Special Section on Workflow Automation: Opportunities and Challenges of Integrating Food Practice into Clinical Decision-Making

Mustafa Ozkaynak[1], Stephen Voida[2], Emily Dunn[1]

[1] College of Nursing, University of Colorado | Anschutz Medical Campus

[2] Department of Information Science, University of Colorado Boulder

Corresponding Author:

Mustafa Ozkaynak, PhD

Associate Professor

University of Colorado | Anschutz Medical Campus

College of Nursing

Campus Box 288-18 Education 2 North Building

13120 E. 19th Avenue Room 4314

Aurora, CO 80045 USA

Telephone Number: 303 724 8273

Fax Number: 303 724 8559

mustafa.ozkaynak@cuanschutz.edu

t: @mozkaynak

NOTE: This is the authors' version of the submitted (revised) manuscript.

Cite as: Mustafa Ozkaynak, Stephen Voida, and Emily Dunn. 2022. Opportunities and challenges of integrating food practice into clinical decision making. *Applied Clinical Informatics (Special Section on Workflow Automation)* 13, 1 (February 2022), 252–262. doi:10.1055/s-0042-1743237

Abstract

Background: Individual food practice plays an important role in health. Food practice data collected in daily living settings can inform clinical decisions. However, integrating such data into clinical decision-making is burdensome for both clinicians and patients, resulting in poor adherence and limited utilization. Automation offers a variety of benefits in this context, minimizing this burden, resulting in a better fit with a patient's daily living routines, and creating opportunities for better integrating into clinical workflow. Although the literature on patient-generated health data (PGHD) can serve as a starting point for the automated collection and use of food practice data, more diverse characteristics of food practice data provide additional challenges.

Objectives: We describe a series of steps for integrating automated data collection and data processing about food practices into clinical decision-making. These steps include: (1) sensing food practice; (2) capturing food practice; (3) representing food practice; (4) reflecting the information to the patient; (5) incorporating data into the EHR; (6) presenting information to clinicians; and (7) integrating data into clinical decision-making.

Methods: We elaborate on automation opportunities and challenges in each step, providing a summary visualization showing the flow of food practice-related data from daily living settings to clinical settings, as well as the role of workflow automation in encouraging data collection and treatment adherence and in supporting clinical decision-making.

Results: Our elaboration highlights the following implications: (1) There are multiple ways of automating workflow related to food practice; (2) Some of the steps occur in daily living and others in clinical settings. Food practice data and necessary context information should be integrated into clinical decision-making to enable action; (3) As accuracy becomes important for food practice data, macro-level data may have advantages over micro-level data in some situations; and (4) Relevant systems should be designed to eliminate disparities in leveraging food practice data.

Conclusion: Our work confirms previously developed recommendations in the context of PGHD work and provides additional specificity about how these recommendations apply to the domain of food practice.

Keywords:

clinical decision-making

workflow

food practice

clinical informatics

self-tracking

1. Introduction

Food practice is a complex set of routines that include shopping for, growing, cooking, eating, and disposing of food. Although the scope of food practice could include industrial activities, in this paper we focus on individual food practices. Individual food practices play a critical role in management of chronic medical conditions (e.g., diabetes[1], anticoagulation therapy[2], heart failure[3]). Data on food practice are often collected by patients are part of chronic disease management. These data are instances of "observations of daily living"[4] or patient-generated health data (PGHD). The term PGHD is used in this work, to describe both types of data collection. PGHD refers to health-related data (not necessarily limited to food practice) that is created, recorded, or gathered by patients, family members or caregivers.[5] Key features of food practices as PGHD are: (1) the patient captures the data; (2) the data are obtained outside of the clinical setting; and (3) the data can be collected longitudinally and with high frequency. Potential benefits of such data include insight into a patient's food practices, informed revision of care plans, and reducing unnecessary clinic visits. Data related to individual food practice is not as structured as many PGHD (e.g., blood pressure, mood, or weight), which can be easily quantified. As technology and patient ergonomics approaches continue to mature[6] and patients become more actively engaged in producing PGHD, the amount of food practice data generated grows substantially.[6] Integrating data on food practice into the electronic health records (EHR) can lead to more individualized therapy plans and better patient outcomes.[7]

The challenges highlighted in the literature related to capturing and utilizing PGHD (technical, social, and organizational, broadly categorized[8-11]) are also valid for and relevant to food practice data. These challenges can significantly lead to patient[12] and clinician[13] burden. As a result, integration of food practice data into the EHR has been limited, and decision support capabilities around food practice data are generally basic[9]. This presents the opportunity to identify a scheme to automate such data. Identifying the necessary steps for integrating food into clinical decisions can serve as the basis for developing interventions for automating these steps. Workflow automation can facilitate capturing food practice as a situated action[14] and help clinicians and patients to collaboratively identify social and environmental influences on food practice.[15] Workflow automation can also play a key role in facilitating the management and presentation of these data within the clinical care context, allowing food practice data to become a part of medical record review and clinical decision-making processes. Overall, workflow automation of food practice data stands to inform culturally appropriate and individualized therapies.[16]

Broadly, workflow automation, which can be defined as streamlining a sequence of activities through technology and pre-defined rules, minimizes the overhead and work associated with regular and predictable data collection and analysis processes.[17, 18] Workflow automation can be advantageous as it provides a temporal structure for the food practice data and information. Such structure can help to prompt *in situ* data collection and ensure availability of the resulting information at the right time. Automated collection of food data by patients has led to the development of innovative input methods such as photo-based food journaling,[12, 19] detection of chewing sounds,[20, 21] or the scanning of receipts[22] or barcodes; we examine some of these roles for automation in *expanding the base* of food practice data here. However, *integration of food practice data* in clinical decision-making also necessitates additional steps in which automation can play a constructive role. The purpose of this research is to create a comprehensive roadmap for integrating information about food practice into clinical decision-making and identifying the associated challenges and opportunities with workflow automation in this domain.

2. Current Practice of Capturing Food Practice Data

In the clinical setting, assessments of food practices vary widely between institutions and clinicians, but often include a brief nutrition history or abbreviated food frequency questionnaires.[23] These instruments elicit questions to assess daily food habits and intake of a finite selection of foods.[24] The most popular instruments are questionnaires related to the intake of high saturated fat, and high-fiber foods. Although useful in population research, these instruments lack the ability to accurately estimate nutrient intakes and detect changes in an individual's dietary habits.[25] Recently, the Dietary Risk Score, a 9-item survey for patients, was significantly correlated with Healthy Eating Index-2015, a 160-item food frequency questionnaire. This tool is useful in identifying patients with self-reported suboptimal intake; however, its effectiveness in the clinical setting has not been assessed.[26] Many instruments requiring 24-hour recall were designed to assess individual dietary intake with some requiring a minimum of three days of recorded data. The Automated Multiple Pass method (AMPM) relies on administration by trained personnel, and heavily on patient literacy level, memory, and ability to estimate portion sizes.[27] The AMPM assesses 24-hour dietary intake with limited provider burden, but requires motivated participants and tends to underreport energy and protein intake for those who are obese.[28]

Other tracking methods, such as food records, are intended to be completed in real time and have a greater potential for accuracy, especially when foods are weighed and measured prior to consumption. This diligence, however, may lead to changes in the intake of food but can be used as a behavioral intervention to encourage awareness of eating patterns. However, the accuracy of records can be adversely affected if proper objective measurement is not feasible.

3. Workflow for integrating food practice in clinical decision-making

Seamless integration of food practice into clinical decision-making can improve health outcomes, result in improved clinician–patient communication[29-35] and the development of more individual therapy plans[36-38]. We identify important steps for integrating food practice into decision-making (Figure 1) based on a review of the relevant scientific literature[39-42] and a collaborative inquiry among the member of our multidisciplinary research team about where

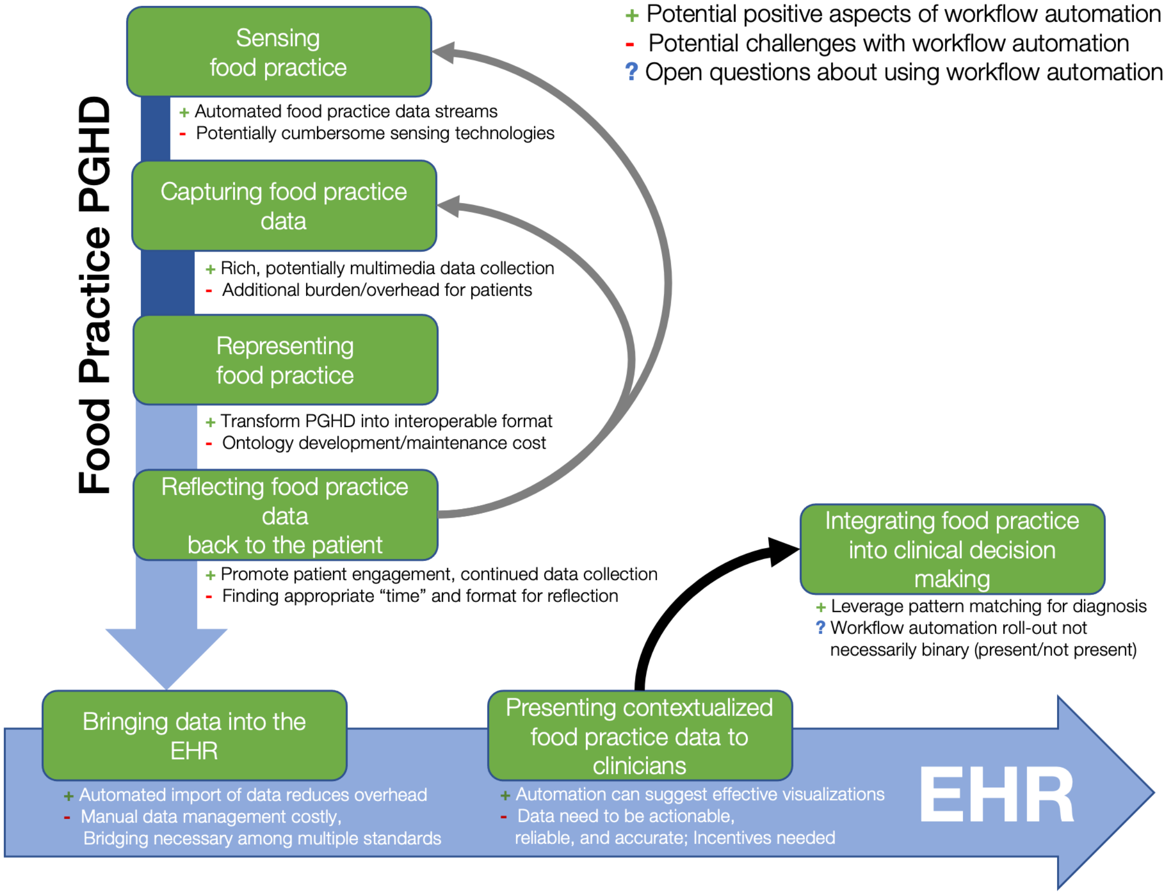

Figure 1. Workflow for integrating food practice in clinical decision-making.

food practice-related information is stored at each step, how automation might work to transform this information, and what influence(s) it might have on and for various stakeholders in the overall clinical decision-making process. Our orienting literature included articles spanning health informatics, human factors engineering, information sciences and nutrition sciences. Our overall finding from this review is that automating workflow at each step in the food practice clinical data pipeline is possible. Workflow automation can be beneficial despite some barriers and the need to ensure smooth transitions from one step to another.[43, 44]

We use the example of prediabetes management, to better explain workflow automation opportunities to integrate food practice in clinical decision-making. Prediabetes occurs when blood glucose levels are elevated but not high enough for a diagnosis of type 2 diabetes. When, on multiple occasions, a patient has a fasting blood glucose between 100–125 mg/dL or a hemoglobin A1C level between 5.7%–6.4%, a diagnosis of prediabetes should be given.[45] Clinicians may refer to prediabetes as elevated fasting glucose or impaired glucose tolerance, depending on the method of diagnosis. It is estimated, that between 2013–2016, 33% of adults in the United States had prediabetes and 12% had type 2 diabetes.[46] Of those diagnosed with prediabetes, up to 41% are expected to progress to type 2 diabetes mellitus within the next 7.5 years.[47] The primary recommendation for treatment of prediabetes is lifestyle intervention to promote loss and maintenance of 7% of initial body weight.[48] Primary care has been identified as an ideal setting to initiate lifestyle interventions that promote weight management, like healthy eating.[49] Primary care providers (PCPs) are ideally placed to provide nutritional support to patients as they represent the initial point of contact within the health-care system and their nutrition care is held in high regard by patients.[50]

Food practice information can allow clinicians for providing effective, individualized lifestyle intervention at the initial point of contact. Specific to prediabetes, food practice information could suggest effective patient goals such as decreased intake of; sugar, sweetened beverages, fast food and increased intake of non-starchy vegetables, or proper meal spacing.

3.1 Sensing food practice

Sensing food practice refers to detecting the occurrence of a food practice. The use of automated technologies to record instances of and details about food consumption in one of the most well-established applications of workflow automation to reduce the patient burden associated with keeping diaries and increase adherence to food-related data collection needs. These approaches utilize a variety of sensors either to log instances of eating (frequency, duration) or to attempt to infer the content of snacks and meals (e.g., high carbohydrate foods). A comprehensive review of research in wearable food intake monitoring[51] have provided an overview of different applications of food intake monitoring (i.e., caloric intake, eating behavior, and inpatient care), sensing of different food intake mechanisms (i.e., biting, chewing, swallowing), and various approaches for sensing (e.g., acoustic, visual/camera-based techniques, use of inertial sensors like gyroscopes and accelerometers, piezoelectric sensing of chewing and swallowing, and detection via other, indirect biosignals). Some of the outstanding challenges identified in the large-scale deployment of these kinds of sensing techniques include the comfort and practicality of wearing various sensors outside of a laboratory environment and accurate classification of food type, portion size, ingredient composition, and nutritional content.

Recent examples of innovative sensor-based food monitoring include: wearable devices that fuse multiple sensor streams (camera/visual, inertial sensors, proximity sensors, and vibration sensing) in an eyeglass-like form factor,[52] installation of a proximity sensor in a necklace-like mount to detect chewing,[53] augmentation of an eating utensil with photocells, inertial sensors, and resistance sensing (to measure the conductance of different food items),[54] and the use of wrist-worn inertial sensors to detect hand and arm movements associated with lifting food to the mouth.[55] Many of these experiments are only at the prototype or proof-of-concept stage.

The accuracy of sensing technologies for detecting, for example, instances of chewing are reported to range from 76.1% accuracy using inertial (accelerometer-based) detection to 95.3% when using proximity sensors. Studies conducted in the field however, have resulted in lower overall detection accuracy rates.[53] Some of the key challenges in detecting events include, wearability and comfort concerns, differentiation between eating and drinking episodes, and mobility confounds (wearability necessitates real-world use, which inevitably leads to non–food-related head movements).[56-58]

Sensor-based approaches can either be employed as a form of *semi-automatic* data collection[59] —that is, to log instances of eating that are intended to be annotated using human computation approaches,[60] or retrospectively manually recorded with more detail by the patient (e.g.,[54, 61-63]); or as *fully automatic* food intake sensing platforms—that is, as a complete substitute for manual data entry. Automatic journaling at a coarse granularity (e.g., logging instances or durations of eating episodes) is still much more robust and reliable than attempting to infer specific food content and portion size, although given the active research in these areas, these technologies may be ready for more broad-based deployment and real-world use in the next several years.

In cases of prediabetes, sensor systems can provide insight into daily eating habits that provide opportunities for intervention. Continuous blood glucose monitoring can create an objective record of the impact of meal timing and food choices given a particular patient's metabolism and pancreatic function. Increased awareness of these measurements can serve as the basis for constructive feedback on eating habits, including contextualized education on the effect of meal timing, eating practices and glycemic load on blood glucose levels (see also Section 3.4).

3.2 Capturing food practice data

Capturing food consumption data is a common focus of self-tracking health apps on mobile devices.[64, 65] These apps range from the direct translation of validated clinical instruments to elaborate, multimedia journaling platforms that augment the food-tracking/logging experience to increase accuracy, adherence, or patient engagement. Computer-aided diaries (e.g., AMPM[66]) that add additional structure and detail, can improve the accuracy of patient-reported dietary food recall, with resulting energy intake computations varying less than 3% from gold-standard total energy expenditure analyses based on the doubly labeled water technique.[67] However, these kinds of in-depth, computer-based dietary recall techniques still pose significant time and effort burdens to respondents and clinicians.

In order to address these data collection burdens, mobile food tracking research have experimented with streamlined data entry—for example, using lightweight interface designs inspired by social media platforms (e.g., the "+1" design pattern for re-entering or "up-voting" a prior entry).[68] Other apps have adopted interfaces that allow quick logging of store-bought food items using UPC scanning.[69, 70] The main limitation of barcode-scanning apps is that they only accelerate data entry for packaged foods purchased and consumed from grocery or convenience stores.

Photography[12] and video[71] have also been used to streamline and enrich the data collection experience. In some cases, these multimedia captures are used as "placeholders" for post-hoc elaboration by the patient after the meal;[63] in others, photographs and media artifacts are shared with others, either to crowdsource food identification and tagging by crowdworkers[60] or nutritionists,[72] or as conversational tokens on social media platforms like Instagram,[73] to invoke social support as a key motivator and adherence reinforcement mechanism. Recently, multimedia data were processed using computer vision techniques to accomplish automatic food and portion size recognition, albeit with limited accuracy.[74] These multimodal techniques show promise but are still at a relatively early stage of development and have not been widely adopted in commercial food-tracking applications.

Instead of focusing solely on streamlining and automation, some food journaling apps have aimed to increase user engagement by incorporating techniques associated with gamification, such as providing challenges to motivate continued adherence to data collection[75] or rewards for successfully meeting food journaling benchmarks[76]. Nudges[77] can be a powerful behavioral modification and habit formation technique, which is potentially useful for helping patients to internalize food journaling practice. In contrast, the implicit or inadvertent use of "negative nudges" in the design of popular-food tracking applications (e.g., differential burden of entering different food types, with less healthy meals often incurring more overhead to track, difficulty in "recovering" missed data after a lapse in data entry, and stigma associated with use of a food tracking app) have been shown to deter long-term use and lower adherence to computer-assisted data collection of food intake.[78]

Patients with prediabetes can benefit from workflow automation in collecting data (along with needed context information). For example, carbohydrate content of consumed or to-be-consumed food could be captured and compared to the patient's personal goals. Furthermore, positive feedback could be provided for meeting dietary goals such as adequate intake of fiber. In this paper, we define context as a manifestation of the characteristics of any environment or situation in which the user is embedded. Dimensions of context may include physical (e.g., location), organizational (e.g., the user's job hours), social (e.g., friends), cultural (e.g., food consumption habits) and temporal (e.g., daily or weekly routines).

3.3 Representing food practice

Ontologies can help represent knowledge about food practice, organize relevant information, enable information sharing, and guide the subsequent steps shown in Figure 1[79, 80]. Ontologies are particularly successful for managing heterogenous information (structured, semi-structured and unstructured) drawn from different resources. Ontologies are typically modeled using an editor (e.g., Protege[81]) that provides a graphical representation of the phenomena of interest such as food practice. Reusability is another advantage of ontologies. Well-designed ontologies reuse, as appropriate, terms from other well-established ontologies to eliminate duplication. This enables integration of otherwise disparate ontologies (and their associated data) across domains.[82] Querying can then occur across datasets that use a common vocabulary. Ontologies facilitate many practical applications potentially relevant to representing food practice, such as annotating entities or items, conducting semantic similarity analysis[83], or even finding unexpected patterns in streams of data (e.g., food logs).

Ontologies support interoperability and can accelerate the workflow automations illustrated in Figure 1. Ontologies allow for representations that can be interpreted by computers. Such representations allow for harmonizing heterogenous food data and using the results to provide contextual explanations for other clinical data. These transformations can either be enacted algorithmically (e.g., as the output of automated data importation and processing scripts) or identified through automation services to prompt opportunities for human-driven alignment of various unstructured or novel data into more clearly defined categories and representations. Once data are organized into these ontologies, it becomes possible to link information to subsequent visualizations, integrate information into formalized EHR systems, and create decision support triggers for clinicians and patients in the following steps of Figure 1.

Key steps necessary for developing a food ontology include: (a) identifying the scope and purpose of an ontology (i.e., is it for a specific health condition such as prediabetes, or it is for general wellness); (b) identifying and importing appropriate classes from existing reference ontologies (e.g. FOBI[84], FoodOn[80] and others[85, 86]); and (c) creating new classes/relationships for any conceptualization required for models and themes within the previously identified scope and purpose but not found in existing ontologies. Ontologies to facilitate the workflow shown in Figure 1 should be able to: (1) represent real data related to food practice routines (e.g., buying soda from vending machines) and contexts (e.g., time of day); (2) utilize data elements (e.g., type of food and ingredients) that can later be aggregated with clinical data; (3) be reusable and interoperable with other ontologies; and (4) facilitate automated functions like personalized food recommendations.

3.4 Reflecting food practice information back to the patient

As patients collect data on their food practice, reflecting food practice information derived by data (e.g., *how much soda does the patient purchase? is there a pattern to cravings for and purchases of soda?*) back to them in a way that is congruent with their health and information literacy can be a source of useful feedback.[87] Such feedback gives patients an opportunity to adjust both their food consumption behaviors and their data collection practices. Interactive visualizations that leverage data science and visual analytics methods can be effective in mitigating issues of information overload[88] and can facilitate understanding of food practice information by lay people. Furthermore, the timing and context in which these data are made available can have a large impact in the extent to which they are perceived to drive insight generation and effective action on the patient's behalf.[89]

The science behind interactive visualizations integrates concepts and methods from machine learning, health informatics, human factors engineering, and cognitive psychology to aid interpretation of complex data.[88, 90] However, visual analytics has not been extensively studied in the context of heterogeneous food practice.

Future studies in this area to automate workflow should focus on integrating food practice information into an individual's daily routine and providing information to the patient at the "right" time; that is, when the patient needs to make a decision (i.e., not too late, not too early). Predictive models are also needed to anticipate when a patient might need such information.

In the context of prediabetes, effective workflow automation could leverage smartphone sensor data, GPS-based geolocation data indicating arrival at or near eating establishments, and information stored on a patient's calendar to anticipate moments in which notifications about current blood glucose status (if available) and past food consumption choices resulted in different kinds of glycemic control outcomes. Socially and cognitively opportune moments to present postprandial meal summaries and prompts for manual annotation can also increase patient engagement with the effects of their food consumption choices.

3.5 Incorporating data into the EHR

Various food practice data could be incorporated into the EHR to support clinical decision-making. These elements might include data generated from currently-used self-report food practice questionnaires[23, 24] and surveys[26]; to detailed food consumption records in textual[64, 65, 68] or photographic formats[12, 60] (with the potential of data organized on a meal-by-meal basis or aggregated to provide an overview of dietary macronutrient content) to information about meal duration and frequency[52-55] to summaries of food purchasing behavior.[68, 69] Integration of food practice data into the EHR is dependent on effectively bridging among a variety of platforms, standards, and methods. A literature review by Tiase et al.[91] reported 19 studies that integrated

PGHD into EHRs. Although these studies did not focus specifically on food, food practice can use the same platforms, standards, and methods previously developed for PGHD (e.g., biometric and patient activity, questionnaires and surveys, and health history) as a starting point. However, given the potentially granular nature of food practice data and wide variety of data types, this kind of integration represents another significant opportunity for workflow automation to play a central role. Food practice data can be transferred actively by the patient into the EHR or passively by uploading automatically without patient effort. Passive transfer would minimize patient burden and better automate workflow. Workflow automation can also be employed to minimize provider work, which includes linking data to the correct patient record or matching it to the patient ID. Passive delivery of food practice data to the EHR would also facilitate efficient provider workflows.[92]

Developer platforms like Apple HealthKit and technical information exchange mechanisms like application programming interfaces (APIs) and Fast Healthcare Interoperability Resources (FHIR®) are essential for incorporating food practice data into the EHR. However, these more general-purpose platforms and programming standards will likely need to be enhanced to better accommodate characteristics specific to food practice data. Adoption of new interoperability standards and standardized APIs to simplify integration may help decrease the EHR delivery burden and enhance the long-term sustainability of food practice initiatives. Based on our prior work{Cornet, 2018 #135;Gance-Cleveland, 2019 #147} and the PGHD literature, we identify five concerns related to leveraging technical infrastructures for EHR integration: (1) addressing connectivity issues, both in terms of information privacy and availability of bandwidth for health data on patients' devices and data plans; (2) matching collected food practice data to the patient's EHR; (3) establishing consensus on legal issues (e.g., who has access to the data; who is responsible entering data) and liabilities (responsibility of the providers with the data); (4) developing validated intelligent filtering, trending, and alerting algorithms; (5) developing a digital ecosystem for food practice data. Research advances across these concerns will be key to automating the process of incorporating food practice data into the EHR.

3.6 Presenting contextualized food practice data to clinicians

Food practice data alone can help providers individualize therapy plans. However, food practice data (e.g., frequency of restaurant visits) can be rendered even more effective when complementing clinical data (e.g., lab results) in EHRs. Clinical data can be better explained and interpreted using food practice data. Such blending of data enriches computerized decision support. Moreover, food–drug interactions can be better managed in conversations between providers and patients through shared decision making with this food practice data[93].

In the case of prediabetes management, patients with impaired fasting glucose levels may benefit from assessment of meal timing data and diet composition in light of lab-produced blood glucose and A1C measurements and prior dietary recommendations. However, this kind of seamless blending of clinical history, laboratory data, and PGHD require interoperability between food practice data and existing clinical data in the EHR—as well as automation that can extract the relevant information across these data types and create a legible and contextually relevant visualization of how they relate to one another. Currently proposed architectures focus on incorporating data into EHRs; [94] however, blending food practice and clinical data requires further work in developing standards for food–clinical data interoperability and in developing intuitive visualizations to show these data side-by-side in contextually relevant ways.

Presenting numerical data (about food practice only or about the blend of food practice and clinical data) enriched by contextual cues (e.g., *What is the source of this data? When, where, and by whom was it collected?) and* qualitative narratives can inform clinical decision-making and improve the involvement of patients.[8, 95] Automation, including the algorithmic selection of the data that will comprise these multi-modal narratives and how they will be displayed to clinicians, is essential. Challenges and barriers reported in presenting PGHD are also valid for food practice data. These challenges include the lack of actionable data, reliability and accuracy of the data, workflow disruption, technical issues, and a lack of incentives.[8, 95, 96] Furthermore, food practice data need to be summarized so that patterns can be easily visualized by health care professionals who will eventually need to rapid sensemaking and decision making.[97, 98]

Perceived or objective problems with the reliability and accuracy of data can affect use of food practice data. Higher reliability and accuracy of data may come at the cost of the level of data (i.e., more accurate data may arrive less frequently; more frequent data may be noisier). Any workflow automation intervention should account for tradeoffs in maximizing legibility, reliability, and accuracy. In the end, the sources and measures of robustness of data should be honestly communicated to providers to establish trust in the system.

3.7 The ultimate goal: Integrating food practice into clinical decision-making

Food practice information is most useful when it can be seamlessly integrated into clinical decision-making. Workflow automation interventions related to food practices, should not merely provide food information, but should facilitate action (e.g., determining interventions, initiating provider referrals or facilitating coordination across medical disciplines). In some cases, clinical technology platforms might automatically detect correlations between clinical and food practice data in the EHR. For example, the platform may use rule-based algorithms to prompt the care provider to review food consumption patterns (e.g., frequent high-fat and high-carbohydrate meals from fast-food restaurants) provided by a patient that might explain abnormal lab results (e.g., high LDL). This automated recommendation might then provide the primary care provider with resources and potential interventions that would aid in discussing and potentially improving the quality of the patient's food consumption.

However, this "best case" example of workflow automation of food practice data into clinical practice is still somewhat of a future vision for technology's role in clinical decision-making. Integration of any PGHD (not just food practice data) into the EHRs has been extremely limited to date, and decision support capabilities are, for the most part, basic.[9] Several clinical workflow automation related issues have previously been identified[99] for utilizing PGHD in the clinical decision-making process, which can also be valid for food practice data. Relevant systematic interventions can benefit from co-design approaches[100, 101] that leverage the strengths of computational and clinicians' pattern recognition expertise[102] and support the optimal temporal order of user activities.

While automating workflow to integrate food practice into clinical decision-making can lead to a broader use of food practice data, the presence or absence of automation is not a binary variable. In many applications, some of the activities are automated, while others are not. For example, many decision-support tools such as dashboards, reminders, and alerts can automate particular activities, assuming that they will be designed to fit the clinical workflow. Additional automated decision support interventions based on machine learning approaches have been developed. However, their consistency with clinical guidelines is currently not sufficient to make them feasible for daily use.[103]

The patients' role in these approaches is not necessarily limited to providing data. There are also opportunities to empower patients, giving them a more active role in shared decision making and co-creation of therapy plans that are informed by food practice data. We also believe that this kind of patient empowerment will also improve provider–patient communication and collaboration.[104-106]

4. Discussion

In this work, we outline a roadmap to integrate food practice data into clinical decision-making. We identify some of the critical steps for integration and explain how these steps can be automated. Automation is particularly critical for food practice assessment, given the diverse characteristics of food practice data and the inherent overhead in collecting these data and incorporating them into existing, highly structured EHR systems. There is no single pathway for integrating automation in this domain. Automation can be accomplished by aggregating multiple smaller informatics interventions (e.g., self-tracking apps, APIs to store, analyze, or visualize food practice data) or larger-scale, centralized interventions—for example, the development of a food information exchange system. Such an exchange might connect food sources (e.g., restaurants, grocery stores) directly to health care organizations for patient-level information exchange. Workflow automation stands to reduce the friction between each pair of transitions illustrated in Figure 1, encouraging collection of better, more robust data and enabling more productive use of that data throughout the health information systems pipeline, with the net result of better clinical decision-making, overall. The arrows in the diagram also show where automation-driven feedback loops might influence patient adherence to data collection and prescribed treatments, and shows the point at which clinical decision-making can be informed through application of these workplace automation techniques.

Despite many advantages of automation in integrating food practice information into clinical decision-making, some unintended consequences should also be examined. For example, misrecognition of food items, a common problem with contemporary sensing and image recognition technologies, requires manual data correction, either by the patient, clinician, or both. Cordeiro et al. argued that full automation might undermine the mindfulness benefit of food journaling[12].

Figure 1 highlights activities related to food practice and its integration into clinical decision-making. Some of these activities occur in the patient's daily living and others in clinical settings. Automation should be congruent with the context in which the activity occurred. Connecting data collected in daily living settings with clinical decision-making contexts may present challenges.[7] An effective way of overcoming these challenges could include employing a participatory approach when designing and implementing relevant informatics systems. Because the boundaries involve both settings, a diverse set of users and stakeholders should be involved in co-design to leverage all needed explicit and tacit knowledge[101] in bridging between the needs/perspectives of patients (and their proxies) and clinicians.[107] Multidisciplinary research and design teams are needed given that each step in the workflow focuses on different kinds of expertise and disciplinary backgrounds.

Accuracy of the data is an important consideration for the adoption of these kinds of systems by both clinicians and patients.[44, 108] We posit that, counter-intuitively, accuracy can be improved by collecting food practice data based on abstractions and aggregations of behavioral signals. For example, micro-level data such as the amount of protein and fat content in each meal may not be easily captured accurately; however, by using currently available sensors, accurate macro-level data can be acquired about where the patient shops for food (e.g., at a fast food restaurant vs. in a grocery store, differentiated using GPS location sensing) or roughly what type of food is purchased (salad materials vs. snacks using photographed receipts) or how it is cooked (fried vs. boiled using kitchen sensors). We argue that macro- or summary-level information (e.g., the types of restaurants visited, types of food purchased at the grocery store) might be sufficient in many situations and would be easier to integrate into action-oriented clinical decisions. Macro-level information can show overall food habits and be a predictor of health outcomes.[109]

It is also essential that diversity, equity, and inclusion be a part of the design and implementation of informatics interventions that integrate food practice information into clinical decision-making. Food practices differ substantially across racial, ethic, and socioeconomic boundaries, and algorithmic interventions have been shown to (intentionally and unintentionally propagate various biases.[110] Health systems and policy makers must monitor food practice data usage and benefits across populations and remain vigilant so that they can change course as needed.

Our work confirms previously developed recommendations[111] developed in the context of PGHD and provides additional specificity about how these recommendations apply to the domain of food practice. Employing frameworks such as lived informatics[112] will help us better study the challenges and benefits of collecting and using food practice data. Although progress in developing the workflow automation components of this research vision is being made across multiple disciplines and domains, there are still opportunities for:

- better supporting robust and unobtrusive automated data collection about food practices (e.g., continuing to refine sensor-based approaches and balancing patient engagement with automation);

- continuing to refine manual data collection interfaces (e.g., lightweight journaling and automated annotation of food practice data with contextual cues);
- developing tools to assist clinical informatics practitioners in creating comprehensive and effective ontologies to represent a breadth of food practice information, as well as automation solutions for converting various data streams into these representational formats;
- conducting design research and validation studies to assess the most effective means of reflecting food practice information (and related prompts and "nudges") back to the patient, including studies about how these systems postiviely and negatively affect patient engagement and adherence;
- validating approaches and algorithms to align and integrate patient-generated food practice information with other clinical data streams in commercial EHR systems;
- designing and evaluating information visualizations to support clinical review of food practice information both in the context of the pre-appointment medical history review and during the patient visit, including studies comparing different levels of automation in food practice data selection and summarization; and
- more formalized randomized control trials of workflow automation systems supporting the integration of food practice into clinical decision-making to assess patient outcomes and physician acceptance of these systems in typical use cases.

Broadly, future research in this area should focus on more specific conceptual, design, and methodological work that highlights the unique features of food, human–food interaction, and the implications of food practice data automation on policy, research, health, and health care delivery.

5. Clinical Relevance Statement

Food consumption plays a critical role in the health management of various chronic conditions. Inadequate nutrition is also a major contributor to delayed healing in acute conditions. An important obstacle for integrating food-related factors into clinical decisions for optimal therapy plans is that healthcare providers (e.g., physicians, nurse practitioners) may not have an accurate understanding of routines related to and contexts surrounding patients' food practices (e.g., growing, shopping, cooking, eating). We identify important steps for integrating food practice into clinical decision-making. Automating workflow at each of these steps is possible and can be beneficial, despite some barriers. Development of smooth transitions from one step to another can improve the flow of patient care and, eventually, lead to better patient outcomes.

6. Acknowledgement

The authors thank Suzanne Lareau for editorial support and the members of the CU Boulder Too Much Information (TMI) research group for their feedback on the manuscript and our visual representations of the food practice information pipeline.

7. Conflict of Interest

No conflict of interest to declare.

8. Protection of Human and Animal Subjects

No Human and/or animal subjects were included.

9. Multiple Choice Questions

9.1. Which of the following is one of the typical characteristics of food practice data?

a. It can’t inform therapy plans.

b. It is always well structured.

c. Ontologies can be used to represent it.

d. Typically, collected in specialized clinical settings.

The correct answer is (c). Ontologies can help to represent knowledge about food practice, organize relevant information, enable information sharing, because ontologies are particularly successful for managing heterogenous information (structured, semi-structured and unstructured) drawn from different resources.

9.2. Which of the following statement related to challenges to the integrating food practice data into clinical decision-making is true?

a. Automation cannot be accomplished for the integration.

b. If clinical workflow is not taken into account, the integration can fail.

c. Ontologies have inherent flaws to represent food practice knowledge.

d. Current patents are obstacles for such integration.

The correct answer is (b). Several clinical workflow related issues were identified for utilizing PGHD in the clinical decision-making process in the literature, which can also be valid for food practice data.

10. References

1. Brons A, Oosterveer P and Wertheim-Heck S. Inconspicuous sustainability in food practices of Dutch consumers with type 2 diabetes. *Environmental Sociology* 2021; 7: 25-39. DOI: 10.1080/23251042.2020.1841371.

2. Ozkaynak M, Valdez R, Hannah K, et al. Understanding Gaps Between Daily Living and Clinical Settings in Chronic Disease Management: Qualitative Study. *J Med Internet Res* 2021; 23: e17590. 2021/02/26. DOI: 10.2196/17590.

3. Cornet V, Voida S and Holden RJ. Activity Theory Analysis of Heart Failure Self-Care. *Mind Cult Act* 2018; 25: 22-39. 2017/09/21. DOI: 10.1080/10749039.2017.1372785.

4. Brennan PF, Downs S and Casper G. Project HealthDesign: rethinking the power and potential of personal health records. *J Biomed Inform* 2010; 43: S3-S5. 2010/10/22. DOI: 10.1016/j.jbi.2010.09.001.

5. (ONC) TOotNCfHIT. What are patient-generated health data?, (2018, accessed 05/05/2021 2021).

6. Ozkaynak M, Novak LL, Choi YK, et al. Emerging Methods for Patient Ergonomics. In: Holden RJ and Valdez RS (eds) *The Patient Factor: A Handbook on Patient Ergonomics*. New York: Elsevier, 2021.

7. Ozkaynak M, Valdez RS, Holden RJ, et al. Infinicare framework for an integrated understanding of health-related activities in clinical and daily-living contexts. *Health Systems* 2018; 7: 66-78.

8. Zhang R, Burgess ER, Reddy MC, et al. Provider perspectives on the integration of patient-reported outcomes in an electronic health record. *JAMIA Open* 2019; 2: 73-80. DOI: 10.1093/jamiaopen/ooz001.

9. Demiris G, Iribarren SJ, Sward K, et al. Patient generated health data use in clinical practice: A systematic review. *Nursing Outlook* 2019; 67: 311-330. DOI: https://doi.org/10.1016/j.outlook.2019.04.005.

10. Austin E, Lee JR, Amtmann D, et al. Use of patient-generated health data across healthcare settings: implications for health systems. *JAMIA Open* 2020; 3: 70-76. 2020/07/02. DOI: 10.1093/jamiaopen/ooz065.

11. Adler-Milstein J and Nong P. Early experiences with patient generated health data: health system and patient perspectives. *J Am Med Inform Assoc* 2019; 26: 952-959. 2019/07/23. DOI: 10.1093/jamia/ocz045.

12. Cordeiro F, Bales E, Cherry E, et al. Rethinking the Mobile Food Journal: Exploring Opportunities for Lightweight Photo-Based Capture. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. Seoul, Republic of Korea: Association for Computing Machinery, 2015, p. 3207–3216.

13. Ye J. The impact of electronic health record–integrated patient-generated health data on clinician burnout. *Journal of the American Medical Informatics Association* 2021. DOI: 10.1093/jamia/ocab017.

14. Comber R, Hoonhout J, Halteren Av, et al. Food practices as situated action: exploring and designing for everyday food practices with households. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Paris, France: Association for Computing Machinery, 2013, p. 2457–2466.

15. Hardcastle SJ, Thøgersen-Ntoumani C and Chatzisarantis NL. Food Choice and Nutrition: A Social Psychological Perspective. *Nutrients* 2015; 7: 8712-8715. 2015/12/17. DOI: 10.3390/nu7105424.

16. Orji R and Mandryk RL. Developing culturally relevant design guidelines for encouraging healthy eating behavior. *International Journal of Human-Computer Studies* 2014; 72: 207-223. DOI: https://doi.org/10.1016/j.ijhcs.2013.08.012.

17. Ozkaynak M, Unertl KM, Johnson S, et al. Clinical Workflow Analysis, Process redesign and Quality Improvement. In: Finnel JT and Dixon BE (eds) *Clinical Informatics Study Guide*. New York: Springer, 2016, pp.135-161.

18. Zayas-Cabán T, Haque SN and Kemper N. Identifying Opportunities for Workflow Automation in Health Care: Lessons Learned from Other Industries. *Appl Clin Inform* 2021; 12: 686-697. 2021/07/29. DOI: 10.1055/s-0041-1731744.

19. Arab L, Estrin D, Kim DH, et al. Feasibility testing of an automated image-capture method to aid dietary recall. *Eur J Clin Nutr* 2011; 65: 1156-1162. 2011/05/19. DOI: 10.1038/ejcn.2011.75.

20. Rahman T, Adams AT, Zhang M, et al. BodyBeat: a mobile system for sensing non-speech body sounds. 2014, p. 2-13.

21. Zhang S, Zhao Y, Nguyen DT, et al. NeckSense: A Multi-Sensor Necklace for Detecting Eating Activities in Free-Living Conditions. *Proc ACM Interact Mob Wearable Ubiquitous Technol* 2020; 4: Article 72. DOI: 10.1145/3397313.

22. Mankoff J, Hsieh G, Hung HC, et al. Using Low-Cost Sensing to Support Nutritional Awareness. In: *UbiComp 2002: Ubiquitous Computing* (eds Borriello G and Holmquist LE), Berlin, Heidelberg, 2002// 2002, pp.371-378. Springer Berlin Heidelberg.

23. Basiotis PP, Welsh SO, Cronin FJ, et al. Number of days of food intake records required to estimate individual and group nutrient intakes with defined confidence. *J Nutr* 1987; 117: 1638-1641. 1987/09/01. DOI: 10.1093/jn/117.9.1638.

24. Johnson RK. Dietary intake--how do we measure what people are really eating? *Obes Res* 2002; 10 Suppl 1: 63S-68S. 2002/11/26. DOI: 10.1038/oby.2002.192.

25. Block G, Gillespie C, Rosenbaum EH, et al. A rapid food screener to assess fat and fruit and vegetable intake. *Am J Prev Med* 2000; 18: 284-288. 2000/05/02. DOI: 10.1016/s0749-3797(00)00119-7.

26. Johnston EA, Petersen KS, Beasley JM, et al. Relative validity and reliability of a diet risk score (DRS) for clinical practice. *BMJ Nutr Prev Health* 2020; 3: 263-269. 2021/02/02. DOI: 10.1136/bmjnph-2020-000134.

27. Gills SM, Baker SS and Auld G. Collection Methods for the 24-Hour Dietary Recall as Used in the Expanded Food and Nutrition Education Program. *J Nutr Educ Behav* 2017; 49: 250-256 e251. 2016/11/24. DOI: 10.1016/j.jneb.2016.10.009.

28. Freedman LS, Commins JM, Moler JE, et al. Pooled results from 5 validation studies of dietary self-report instruments using recovery biomarkers for energy and protein intake. *Am J Epidemiol* 2014; 180: 172-188. 2014/06/12. DOI: 10.1093/aje/kwu116.

29. Monaghan M, Hilliard M, Sweenie R, et al. Transition readiness in adolescents and emerging adults with diabetes: the role of patient-provider communication. *Curr Diab Rep* 2013; 13: 900-908. 2013/09/10. DOI: 10.1007/s11892-013-0420-x.

30. Patel NJ, Datye KA and Jaser SS. Importance of Patient-Provider Communication to Adherence in Adolescents with Type 1 Diabetes. *Healthcare (Basel)* 2018; 6 2018/03/31. DOI: 10.3390/healthcare6020030.

31. Peterson EB, Ostroff JS, DuHamel KN, et al. Impact of provider-patient communication on cancer screening adherence: A systematic review. *Prev Med* 2016; 93: 96-105. 2016/11/05. DOI: 10.1016/j.ypmed.2016.09.034.

32. Ratanawongsa N, Karter AJ, Parker MM, et al. Communication and medication refill adherence: the Diabetes Study of Northern California. *JAMA Intern Med* 2013; 173: 210-218. 2013/01/02. DOI: 10.1001/jamainternmed.2013.1216.

33. Schoenthaler A, Allegrante JP, Chaplin W, et al. The effect of patient-provider communication on medication adherence in hypertensive black patients: does race concordance matter? *Ann Behav Med* 2012; 43: 372-382. 2012/01/25. DOI: 10.1007/s12160-011-9342-5.

34. Schoenthaler A, Chaplin WF, Allegrante JP, et al. Provider communication effects medication adherence in hypertensive African Americans. *Patient Educ Couns* 2009; 75: 185-191. 2008/11/18. DOI: 10.1016/j.pec.2008.09.018.

35. Young HN, Len-Rios ME, Brown R, et al. How does patient-provider communication influence adherence to asthma medications? *Patient Educ Couns* 2017; 100: 696-702. 2016/12/06. DOI: 10.1016/j.pec.2016.11.022.

36. Janson SL, McGrath KW, Covington JK, et al. Individualized asthma self-management improves medication adherence and markers of asthma control. *J Allergy Clin Immunol* 2009; 123: 840-846. 2009/04/08. DOI: 10.1016/j.jaci.2009.01.053.

37. Lewis MP, Colbert A, Erlen J, et al. A qualitative study of persons who are 100% adherent to antiretroviral therapy. *AIDS Care* 2006; 18: 140-148. 2005/12/13. DOI: 10.1080/09540120500161835.

38. Sanders MJ and Van Oss T. Using Daily Routines to Promote Medication Adherence in Older Adults. *American Journal of Occupational Therapy* 2013; 67: 91-99. DOI: 10.5014/ajot.2013.005033.

39. Lewinski AA, Drake C, Shaw RJ, et al. Bridging the integration gap between patient-generated blood glucose data and electronic health records. *Journal of the American Medical Informatics Association* 2019; 26: 667-672. DOI: 10.1093/jamia/ocz039.

40. Marquard JL, Garber L, Saver B, et al. Overcoming challenges integrating patient-generated data into the clinical EHR: Lessons from the CONtrolling Disease Using Inexpensive IT – Hypertension in Diabetes (CONDUIT-HID) Project. *International Journal of Medical Informatics* 2013; 82: 903-910. DOI: https://doi.org/10.1016/j.ijmedinf.2013.04.009.

41. Plastiras P and O'Sullivan D. Exchanging personal health data with electronic health records: A standardized information model for patient generated health data and

observations of daily living. *International Journal of Medical Informatics* 2018; 120: 116-125. DOI: https://doi.org/10.1016/j.ijmedinf.2018.10.006.

42. Sujansky W and Kunz D. A standard-based model for the sharing of patient-generated health information with electronic health records. *Personal and Ubiquitous Computing* 2015; 19: 9-25. DOI: 10.1007/s00779-014-0806-z.

43. Gandrup J, Ali SM, McBeth J, et al. Remote symptom monitoring integrated into electronic health records: A systematic review. *Journal of the American Medical Informatics Association* 2020; 27: 1752-1763. DOI: 10.1093/jamia/ocaa177.

44. West P, Kleek MV, Giordano R, et al. Common Barriers to the Use of Patient-Generated Data Across Clinical Settings. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. Montreal QC, Canada: Association for Computing Machinery, 2018, p. Paper 484.

45. Association AD. 2. Classification and Diagnosis of Diabetes: Standards of Medical Care in Diabetes—2021. *Diabetes Care* 2021; 44: S15-S33. DOI: 10.2337/dc21-S002.

46. Centers for Disease Control and Prevention. *National Diabetes Statistics Report*. 2020 2020. Atlanta, GA.

47. Ackermann RT, Cheng YJ, Williamson DF, et al. Identifying adults at high risk for diabetes and cardiovascular disease using hemoglobin A1c National Health and Nutrition Examination Survey 2005-2006. *Am J Prev Med* 2011; 40: 11-17. 2010/12/15. DOI: 10.1016/j.amepre.2010.09.022.

48. Association AD. 3. Prevention or Delay of Type 2 Diabetes: Standards of Medical Care in Diabetes—2021. *Diabetes Care* 2021; 44: S34-S39. DOI: 10.2337/dc21-S003.

49. Harris MF, Fanaian M, Jayasinghe UW, et al. What predicts patient-reported GP management of smoking, nutrition, alcohol, physical activity and weight? *Aust J Prim Health* 2012; 18: 123-128. 2012/05/04. DOI: 10.1071/PY11024.

50. Ball L, Johnson C, Desbrow B, et al. General practitioners can offer effective nutrition care to patients with lifestyle-related chronic disease. *J Prim Health Care* 2013; 5: 59-69. 2013/03/05.

51. Vu T, Lin F, Alshurafa N, et al. Wearable Food Intake Monitoring Technologies: A Comprehensive Review. *Computers* 2017; 6: 4.

52. Bedri A, Li D, Khurana R, et al. FitByte: Automatic Diet Monitoring in Unconstrained Situations Using Multimodal Sensing on Eyeglasses. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Honolulu, HI, USA: Association for Computing Machinery, 2020, p. 1–12.

53. Chun KS, Bhattacharya S and Thomaz E. Detecting Eating Episodes by Tracking Jawbone Movements with a Non-Contact Wearable Sensor. *Proc ACM Interact Mob Wearable Ubiquitous Technol* 2018; 2: Article 4. DOI: 10.1145/3191736.

54. Kadomura A, Li C-Y, Chen Y-C, et al. Sensing fork: eating behavior detection utensil and mobile persuasive game. *CHI '13 Extended Abstracts on Human Factors in*

Computing Systems. Paris, France: Association for Computing Machinery, 2013, p. 1551–1556.

55. Thomaz E, Essa I and Abowd GD. A Practical Approach for Recognizing Eating Moments with Wrist-Mounted Inertial Sensing. *Proc ACM Int Conf Ubiquitous Comput* 2015; 2015: 1029-1040. 2015/09/01. DOI: 10.1145/2750858.2807545.

56. Gerhardsson KM and Laike T. User acceptance of a personalised home lighting system based on wearable technology. *Applied Ergonomics* 2021; 96: 103480. DOI: https://doi.org/10.1016/j.apergo.2021.103480.

57. Kalantarian H, Alshurafa N, Le T, et al. Monitoring eating habits using a piezoelectric sensor-based necklace. *Comput Biol Med* 2015; 58: 46-55. 2015/01/24. DOI: 10.1016/j.compbiomed.2015.01.005.

58. Kalantarian H and Sarrafzadeh M. Audio-based detection and evaluation of eating behavior using the smartwatch platform. *Comput Biol Med* 2015; 65: 1-9. 2015/08/05. DOI: 10.1016/j.compbiomed.2015.07.013.

59. Choe EK, Abdullah S, Rabbi M, et al. Semi-Automated Tracking: A Balanced Approach for Self-Monitoring Applications. *IEEE Pervasive Computing* 2017; 16: 74-84. DOI: 10.1109/MPRV.2017.18.

60. Mamykina L, Miller AD, Grevet C, et al. Examining the impact of collaborative tagging on sensemaking in nutrition management. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Vancouver, BC, Canada: Association for Computing Machinery, 2011, p. 657–666.

61. Ye X, Chen G, Gao Y, et al. Assisting Food Journaling with Automatic Eating Detection. *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. San Jose, California, USA: Association for Computing Machinery, 2016, p. 3255–3262.

62. Meegahapola L, Ruiz-Correa S, Robledo-Valero VdC, et al. One More Bite? Inferring Food Consumption Level of College Students Using Smartphone Sensing and Self-Reports. *Proc ACM Interact Mob Wearable Ubiquitous Technol* 2021; 5: Article 26. DOI: 10.1145/3448120.

63. Mamykina L, Mynatt E, Davidson P, et al. MAHI: investigation of social scaffolding for reflective thinking in diabetes management. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Florence, Italy: Association for Computing Machinery, 2008, p. 477–486.

64. Hingle M and Patrick H. There Are Thousands of Apps for That: Navigating Mobile Technology for Nutrition Education and Behavior. *J Nutr Educ Behav* 2016; 48: 213-218 e211. 2016/03/12. DOI: 10.1016/j.jneb.2015.12.009.

65. Fox S and Duggan M. *Tracking for Health*. 2013. Pew Research Center.

66. Moshfegh AJ, Rhodes DG, Baer DJ, et al. The US Department of Agriculture Automated Multiple-Pass Method reduces bias in the collection of energy intakes. *Am J Clin Nutr* 2008; 88: 324-332. 2008/08/12. DOI: 10.1093/ajcn/88.2.324.

67. Livingstone MB and Black AE. Markers of the validity of reported energy intake. *J Nutr* 2003; 133 Suppl 3: 895s-920s. 2003/03/04. DOI: 10.1093/jn/133.3.895S.

68. Andrew AH, Borriello G and Fogarty J. Simplifying mobile phone food diaries: design and evaluation of a food index-based nutrition diary. *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare*. Venice, Italy: ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2013, p. 260–263.

69. Siek KA, Connelly KH, Rogers Y, et al. When Do We Eat? An Evaluation of Food Items Input into an Electronic Food Monitoring Application. In: *2006 Pervasive Health Conference and Workshops* 29 Nov.-1 Dec. 2006 2006, pp.1-10.

70. Deng L and Cox LP. LiveCompare: grocery bargain hunting through participatory sensing. *Proceedings of the 10th workshop on Mobile Computing Systems and Applications*. Santa Cruz, California: Association for Computing Machinery, 2009, p. Article 4.

71. Zhang Y and Parker AG. Eat4Thought: A Design of Food Journaling. *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. Honolulu, HI, USA: Association for Computing Machinery, 2020, p. 1–8.

72. Wang DH, Kogashiwa M and Kira S. Development of a new instrument for evaluating individuals' dietary intakes. *J Am Diet Assoc* 2006; 106: 1588-1593. 2006/09/27. DOI: 10.1016/j.jada.2006.07.004.

73. Chung C-F, Agapie E, Schroeder J, et al. When Personal Tracking Becomes Social: Examining the Use of Instagram for Healthy Eating. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. Denver, Colorado, USA: Association for Computing Machinery, 2017, p. 1674–1687.

74. Ming Z-Y, Chen J, Cao Y, et al. Food Photo Recognition for Dietary Tracking: System and Experiment. In: Cham, 2018, pp.129-141. Springer International Publishing.

75. Epstein DA, Cordeiro F, Fogarty J, et al. Crumbs: Lightweight Daily Food Challenges to Promote Engagement and Mindfulness. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. San Jose, California, USA: Association for Computing Machinery, 2016, p. 5632–5644.

76. Luhanga ET, Hippocrate AAE, Suwa H, et al. Happyinu: exploring how to use games and extrinsic rewards for consistent food tracking behavior. In: *2016 Ninth International Conference on Mobile Computing and Ubiquitous Networking (ICMU)* 4-6 Oct. 2016 2016, pp.1-7.

77. Thaler RH and Sunstein CR. *Nudge: Improving decisions about health, wealth, and happiness*. London: Penguin Books, 2008.

78. Cordeiro F, Epstein DA, Thomaz E, et al. Barriers and Negative Nudges: Exploring Challenges in Food Journaling. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. Seoul, Republic of Korea: Association for Computing Machinery, 2015, p. 1159–1162.

79. Cantais J, Domínguez D, Gigante V, et al. An example of food ontology for diabetes control. 2005.

80. Dooley DM, Griffiths EJ, Gosal GS, et al. FoodOn: a harmonized food ontology to increase global food traceability, quality control and data integration. *npj Science of Food* 2018; 2: 23. DOI: 10.1038/s41538-018-0032-6.

81. Musen MA and Protégé T. The Protégé Project: A Look Back and a Look Forward. *AI Matters* 2015; 1: 4-12. DOI: 10.1145/2757001.2757003.

82. Courtot M, Gibson F, Lister A, et al. MIREOT: the Minimum Information to Reference an External Ontology Term. *Nature Precedings* 2009. DOI: 10.1038/npre.2009.3576.1.

83. Hoehndorf R, Schofield PN and Gkoutos GV. The role of ontologies in biological and biomedical research: a functional perspective. *Brief Bioinform* 2015; 16: 1069-1080. 2015/04/10. DOI: 10.1093/bib/bbv011.

84. Castellano-Escuder P, González-Domínguez R, Wishart DS, et al. FOBI: an ontology to represent food intake data and associate it with metabolomic data. *Database* 2020; 2020. DOI: 10.1093/databa/baaa033.

85. Dragoni M, Bailoni T, Maimone R, et al. HeLiS: An Ontology for Supporting Healthy Lifestyles. In: Cham, 2018, pp.53-69. Springer International Publishing.

86. Youn J, Naravane T and Tagkopoulos I. Using Word Embeddings to Learn a Better Food Ontology. *Front Artif Intell* 2020; 3: 584784-584784. DOI: 10.3389/frai.2020.584784.

87. Rabbi M, Pfammatter A, Zhang M, et al. Automated Personalized Feedback for Physical Activity and Dietary Behavior Change With Mobile Phones: A Randomized Controlled Trial on Adults. *JMIR mHealth uHealth* 2015; 3: e42. DOI: 10.2196/mhealth.4160.

88. Caban JJ and Gotz D. Visual analytics in healthcare – opportunities and research challenges. *Journal of the American Medical Informatics Association* 2015; 22: 260-262. DOI: 10.1093/jamia/ocv006.

89. Li I, Dey A and Forlizzi J. A stage-based model of personal informatics systems. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Atlanta, Georgia, USA: Association for Computing Machinery, 2010, p. 557–566.

90. Heer J and Shneiderman B. Interactive dynamics for visual analysis. *Commun ACM* 2012; 55: 45–54. DOI: 10.1145/2133806.2133821.

91. Tiase VL, Hull W, McFarland MM, et al. Patient-generated health data and electronic health record integration: a scoping review. *JAMIA Open* 2020; 3: 619-627. DOI: 10.1093/jamiaopen/ooaa052.

92. Kumar RB, Goren ND, Stark DE, et al. Automated integration of continuous glucose monitor data in the electronic health record using consumer technology. *J Am Med Inform Assoc* 2016; 23: 532-537. 2016/03/29. DOI: 10.1093/jamia/ocv206.

93. Chung C-F, Dew K, Cole A, et al. Boundary Negotiating Artifacts in Personal Informatics: Patient-Provider Collaboration with Patient-Generated Data. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social*

Computing. San Francisco, California, USA: Association for Computing Machinery, 2016, p. 770–786.

94. Marceglia S, Fontelo P, Rossi E, et al. A Standards-Based Architecture Proposal for Integrating Patient mHealth Apps to Electronic Health Record Systems. *Appl Clin Inform* 2015; 6: 488-505. DOI: 10.4338/ACI-2014-12-RA-0115.

95. Lakshmi U, Hong M and Wilcox L. Integrating Patient-Generated Observations of Daily Living into Pediatric Cancer Care: A Formative User Interface Design Study. In: *2018 IEEE International Conference on Healthcare Informatics (ICHI)* 4-7 June 2018 2018, pp.265-275.

96. Wu DTY, Xin C, Bindhu S, et al. Clinician Perspectives and Design Implications in Using Patient-Generated Health Data to Improve Mental Health Practices: Mixed Methods Study. *JMIR Form Res* 2020; 4: e18123. DOI: 10.2196/18123.

97. Huba N and Zhang Y. Designing patient-centered personal health records (PHRs): health care professionals' perspective on patient-generated data. *J Med Syst* 2012; 36: 3893-3905. 2012/05/31. DOI: 10.1007/s10916-012-9861-z.

98. Chiauzzi E, Rodarte C and DasMahapatra P. Patient-centered activity monitoring in the self-management of chronic health conditions. *BMC Med* 2015; 13: 77. 2015/04/19. DOI: 10.1186/s12916-015-0319-2.

99. Cheng KG, Hayes GR, Hirano SH, et al. Challenges of integrating patient-centered data into clinical workflow for care of high-risk infants. *Personal and Ubiquitous Computing* 2015; 19: 45-57. DOI: 10.1007/s00779-014-0807-y.

100. Ozkaynak M, Reeder B, Park SY, et al. Design for improved workflow. In: Sasangohar F and Sethumadhavan A (eds) *Design for Healthcare*. New York: Elsevier, 2020.

101. Ozkaynak M, Sircar CM, Frye O, et al. A Systematic Review of Design Workshops for Health Information Technologies. *Informatics* 2021; 8: 34.

102. Feller DJ, Burgermaster M, Levine ME, et al. A visual analytics approach for pattern-recognition in patient-generated data. *Journal of the American Medical Informatics Association* 2018; 25: 1366-1374. DOI: 10.1093/jamia/ocy054.

103. Burgermaster M, Son JH, Davidson PG, et al. A new approach to integrating patient-generated data with expert knowledge for personalized goal setting: A pilot study. *International Journal of Medical Informatics* 2020; 139: 104158. DOI: https://doi.org/10.1016/j.ijmedinf.2020.104158.

104. Chung C-F. Supporting patient-provider communication and engagement with personal informatics data. *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*. Maui, Hawaii: Association for Computing Machinery, 2017, p. 335–338.

105. Chung C-F, Wang Q, Schroeder J, et al. Identifying and Planning for Individualized Change: Patient-Provider Collaboration Using Lightweight Food Diaries in Healthy Eating and Irritable Bowel Syndrome. *Proc ACM Interact Mob Wearable Ubiquitous Technol* 2019; 3: Article 7. DOI: 10.1145/3314394.

106. Schroeder J, Hoffswell J, Chung C-F, et al. Supporting Patient-Provider Collaboration to Identify Individual Triggers using Food and Symptom Journals. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. Portland, Oregon, USA: Association for Computing Machinery, 2017, p. 1726–1739.

107. Luo Y, Liu P and Choe EK. Co-Designing Food Trackers with Dietitians: Identifying Design Opportunities for Food Tracker Customization. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, 2019, pp.Paper 592.

108. Weissmann J, Mueller A, Messinger D, et al. Improving the Quality of Outpatient Diabetes Care Using an Information Management System: Results From the Observational VISION Study. *J Diabetes Sci Technol* 2015; 10: 76-84. 2015/08/01. DOI: 10.1177/1932296815595984.

109. Bhutani S, Schoeller DA, Walsh MC, et al. Frequency of Eating Out at Both Fast-Food and Sit-Down Restaurants Was Associated With High Body Mass Index in Non-Large Metropolitan Communities in Midwest. *American Journal of Health Promotion* 2016; 32: 75-83. DOI: 10.1177/0890117116660772.

110. Eubanks V. *Automating Inequality: How High-tech Tools Profile, Police and Punish the Poor.* . New York, NY: St. Martin's Press, 2018.

111. Woods SS, Evans NC and Frisbee KL. Integrating patient voices into health information for self-care and patient-clinician partnerships: Veterans Affairs design recommendations for patient-generated data applications. *Journal of the American Medical Informatics Association* 2016; 23: 491-495. DOI: 10.1093/jamia/ocv199.

112. Munson SA. Rethinking assumptions in the design of health and wellness tracking tools. *interactions* 2017; 25: 62–65. DOI: 10.1145/3168738.