

Co-Designing Food Trackers with Dietitians:

Identifying Design Opportunities for Food Tracker Customization

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ABSTRACT

We report co-design workshops with registered dietitians conducted to identify opportunities for designing customizable food trackers. Dietitians typically see patients who have different dietary problems, thus having different information needs. However, existing food trackers such as paper-based diaries and mobile apps are rarely customizable, making it difficult to capture necessary data for both patients and dietitians. During the co-design sessions, dietitians created representative patient personas and designed food trackers for each persona. We found a wide range of potential tracking items such as food, reflection, symptom, activity, and physical state. Depending on patients' dietary problems and dietitians' practice, the necessity and importance of these tracking items vary. We identify opportunities for patients and healthcare providers to collaborate around data tracking and sharing through customization. We also discuss how to structure co-design workshops to solicit the design considerations of self-tracking tools for patients with specific health problems.

CCS CONCEPTS

• **Human-centered computing** → **User centered design; Participatory design; Interface design prototyping;**

KEYWORDS

Food tracking, customization, co-design workshop, self-tracking, health, personal informatics

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1 INTRODUCTION

Food tracking, a prevalent approach in self-monitoring, helps people gain awareness of their food practices and improve their diet [15, 16]. From healthcare providers' perspectives, the data collected through food tracking has clinical values for assessing patients' nutrient intake and providing treatment. For example, by examining patients' food intake, providers can identify symptom triggers (e.g., food allergy [34], gastrointestinal problems [52]), and understand how patients' eating habits affect their health [30, 45, 46]. Traditional techniques to collect food intake include questionnaires, interviews, and paper-based diaries [12, 24, 50, 66]. Today, many people turn to digital food tracking tools (e.g., a personal digital assistant (PDA) [25], mobile phone [61], computer [62]) for convenience, while some still prefer tracking food on paper [63].

As food is central to people's daily life, food data cover a broader context beyond what people eat. Food data could include when they eat, where they eat, who they eat with, how they feel about the food, and what they do before or after eating [33, 42]. However, among the numerous food tracking applications that are available in the market (e.g., MyFoodDiary [6], MyFitnessPal [5], Bitesanp [1]), most focus on collecting nutrition facts (e.g., calorie, protein, carbohydrates, sugar, fat, fiber) of every meal, providing limited flexibility for people to choose what to track about their food.

We see a growing interest in the Human-Computer Interaction community in learning about the tracking needs of people with specific health issues and how they use existing tracking apps [22, 27, 29, 36, 47]. In the context of food tracking, researchers have found that people's tracking needs associate with not only the dietary problems they combat (e.g., eating disorders [27, 28], irritable bowel syndrome (IBS) [22, 36]), but also their lifestyle, medication, and day-to-day activities [56].

The mainstream food tracking tools (e.g., MyFoodDiary [6], MyFitnessPal [5], Bitesanp [1]) do not support addressing these diverse and sophisticated needs. The lack of flexibility in configuring what to track has become one of the barriers

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that prevent providers from using patients' data [22]. Moreover, using tracking tools that are not appropriately designed for people with specific needs can lead to unintended consequences, such as over-restricting behaviors, and even exacerbation of health problems [27, 28]. The mismatch between the design of existing tracking tools and people's tracking needs sheds a light on the benefits of designing tracking tools that are customizable [17, 38, 40]. By extending the concept of customization, we aim to design flexible food tracking tools that dietitians and patients with various dietary problems can collaboratively use. As the first step, we set out to understand the information that patients with different dietary problems need to track from dietitians' perspectives, and rethink the design of food trackers to support the information needs. Specifically, we have two research questions:

- RQ1: What do patients with dietary problems need to track to facilitate working with dietitians? (Tracking needs)
- RQ2: How to customize food trackers to support patients with various dietary problems? (Tailoring tracker design)

To answer the research questions, we conducted individual co-design workshops with six registered dietitians. During the workshop, we asked each participant to describe two patient types they commonly see (which we referred to as "patient persona"), and to create food trackers for those personas using paper-based prototyping widgets. When participants were creating trackers, we asked them to think aloud such that we can understand their tracking needs and design rationale. The 12 patient personas had common attributes while demonstrating unique characteristics in terms of age, dietary problems, symptoms, and goals. Patient personas interplaying with each dietitian's practice resulted in diverse and individualized tracker designs regarding what to track and how to track.

The contributions of this work are (1) structuring co-design sessions involving healthcare providers to solicit design considerations of self-tracking tools for patients with specific health problems, (2) identifying customization dimensions of food trackers, and (3) providing the opportunities of customization in promoting the patient-provider collaboration.

2 RELATED WORK

Food tracking has been a long-standing practice for various purposes. The related work presented herein covers backgrounds in food tracking, and tools designed to support this practice. We also describe design efforts in customizable self-tracking tools to support diverse tracking needs.

Food Tracking

Food tracking originated from food assessment in clinical practices, which aimed to help providers assess patients' nutrition intake and understand their eating habits [12]. Typical food assessment methods are interviews (e.g., food recall [24],

diet history [14]), questionnaires (e.g., food frequency questionnaire (FFQ) [66]), and paper-based diaries (e.g., dietary records [50]). Different food assessment methods serve different purposes. For example, the 24-hour food recall assesses recent food intake, and dietary history focuses on understanding long-term eating patterns [12]. As people's food practices vary with their age, culture, and preferences, it is common for providers to modify existing food assessment methods in order to suit people with different diets. For example, there are various versions of food frequency questionnaires (FFQ), such as FFQ for children [55], FFQ for women [51], and FFQ focusing on vitamin intake [13].

On the other hand, dietary problems are often associated with various health issues such as obesity [32], diabetes [49], eating disorders [43], gastrointestinal distress [52], or comorbidities of these issues. As such, when assessing patients' food intake, providers also need to examine other information such as symptoms, exercise, or mental status [32, 43, 49, 52]. Taking eating disorder patients as an example, providers usually need to collect their behavior restraints, weight concerns, and shape concerns besides food intake [43]. Likewise, for obese patients, it is usually important to collect energy expenditure and water intake [32].

With the advances in mHealth technology, many commercial applications (e.g., MyFitnessPal [5], Lose It [4], MyFoodDiary [6], Bitesnap [1], YouAte [9]) are marketed to support food tracking in people's daily life. Although these applications outperform traditional food assessment methods with better adherence [61] and higher accuracy [23], most of them focus on weight loss and calorie watching, which are not appropriate for those with specific tracking needs [22, 27, 28, 36, 60, 69]. As an instance, the most important goal for irritable bowel syndrome (IBS) patients is to identify the food triggers that cause their IBS symptoms [22, 36]. However, even with the tools that support self-experimentation through tracking food and symptoms, the levels of details needed for each patient differ from one another because of their different lifestyle and stage of the syndrome [22, 36]. Furthermore, Eikey and colleagues found that women suffering from eating disorders are subject to misuse of food trackers and obsessive logging because many of the trackers afford detailed calorie tracking [27, 28]. Such design could increase the acute awareness of numbers and even exacerbate eating disorders. The premise of our work is that the mismatch between existing food tracker design and the diverse tracking needs of people can be addressed by the customizability of the tracking tool.

Customization in Self-Tracking

Despite the dramatic increase of self-tracking apps and devices, it can be challenging for people to find a tool that perfectly matches their tracking needs. For example, Epstein and colleagues found that most menstrual tracking apps are

designed for general tracking purposes without considering women's life stages (e.g., adulthood, pregnancy, menopause), thereby failing to meet their tracking expectations [29]. In a study examining bipolar disorder patients' use of mood trackers, Murnane and colleagues found that people were dissatisfied with the fixed-length questionnaires and lack of personalized feedback [48]. Moreover, many of the patients, whose conditions are not well-understood (e.g., enigmatic disease), attempt to develop their own tracking regimen: tracking a variety of information (e.g. pain, symptoms, emotion, mood) at the beginning, and adjust their tracking items over time [47].

Most tracking apps do not provide the level of customization that people need. As such, self-trackers who have technical skills build custom tools [20], whereas others turn to manual tracking such as bullet journals [11]. However, building software or creating a bullet journal requires tremendous configuration efforts, which is not realistic for everyone. People also use other tools that are not intended for self-tracking but provide some customization feasibility (e.g., a spreadsheet, calendar, paper notes, social media) [20, 21].

To the best of our knowledge, current food tracking tools do not yet fully support customization for people with different food tracking goals. Even for general purpose self-tracking tools, only a handful of them support partial customization (e.g., Daytum [2], RescueTime [7], SleepTight [19]), and very few support full customization (e.g., OmniTrack [38], KeepTrack [3]). Among these apps, OmniTrack is the most flexible one, which enables people to create their own tracking apps by configuring an input schema (data fields) of their choice and linking to external services (e.g., Fitbit) [38]. However, existing models of customization assume that self-trackers know exactly how they want to customize their tracking regimen. This model may not work in the healthcare context where healthcare providers are one of the key stakeholders utilizing the patient-generated data in their care practice. In this light, we examine how to design a flexible and customizable self-tracking tool that can cover the level of customization required in food tracking, especially when the tracking requires collaboration between a patient and healthcare provider.

Co-Design in Healthcare Research

To elicit design opportunities from people with specific needs, co-design is commonly employed, where stakeholders are empowered to actively participate in the stage of product design and development [10, 57, 58]. In HCI and healthcare research, co-design has been widely used, especially for acquiring knowledge from domain experts and facilitating design discussions [31, 35, 37, 64]. In designing health information technologies, co-design enables close collaboration among designers, researchers, patients, and healthcare providers. To explore design opportunities, researchers have conducted co-design sessions with chronically-ill teens [35], clinicians and

health informatics experts [37], and oncologists and cancer patients [31]. As with these co-design studies and other formative studies conducted to gather healthcare providers' perspective at the early phase of technology design [22, 26, 65, 68], we aim to elicit dietitians' tracking needs for treating patients who combat different dietary problems. We prioritized to examine dietitians' information needs first because (1) in our study context, data collection is usually initiated by the clinicians [67] and (2) the data are being collected and utilized as part of the clinical treatment.

3 METHOD

We conducted individual co-design workshops with six registered dietitians, preceded with pre-design activities and followed by de-briefing interviews. We conducted individual sessions instead of group sessions, because we were interested in identifying uniqueness and breadth of individual dietitians' practice. This study was approved by the university's Institutional Review Board (IRB).

Participants

To recruit registered dietitians, we first drew up a list of 68 dietitians whose contact information was found on the websites of various local nutrition services. Among the 68 dietitians we contacted, six dietitians responded to us. They all met the following inclusion criteria: individuals who (1) are registered and accredited dietitians, (2) have been working as registered dietitians for more than 6 months, (3) have been providing services to patients with dietary problems, and (4) employ (technology or non-technology based) food diary in their practice. All six participants were female (all the dietitians in our recruiting pool were female), and their age ranged from 27 to 67 ($M = 38.5$, $SD = 6.64$). The six participants had diverse training from different regions within the U.S., and are currently working in different clinic environments (see Table 1 for their background). According to participants' preferences, we conducted four co-design workshops at our research lab (P1, P2, P3, P5), and the other two at participants' office (P4, P6). Each workshop lasted from 70 to 90 minutes. Three workshops involved two researchers and the other three involved three researchers. At the end of the study, each participant was compensated with a \$75 gift card.

Co-Design Workshop

Each co-design session consisted of a pre-design activity, co-design activity, and debriefing interview. Here, we describe the activities in detail and the rationale of such composition.

Pre-design Activity. Persona has been widely used in design as a tool to build empathy between users and designers [54]. In designing consumer health technologies, researchers found that patient persona was effective in addressing the

ID	Age	Sex	Practice years	Work environment	Training background	Expertise
P1	68	F	30	Private practice	Health Education & Nutrition Sciences	WM, ED, diabetes, GI
P2	34	F	11	Medical center & private practice	Mental Health & Dietetics	WM, ED
P3	27	F	2	Eating disorder treatment center & private practice	Public Health & Nutrition Sciences	WM, ED, GI
P4	43	F	20	Private practice & corporate wellness	Nutrition Sciences & Dietetics	WM, ED, diabetes, nutrition during pregnancy, digestive issues
P5	34	F	9	Eating disorder treatment center	Nutrition Sciences & Dietetics	ED, diabetes
P6	60	F	30	Private practice	Nutrition Sciences	WM, GI, ED, diabetes, pregnancy, rehabilitative, autoimmune, cardiac issues

Table 1: Participant profiles (WM = weight management, ED = eating disorder, GI = gastrointestinal distress).

needs and challenges of health consumers, especially for those who have comorbidities [41]. Therefore we asked participants to describe two patient personas including the patient’s age, sex, dietary problems, symptoms, and treatment goals. The remaining conversations and co-design activities centered on these personas. Focusing on each patient persona, participants described their typical treatment workflow—for instance, what the first session looks like, what information to collect, and what tools to use for tracking and sharing data. Having them describe a concrete context of work and patient’s health concerns, participants were able to reflect on their everyday practice so as to be prepared for the next co-design activity.

Co-Design Activity. After the pre-design activity, we used paper prototypes [59] as a tool to foster dietitians’ creativity and to facilitate the co-design activity effectively. Inspired by Kim and colleagues’ survey on common tracking field types in commercial tracking applications [38], we provided participants with a set of paper-based widgets in different field types (e.g., text box, numeric, date, time, radio-button, location, Likert scale, image, checkbox). We also provided images of external sources (e.g., Fitbit, Apple Watch, glucometer), assuming that data from these sources can be integrated, if needed. We also prepared blank widgets in case participants want to create a new field type on their own. The paper widgets were larger than the actual size of those shown in a mobile



Figure 1: A dietitian participant designing a food tracker with researchers in her office.

phone screen, which gave participants enough space to label, mark, and annotate. By assembling the widgets, participants could easily design the trackers and modify them.

Using a large white board (635 x 762 mm) as a frame, participants were asked to create one food tracker for each patient persona they described and to think aloud during the process. Participants could choose any widgets they liked to use, modify existing widgets, and annotate the items they added. To follow up with their tracker design, we asked questions, including why such information is important to track, whether this is required or optional, why they choose to use a particular widget, and how often this information is needed to be tracked. When multiple widgets were added into a food tracker, we asked the participant to think about how they want to arrange the widgets.

Some participants dived into the co-design activity right after we explained the procedure, whereas others showed hesitation due to the unfamiliarity with this process and worried about the quality of their design. To reduce their concerns, we clarified that our goal was to understand the tracking needs of different patients instead of evaluating their design. We gave participants as much time as they needed, and prompted them to start with the most important information they would like to have by asking “what information do you currently collect from the patient,” “how do you currently collect this information,” and “what is the information that you wish to collect but couldn’t.”

De-briefing. At the end of the study, we asked participants to reflect on their tracker design. We asked them how they would use the data collected from the food trackers they designed and how they would want to share the data (synchronously, asynchronously) with the patient. Participants also reflected on the experience of participating in the co-design workshop.

Data Analysis

Our dataset includes the audio recordings of the entire co-design workshops and paper prototypes that participants created. All the audio recordings were transcribed to text. Three researchers analyzed the first two audio transcriptions individually to note prominent themes using open coding,

Patient ID ¹	Created by	Age	Sex	Symptoms & Health Conditions	Goals
D-1	P1	Mid-50s	M	Weight gaining, prediabetes (A1C = 7)	Not rely on insulin, maintain his job
WM-1	P1	30	F	Weight gaining, in good health	Identify what in her diet caused the weight gaining
WM-2	P2	11-16	F	Overweight, body-image focused, low self-esteem, anxiety	Build self-esteem, make food choices she feels good about, increase food variety
WM-3	P4	60	M	Overweight, new diabetes (A1C = 8.5)	Decrease calorie, balance glucose level
WM-4	P4	50	F	Overweight, in good health	Lose weight, decrease calorie, drink enough water
WM-5	P6	45-50	F	Overweight	Get healthier, lose weight
ED-1	P2	20	F	Anorexia Nervosa, over-restricting eating, over-exercise	Increase calorie & food variety
ED-2	P3	22	F	Anorexia & Orthorexia tendencies (non diagnosed)	Regain menstrual cycle, overcome social isolation & preoccupations on food
ED-3	P5	18	F	Other specified feeding or eating disorder (OSFED), Anorexia & Orthorexia tendencies, severe Obsessive-Compulsive Disorder	Improve life quality, overcome social isolation, increase calorie & food variety
ED-4	P5	45	F	Bulimia Nervosa, prediabetes, weight gaining, fatty liver	Decrease calorie, eat more protein
GI-1	P3	Mid-40s	F	Gastrointestinal (GI) distress, diarrhea, constipation	Identify the foods that trigger her GI symptoms
GI-2	P6	45	F	Gastrointestinal distress, sleep problem	Identify the foods that trigger her GI symptoms

Table 2: Patient personas that dietitian participants created during the co-design workshops (D = diabetes, WM = weight management, ED = eating disorder, GI = gastrointestinal distress).

then they met several times to discuss each theme to generate affinity notes and to update affinity diagram [53]. Then two researchers repeated this process to analyze the rest of the transcripts. We also digitized the paper prototypes using Sketch [8], and analyzed the tracker design by referring to the audio transcript section where participants described the rationale behind their tracker design. We specifically examined tracking items, tracking frequency, and data format.

Despite the relatively small sample size, the study generated rich data, including 12 patient personas and 12 paper-based food trackers, and six workshop audio files which were transcribed to 58,858 words. The data collected during the study enabled us to uncover the commonalities as well as differences among the patients and their tracking needs, and multiple customization dimensions for food tracker design.

4 RESULTS

Our dietitian participants treat diverse patients, whose ages range from 11 to 85, and who are mostly female (75–90%). Based on the patients they commonly see, participants described 12 patient personas, which we categorized into four groups based on their primary dietary problems: diabetes (D), weight management (WM), eating disorder (ED), and gastrointestinal distress (GI). These personas shared some characteristics regarding age, dietary problems, symptoms, and goals (Table 2), but they were also different in unique ways. In the first section of the result, we provide background information on a typical treatment workflow and current ways of using food diary data in their practice. We then answer the two research questions—tracking needs and tailoring tracker design.

¹We use “D-#” to denote diabetic patients, “WM-#” to denote weight management patients, “ED-#” to denote eating disorder patients, and “GI-#” to denote patients with gastrointestinal distress.

Current Treatment Workflow and Tracking Tools

All participants consider food tracking an important part of the treatment. When a new patient visits, three participants (P1, P4, P6) require them to bring a food diary, while others (P2, P3, P5) introduce the food diary during the first or second session based on how the meeting progresses. Patients are asked to continue keeping a record of food diary throughout the treatment. Participants review the food diary data during the in-person session and between visits to provide feedback, discuss patients’ progress, and help them troubleshoot. From patients’ food diary, participants “look for food patterns” (P1) and “identify potential problems” (P6). During the face-to-face meeting, participants examine other factors that might affect patients’ diet such as medical history and social environment. By synthesizing the information from different sources, participants provide education, help patients set diet-related goals, and customize meal plans.

Although the high-level treatment workflows are similar across our participants, the specifics of how each participant practices vary. For instance, while most participants meet their patients in the clinic, P2 goes to her patients’ home to help them set up the cooking environment. The length of each session also greatly varies depending on participants: the first session could last from 15 to 150 minutes, and later sessions could last from 15 to 45 minutes. Their ways of working with patients, motivation strategies, and the pace of treatment differ from dietitian to dietitian. Moreover, the same dietitian could practice differently depending on the type of patient they see.

As for the food tracking tools they currently employ, we saw a mix of paper-based diaries and mobile apps (i.e., MyFitnessPal (P1, P4), Fitbit (P1), Recovery Record (P2, P3, P5), Healthie (P3), Lose It! (P4, P6), Cronometer (P4)). Some participants also use 24-hour food recall (P5, P6), spreadsheet (P4), and email (P3). In most cases, participants recommend their patients to

ID	Created by	Food	Reflection	Activity	Symptoms	Physical states
D-1	P1	food items, meal type, time, portion size.		sleep		glucose, BP
WM-1	P1	food items, meal type, time, nutrition facts, portion size				weight
WM-2	P2	food items, meal type, time	body image, things to be proud of, self-care behaviors, treats, food groups, emotion on food	exercise (type, location)		
WM-3	P4	food items, meal type, time, nutrition facts, portion size, location				glucose
WM-4	P4	food items, meal type, time, nutrition facts, portion size, location, water	hunger/fullness level, eating strategy			
WM-5	P6	food items, meal type, time, nutrition facts, portion size, water	mood, hunger satisfaction rating	exercise (type, time, duration, intensity), sleep		weight
ED-1	P2	food items, meal type, time	body image, things to be proud of, self-care behaviors, challenge food, emotion on food	exercise (type, duration)	ED-behavior	
ED-2	P3	food items, meal type, time	hunger/fullness level, mood	exercise (type, time)	ED-behavior	
ED-3	P5	food items, meal type, time, location	hunger/fullness level, mood, thoughts		ED-behavior	glucose, weight
ED-4	P5	food items, meal type, time, location	hunger/fullness level, mood, thoughts		ED-behavior	
GI-1	P3	food items, meal type, time	hunger/fullness level, mood	exercise (type, time)	GI symptoms, time	
GI-2	P6	food items, meal type, time, nutrition facts, portion size	mood	exercise (type, time, duration, intensity), sleep	GI symptoms, time, severity	

Table 3: Items that can be captured by patients with dietary problems to facilitate collaboration with dietitians. A total of thirty two tracking items were identified, and then grouped into five categories. (BP = blood pressure).

use any tool that suits individuals' preferences (e.g., paper-based diary for older patients and mobile apps for younger patients). We did not find any participants who currently customize tracking items for individual patients; however, for eating disorder patients, a specialized tool designed for this population (i.e., Recovery Record) was often recommended.

RQ1. Tracking Needs

By *tracking needs*, we mean the data that can only be captured through patient's tracking to fulfill dietitians' information needs. We identified 32 unique items that can be collected from patients' food diary to aid dietitians in their treatment. These items were grouped into five categories: *food* (7), *reflection* (12), *activity* (6), *symptom* (4), and *physical state* (3) (See Table 3 for details). Depending on patients' dietary problems and dietitians' practice, the necessity and importance of these tracking items vary. Tracking needs consist of not only the factual information (food, activity, symptom, physical state) for dietitians to identify patterns of behavior, but also subjective data (reflection) for patients to contemplate their own eating behaviors. In this regard, food tracking served a dual purpose of assessment and treatment [39].

Food. Tracking food-related information was expected for all of the patient personas. Specifically, all of them were expected to capture meal time (start/end) and meal type (breakfast, lunch, dinner, snack), from which dietitians can infer regular/irregular diet, job situation (e.g., on a shift), or major life

transition. Items in the food category include food and its contextual information such as location: P4 and P5 wanted to know the location where patients eat, because they were interested in whether the meals were homemade or store-bought.

We also found differences in tracking needs for patients with different dietary problems. For weight management patients, especially those having a goal of reducing calorie intake (WM-1, WM-3, WM-4, WM-5), it was recommended to track nutrition facts (e.g., calorie, carbohydrate, fat, sugar, sodium, fiber) and portion size. Through tracking these numbers, patients could learn how to figure out “*the value of their foods*” (P6), compare different foods (P4), and try to “*balance calorie in and out*” (P1). Despite having a weight management issue, WM-2 was *not* recommended to track nutrition facts and portion size because of her low-self esteem issue. For patients with eating disorders (ED-1, ED-2, ED-3, ED-4) or with low-self esteem (WM-2), tracking nutrition facts and portion size can be counterproductive, because patients are easy to get “*obsessed*” (P2), and the numbers can be “*overwhelming*” (P2, P3) and even “*trigger ED-behaviors*” (P5).

Reflection. To develop awareness and mindfulness, participants suggested that patients reflect on their food choices, their body, activities, and feelings. As some dietary problems are highly related to mental health issues (e.g., body image focused, low self-esteem), some dietitians used tracking as an intervention to foster self-reflection and mindfulness [44].

Participants suggested a variety of items to reflect on, with some overlaps across different patient types. Three dietitian participants (P3, P4, P5) employed a standard measure—the hunger/fullness level for patients with different dietary conditions (WM-4, ED-2, ED-3, ED-4, GI-1). The goal of tracking hunger/fullness level was to help patients build trust in their internal body cues, such that they can eventually “*make independent food choices*” instead of being affected by external cues such as “*diet magazines and nutrition labels*” (P3). P6 was similarly interested in capturing internal body cues, but with a different measure—hunger satisfaction rating, which has different scale and interpretation from hunger/fullness level (e.g., a person can feel full but not satisfied). Besides, considering that patients’ mood can interplay with the food they eat, three participants (P3, P5, P6) suggested mood tracking for their patients (WM-5, ED-2, ED-3, ED-4, GI-1, GI-2). To motivate patients to form a habit of reflecting on “*what’s going through their head and body*,” P5 also wanted ED-3 and ED-4 to track any thoughts they have and anything they like to express.

Different from other dietitians, P2 was particularly keen on reinforcing positive thinking for her patient personas (WM-2, ED-1). P2 encouraged them to reflect on their body image, things to be proud of, and activities conducted to “*honor your body*” (e.g., self-care behaviors: dancing, taking a bath, going for a walk, talking with friends). She also emphasized the importance of tracking emotion towards food, which intends to help patients make food choices that make them feel good.

Participants also recommended individually-tailored reflection topics. For example, pointing out WM-2’s mental health issue, P2 suggested her having treats as a praise of making progress, and reflecting on the food groups to make sure she is “*getting all the different food groups*.” Given that eating disorder patients often have certain “*challenge foods*” (i.e., the food they are afraid of eating), P2 suggested ED-1 to reflect on her challenge foods to overcome such fear. To keep WM-4 mindful of the food portion size, P4 wanted her to reflect on her eating strategy (e.g., “*was I thinking about eating half of it?*”).

Activity. Exercise and sleep were two activity types that were brought up during the co-design. Opinions were divided on whether to track exercise. Three participants (P2, P3, P6) were keen on exercise tracking for the personas they created. P3 wanted to see exercise type and duration for both personas (ED-2, GI-1); and P6 wanted to see more details (e.g., intensity) to understand how patients spend their energy and how their exercise might relate to their food practices for both personas (WM-5, GI-2). In addition, P2 emphasized that the purpose of having eating disorder patients track exercise is to prevent extreme exercise while encouraging light exercise.

However, not all participants were in favor of tracking exercise, as P4 explained: “*people subtract the calories [consumed*

from exercise], [...] And if this is not accurate, they’re eating more calories, and then they’re not losing weight”.

Two participants (P1, P6) were interested in tracking sleep. P1 recommended D-1 to track sleep because she believed that diabetes and sleep problems are closely related. P6 suggested both WM-5 and GI-2 track sleep because sleep can affect their diet, for example: “*You don’t sleep, it changes what you want to eat the next day, you want fat and sugar*” (P6).

Symptom. ED and GI patients experience specific symptoms, which need to be tracked. Tracking symptoms can help dietitians find out the source of problem and provide appropriate treatment and support. When treating GI patients, participants (P3, P6) wanted their symptom information to include detailed descriptions (e.g., diarrhea, constipation, gas) and time stamps to identify the foods that trigger their GI symptoms. In addition, P6 mentioned that capturing the severity of the symptom is also helpful.

All participants (P2, P3, P5), who created ED personas, stated that they need to know ED-behaviors (e.g., purging, over-exercising, vomiting, and use of laxatives), which are considered symptoms, and thus to be tracked. Being aware of ED symptoms allows participants to provide support when needed, while enabling patients to understand how their ED-behaviors occur and learn to cope with them.

Physical State. Physical states such as weight, blood glucose, and blood pressure were of interest to some participants (P1, P4, P5, P6). For patients with diabetes (D-1, WM-3, ED-3), tracking blood glucose level was necessary; and for some WM and ED patients (WM-1, WM-5, ED-3), tracking weight was expected. Capturing physical states could help participants examine what types of food or activity might cause changes in these health indicators.

RQ2. Tailoring Tracker Design

In RQ1, we reported how tracking needs might differ depending on patients’ dietary problems and dietitians’ style of practice. These differences on tracking needs were manifested in the tracker design. Besides customizing what items to track, participants also tailored the trackers by incorporating when to track (timing/frequency of tracking), how to track (data format), how to support tracking, and what to share between dietitians and patients.

Timing and Frequency of Tracking. Participants expected patients to track different items at various time- and frequency resolution—for instance, tracking with food, when an activity or symptom occurs, once a day, twice a day, or once a week. In the case of *food*, participants expected patients to track their food whenever they eat, right before or after they eat, and together with their food-related *reflection* (e.g., hunger/fullness

Figure 2 displays four digitized food tracker widgets (a, b, c, d) designed for different user groups: WM-4 (a), WM-5 (b), ED-1 (c), and ED-3 (d). Each widget is a collection of form elements for tracking various aspects of eating and well-being.

- Widget (a) - WM-4:** Includes fields for Time (7:00am), Meal Type (Breakfast), Hunger & Fullness Level (Before and After), Nutrition Facts (Calories, Carbs, Fiber, Fat, Sodium), Food Items (Before and After), Portion Size, and Water Intake (4 cups).
- Widget (b) - WM-5:** Includes fields for Time (7:00am), Meal Type (Breakfast), Portion Size, Hunger Satisfaction Rating, Mood (Happy, Neutral, Sad, Angry), Nutrition Facts, Food Items, and Water Intake (4 cups).
- Widget (c) - ED-1:** Includes fields for Time (7:00am), Meal Type (Breakfast), Food Items, Emotion on Food, Body Image, Challenge Food, Eating Disorder Behaviors (Over Exercising, Purge, Bingeing, Fears of choking or vomiting, Intense anxiety), Self-care behaviors (Dance, Take a bath, Go for a walk, Talk with friends, Praise myself, Get myself a gift, Watch a movie), Exercise, and Duration (From 7:00am to 8:00am).
- Widget (d) - ED-3:** Includes fields for Time (7:00am), Meal Type (Breakfast), Mood (Happy, Hungry, Angry, Sad, Surprising, Disgusting), Thoughts, Eating Disorder Behaviors (Over Exercising, Purge, Bingeing), and Glucose Level.

Figure 2: The digitized version of paper-based food trackers for WM-4 (a), WM-5 (b), ED-1 (c), and ED-3 (d). Items grouped together are meant to be tracked together at the same time. Icons next to the title represent alternative ways to capture the information (e.g., taking a photo is an alternative way to capture food items).

level before and after each meal, mood before each meal, emotion on food after each meal) (P2, P3, P4, P5). Other types of reflection may be tracked less frequently, such as once a day (e.g., body image, self-care behaviors) or once a week (e.g., treats, food group covered) (P2). *Symptoms*, with their exact time stamps, needed to be tracked whenever they occur (P2, P3, P5, P6). *Activity* and *physical states* were expected to be tracked on a regular basis, such as once a day (e.g., exercise, sleep, blood glucose, blood pressure) (P1, P2), twice a day (e.g., blood glucose) (P4), or once a week (e.g., weight) (P1, P6).

Data Format. As participants assembled paper widgets of different field types, they devised how to best capture tracking items in which data format (Table 4). In addition to the widgets we provided, participants created two new widgets: a barcode scanning and emoji.

Figure 2 shows the digitized version of the paper-based prototype for WM-4, WM-5, ED-1, and ED-3, designed by P4, P6, P2, and P5 respectively. The same item can be tracked in different formats. For example, food portion size can be tracked with a text box (WM-5, Figure 2-b), drop-down menu,

Tracking item	Data format (#)	Tracking item	Data format (#)	Tracking item	Data format (#)
food item	text & audio (4), text & audio & photo (8)	hunger/fullness level	Likert scale (5)	exercise type	text (4), checklist (2)
meal type	text (3), drop-down menu (9)	hunger satisfaction rating	Likert scale (1)	exercise time	Fitbit (2), auto-generated time (2)
meal time	auto-generated time (4), drop-down menu (8)	eating strategy	text (1)	exercise location	auto-generated location (1)
meal location	auto-tracked location (12)	body image	text (2)	exercise duration	text (1), text & Fitbit (2)
portion size	text (2), photo (2), drop-down menu (2)	things to be proud of	text (2)	exercise intensity	text & Fitbit (2)
nutrition fact	auto-generated text (2), barcode (3)	self-care behavior	checklist (2)	sleep	rating & Fitbit (1), Fitbit (2)
water	drop-down menu (1), add button (1)	emotion on food	text (2)	ED-behavior	text (1), checklist (3)
glucose	Glucometer (3)	challenge food	text (1)	GI-symptom	checklist (2)
BP	BP monitor (1)	food group	checklist (1)	symptom time	auto-generated time (2)
weight	clinical scale (2)	treats	text (1)	symptom severity	Likert scale (1)
mood	checklist (2), audio & checklist (2), emoji (1)	thoughts	text (2)		

Food
 Physical state
 Reflection
 Activity
 Symptom

Table 4: Data format that dietitian participants expressed to capture different tracking items.

or before/after meal photos (WM-4, Figure 2-a). When tracking water intake, a drop-down menu (Figure 2-a) was used to capture total daily water intake, and a counter (Figure 2-b) was used to capture in-situ water intake. For mood tracking, P6 used a checklist of emoji (Figure 2-b), while P5 provided an option of audio recording (Figure 2-d). P5 pointed out that for eating disorder patients, audio-recording may afford them to record frank thoughts without feeling “*shame about the things they logged,*” because there is no visual feedback after the recording.

Supporting Features. Although the focus of the co-design activity was to identify tracking needs, participants naturally expanded the scope of design to devise ways to support patients in general. For example, P1 and P4 designed reminders to encourage patients to drink water (D-1, WM-3, WM-4), eat snack (D-1), and watch calorie limit (WM-1). P5 designed a prompt that automatically notifies ED-3 and ED-4 (as a positive reinforcement) when they had a “challenge food.” To provide support between visits, P2 designed a help button for emergency contact; P3 and P5 wanted to access patients’ data as they come in and make comments (ED-2, GI-1, ED-3, ED-4); P6 recommended a chat room where she can talk to WM-5 and GI-2 through instant messages. Furthermore, P5 and P6 wished that when patients log any negative mood, the tracker can be smart enough to provide in-situ support using external sources such as a list of coping skills for anxiety management (e.g., “*meditation, gratitude*”) and links to educational resources (e.g., “*body positive books and podcasts*”).

Data Sharing Preferences. While most of the tracking data were expected to be shared between patients and dietitians, it was not always the case. Depending on the sensitivity of the information and patients’ acceptance, some items were more appropriate to be left with patients only, and others with dietitians only. For example, because eating disorder patients “*value low weight and [tend to] restrict food,*” P3 and P5 preferred not to have them track their weight. Instead, they

record patients’ weight information every time when a patient visits a clinic. On the other hand, although information such as personal thoughts and emotion is helpful for patients to track, some patients might not want to share with dietitians due to “*the feeling of shame and fear of judgement*”(P5). As such, P5 suggested that patients decide what to share with providers. As the treatment progresses, patients may be “*willing to share more with the clinicians*” because shame might have decreased throughout the recovery (P5).

5 DISCUSSION

Our study extends previous personal informatics research in two regards: First, we identify various customization dimensions in food tracking based on the similarities and differences across patients’ condition and dietitians’ style of practice. Second, the way we structured the co-design workshops provides insights for others interested in working with healthcare providers to identify design opportunities. In this section, we discuss implications on these topics.

Customizing Trackers to Generate Relevant Data

We were motivated to conduct this study to address limitations in current tracking tools, one of which is the lack of customizability in the tool design [20]. Such limitation makes it difficult to capture relevant data for stakeholders. In the healthcare field, the inability to customize tracking items frustrates patients and providers, hindering them from effectively utilizing patient-generated data (PGD) [22, 67]. To generate clinically relevant data from patient’s self-tracking, Zhu and colleagues suggest involving clinicians early, preferably during the tracking configuration stage so that clinicians can provide concrete guidance on what to track and how to track [67]. Furthermore, to design self tracking tools to generate clinically-relevant data, Choe and colleagues suggest HCI researchers working closely with clinical stakeholders at the early phase of design stage [18].

Through co-designing with dietitians, we identified a set of customization dimensions, including tracking items, timing

and frequency of tracking, data format, among others. When given a chance, participants customized food trackers based on the health conditions patients experience, as well as their style of practice. Although the former is well exemplified in various tools designed for specific patient groups (e.g., Recovery Record for eating disorder patients), the latter has been less explored. In our work, we were surprised to observe the diversity of treatment style, while identifying commonalities across dietitians. As such, we see opportunities in supporting dietitians to create and share “tracking templates” for different patients, which can be uploaded for other dietitians to search, download, adopt, and modify. Dietitians can pick different tracking templates for different patients created by either themselves or by other dietitians and fine-tune the template for each patient. This approach can reduce efforts required to customize and configure trackers from scratch whilst satisfying individuals’ tracking needs. Although OmniTrack, an open-source customizable tracker, allows people to customize trackers for their respective tracking needs [38], it does not support the creation and sharing of tracking templates. To strengthen the customizability and reusability of OmniTrack, studies like ours can inform the design of tracking templates for dietitians as well as patients having different dietary problems. Furthermore, we envision that our design approach can be applicable to other clinical domains beyond food tracking to make the self-tracking data relevant to clinical contexts.

Supporting Patient-Provider Collaboration

Collecting and sharing patient-generated data is a collaborative work in which a provider and patient play an equally important role. Although we identified various customization dimensions in food tracking from providers’ perspective, our findings are limited without soliciting patients’ perspective, as they too have the needs to customize tracking items [19, 47]. Thus, involving patients during the design and evaluation is an important next step.

In addition, our study indicates that self-tracking in the clinical context is a dynamic process. The tracking needs could change as the treatment progresses, which suggests that tracking tools should support providers to revise the tracking regimens based on the stage of treatment. In the meantime, patients’ data sharing preferences may change depending on their recovery progress and relationships with providers. Therefore, the tracking tool should also enable patients to adjust what to share, whom they share with, and when to share. Going forward, it warrants real-world deployment studies to examine how such customizable trackers affect the collaboration between patients and providers.

Using Patient Persona for Contextualization

In our work, the process of creating and sharing personas helped both researchers and participants be contextualized

in patients’ experience before starting the hands-on design activities. Patient personas allowed participants to articulate their design precisely and realistically. When we asked participants why they decided to track specific information or use a particular widget, their answers were closely tied to the patient persona they were designing for. As participants added more tracking items, they constantly thought about whether the information is necessary, which widget to use, and whether the information is appropriate to share.

Typically, significant user research precedes persona creation; but in our case, each participant could easily describe two patient personas based on years of clinical experience. The descriptions were detailed and nuanced, although it was inevitable that personas reflected the perspective of providers more so than that of patients. It may be presumptuous to think that these patient personas perfectly capture patients’ lived experience and their concerns. However, given that the goal of this work was to understand how patients’ tracking can facilitate working with healthcare providers and fulfill their information needs, we believe that integrating patient personas in the co-design session was a good first step to bridge the information gap.

Fostering Creativity Through Paper-Based Widgets

We believe that the paper-based widgets were critical in fostering dietitians’ creativity in the design process. Before the co-design activity, while being asked about what information each patient persona needs to track, participants’ answers were mostly constrained by the tracking tools that they are currently using (e.g., MyFitnessPal, Recovery Record, paper-based diaries). After we introduced the paper-based widgets, however, participants started to think about more possibilities: besides what the current tools capture, they considered whether those tools are capturing the necessary metrics appropriately, what else they would need for providing better treatment, and what patients would need for their reflection. The widgets provided in the form of modularized data fields served as building blocks for participants to start the design process with ease. However, we believe that it is important to provide opportunities to think beyond what we provide, such as by providing blank notes and encouraging to annotate the widgets.

6 CONCLUSION

In this paper, we reported findings from six individual co-design sessions with registered dietitians conducted to understand how customizing food trackers can fulfill dietitians’ information needs. During the co-design sessions, dietitian participants created representative patient personas and designed food trackers for each persona. We found a wide range of potential tracking items with their timing and format of tracking, which could potentially generate clinically meaningful self-tracking data and fulfill dietitians’ information

needs. Incorporating patient personas and paper-based widgets helped us working effectively with healthcare providers and solicit concrete design ideas. Our work calls for a new type of customizable tracker that supports patients and providers to collaborate around data tracking and sharing.

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