Development of a Decision Support System to Generate Data-Powered Personalized Nutrition Recommendations for Diabetes Self-Management

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Abstract

The abundance of diet data generated by self-monitoring technologies presents an opportunity for data-powered personalization of diet recommendations. This aligns with diabetes education best practices, specifically that clinicians should work with patients to develop individualized self-management plans. Despite the potential for leveraging self-monitoring data to improve dietary management of type 2 diabetes, there are few tools that turn it into decision support. The goal of the research presented here was to develop a suggestion system to generate data-driven and clinically appropriate personalized dietary recommendations for patients with type 2 diabetes. To build our suggestion system, we iteratively coded data from interviews with 10 dietitians to develop a decision tree that represents the process dietitians use to suggest dietary changes to promote better glucose control. Next, we automated this process for patient-generated data by developing an ontology and an R program to make this process computable. Finally, we evaluated the program against a clinician-generated gold standard. Two dietitians found the decision tree to be an accurate knowledge representation. Further, they reported it was potentially useful in clinical practice. The program output was 69% and 83% consistent with the gold standard for each of two patient datasets. The suggestion system presented here represents a step towards a decision support tool for dietary management of T2D that could be applied in the clinical and personal informatics domains. As clinicians see the utility of patient generated data in healthcare, many will want to it to connect with their patients and make care more personalized. Furthermore, our suggestion system also provides a basis for providing individuals engaging in self-monitoring a more actionable synthesis of their data.

Introduction

The ubiquity of self-monitoring technologies has improved the quantity and quality of patient-generated diet data. This abundance of diet data presents the opportunity for data-powered personalization of diet recommendations and counseling, aligning with diabetes self-management education best practices, specifically that clinicians should work with patients to develop individualized dietary self-management plans[1].

Though they are not free of bias, data from dietary self-monitoring technologies can provide a more comprehensive picture of a patient's eating patterns than paper-based approaches traditionally used in dietetics, such as 3-day food records or 24-hour dietary recall interviews[2]. However, the volume of data produced by these technologies makes their application in clinical practice time consuming. Further, they may promote apophenia (i.e., the human tendency to see patterns even where there are none)[3]. Such comprehensive self-monitoring data can yield important insight about the relationship between diet and blood glucose; however, the self-discovery process is complex and not always reliable[4]. Despite the potential for leveraging dietary self-monitoring data to improve dietary management of type 2 diabetes (T2D), there are few tools to reduce its complexity and turn it into decision support. In this work we investigate the possibility of using knowledge engineering techniques to develop a decision support system powered by patient self-monitoring data that mimics the decision-making of registered dietitian nutritionists (RDNs) to automatically generate personalized nutrition recommendations.

In the hospital setting, a transition to data-driven clinical decision support was made possible by the proliferation of data streams in intensive care units during the mid-20th century. Systems like Health Evaluation through Logical Processing (HELP) used data to develop a comprehensive representation of a patient and lead to automated clinical decision support that included recommendations for orders and procedures[5]. Suggestion systems are a subset of clinical decision support systems that combine data with a knowledge base to suggest an appropriate intervention[5]. Suggestion systems mimic human decision-making and have been demonstrated to be effective in representing expert decision-making[5].

We adopted an analogous approach to support the design and evaluation of a novel health information technology system that produces data-powered, personalized dietary suggestions for patients with T2D. Although a knowledge representation that generates diet recommendations for patients with diabetes has been developed[6], it does not leverage patient generated diet data. An important next step in the development of a useful suggestion system is representing how RDNs transform information about an individual patient's diet into recommendations for improving his/her personal glycemic response. Importantly, this clinician knowledge is not found in textbooks or clinical guidelines. Therefore, the goal of the research presented here was to develop a suggestion system to generate data-driven personalized dietary recommendations for patients with T2D in a way that mimics expert decision-making. To build our suggestion system, we first developed a knowledge representation of the process RDNs use to suggest dietary changes that may promote better glucose control. Next, we automated this process for patient-generated data. Finally, we evaluated the program against a clinician-generated gold standard.

Methods

We conducted a qualitative study to develop a suggestion system, then automated and evaluated it. Participants (n=2) with T2D collected the meal data used in this study with a mobile application designed to support dietary self-monitoring during Fall 2014. Participants took a photo and recorded a text description of each of their meals during a 30-day period. These participants also recorded their pre-meal and two-hour-post-prandial blood glucose. An expert RDN used the USDA nutrition database to estimate calories and macronutrient (i.e., protein, fat, carbohydrate, and fiber) composition of each meal based on the meal photos and text descriptions. Datasets included meals (P1 n=72; P2 n=105) linked to BG readings (P1 n=304, P2 n=211) as well as information about meal type (i.e., breakfast, lunch, dinner, snack), blood glucose change, and calorie content and macronutrient content, from which the proportion of calories from each macronutrient were derived (e.g., proportion of calories from carbohydrate). Additional study details are reported elsewhere[4].

Interview data were collected as part of a qualitative study with RDNs (n=10, 100% female, aged 25-40, 100% had a graduate degree in nutrition, 100% had counseled patients with T2D) to assess the usability of an interface for synthesizing and viewing patient-generated meal data. Additional study details are reported elsewhere[7]. During these interviews, participants were also asked to "think aloud" through the process of using meal photos and macronutrient composition of the meals in the photos to counsel a patient. These interviews were recorded and transcribed. The current study includes a secondary analysis of these data. The Columbia University Medical Center IRB approved all methods for this study.

The first author coded sections of the interviews describing counseling procedures using process coding[8]. In process coding, text segments are annotated with a gerund (i.e., an action word usually ending in –ing). Interviews were coded until saturation was reached (i.e., new codes were no longer arising from the data)[9]. Through an iterative decision tree modeling analysis[10], these first level codes were combined into higher-level codes (i.e., main themes) that were ordered sequentially to represent the RDNs' counseling process. The 2010 Dietary Guidelines for Americans (DGA)[11] were consulted to make relevant decision points more specific. Two RDNs who participated in the interviews examined the visual representation of the decision tree model during a second interview with the first author. They were asked to assess face validity of the decision tree as well as the usefulness of the decision tree as a knowledge representation.

Next, we automated the decision tree model by translating it into a machine-readable form to facilitate the computer reasoning necessary to transform meal data into goals. First, we created a task-specific ontology, consisting of classes and attributes derived from the main themes. Then, the decision tree model was used as a basis for a series of functions that transform meal data into personalized patient goals. Functions were written in R Version 3.0.7 (The R Foundation for Statistical Computing, Vienna, Austria).

We evaluated the output of the suggestion system against an expert-generated gold standard. Two certified diabetes educators (CDEs), one an RDN and one an RN, worked with the supervising author in an iterative process to develop an set of recommendations for two patients using a set of meal photos and associated macronutrient data for 30 days worth of meals. Importantly, these highly trained and very experienced experts had unlimited time to examine the raw data to develop a set of recommendations for each patient. For each patient, the CDEs met four times for 60-90 minutes and developed a consensus gold standard. The first author qualitatively compared program output to the gold standard to assess initial validity.

Results

Initial coding resulted in 36 process codes and seven themes representing the clinical decision making process. The themes were: 1) Using BG impact to reduce the size of the dataset, mostly by focusing on impactful meals; 2) Identifying target BG ranges/excursions, which included identifying BG changes that exceeded 50 mg/dl; 3) Assessing portion size and macronutrient content, which included "eyeballing" carbohydrate content, and assessing calorie content, portion size, and proportions of macronutrients in a meal; 4) Assessing patterns/trends and deviations, which included assessing variation in meals and identifying “red flags”; 5) Using knowledge about metabolism, time of day, and guidelines to identify patterns and compare macronutrient intake to recommendations; 6) Developing hypotheses, which included working backwards and getting additional information from a patient to identify problems and inform goals; and 7) Simplifying the counseling message.

The decision tree modeling analysis resulted in a knowledge representation that consisted of a four-step process (Figure 1). The first step in the process was assessing BG impact and reducing the dataset by splitting it into high and low blood glucose impact meals. Based on information provided during the gold-standard generation, the decision rule was set at a BG change of ≥50mg/dl at 2 hours after the meal. The second step was identifying ranges and excursions using recommended macronutrient ranges for meals in both the low impact and high impact datasets. As there were no diabetes-specific recommendations for macronutrient ranges, we used the DGA to establish the proportion of calories from each macronutrient (i.e., carbohydrate=45-65%, fat=20-35%, protein=10-35%). Fiber recommendations suggested 25-30 grams/day, rather than a proportional range. Considering the typical American’s under consumption of fiber, we set the threshold for fiber at 8g/meal. The third step in the process was identifying patterns by comparing deviations from the guidelines between the low and high impact meals. The decision rules for this comparison were as follows: If the low impact meals have more of the macronutrient, eat more of that macronutrient; if the high impact meals have more of the macronutrient, eat less of the macronutrient; if there is no difference, present no goal. The fourth step was developing a goal using knowledge about time of day. This step translates deviations between low and high impact meals into human-readable goals, and makes them meal-specific to account for differences in blood glucose change throughout the day and to make goals more actionable.

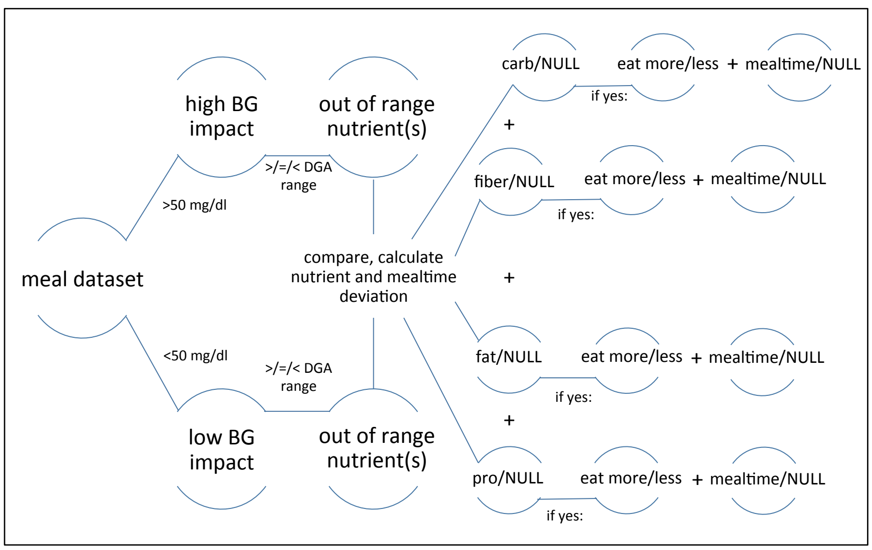

Figure 1. Decision Tree Model for Diabetes Goal Setting Based on Qualitative Analysis.

We validated the decision tree with two RDNs who independently determined that it represented an appropriate process of determining dietary goals for patients with T2D. They suggested that some macronutrients were less likely to impact blood glucose change and that the timing of snacks should be considered. Both RDNs were enthusiastic about the prospect of an automated system to identify meal-BG patterns.

To automate the system, we developed an ontology and a set of functions to reason over the knowledge representation. The ontology consisted of five classes: BG change, macronutrients, meal type, deviation from guideline, and goal. Macronutrient and goal classes had subclasses to represent each of the macronutrients of interest. Attributes varied by class and reflected decision rules. BG change attributes were high or low; each macronutrient could have the attribute high, low, or in range based on DGA, except fiber, which was high or low because there was no range; meal type attributes were breakfast, lunch, dinner, or snack; deviation was -1, 0, or 1 based on a simple subtraction low impact - high impact; goal attributes were eat more, eat less, or null. The input for the R functions was a data frame that consists of one row per meal and columns for meal type (i.e., breakfast, lunch, dinner, snack), BG change, proportion of calories from carb, proportion of calories from protein, proportion of calories from fat, and grams of fiber; the output of data-to-goals is four lists of goals, one list per meal. In order to make the computation more efficient and to approximate the “eyeballing” the RDNs used, high and low impact meals were grouped by meal type and an average score comparing the typical meal to the dietary guideline was calculated and rounded to the nearest whole number score. In order to assess deviations the following heuristic was used: High = 1/In range = 0/Low = -1**;** Deviation = low – high**;** If negative → "eat less"/If positive → "eat more".

The program output and the gold standard were about 69% consistent for P1 (Table 1) and 83% consistent for P2 (Table 2). It is important to note that because the CDEs were given access to the raw meal photo data during the development of the gold standard, some gold standard components were not possible to match to the goal output from the program. For example, the CDEs observed the "texture of carbohydrates has an impact on BG."

Discussion

This paper outlines and validates a novel method for generating personalized nutritional recommendations for individuals with T2D using their self-monitoring data and knowledge engineering methods. This work represents an extension of previous knowledge representations to support dietary self-management of T2D[6] by incorporating information from RDNs and CDEs about the counseling process as well as clinical guidelines. We successfully avoided many of the common problems that arise during knowledge engineering[12,13]. In particular, we targeted a very specific, well-defined problem that clinicians are eager to receive help with. Additionally, our team included several domain experts, as well as a knowledge engineer with domain expertise in nutrition. Although some have argued that building computer systems to mimic expert decision making is futile due to human ability to synthesize multiple data sources and make intellectual decisions without explaining a stepwise process for arriving at those decisions[14], this task in particular differs for several important reasons. First, when counseling based on large sets of objective data about meals human experts may be prone to apophenia[3], noting patterns where there are not, in order to make a large set of data more manageable. Second, clinicians cannot be aware of all published evidence. For example, RDNs suggested some macronutrients (i.e., fat) did not physiologically influence blood glucose; however, this clinical assumption is not borne out in the literature. This suggests the potential benefit of a system that can integrate new knowledge as it arises through consensus in the literature and future application of symbolic methods in this area. As noted in the literature on expert systems, using a system like the one presented here may facilitate the translation of research to practice[13], thereby improving the quality of expert nutrition advice, which often relies heavily on personal experience, bias, and habit.

Table 1. Qualitative Evaluation of Recommender Performance for P1

Recommender	Gold Standard	Evaluation
Breakfast eat more carb	•When breakfasts had higher proportion of carbs (more than 40%) and lower in protein (less than 40%), there is a higher differential (over 100) in 1 hour •High carb (over 40%) in breakfast meals, combined with low protein (20%) lead to high excursions •When breakfasts include more than 1 serving of fruit there is a higher differential (over 100) in 1 hour •The majority of high impact meals are breakfasts • High fiber and mod carb leads to low impact	Inconsistent
Breakfast ok on fiber	•Overall, this person includes relatively high amount of fiber (over 5g per meal on average) •High fiber (over 15g) and moderate carb (20-40%) leads to low impact (lower than 50)	Consistent
Breakfast ok on protein	•High carb (over 40%) in breakfast meals, combined with low protein (20%) lead to high excursions •In meals with fat around 35-40% and low protein (under 10g), mild impact (only in some clusters)	Inconsistent
Breakfast ok on fat	•No excessive amounts of fat (greater than 35% of calories come from fat) •In meals with fat around 35-40% and low protein (under 10g), mild impact (only in some clusters)	Consistent
Lunch ok on carb	•Long break between breakfast and lunch and over-restriction of carbs in lunch lead to high excursion •Overall, this person is less restrictive in carbs •High fiber (over 15g) and moderate carb (20-40%) leads to low impact (lower than 50)	Both
Lunch ok on fiber	•Overall, this person includes relatively high amount of fiber (over 5g per meal on average) •High fiber (over 15g) and moderate carb (20-40%) leads to low impact (lower than 50)	Consistent
Lunch ok on protein	•High proportions of calories (over 50%) in lunch and dinner come from protein •Lunch: high inclusion of protein (over 55%) with generally mild glycemic impact	Consistent
Lunch ok on fat	•No excessive amounts of fat (greater than 35% of calories come from fat) •In meals with fat around 35-40% and low protein (under 10g), mild impact (only in some clusters)	Consistent
Dinner ok on carb	•Overall, this person is less restrictive in carbs	Consistent
Dinner eat less fiber	•Overall, this person includes relatively high amount of fiber (over 5g per meal on average) •High fiber (over 15g) and moderate carb (20-40%) leads to low impact (lower than 50)	Both
Dinner ok on protein	•High proportions of calories (over 50%) in lunch and dinner come from protein •High inclusion of protein (over 55%) with generally mild glycemic impact (at lunch in particular)	Consistent
Dinner eat less fat	•No excessive amounts of fat (greater than 35% of calories come from fat) •In meals with fat around 35-40% and low protein (under 10g), mild impact (only in some clusters)	Inconsistent
Snack eat more carb	•High fiber (over 15g) and moderate carb (20-40%) leads to low impact (lower than 50) •Overall, this person is less restrictive in carbs •High carb (over 40%) in breakfast meals, combined with low protein (20%) lead to high excursions	Inconsistent
Snack ok on fiber	•Overall, this person includes relatively high amount of fiber (over 5g per meal on average) •High fiber (over 15g) and moderate carb (20-40%) leads to low impact (lower than 50)	Consistent
Snack ok on protein	No mention of protein at snack	Consistent
Snack ok on fat	No excessive amounts of fat (greater than 35% of calories come from fat)	Consistent

Table 2. Qualitative Evaluation of Recommender Performance for P2

Recommender	Gold Standard	Evaluation
Breakfast ok on carb	•Generally, this person is quite restrictive in carbs (under 60g for most meals) •Moderate amount of carb (around 30g-40g) combined with higher fiber (around 9-10g or higher) lead to more moderate impact •Breakfast – generally minimal excursion (carbs between 13 and 15, which is lower than for other types of meals because of the proportionately higher fiber, around 9g or higher, as compared to other meals) •High carbohydrate meals (over 40g) that have more even inclusion of other macronutrients have more moderate impact (around 50 or below; particularly for dinner) – but low certainty because only few cases	Consistent
Breakfast ok on fiber	•Breakfast – generally minimal excursion (carbs between 13 and 15, which is lower than for other types of meals because of the proportionately higher fiber, around 9g or higher, as compared to other meals) •Higher fiber does not seem to have a positive impact on BG (meals with low fiber, lower than 5g, have low glycemic impact) •High fiber (over 10g) and high fat (45-60%) together lead to low impact •Refined carbs (corn chowder) contribute to high impact	Both
Breakfast ok on fat	•High fiber (over 10g) and high fat (45-60%) together lead to low impact	Inconsistent
Breakfast ok on protein	•High carbohydrate meals (over 40g) that have more even inclusion of other macronutrients have more moderate impact (around 50 or below; particularly for dinner) – but low certainty because only few cases	Consistent
Lunch ok on carb	•Generally, this person is quite restrictive in carbs (under 60g for most meals) •Moderate amount of carb (around 30g-40g) combined with higher fiber (around 9-10g or higher) lead to more moderate impact	Consistent
Lunch ok on fiber	•Moderate amount of carb (around 30g-40g) combined with higher fiber (around 9-10g or higher) lead to more moderate impact •Higher fiber does not seem to have a positive impact on BG (meals with low fiber, lower than 5g, have low glycemic impact)	Consistent
Lunch ok on fat	•Lunch – when greater than 45% of calories came from fat, the meals often had high excursion •High fiber (over 10g) and high fat (45-60%) together lead to low impact	Both
Lunch ok on protein	•High carbohydrate meals (over 40g) that have more even inclusion of other macronutrients have more moderate impact (around 50 or below; particularly for dinner) – but low certainty because only few cases	Consistent
Dinner ok on carb	•Generally, this person is quite restrictive in carbs (under 60g for most meals) •Moderate amount of carb (around 30g-40g) combined with higher fiber (around 9-10g or higher) lead to more moderate impact •High carb meals (over 40g) that have more even inclusion of other macronutrients have more moderate impact (around 50 or below; particularly for dinner), but low certainty - few cases	Consistent
Dinner ok on fiber	•Moderate amount of carb (around 30g-40g) combined with higher fiber (around 9-10g or higher) lead to more moderate impact •High carb meals (over 40g) that have more even inclusion of other macronutrients have more moderate impact (around 50 or below; particularly for dinner), but low certainty - few cases •Dinner – the lunch trend of high proportions does not hold. •At dinner, similarly high proportions of fat and protein did not lead to high excursions, potentially because of higher fiber (10g and above), but low certainty - variability •Higher fiber does not seem to have a positive impact on BG (meals with low fiber, lower than 5g, have low glycemic impact)	Consistent
Dinner ok on fat	•High carb meals (over 40g) that have more even inclusion of other macronutrients have more moderate impact (around 50 or below; particularly for dinner), but low certainty - few cases •Dinner – the lunch trend of high proportions does not hold. •At dinner, similarly high proportions of fat and protein did not lead to high excursions, potentially because of higher fiber (10g and above), but low certainty - variability •High fiber (over 10g) and high fat (45-60%) together lead to low impact	Consistent
Dinner ok on protein	•High carb meals (over 40g) that have more even inclusion of other macronutrients have more moderate impact (around 50 or below; particularly for dinner), but low certainty - few cases •Dinner – the lunch trend of high proportions does not hold. •At dinner, similarly high proportions of fat and protein did not lead to high excursions, potentially because of higher fiber (10g and above), but low certainty - variability	Consistent

RDNs agreed in their interviews that if some of the detective work of analyzing patient generated data were taken out of a clinical encounter, more time could be spent on guided practice and problem solving, potentially improving patient experience and success in achieving dietary self-management goals. While the experts who developed the gold standard for this study had unlimited time and multiple meetings to discuss and develop a consensus set of recommendations, a typical clinical encounter is 15-45 minutes. This suggests that this sort of decision support could feasibly become part of a clinical workflow, an essential component of CDS adoption[15]. Furthermore as FHIR resources become more common, they will support the integration of patient-generated data with clinical practice[17].

The expert system presented in this study was validated qualitatively on proximal outcomes. Though it is important that nutrition experts noted its potential utility and that the knowledge representation framework itself reasonably represented the process of generating a goal from patient data, future validations might assess the accuracy of the output by providing the dietitians and recommender the same data and a closed set of goals. Future studies should also evaluate the effect of the system on patient behavior change. It is possible that the suggestion system is better at identifying true patterns than experts, which would require a comparative effectiveness evaluation to assess. The current system does not treat morning and evening snacks separately; this will be implemented in future versions as both the literature[17] and the RDNs suggested BG change varies throughout the day. Finally, this system is limited by its reliance upon a fairly extensive self-monitoring data, a known challenge for many patients[18].

Future directions for this research include linking the recommendation system to more specific action plans because people tend to be more successful when they lay out how they will achieve their goal. In previous research, our team developed a knowledge base for diabetes problem solving, consisting of culturally appropriate action plans[19]; these can be connected to the goals presented here, thus providing patients with a context-relevant set of action plans from which to choose in order to support their goal attainment. The system presented here could also be linked to a food ontology in order to suggest personalized specific food suggestions that meet the macronutrient goals. Additional directions include the implementation of computational modeling to improve the quality of the pattern recognition among the meals presented in a patient's data. Finally, future iterations of this system could incorporate other contextual data generated along with meal data in order to better tailor action plans for "just in time" interventions[20] to help patients overcome barriers to achieving their dietary goals.

Conclusion

The suggestion system presented here represents a step towards a decision support tool for dietary management of T2D that could be applied in the clinical and personal informatics domains. As patient generated data becomes increasingly widespread and clinicians see its utility, many will want to employ it to connect with their patients and make care more personalized. The suggestion system presented here also provides a basis for providing individuals engaged in self-monitoring a more actionable synthesis of their data.

References

1. Funnell MM, Brown TL, Childs BP, Haas LB, Hosey GM, Jensen B, Maryniuk M, Peyrot M, Piette JD, Reader D, Siminerio LM. National standards for diabetes self-management education. Diabetes Care. 2009 Jan 1;32(Supplement 1):S87-94.
2. Wharton CM, Johnston CS, Cunningham BK, Sterner D. Dietary self-monitoring, but not dietary quality, improves with use of smartphone app technology in an 8-week weight loss trial. Journal of nutrition education and behavior. 2014 Oct 31;46(5):440-4.
3. Boyd D, Crawford K. Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. Information, communication & society. 2012 Jun 1;15(5):662-79.
4. Mamykina L, Levine ME, Davidson PG, Smaldone AM, Elhadad N, Albers DJ. Data-driven health management: reasoning about personally generated data in diabetes with information technologies. Journal of the American Medical Informatics Association. 2016 Mar 16;23(3):526-31.
5. Haug PJ, Gardner RM, Evans RS, Rocha BH, Rocha RA. Clinical decision support at Intermountain Healthcare. Clinical decision support systems. 2007:159-89. New York: Springer.
6. Chen JX, Su SL, Chang CH. Diabetes care decision support system. In Industrial and Information Systems (IIS), 2010 2nd International Conference on 2010 Jul 10 (Vol. 1, pp. 323-326). IEEE.
7. Feller DJ, Levine ME, Burgermaster M, Albers DJ, Mamykina L. Using visual analytics and patient-generated data to support clinical decision-making in the context of nutritional therapy for individuals with diabetes. ARCH Lab; 2017 (Unpublished).
8. Saldaña J. The Coding Manual for Qualitative Researchers. 2 edition. Los Angeles: SAGE Publications Ltd; 2012.
9. Patton MQ. Qualitative Research & Evaluation Methods. 3rd edition. Thousand Oaks, Calif: SAGE Publications, Inc; 2001.
10. Miles MB, Huberman AM. Qualitative Data Analysis: An Expanded Sourcebook. 2nd edition. Thousand Oaks: SAGE Publications, Inc; 1994.
11. US Department of Health and Human Services. US Department of Agriculture. Report of the Dietary Guidelines Advisory Committee on the Dietary Guidelines for Americans, 2010.
12. Heathfield HA, Wyatt J. Philosophies for the design and development of clinical decision-support systems. Methods of information in medicine. 1993 Feb;32(1):1-8.
13. Carter JH. Design and implementation issues. In Clinical Decision Support Systems 2007: 64-98. New York: Springer.
14. Engle Jr RL. Attempts to use computers as diagnostic aids in medical decision making: a thirty-year experience. Perspectives in biology and medicine. 1992;35(2):207-19.
15. Clayton PD, Hripcsak G. Decision support in healthcare. International journal of bio-medical computing. 1995 Apr 1;39(1):59-66.
16. Mandel JC, Kreda DA, Mandl KD, Kohane IS, Ramoni RB. SMART on FHIR: a standards-based, interoperable apps platform for electronic health records. J Am Med Inform Assoc. 2016;23(5):899-908. doi:10.1093/jamia/ocv189.
17. Monnier L, Colette C, Boegner C, Pham TC, Lapinski H, Boniface H. Continuous glucose monitoring in patients with type 2 diabetes: Why? When? Whom?. Diabetes & metabolism. 2007 Sep 30;33(4):247-52.
18. Klasnja P, Pratt W. Healthcare in the pocket: mapping the space of mobile-phone health interventions. Journal of biomedical informatics. 2012 Feb 29;45(1):184-98.
19. Cole-Lewis HJ, Smaldone AM, Davidson PR, Kukafka R, Tobin JN, Cassells A, Mynatt ED, Hripcsak G, Mamykina L. Participatory approach to the development of a knowledge base for problem-solving in diabetes self-management. International journal of medical informatics. 2016 Jan 31;85(1):96-103.
20. Nahum-Shani I, Smith SN, Tewari A, Witkiewitz K, Collins LM, Spring B, Murphy S. Just in time adaptive interventions (JITAIS): An organizing framework for ongoing health behavior support. Methodology Center technical report. 2014(14-126).