caused by improper calibration and initialization of the load cell (the results are negative in load cell sensor data), hence, I excluded data from those two sessions. I then calculated the load cell data from the true detected cycles. The sum of the positive load cell data was calculated once the second if condition (roll velocity is less than

Table 3.1: Performance of the pick-up detection of 10 participants

Participants	True detect	Undetected	False detect
1	18	1	1
2	16	4	2
3	11	6	7
4	21	0	1
5	24	3	0
6	21	2	2
7	40	3	4
8	14	1	4
9	16	3	4
10	21	1	1

thresholdvalue2) is satisfied in the algorithm 1 and the roll angle data is less than the threshold value T and larger than the threshold value -T (i.e., the fork is horizontally facing upward). After investigating the sensor data, here I set the threshold value as 15. Then I computed the average load cell value (Loadcell). Inspired by FluidMeter project [52], I computed the Pearson correlation coefficients of the load cell value and the ground truth weight data. After further excluding 4 outliers from the dataset (i.e., the load cell value are negative values), the Pearson correlation coefficient value was (r = 0.878) among 166 true detected pick-ups.

3.4.4 *Weight Estimation Accuracy*

I calculated the weight estimation accuracy by training a linear regression model based on the true detection gesture cycles. The model was trained based on the dataset using a Leave-one-intake-out cross-validation following previous work

[106]. The data was split into N-folds where N is the 166 true detected gestures (see Figure 3.9).

I followed previous work [52] to calculate the weight estimation accuracy by computing the Mean Absolute Percentage Error (MAPE) as the metric to evaluate the result of the estimation. I calculated the MAPE for the pick-ups that have food on it. In the data set, four pick-ups were further excluded since the weight ground truth is 0 caused by food falling down after the pick-up gestures. The MAPE focuses on the absolute error caused by the estimation for each pick-up food weight. The MAPE was calculated to be 26.297%, which was relatively low compared with previous work [106], and the mean absolute error was calculated to be 1.357g.

3.5 DISCUSSION

To further understand the reason for the false and undetected gestures, I plotted and investigated the data. I discovered that undetected gestures occur when participants try to pick up food too quickly: This is not detected by our method since the method monitors the roll velocity in a longer time span.

The weight estimation resulted in an error rate of 26.297% in MAPE. I investigated the dataset to explore the cause of this error rate. Negative values were found in the load cell data, which may have been caused by the feeding gesture or the food poking gesture. Since the feeding gesture is connected to the food poking gesture, a latency issue may have affected the result of weight estimation. The angle of the load cell on the fork may have also influenced the sensor data since the force values from the load cell are influenced by the angle between the fork and

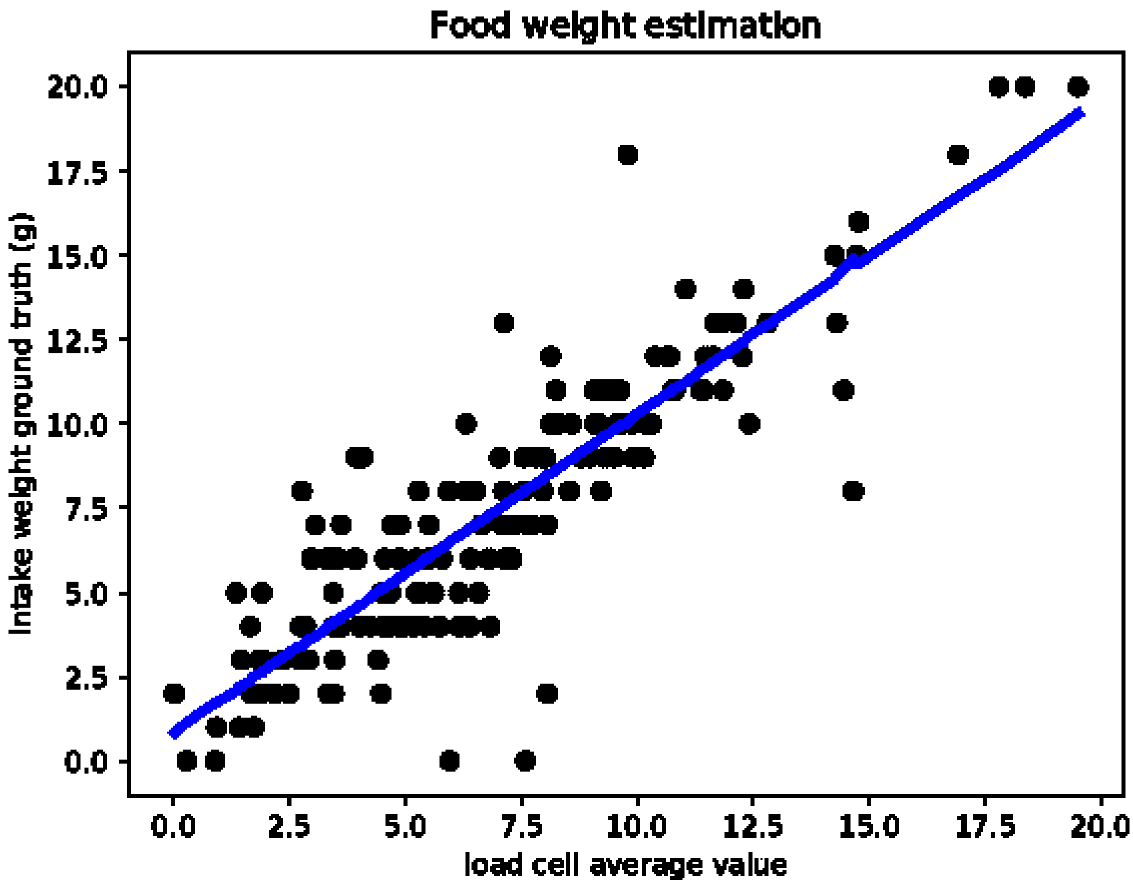

Figure 3.9: The scatter plot of the food weight amount in grams (i.e., the ground truth amount) and the average value of the load cell value of 166 points

the gravity direction. Users may potentially use this fork at an angle, which will cause the force value to be lower than the ground truth. In future work, I intend to leverage the MPU 6050 sensor's vertical acceleration data to counter-balance the angle problem generated by the load cell.

3.6 limitations

3.6.1 *Prototype Size and Utensil Variety*

My prototype is still bulky for most users due to the size of the control board. Currently, the device is approximately twice as large as a normal eating utensil, which could influence the user's eating gestures. A study is needed to investigate whether the prototype size could influence the user's eating gesture and the detection accuracy. While I was able to develop a successful prototype, further iterations of the prototype are needed to deliver a more acceptable, simple, and robust smart utensil. Specifically, I plan to iterate future prototype designs to reduce their size and match that of traditional eating utensils, while also working on improving the eating behavior recognition function. One of the challenges associated with these improvements will be the simplification of the set-up process as our smart utensil should be used frequently.

There maybe potentially be different eating patterns while using a variety of different utensils such as a spoon; this question remains unexplored. For future iterations, the utensil may be designed with an interchangeable part at the tip of the tool to switch from a fork end to a spoon end. This change would allow me to investigate the eating detection with other types of utensils as well as other food types.

3.6.2 *Eating Activity and Eating Setting*

My study did not consider potentially distracting events such as sharing a meal with other people and multi-tasking while eating. These occur regularly in real-life situations and might influence the detection algorithm. [165].

Water was not provided during the session since there was already syrup from the fruit cup I provided, and I was not concerned about choking. Additionally, a drinking gesture could have disrupted the data as well as the overall flow of the study. Thus, I opted to control this aspect of the experiment. In future studies, I may look into providing liquids. I am interested in investigating the effect of drinking gestures and how drinking gestures may influence the gesture detection. For the sake of simplicity, the food provided was also limited to two different types of fruit. In the future, I may look into expanding the types of food to test how that may affect the gesture detection. For the food weight estimation, the calories of each bite of food and the total amount of energy of the consumption at the detection procedure was not considered.

3.6.3 *Eating Behavior and Eating Patterns*

While everyone has their own unique eating patterns, our method is not able to distinguish such unique patterns yet. To effectively develop an individualized method, much more data needs to be collected in real world settings. Data collection in real-world settings will be particularly important as noise could also be a contributing factor to errors. Another limitation is that our method detects food pick-up gestures rather than the actual bite itself [87]. To monitor the eating rate, bite detection is needed in real-world settings such as a user picking up food without feeding themselves. However, my current method can not detect such behaviour.

3.6.4 *Longitudinal and In-the-field study*

The experiment was conducted with only one session per participant. I am interested in the results of a longitudinal study to validate our method in a longer period of time. Besides, the current data collection sessions are conducted in the lab. The in-the-field study [153] such as data collection with the eaters in a university cafeteria [31] will be fruitful to generalize the method in a larger scope.

3.7 FUTURE WORK

3.7.1 *Real time intervention on eating rate*

Building on the detection of the food pick-up gesture and the estimation of the food weight on the utensil according to the method that I described in this chapter, I could then potentially compute the eating rate by dividing the food weight by the time interval between two consecutive food pick-up gestures. With a device that could provide eating rate detection, researchers could design various feedback mechanism to interrupt a user's eating rate during a meal. Such real-time feedback intervention (i.e., vibration on 10s fork [3]) could provide an in-situ effect on the eating regulation [7]. When such solutions are ready, I hope the device will be

3 https://slowcontrol.com/en-us/

useful in the future so the users' awareness about their eating behaviours can be enhanced [169].

3.7.2 *Improving the Detection Method*

The detection method could be potentially improved in the future study. Patil *et al.* applied the ProtoNN algorithm [49] to train their model and applied the predictor into an Arduino to conduct the gesture recognition. Inspired by Patil *et al.* [123], I aim to look for other methods to detect the eating gesture with the capacity to deploy on the prototype itself and then compare different methods. Moreover, the lower accuracy rate will need to be improved to promote acceptance.

3.7.3 *Deploying the Algorithm*

Currently, I am working on deploying the algorithm to the prototype itself. I hope that the method performs sufficiently to work in a real-life setting as a standalone prototype [33]. In addition, recruiting left handed users would allow us to explore the generalizability of our results. I will also investigate the users' subjective experiences about using our utensil, since it is a new design.

4 DESIGN AND IMPLEMENTATION OF THE PNEUMATIC FORK

4.1 LITERATURE REVIEW

In this section, I discuss current literature focusing on the relationship between eating rate and health; I will review techniques that could detect eating behavior and provide feedback to users; I analyze the theory and techniques that are used for behavior modification and intervention; and, finally, I review literature on shape-changing as well as pneumatic interfaces.

4.1.1 *Eating rate and health*

Eating rate influences the health and well-being of individuals [113][138]. Ohkuma, *et al.* [113], conducted a systematic review of studies focusing on the relationship between eating rate and obesity. They concluded that eating quickly is positively associated with an increased Body Mass Index (BMI) and obesity. Moreover, Robinson *et al.* [138] also systematically reviewed studies that manipulated eating rate, and showed its impact on food intake and hunger. They reviewed factors such as verbal instruction from the researcher, altering food texture, manipulating food delivery, and computerized feedback as manipulation to alter eating rate in experiments. Robison *et al.* found that a decrease in eating rate is associated with a reduction in energy intake. Kim *et al.* found that a high eating rate is associated with an increased risk of endoscopic erosive gastritis in Korean adults [74]. These studies show that decreasing eating rate is key for improved health. Besides, reducing the eating rate is also the first basic principle of mindful eating, which focuses on the enjoyment of food without judgement of sensations [109]. More recently, Bolhuis and Keast [17] found that participants who ate with a spoon had a higher eating rate than those who used a fork in a laboratory setting. The two groups of participants spent similar time on four different lunch sessions, but generally, spoon users consumed more. This research suggests that the choice of eating utensil affects users' eating rate, and ultimately, their health as well.

4.1.2 *Techniques to detect eating and provide feedback*

Various devices exist to detect eating behavior, some of which provide feedback and intervention when necessary. As briefly mentioned earlier, one of the commercial smart devices in the market is the 10s Fork [1], designed by Slow Control. This fork is able to provide feedback on eating rate through vibration and light. The fork counts the time interval between each bite and vibrates when the interval does not reach a programmed threshold. Hermans *et al.* [56] [54] conducted a qualitative study on the 10s Fork. They carried out a three-day study with 11 participants to investigate acceptability, perceived efficacy, and user experience. Hermans *et al.* found the 10s Fork was comfortable to use and sufficiently accurate.

1 https://slowcontrol.com/en-us/

However, participants felt they were not the target user (i.e., participants did not regard their high eating rate as a health problem) and thus *lacked the motivation* to continue using it. Hermans *et al.* [55] also conducted a between-subject laboratory experiment on the effect of the 10s Fork. They found that the vibrotactile feedback on the 10s Fork could successfully reduce the number of bites per minute when users were eating fast. However, the researchers did not confirm that slower eating led to a reduction in food consumption. Kim *et al.* [79] designed Slowee, which applies Electromyography (EMG) and piezo sensors to detect chewing and swallowing, in order to provide eating speed guidance through light and vibration feedback. Their pilot studies showed a positive improvement in the eating habits of participants. However, design of the Slowee is elaborate with sensors on headphones and a necklace to detect the eating action. Besides, Slowee is equipped with feedback unit containing a light and a wristband to provide visual and vibration feedback to users. Inspired by Slowee, Kim *et al.* invented a wristband which can provide eating movement detection and vibration feedback, and a tabletop unit to give visual feedback [80]. Their pilot study results showed that eating time increases with the visual and tactile feedback and that tactile feedback could further help participants to reduce the total amount consumed per bite.

Kadomura *et al.* [69] designed and implemented a smart fork called Sensing Fork to recognize eating behavior for children. To provide positive feedback on good eating behavior, Kadomura *et al.* also designed and prototyped the Hungry Panda game [68]. This game-based application provided visual feedback according to the eating behavior detected by the fork. In the second version of the game, they addressed the issues of picky and distracted eating [70], which were two of the most commonly identified eating problems of Japanese children. Kadomura *et* *al.*'s longitudinal, in-the-field study showed that the system was acceptable to the children participants, and could improve children's eating behavior.

Smartwatches have gained popularity as commercial devices used to promote general health and wellness improvement, such as self-monitoring of human activity and providing feedback on it [136]. Thomaz *et al.* [153] presented a practical approach that leveraged an inertial sensor from a smartwatch to identify the eating moment. They conducted a semi-controlled lab study to train an eating moment classifier based on inertial sensor data, then validated the classifier in two in-the-wild studies. The inertial sensor was able to effectively detect the user's eating behavior. Compared with other modalities such as first-person images captured by camera and acoustic sensing data captured by earbuds, inertial sensing is beneficial because it does not interfere with user privacy [152]. Maintaining user privacy also makes motion tracking more appropriate when applying this modality to detect intake behavior in research studies. Mirtchouk *et al.* [105] concluded that the combination of multiple sensing modalities and focused, personal free-living data could improve accuracy of eating detection.

Several other devices have been used to measure food consumption. One such device, the MandoMeter [2], leverages a scale that tracks food consumption through tracking the weight change of the meal and provides visual feedback on a smartphone application. Using computer vision techniques also allows for the tracking of food consumption, and represents the potential to recognize the type of food being consumed. One of these techniques was applied to a device, SmartPlate [3]. This device includes a weight tracking plate and a smartphone application that could take pictures of the food on the plate to provide visual analysis data on the

2 https://mando.se/en/mandometer-method/the-mandometer-device/
3 https://www.getsmartplate.com/

meal. Both the MandoMeter and the SmartPlate require additional equipment in the form of a weight scale and the feedback is, in both cases, from a smartphone graphical user interface.

4.1.3 *Digital Behavior interventions*

Regarding behavior interventions, Rose *et al.* [140] reviewed 27 studies on digital interventions for improving the diet and physical activity behaviors of adolescents. The digital interventions they studied include web sites, text messages, games, multicomponent interventions, emails, and social media. They found digital interventions that incorporate education, goal setting, self-monitoring, and parental involvement had a significant effect on behaviour change. Hermsen *et al.* [58] similarly reviewed studies on digital technologies for changing habits. They found that feedback generated through digital technology could be an effective way to disrupt and change undesired habits. Altogether, these findings suggest that applying digital technology to improve eating behavior is a promising intervention.

4.1.4 *Shape-changing interfaces*

One way to modify behavior is by generating physical interference that limits user movement. Maimani and Roudaut [3] used *jamming technology*, which use pneumatic actuation to inflate or deflate a material filled with particles, to change the stiffness of a suit to restrict body movement. They studied different materials and particles for jamming and compared the size of patches for jamming in their experiment. Maimani *et al.* also showed the application of such a suit in a haptic game. Delazio *et al.* [28] introduced a wearable interface which provides force and vibration to the upper body. They conducted a series of user studies to validate their approach and provided prototype applications in virtual reality. Pohl *et al.* [129] designed a strap which could provide compression feedback on body. This device could inhibit physical movements based on compression and it was incorporated in a jogging game. These approaches suggest that pneumatic actuated shape-changing devices are feasible.

Regarding the design of shape-changing interfaces, Qamar *et al.* [132] reviewed literature on material science and Human-Computer Interaction (HCI) from an HCI research perspective. In their work, they studied various approaches to shape-changing device design. One shape-changing method studied is the application of a pneumatic actuated interface. He *et al.* [53] introduced a pneumatic armband with tactile sensation and explored different possibilities for human device interaction with a haptic interface. To provide notifications, Pohl *et al.* [127] generated compression feedback by applying pneumatic actuation and an inflatable structure. They produced prototypes to study the compression feedback in their studies [128]. Teng *et al.* [151] built a light-weight pneumatic interface which was wearable on the palm and used in Virtual Reality, to provide a shape-changing object to increase immersiveness and allow for object manipulation. Their work shows the feasibility of a hand held pneumatic shape-changing interface. Fundamental to these pneumatic structures was an inflatable object. Sareen *et al.* [143] introduced a design and fabrication technique for making large, pneumatic artifacts. They showed that their pressure-based interfaces are strong enough to withstand various weights.

Bendable eating utensils, such as Sure Hand Bendable Utensils [4], exist as an assistive device to aid older adults in eating. To solve hand tremor issues, Liftware provides Liftware Steady and Liftware Level, two products for people who have mobility limitations [5]. However, these apparatus are designed to support, rather than intervene with eating.

There are various technologies focusing on eating behavior, however, to date, there are no studies on applying pneumatic actuation to eating utensils. Thus we plan to develop a utensil that can leverage a pneumatic interface to provide physical resistance to improve eating behavior.

4.2 research questions (problem statement)

I plan to study the means to apply physical resistance to an eating utensil. My research questions are the following:

i. Is it feasible to implement an eating utensil which could provide a pneumatic, actuated shape-changing physical resistance to interfere with users' fast eating behavior?

4.3 methodology (potential solution)

My first goal is to validate the feasibility of embedding physical resistance into an eating utensil. My task is to develop a prototype. The essential functions of this prototype are the ability to detect the eating action behavior and to provide different levels of physical resistance by changing the stiffness and the shape of

4 https://www.performancehealth.com/sure-hand-bendable-utensil
5 https://www.liftware.com/

the device. The primary function of this prototype is to provide resistance, based on the detection of fast eating behaviour, to interfere with eating activity.

For the physical resistance, I plan to implement different levels of rigidity on the handle of the eating utensil, to achieve a shape-changing effect. The handle of the eating utensil would be pneumatic and capable of changing its rigidity and shape by inflating and deflating. The inflating behavior of the device would increase the air pressure of the pneumatic component, thereby increasing the stiffness of the device and facilitates eating. The deflation would reduce the rigidity of the handle of the eating utensil. The pneumatic system could control the specific rigidity of the handle of the device when in use. If the stiffness is low, the device will provide high levels of physical resistance because it is easy to bend and lose the capability: the shape would be changed so that people cannot use the eating utensil. The food would not be able to stay on the utensil when attempting to deliver food from plate to mouth. If the level of rigidity is high, the device will work as a regular eating utensil. The fork's control part will be designed to regulate the shape changing effect. Specifically, it will inflate itself to facilitate the food intake behaviour. After the detection of a bite, the device will deflate to resist food intake behaviour. To avoid spilling the food, the fork will not deflate and bend during the movement of lifting a bite of food from table to user's mouth. After waiting for a specific period of time, the fork will inflate to enable the next bite. I regard this type of physical resistance as a stubborn feedback, which should help the users to regulate their eating habits.

Regarding feedback, the pneumatic control system of the device would include a mini pump, a mini solenoid valve, a small battery, and a small Arduino board with Inertial-Measurement-unit (IMU). The final target of the prototyping is to

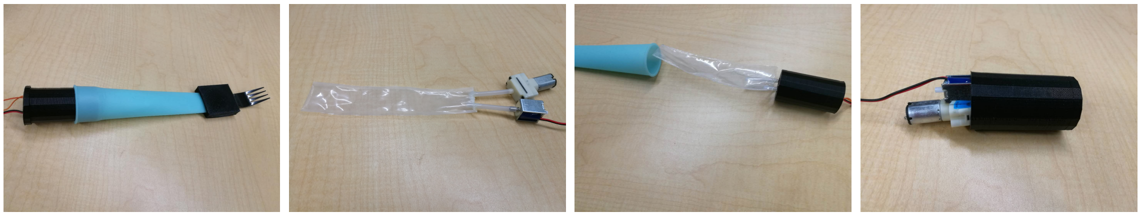

Figure 4.1: A low-fidelity prototype that I built for the shape-changing utensil

build a self-contained device with a controller section. I will test the prototype device to check its functionality, before deploying it in a real world experiment.

4.4 DEMONSTRATION OF THE PROTOTYPE

I have also conducted design brainstorm sessions to gather and compare different design ideas for the physical resistance required to intervene with a high eating rate. Based on the design session and further investigation of eating-related technologies, I have decided on the shape-changing interface design. Compared to other design ideas, a pneumatic actuation shape-changing idea has not been explored thoroughly in eating behaviour applications. Also, pneumatic actuation is safe in the eating context. I wish to explore the design space by using a pneumatic, shape-changing interface design in an eating utensil prototype. The bending effect will interfere with eating and it will provide feedback and reinforcement to encourage users to wait between bites to slow down the eating rate. Meanwhile, I have been developing low fidelity prototypes.

Currently, I am building the middle-fidelity prototype of my eating utensil and testing the shape-changing aspect and eating detection ability. I have built a prototype of the pneumatic shape-changing utensil which is shown in Figure 4.1 . The middle fidelity prototype contains a small pump, a mini solenoid valve, and an airbag. The handle of the eating utensil is pneumatic and can change its rigidity and shape by inflating and deflating. The inflating behavior of the increases the air pressure of the pneumatic part, providing stiffness to facilitate eating. deflation the device reduces the rigidity of the handle to interfere with eating 4.2.

Figure 4.2: An initial, very low fidelity prototype utensil that shape-changes. The prototype bends when deflated, thereby intervening with the eater's behavior

4.5 FUTURE WORK

From this research project, I first plan to produce and improve a shape-changing eating utensil prototype. Based on our knowledge, it would be the first prototype of its kind to leverage a pneumatic structure in an eating context. This prototype is intended to change stiffness to provide in-situ, physical resistance to interfere with a high eating rate or poor eating behavior [7]. As described above, although there are numerous devices that attempt to improve eating behaviors, there is a need for further exploration in identifying appropriate technological interventions for assisting with eating behaviors. For a future study, we plan to develop a prototype, which can detect eating behavior using a motion sensor, and provide various levels of physical resistance. When fast eating is detected, physical resistance should be applied via changing the stiffness and the shape of the device.

Currently, the device is approximately twice as large as a normal eating utensil. I plan to iterate future prototype designs to reduce their size to more closely match that of traditional eating utensils, while also working on the eating behavior recognition function. I plan to make a self-contained prototype with a controller section for the user experiment.

The evaluation of the design will be based on the results of a series of experiments with the prototype. I plan to carry out a series of user studies on this prototype. First, I plan to investigate the user experience as it related to comfort and acceptability at various levels of physical resistance as the stiffness of the device changes. I also plan to demonstrate the feasibility of embedding physical resistance into an eating utensil. I will then conduct a study of the efficiency of this resistance in reducing eating rate to demonstrate the feasibility of the design idea and its potential effect for changing and improving people's eating behavior.

5 DESIGN AND IMPLEMENT THE BENDABLE FORK

5.1 MOTIVATION

People usually have different eating habits. From previous research, eating too fast is linked to various health risks, such as overweight and obesity[94, 113], metabolic syndrome [162], heart disease, diabetes[133], choking[85], and gastritis [74]. Thus, for fast eaters, decreasing their eating rate could be beneficial to their health.

Various projects previously investigated the health eating guidance and regulation, such as designing a game to motivate the healthier food choice through the grocery shopping [18]. The behavior of food purchase happens prior to the eating action. Researchers also investigate the user experience on using the self-report food logger applications to improve their diets [67]. The food loggers are focus on the meal summaries which happen after meals. This study investigates how feedback could be provided that will help the user make healthier choices during their meal. Researches also investigated eating monitoring technologies, such as using eyeglasses to automatically monitor the diet [12] or using a multi-sensor necklace for detecting eating [167]. These sensing technologies make it achievable to provide real time intervention. In this chapter, I have focused on investigating the in-meal eating intervention to help people regulate their eating.

To help faster eaters reduce their eating speed, various solutions have been proposed, such as providing feedback and a summary of the eater's eating speed. (i.e. Mandometer [1]). The Mandometer is a plate-sized smart scale which is placed under the meal plate to track the weight change and then guide the eating rate for users on a smartphone application. This device is large and intended to be deployed to every dining location. Research has been done on more mobile solutions. To pursue an in-situ effect, I examined previous research and products developed to provide feedback the during meal feedback such as vibration and light stimuli on 10s fork [2] and vibration stimuli on the smartwatch to provide the guidance to the users on their eating speed. However, the other type of during-meal feedback are not explored thoroughly.

To regulate the eating speed, I designed a novel feedback mechanism which can rotate the handle of the fork mechanically and provide feedback to the user to help them notice their problematic eating speed. The rotated handle also interferes with ease of eating and helps the user to slow down the eating. Thus, the novel rotation feedback mechanism provides a visual effect so users will notice that their eating speed has triggered the mechanism to rotate the fork.

5.2 RELATED WORK

5.2.1 *Reinforcement to behavior change*

There are various theories investigating the behavior change interventions to regulate human habits [126]. Providing feedback to help individuals to the improve

1 https://mando.se/en/mandometer-method/the-mandometer-device/
2 http://www.slowcontrol.com/en/

their habits has been investigated in the feedback interventions [81]. Researchers also investigated feedback interventions in digital technologies to change habits [58].

The feedback intervention could be theoretically investigated from the operant conditioning behaviorism [147], which mentioned the behavior could be learnt from interaction with the environment. In this chapter, I leveraged this theory and designed the novel feedback mechanism providing reinforcement to help users form proper eating habits.

5.2.2 *In-meal eating feedback*

There are various projects that previously studied during-meal eating intervention. One example is feedback on wearable devices. For example providing feedback on smartphones [77] or vibration on a wrist band and lights on the table unit [79]. There is feedback on the dining tables. For example, Mandometer provide the visual linegraphs on a smartphone in front of the eaters to help them to regulate their eating rate [39]. Joi *et al.* designed connected tableware to help children eat more vegetables [65]. Kadomura *et al.* developed a fork to detect the food color and provided a smartphone game to motivate the children users to focus on the meal and eating diverse foods [70]. There is also feedback on the utensils. For example, 10s fork provides feedback through vibration and lights on the fork to help eaters to regulate their eating speed [55]. I would like to extend the design space of the feedback mechanism on the eating utensil to explore novel way to help users eat healthier.

5.2.3 *Stubborn feedback*

Typical feedback provided for eating intervention consists of lights and vibration [55] or visual animation or graphs on the phone [39, 70]. For the vibrations and lights, users can easily to ignore the feedback and bypass the deliberated feedback, which is undesirable. For the visual animations or graphs on smart devices (i.e. smartphones), the feedback introduces an extra device to the eating environment, which may also be burdensome to the users. For these reasons, I want to design a stubborn feedback mechanism for the eating utensil which does not require an additional device and can not easily be ignored by the users. Here, I follow the speed bump design on the road which helps the driver to get feedback on their speed both visually and physically, if the driver maintains a high speed on the road. I want to introduce this design concept to the eating habit intervention design. Here the stubborn feedback is a force to physically change the shape of the fork to prevent the users from continuing bad behaviors during dining.

5.3 DESIGN CONCEPT: PHYSICAL REINFORCEMENT ON THE EATING UTENSIL

In this section, I explain the concept of physical resistance for behavior training. Eating behavior consists of different stages of actions and body movements, such as getting food on a utensil, picking up the utensil, and chewing. To reduce the eating rate, we could provide feedback or resistance. For this study, I plan to provide physical resistance on the eating utensil.

In our design, the physical resistance is embedded in the eating utensil. The utensil could change the shape in order to provide physical resistance to people as they eat. The utensil would be able to bend when the eating rate is too high. This would signal to the users that the utensil is not usable. This could force the user to reduce their eating rate. I designed this shape changing character by bending the fork itself as a form of physical resistance. The interference is designed to reinforce for the behavior modification.

Physical interference is straightforward. People can see the change. However, it is different from the haptic feedback like vibration or light and the other visual or audio resistance like an instruction on the smartwatch. The physical resistance is stronger and not easy to bypass. So, they must follow the instruction of the system. This strong effect would help people modify and regulate their eating behavior in a short time. I plan to apply this as a tool for training purposes for correcting the behavior of fast eaters.

This physical resistance could increase people's awareness of their high eating rate and make them follow the regulation procedure to effectively correct their eating rate.

5.4 preliminary design session

I first conducted a brainstorming design session for physical resistance in the HCI lab of University of Manitoba. In that meeting people came up with different ideas for providing feedback and intervention, such as light, vibration, or using a motor to change the angle of the eating utensil end to provide physical resistance. Some of the ideas mentioned change the shape of the eating utensil to make it contain less food on each bite. The participants discussed the different ideas and concluded that the current shape changing idea would be more effective. A survey of current research suggests that it would be the only one prototype that could leverage mechanical bending actuation into the eating utensil to make a shape changing interface, which I believe to be the most promising for this project.

5.5 HARDWARE DESIGN

I designed and developed a smart fork that could detect the eating motion of the user and bend the tip part of the fork when it detects unhealthy eating habits, especially fast eating. The fork is aiming to help fast eaters correct their eating habits and keep a healthier diet. The detection of eating motion is implemented using an Inertial Measurement Unit (IMU) sensor to detect the motion of user's eating behavior, and a load cell to measure the weight of each bite the user is consuming[170]. All the data readings could be transferred to our ground station through bluetooth. To achieve this, the Atmega328p microcontroller was selected as the main control unit of this application. The MPU 6050 inertial measurement unit was selected to obtain gyroscope and accelerometer measurements due to its low difficulty to interface with and wealth of resources available. It uses I2C communication protocol for communication with Atmega328p. As for the load cell, I have selected a 780g load cell and the HX711 load cell amplifier to get the weight data reading. A custom printed circuit board (PCB) was then designed and manufactured to integrate the components together as shown in Figure 5.1 and 5.2.

For the mechanical aspect, I designed a 3D model of the fork structure and manufactured it using 3D printed PLA plastic. The design criteria of the mechanical aspect was primarily focused on the space arrangement, to maintain a compact form factor. This meant that I had to install a servo motor, PCB, vibration motor,

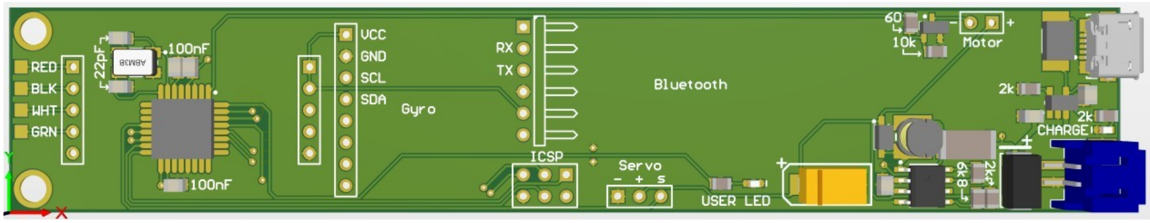

Figure 5.1: Printed circuit board Version 1.

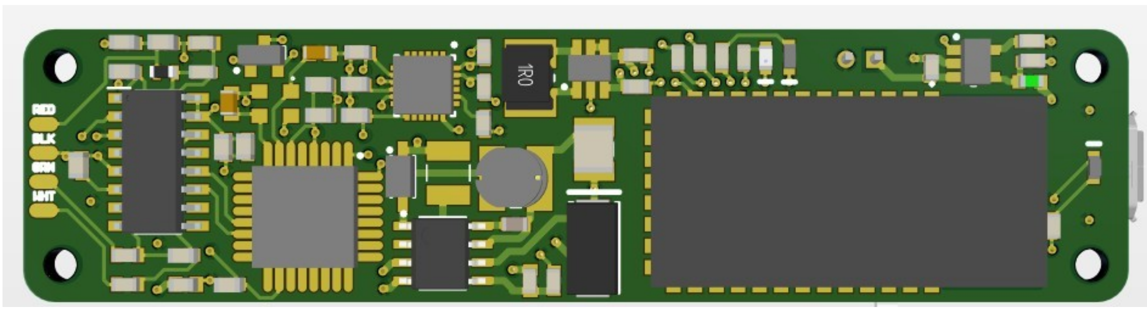

Figure 5.2: Printed circuit board Version 2.

and load cell into the handle of the fork. Overall, the final production could be divided into two parts; fork base as shown in figure 5.3 and body as shown in figure 5.4. The main functionality of the fork base is for mounting the load cell and for connecting to fork tip at the front end and body at the back end. The fork tip is designed to be interchangeable for the purpose of hygiene. The body is designed to house the printed circuit board, servo and vibration motor. The joint part between body and fork base is attached using the heat set brass insert and machine screw to enhance the stability of the overall structure. The printed circuit board (PCB) is installed into the body using standoffs and screws. The standoffs were selected to provide adequate space for the battery housed between printed circuit board and body.

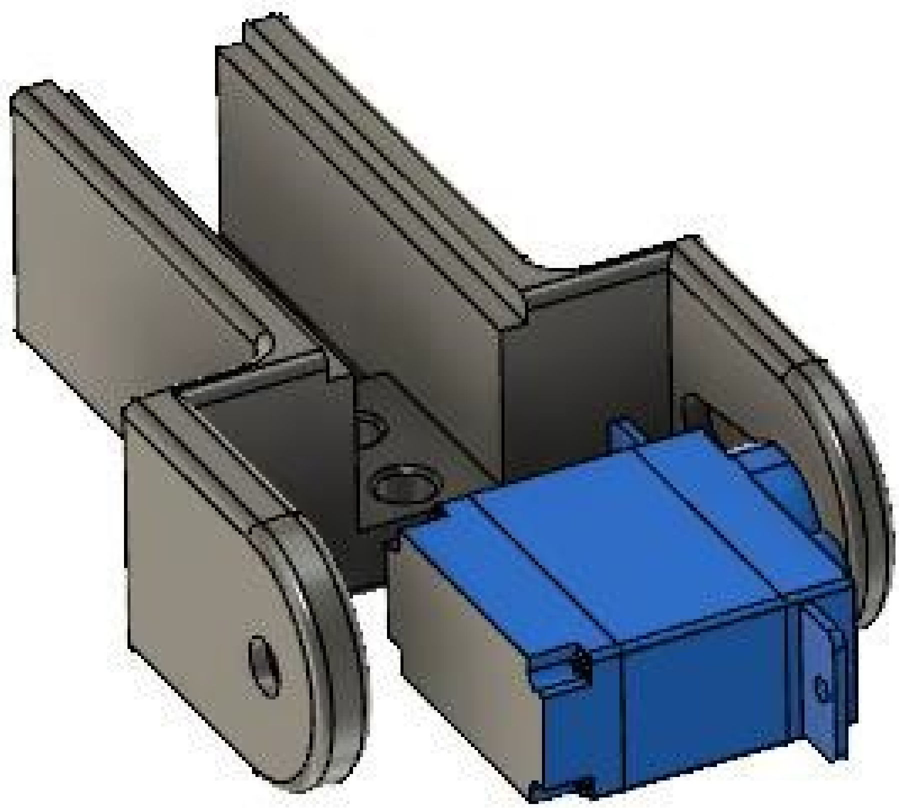

Figure 5.3: The fork base and servo motor.

5.6 METHOD

I leveraged and simplified the detection algorithm proposed in a previous paper [170] and computed the roll velocity to use a threshold value to detect the food pick-up gesture. In the current demo, I set a time interval of 10 seconds. Once the user attempts a food pick up gesture within this time interval, the system will trigger the feedback mechanism. The servo motor will start to apply force to bend the fork tip toward the handle part to prevent the users from poking with the utensil to pick up the food. It will then bend back to its original shape and the user will have to wait for 10 second prior to the next food pickup gesture. If the

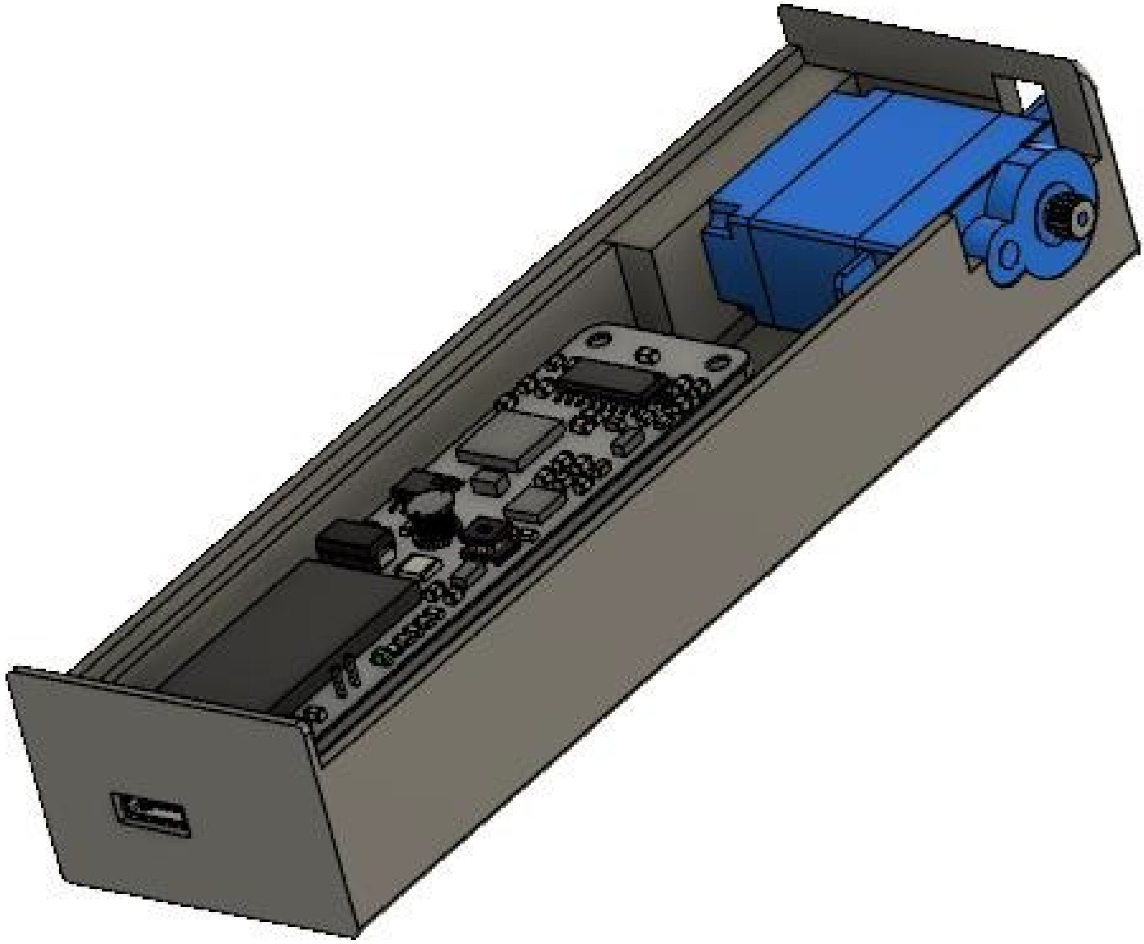

Figure 5.4: The body and PCB.

user tries to pick up the food again without waiting the allotted time period, the fork will bend again. This method will help users by visually showing a bending fork and physically resisting the user's attempts to eat the food.

5.7 DEMONSTRATION

The current fork could sense the user's eating gesture by computing the roll velocity change from the IMU sensor data. Once the food pick-up gesture is

Figure 5.5: The overall structure.

triggered and the time interval between two bites is shorter than the preset value, the servo motor will apply force to bend the fork and provide the bending feedback to the users and to prevent them from eating. Thus, the user will sense the signal to wait longer before having the next bite.

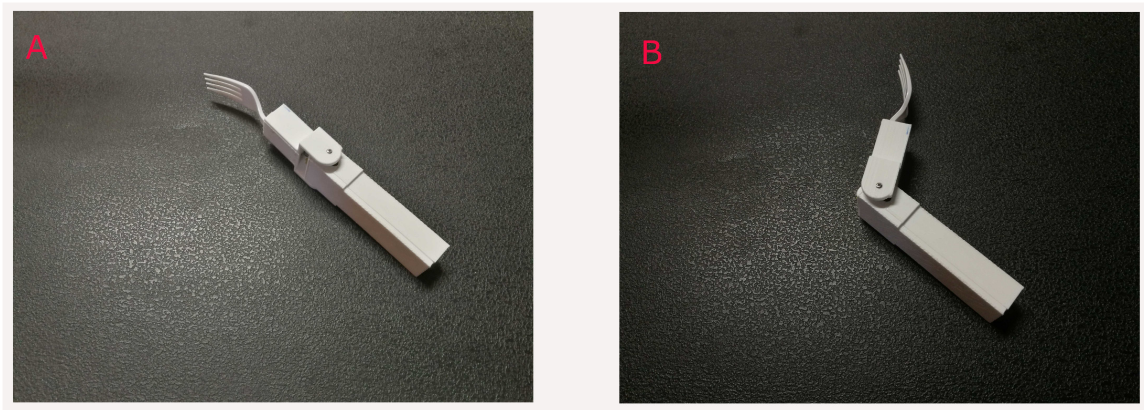

Figure 5.6: The fork structure. A: The fork straight. B: The fork bent.

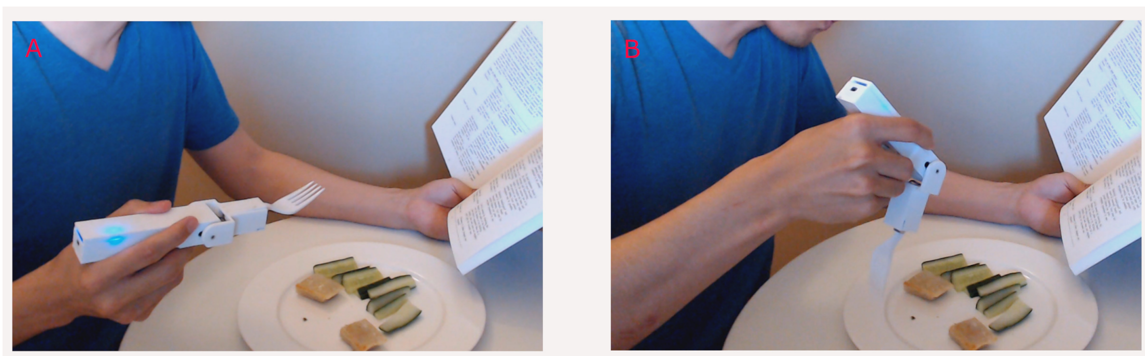

Figure 5.7: The fork bends when the user tries to poke and pick up food without waiting enough time.

5.8 DISCUSSION

In this design, I provided a prototype fork which applied the base eating food pick up gesture detection for the eating intervention. In this demonstration, the fork bends to provide the stubborn feedback to the users, helping them to decrease their eating speed. A real user experiment is needed to investigate the user experience on this kind of feedback mechanism.

5.9 LIMITATION

In the current demonstration system, I only detect the food pick up gesture. Since we aim to modify the eating rate, the food weight detection is missing. In the future we need to add the food weight detection to the system.

A long-term investigation is needed to study whether this device could help the users to improve their eating habits, especially slow down their eating speed.

5.10 FUTURE WORK

The current demonstration was not studied with real users, we would like to invite real users to the lab to use the fork and survey their user experience on using the fork so that I could investigate the real user experience on the feedback.

5.11 SUMMARY

In this chapter, I described the design and development of a novel feedback mechanism embedded into the fork to help users slow down their eating rate. The fork is able to bend its tips when the eating rate is too high, forcing users to decrease their eating rate. Additionally, the bending feedback acted as resistance for users to eat using the fork, which turned to be a physical resistance to slow down eating speed. I hope that this system could help fast eaters to slow down their eating speed.

6 CONCLUSION

Eating is an important daily activity, and researchers have linked eating rate, or how much food people eat within a short interval, to obesity [113], which is currently a serious epidemic in North America [4][107]. Studies show that reducing eating rate, or eating slower, could lower calorie intake [138] and hence, minimize the risk of obesity [113]. Researchers also found high eating rate to be associated with an increased risk of gastritis [74]. In addition, reducing one's eating rate is also a basic principle of mindful eating, and can help avoid overweightness and obesity [109]. Clearly, having good eating habits, especially an appropriate eating rate, is important. To improve eating habits, numerous interventions have been applied in various settings. Prior studies have manipulated eating rate [138], while others have leveraged digital interventions to help modify eating behavior [140]. However, many of these interventions are relatively difficult to apply in everyday life. For example, some require elaborate experimental settings in a laboratory [17] while others require setting up extra devices and equipment such as a special scale [1][2]. Such rather burdensome tools and settings might discourage improvements in eating habits. Thus, I propose the development of an eating utensil, which is compact, easy to carry, and has the capability to intervene with food intake behavior and modify eating rate. With the proposed utensil, users should be able

1 https://mando.se/en/
2 https://www.getsmartplate.com/index.html

to improve their eating behavior relatively independently and without elaborate equipment.

In the Chapter 2, a review of digital intervention and persuasive technologies for eating habits were conducted. Based on a review of the related literature, a design framework for digital interventions was developed, which gives a top-down view of intervention design. To explore the utility of this framework, parallel coordinates were developed upon visually summarizing the reviewed projects in order to probe current trends. Finally, to show the feasibility of using our framework in practice, two design sessions on generating eating improvement design ideas were conducted. Overall, the framework was found to be helpful in guiding (mostly beginner) designers to generate new ideas.

Because eating habits can lead to serious health issues, I am very hopeful that my framework will support future investigation and contribute to the design of eating habit intervention technologies.

Inappropriate eating behavior can trigger various health issues. According to previous studies, fast eating rates could lead to obesity [113], while slow eating rates could lower calorie intake [138]. Researchers further find a high eating rate to be linked to an increased risk of gastritis [74]. Indeed, reducing eating rate is the first fundamental principle of mindful eating [109]. The Chapter 3 proposed a solution to help eaters monitor their eating rate by detecting their food pick-up gesture and calculate the food weight on each pick-up. From this idea, I built a proof-of-concept prototype fork with various sensors. To the extent of our knowledge, this is the first solution to both calculate the food weight and detect food pick-up gestures with data collected from a fork.

The primary goal of the solution of the detecting food pick-up and estimating food weight was to detect both food pick-up gesture and food weight estimation. I conducted an in-lab study that assessed the efficiency of the method by examining the detection of pick-up gestures and the weight of the food per pick-up. The ground truth data of the study was recorded to annotate the sensor data and compute the accuracy. I used a weight scale to track the weight change of the fruit in the bowl and placed a camera in front of the participant to track their hand movement. The data collected from the sensors attached to our prototype was used to develop a food pick-up gesture detection and weight estimation method. I evaluated both features using the data collected from the experiments and found that both models performed well. In the future, I hope to leverage our findings by deploying these features onto the next iteration of my prototype such that the next smart utensil is able to detect food pick-up gestures and calculate the weight of each bite alone. By warning users that they are eating too fast, this solution will be a beneficial asset in healthier eating habits.

Eating is important to health and improper eating behavior could lead to various health issues. Based on previous studies, we know that fast eating rates could lead to obesity [113] and gastritis [74], and slow eating rates can reduce energy intake [138]. This thesis proposes a design that embeds physical resistance into an eating utensil to help fast eaters reduce their eating rate. Based on this idea, I first built a proof-of-concept prototype with physical resistance provided through changing the stiffness and shape of the device. I embedded various levels of physical resistance within the eating utensil prototypes, to provide different levels of intervention by adjusting the level of rigidity in the handle. To the extent of my knowledge, this is the first prototype to leverage a pneumatic structure into an eating utensil. The goal of my research is to determine the underlying factors that contribute to good eating intervention design, and to develop and test prototypes in pursuit of measurable eating habit improvements.

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Part I

APPENDIX

A APPENDIX

A.1 A COMPREHENSIVE OVERVIEW OF THE DIGITAL INTERVENTION DESIGNS ON EATING HABITS FROM LITERATURE REVIEW

Table A.1: A comprehensive overview of the digital intervention designs on eating habits

Ref	Authors	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization
[2]	Adams et al. 2015	Food estimation	Application	Single	During	Per meal	Single	General
[8]	Andreae 2017	Food estimation	Tableware	Single	During	Per meal	Single	General
[9]	Arza et al. 2018	Feedback	Gaming	Single	During	Per meal	Group	General
[11]	Bech-Larsen and Grnhj 2013	Feedback	Multimedia	Single	After	Daily	Single	General
[14]	Bird et al. 2013	Monitoring	Application	Single	Before	Not specific	Single	General
[15]	Blackburne, Rodriguez, and Johnstone 2016	Self-control	Gaming	Single	Not specific	Daily	Single	General
[20]	Brevers et al. 2017	Self-control	Application	Single	Not specific	Not specific	Single	General

Table A.2: A comprehensive overview of the digital intervention designs on eating habits

Ref	Authors	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization
[21]	Chang, Danis, and Farrell 2014	Social influence	Application	Single	Not specific	Not specific	Group	General
[22]	Chen et al. 2011	Education	Website	Multiple	Not specific	Weekly	Group	Tailored
[23]	Chung et al. 2017	Social influence	Application	Single	Not specific	Not specific	Group	General
[24]	Connelly et al. 2012	Monitoring	Application	Single	After	Per meal	Single	General
[27]	Cullen, Liu, and Thompson 2016	Education	Gaming	Single	Not specific	Not specific	Single	General
[32]	Eigen et al. 2018	Social influence	Application	Single	Not specific	Per meal	Group	General
[36]	Epstein et al. 2016	Goal setting	Application	Single	Before	Daily	Group	General
[37]	Fabri, Wall, and Trevorrow 2013	Education	Website	Multiple	Before	Not specific	Group	General
[39]	Ford et al. 2010	Monitoring	Application	Single	During	Per meal	Single	General
[41]	Frenn et al. 2005	Education	Multimedia	Multiple	Not specific	Weekly	Group	General
[42]	Freyne et al. 2012	Monitoring	Application	Single	Not specific	Per meal	Single	Tailored
[44]	Ganesh et al. 2014	Feedback	Gaming	Single	During	Per meal	Single	General
[45]	Gerber et al. 2009	Advice & Reminder	Multimedia	Single	Not specific	Weekly	Single	Tailored
[48]	Grimes, Kantroo, and Grinter 2010	Education	Gaming	Multiple	Not specific	Not specific	Single	General
[55]	Hermans et al. 2017	Feedback	Tableware	Single	During	Per meal	Single	General

Table A.3: A comprehensive overview of the digital intervention designs on eating habits

Ref	Authors	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization
[64]	Hwang and Mamykina 2017	Education	Gaming	Single	Before	Daily	Single	General
[65]	Joi et al. 2016	Education	Gaming	Single	During	Per meal	Group	General
[66]	Jones et al. 2014	Education	Website	Multiple	Not specific	Weekly	Group	Tailored
[70]	Kadomura et al. 2014	Feedback	Gaming	Single	During	Per meal	Group	General
[71]	Kadomura, Tsukada, and Siio 2013	Feedback	Tableware	Single	During	Per meal	Single	General
[72]	Kaptein et al. 2012	Advice & Reminder	Multimedia	Single	Not specific	Daily	Single	Tailored
[73]	Kehr et al. 2012	Self-control	Smart device	Single	Not specific	Daily	Single	General
[75]	Kim et al. 2011	Education	Gaming	Single	Before	Not specific	Single	General
[76]	Kim, Park, and Lee 2016	Feedback	Application	Single	During	Per meal	Single	General
[77]	Kim and Bae 2018	Feedback	Application	Single	During	Per meal	Single	General
[78]	Kim and Bae 2018	Feedback	Application	Single	During	Per meal	Single	General
[79]	Kim et al. 2016	Feedback	Smart device	Single	During	Per meal	Single	General
[80]	Kim et al. 2016	Feedback	Smart device	Single	During	Per meal	Single	General
[84]	Kroes and Shahid 2013	Education	Application	Multiple	Not specific	Not specific	Group	General
[92]	Lawrence et al. 2015	Self-control	Website	Single	Not specific	Daily	Single	General
[95]	Lew et al. 2017	Feedback	Gaming	Single	During	Per meal	Single	General

Table A.4: A comprehensive overview of the digital intervention designs on eating habits

Ref	Authors	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization
[96]	Linehan et al. 2010	Social influence	Application	Single	After	Per meal	Group	General
[97]	Lo et al. 2007	Feedback	Gaming	Multiple	During	Per meal	Single	General
[99]	Lukoff et al. 2018	Social influence	Application	Single	Not specific	Daily	Group	General
[102]	Mansour et al. 2009	Education	Gaming	Single	Not specific	Not specific	Group	General
[110]	Nag, Pandey, and Jain 2017	Advice & Reminder	Application	Single	Before	Not specific	Single	Tailored
[111]	Narumi et al. 2012	Food estimation	Application	Single	During	Per meal	Single	General
[115]	Orji, Mandryk, and Vassileva 2017	Education	Gaming	Single	Not specific	Not specific	Single	Tailored
[117]	Orji, Vassileva, and Mandryk 2013	Education	Gaming	Single	Not specific	Not specific	Group	General
[120]	Park et al. 2015	Education	Gaming	Single	Not specific	Not specific	Single	General
[121]	Parker et al. 2013	Education	Website	Single	Not specific	Daily	Group	General
[124]	Pels, Kao, and Goel 2014	Feedback	Smart device	Single	After	Daily	Single	General
[125]	Peng 2009	Education	Gaming	Single	Not specific	Not specific	Single	Tailored
[130]	Pollak et al. 2010	Advice & Reminder	Gaming	Single	Not specific	Not specific	Single	General

Table A.5: A comprehensive overview of the digital intervention designs on eating habits

Ref	Authors	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization
[135]	Randall, Joshi, and Liu 2018	Feedback	Tableware	Single	During	Per meal	Single	General
[142]	Sakurai et al. 2015	Food estimation	Application	Single	During	Per meal	Single	General
[144]	Schaefbauer et al. 2015	Social influence	Application	Single	After	Per meal	Group	General
[149]	Sugita et al. 2018	Feedback	Application	Single	During	Per meal	Single	General
[150]	Takeuchi et al. 2015	Social influence	Application	Single	Before	Not specific	Group	Tailored
[155]	Thompson et al. 2010	Education	Gaming	Multiple	Not specific	Not specific	Single	Tailored
[156]	Thompson et al. 2012	Education	Website	Single	Not specific	Weekly	Single	General
[157]	Kaptein et al. 2012	Monitoring	Application	Single	After	Per meal	Single	General
[158]	Veling et al. 2014	Self-control	Website	Single	Not specific	Weekly	Single	General
[159]	Villalobos et al. 2011	Monitoring	Application	Single	During	Per meal	Single	General
[163]	Yang et al. 2017	Advice & Reminder	Website	Single	Before	Per meal	Single	Tailored

A.2 DESIGN FROM THE DESIGN WORKSHOP

Table A.6: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D1-1	Monitoring	Smart device	Single	During	Daily	Single	General	P1 designed a lunchbox (D1-1) with a screen and buttons on it. The screen displays the eating rate and present suggestions to regulate eating speed if the user eats too quickly. The lunchbox also displays information on the food to tell the user whether it is healthy or not. Users can set goals in the system and gain rewards based on achievements related to eating behavior improvement.

Table A.7: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D1-2	Monitoring	Application	Single	Before	Not specific	Single	General	P1 designed an application (D1-2). When using the application, food is scanned and the application performs calculations to inform the user if the food is healthy or not. The application shows recommended daily nutritional objectives for each nutritional category. The application shows percentages of consumption relative to a target, then provide emoji feedback.
D1-3	Feedback	Smart device	Single	During	Per meal	Single	General	P1 designed smart glasses for children (D1-3). The system in the glasses can scan the food and if the food is unhealthy, the color of the glasses will change to a cold color like green, blue, or purple. (P1 assumed the cold color could discourage eating).
D1-4	Advice & reminder	Smart device	Single	Before	Not specific	Single	General	P1 designed a smart water bottle (D1-4) with a display which can remind users to drink water by changing the display color and providing vibration feedback. The display also shows the sugar content of the water.

Table A.8: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D2-1	Education	Mutimedia	Single	Before	Not specific	Single	General	P2 designed a solution (D2-1) for people who use YouTube. The design, which leverages advertisements on online video websites, proposes providing healthy eating video advertisements during YouTube video shows. This can help users to learn more about healthy eating improvement while consuming video media.
D2-2	Feedback	Smart device	Single	Before	Daily	Single	General	P2 designed a lunchbox(D2-2) with two physical levels. When users are filling food in the lunchbox, the box detects the food type. If unhealthy food is placed in the lunchbox the lower level will not be available for food storage. This design restricts capacity of the box when filled with unhealthy food. When filled with unhealthy food, the lunchbox will be difficult to open, which provides feedback to users that the food is not suitable for them.

Table A.9: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D2-3	Monitoring	Application	Multiple	After	Per meal	Group	Tailored	P2 designed a smartphone application (D2-3) which can connect with smart utensils to detect eating behavior. Users can share their eating experience with friends and compete with each other in healthy eating development by using this application. The application can provide a score based on eating behavior and rank a user against their friends. The application will also provide personalized written content on healthy eating for users who receive a lower score. The application also provides a small game for users to play while eating and a history record for users to review their eating behavior data.
D3-1	Feedback	Smart device	Single	During	Per meal	Single	General	P3 designed an earphone (D3-1) that can provide healthy eating suggestions when detecting unhealthy eating behavior.
D3-2	Feedback	Tableware	Single	During	Per meal	Single	General	P3 designed a set of novel chopsticks (D3-2) that can restrict the open angle of the chopsticks to control the food portion size in order to control eating speed.

Table A.10: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D3-3	Feedback	Smart device	Single	After	Per meal	Single	General	P3 designed a gum or candy-like product (D3-3) that can change taste based on the caloric intake detected by the tracking system to help improve awareness after a meal. This is a novel feedback approach inspired by the fact that people like to have a gum or candy after their meal.
D3-4	Feedback	Smart device	Single	After	Per meal	Single	General	P3 designed a type of shoe (D3-4) that can change the height of the heel part and shape of the picture on the outer layer screen to provide after-eating feedback.
D4-1	Monitoring	Application	Single	After	Weekly	Single	General	P4 designed an application for smartphone (D4-1). The application would show daily healthy recipes for users to follow. It can also display the weekly caloric intake of a user. One feature of the application design is the "food market", which can present notifications of healthy food on sale in nearby supermarkets or grocery stores and provide coupons.

Table A.11: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D4-2	Feedback	Application	Single	During	Per meal	Single	General	The second smartphone application (D4-2) designed by P4 provides suggested eating speed for different kinds of food based on the food detection. The application can provide ambient music to help slow down eating speed.
D4-3	Feedback	Application	Single	During	Per meal	Single	General	P4 designed an application (D4-3) for smartwatch users. The application provides suggestions regarding food consumption. During a meal, the application could provide real-time vibration and sound feedback if eating speed is higher than suggested. After the meal, the application can show the caloric intake and eating speed, along with a summary of eating behavior to improve in the next meal.
D5-1	Feedback	Application	Single	Before	Not specific	Single	General	Participant 5 designed an application (D5-1) which could show different body images based on the detection of calories and food amounts when users scan food with a smartphone.

Table A.12: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D5-2	Feedback	Tableware	Single	During	Per meal	Single	General	P5 designed a plate (D5-2), which can display various colors and shapes based on the food on it. If the food is healthy, the plate will show beautiful shapes and colors. If the food is unhealthy, the plate will display an ugly shape and color.
D5-3	Feedback	Tableware	Single	During	Per meal	Single	General	The second plate designed by P5 is a movable plate(D5-3). When using this plate during a meal, the plate will move away from the user to make it harder to eat, if the user eats too quickly.
D5-4	Feedback	Tableware	Single	During	Per meal	Single	General	The third plate designed by P5 applies light on it (D5-4). This plate can display various lights which can flash or shake to provide visual feedback when users eat too quickly.
D5-5	Social influence	Application	Single	Before	Per meal	Group	General	P5 designed an application (D5-5) to apply a social influence strategy. When using the application, users can choose the food they plan to eat. Users can make friends when the system matches them with people who choose the same group of healthy food. Subsequently, the friends can support each other to maintain healthy eating behaviors.

Table A.13: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D6-1	Monitoring	Smart device	Single	During	Per meal	Not specific	Tailored	P6 designed a novel intelligent table cloth (D6-1) to control food consumption. The table cloth has the ability to connect smart tableware to measure food consumption and can connect to a smartphone to upload dietary data to monitor a meal. Users can use their phones to share information about dietary experiences and assist with creating dietary schedules. The tablecloth is portable and could be taken anywhere. It also has a screen which displays a timer, as well as nutritional and caloric data. The screen can also be used to show videos and images. The tablecloth could also support a single user to gain social interaction by having video chat on the screen. The tablecloth can provide personalized healthy menus, recipes, and advice for healthy eating according to user's data.

Table A.14: A comprehensive overview of the designs from the design brainstorming session

ID	Strategy	Modality	Stage	Timing	Frequency	Social	Personalization	Description
D7-1	Monitoring	Application	Single	After	Per meal	Group	General	P7 designed a diet-monitoring application for fast eaters (D7-1). The users of the application can share eating-rate related data with family members, who can then choose to award a star, based on the data. The user can take pictures to track the meal and the application can provide an alarm upon the detection of fast eating speeds.
D7-2	Feedback	Smart device	Single	During	Per meal	Single	General	P7 designed a smart chair (D7-2) which can provide music during eating to influence children's eating speed and amount of food consumption.