Opportunities and Challenges of Integrating Food Practice into Clinical Decision-Making

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Abstract

Background 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 benefits in this regard, minimizing this burden resulting in a better fit with a patient's daily living routines, and creating opportunities for better integration into clinical workflow. Although the literature on patient-generated health data (PGHD) can serve as a starting point for the automation of food practice data, more diverse characteristics of food practice data provide additional challenges.

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

Methods We elaborate on automation opportunities and challenges in each step, providing a summary visualization of the flow of food practice-related data from daily living settings to clinical settings.

Results We propose four implications of automating food practice hereinafter. First, there are multiple ways of automating workflow related to food practice. Second, steps may occur in daily living and others in clinical settings. Food practice data and the necessary contextual information should be integrated into clinical decision-making to enable action. Third, as accuracy becomes important for food practice data, macrolevel data may have advantages over microlevel data in some situations. Fourth, 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 on how these recommendations apply to food practice.

Keywords

- clinical decision-making
- workflow
- food practice
- clinical informatics
- self-tracking

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Background and Significance

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] and heart failure[3]). Data on food practice are often collected by patients as 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 as follows: (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 reduction of 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 (EHRs) 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, however, can add significant burden to patient[12] and clinician.[13] 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 gap in fully individualizing food practice 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 context of clinical care, allowing food practice data to become a part of the medical record 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 predefined 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 can provide a temporal structure for food practice data. 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 here, some of these roles for automation in expanding the base of food practice data and 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.

Current Practice of Capturing Food Practice Data

In the clinical setting, assessment 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 intake 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 the Healthy Eating Index-2015, a 160-item food frequency questionnaire. The Dietary Risk Score 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 3 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.

Workflow for Integrating Food Practice in Clinical Decision-Making

Seamless integration of food practice into clinical decision-making can improve health outcomes, resulting improved clinician–patient communication[29–35] and the development of more individualized therapy plans.[36–38] We identified

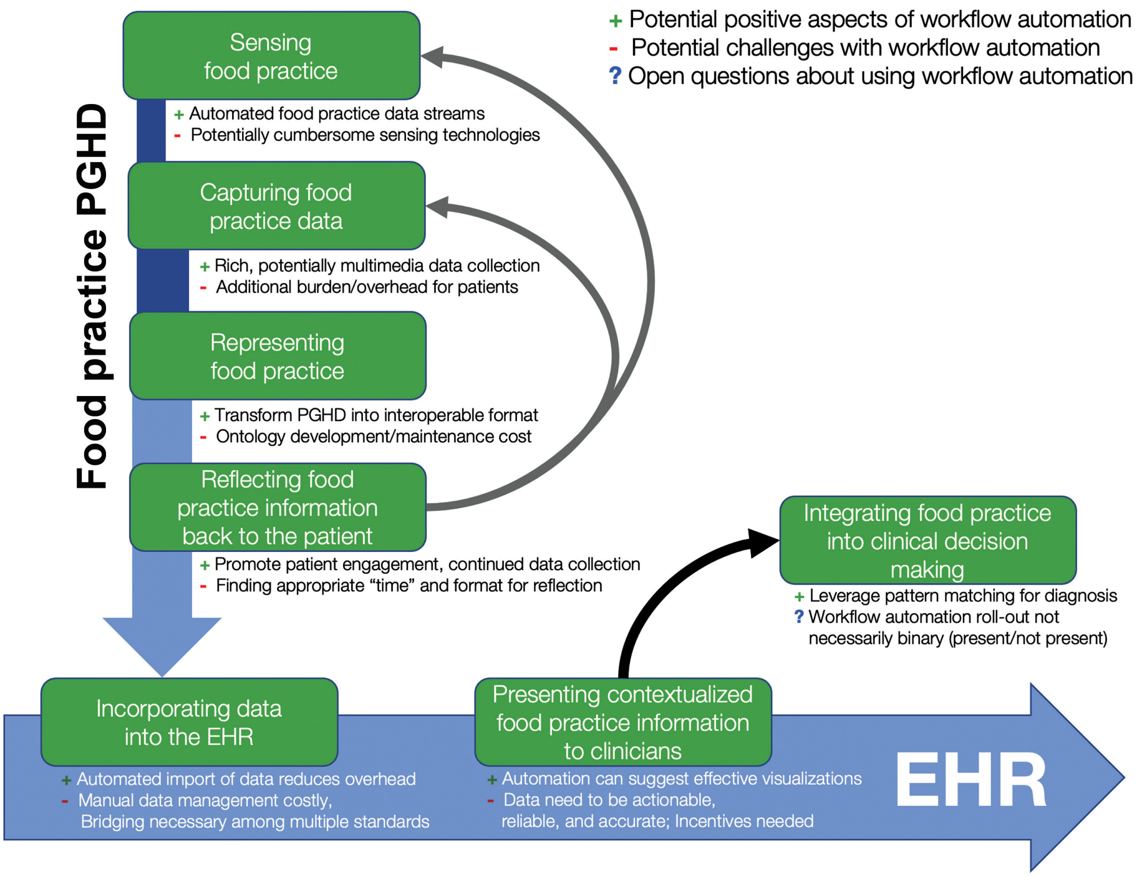

Fig. 1 Workflow for integrating food practice in clinical decision-making. EHR, electronic health record; PGHD, patient-generated health data.

important steps for integrating food practice into decision-making (►Fig. 1) based on a review of the literature.[39–42] Specifically, we used a collaborative inquiry among the members of our multidisciplinary research team about where food practice–related information is stored at each step, how automation might work to transform this information, and what influence(s) the automation 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 findings from this review were that automating workflow at each step in the food practice clinical data pipeline is possible. Workflow automation can be beneficial despite some barriers such as 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 and 125 mg/dL or a hemoglobin A1C level between 5.7 and 6.4%, a diagnosis of prediabetes can be made.[45] It is estimated, that between 2013 and 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] Since many patients with prediabetic signs are overweight or obese, the primary recommendation for treatment is lifestyle intervention to promote loss and maintenance of 7% of initial body weight.[48] Primary care has been identified as an ideal setting for initiating lifestyle interventions that promote weight management, like healthy eating.[49] Primary care providers (PCPs) are ideally positioned 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 provide clinicians with 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, increased intake of nonstarchy vegetables, or proper meal spacing.

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 is 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 and 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 and eating behavior), sensing of different food intake mechanisms (i.e., biting, chewing, and 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, including 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,[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 is 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, 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 semiautomatic data collection[59] (i.e., to log instances of eating that are intended to be annotated using human computation approaches),[60] or retrospectively recorded in more detail (manually) by the patient (e.g.,[54,61–63]); or as fully automatic food intake sensing platforms (i.e., as a complete substitute for manual data entry). Automatic journaling at a coarse level of 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. 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 "Reflecting Food Practice Information Back to the Patient").

Capturing Food Practice Data

Capturing the food consumption data is a common focus of self-tracking health applications on mobile devices.[64,65] These applications 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 the gold standard of total energy expenditure based on the doubly labeled water technique.[67] However, these types of in-depth, computer-based dietary recall techniques still pose significant time and burden on respondents and clinicians.

To address these data collection burdens, mobile food tracking research have experimented with streamlined data entry. For example, using light-weight interface designs inspired by social media platforms (e.g., the "+1" design pattern for reentering or "up-voting" a prior entry).[68] Other applications have adopted interfaces that allow quick logging of store-bought food items using Universal Product Code (UPC) scanning.[69,70] The main limitation of barcode-scanning applications is that they only accelerate data entry for selected 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 other instances, 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 applications have increased 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 internalize food journaling practice. In contrast, the implicit or inadvertent use of "negative nudges" in the design of popular food-tracking applications, have been shown to deter long-term use and lower adherence to computer-assisted data collection of food intake.[78] For example, issues include the 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 application.

Patients with prediabetes can benefit from workflow automation in collecting data (along with needed context information). For example, carbohydrate content of consumed (or food to be consumed) could be captured and compared with 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 (the user's job hours), social (friends), cultural (food consumption habits), and temporal (daily or weekly) routines.

Representing Food Practice

Ontologies can help represent knowledge about food practice, organize relevant information, enable information sharing, and guide the subsequent steps shown in ►Fig. 1.[79,80] Ontologies are particularly successful for managing heterogeneous information (structured, semistructured, and unstructured) drawn from different resources. Ontologies are typically modeled using an editor (e.g., Protege[81]) that provide 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 ►Fig. 1. Ontologies allow for representations that can be interpreted by computers. Such representations allow for harmonizing heterogeneous 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 steps described in ►Fig. 1.

Key steps necessary for developing a food ontology include the following: (1) 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); (2) identifying and importing appropriate classes from existing reference ontologies (e.g., FOBI,[84] FoodOn,[80] and others[85,86]); and (3) 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 ►Fig. 1 should be able to (1) represent 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.

Reflecting Food Practice Information Back to the Patient

As patients collect data on their food practice, reflecting information derived by the data (e.g., how much soda does the patient purchase? Is there a pattern to cravings for, and purchases of soda?) to the patient 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 can be effective in mitigating issues of information overload[88] and can facilitate understanding food practice information by lay people. Furthermore, the timing and context in which these data are made available, can have an impact on the extent to which they drive insight 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 or 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, global positioning system (GPS)-based 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.

Incorporating Data into the Electronic Health Record

Various food practice data could be incorporated into the EHR to support clinical decision-making. Data elements might include data generated from currently used self-reported food practice questionnaires[23,24] and surveys[26]; for 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), information about meal duration and frequency,[52–55] and 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 the Apple HealthKit[93] and technical information exchange mechanisms like application programming interfaces (APIs) and Fast Healthcare Interoperability Resources (FHIR)[94] 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[3,95] and the PGHD literature, we identified the following 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 or 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.

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., laboratory results) in EHRs. Clinical data can be better understood 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.[96]

In the case of prediabetes management, patients with impaired fasting glucose levels may benefit from assessment of meal timing and diet composition, in light of laboratory-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 and existing clinical data in the EHR. This information is enhanced when automation can extract the relevant information across these types of data and create a legible and contextually relevant visualization of how they relate to one another. Currently proposed architectures focus on incorporating data into EHRs[97]; however, blending food practice and clinical data require 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.[8,98] Automation, including the algorithmic selection of the data that will comprise these multimodal 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.[8,98,99] 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 sense making and decision-making.[100,101]

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 while more frequent data may be noisier). Any workflow automation should account for trade-offs 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.

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 relationships 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 provided by a patient (e.g., frequent high-fat and high-carbohydrate meals from fast-food restaurants) that might explain abnormal laboratory results (e.g., high low-density lipoprotein [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[102] for utilizing PGHD in the clinical decision-making process which can also be valid for food practice data. Relevant systematic interventions can benefit from codesign approaches[103,104] that leverage the strengths of computational and clinicians' pattern recognition expertise[105] 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.[106]

The patients' role in these approaches is not necessarily limited to providing data. There are also opportunities to empower patients, that is, encouraging a more active role in shared decision-making, and cocreation of therapy plans that are informed by food practice data. We also believe that this kind of patient empowerment will improve provider–patient communication and collaboration.[107–109]

Discussion

In this work, we outlined 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 applications, 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 and 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 ►Fig. 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. The arrows in the diagram also show where automation-driven feedback loops might influence patient adherence to data collection and prescribed treatments, and show 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]

►Fig. 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 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 codesign to leverage all needed explicit and tacit knowledge[104] in bridging between the needs/perspectives of patients (and their proxies) and clinicians.[110] Multidisciplinary research and design teams are needed, given that each step in the workflow focuses on different kinds of expertise and discipline.

Accuracy of the data are an important consideration for the adoption of these kinds of systems by both clinicians and patients.[44,111] We posit that, counter intuitively, accuracy can be improved by collecting food practice databased on abstractions and aggregations of behavioral signals. For example, microlevel 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 macrolevel data can be acquired about where the patient shops for food (e.g., at a fast food restaurant versus 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 and 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. Macrolevel information can show overall food habits and be a predictor of health outcomes.[112]

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.[113] 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.

Conclusion

Our work confirms previously developed recommendations[114] 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[115] will help us better study the challenges and benefits of collecting and using food practice data. 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. Specific future research opportunities must include (1) developing formative and summative evaluation frameworks and approaches to assess the value of the integration of validating the steps in ►Fig. 1 and (2) pilot testing of the proposed steps for specific conditions such as hypertension.

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 health care providers (e.g., physicians and nurse practitioners) may not have an accurate understanding of routines related to and contexts surrounding patients' food practices (e.g., growing, shopping, cooking, and eating). We identified 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 has the ability to improve the flow of patient care and, eventually, better patient outcomes.

Multiple Choice Questions

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

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

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

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

Protection of Human and Animal Subjects

No human and/or animal subjects were included.

Conflict of Interest

None declared.

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