Alexa, What Should I Eat?

A Personalized Virtual Nutrition Coach for Native American Diabetes Patients Using Amazon's Smart Speaker Technology

Bikesh Maharjan, Juan Li, Jun Kong
Computer Science Department
North Dakota State University
Fargo, USA
{bikesh.maharjan, j.li, jun.kong}@ndsu.edu

Cui Tao
School of Biomedical Informatics
University of Texas Health Science Center at Houston
Houston, USA
Cui.Tao@uth.tmc.edu

***Abstract*—Native Americans are disproportionately affected by diabetes and diabetes complications. To control this disease, self-management, especially diet management is very important. There have appeared many electronic tools to help diabetic patients to manage their diet and control their blood glucose level. However, due to their lack of consideration of the special requirement of this ethical group, these tools are not well-accepted by Native American communities. In this paper, we propose a culturally appropriate tool to help this population to manage their disease. Specifically, we propose a voice-based Artificial Intelligence-powered virtual assistant to help Native American diabetic patients to manage their daily diet, and to learn food and nutrition-related knowledge. Voice is the most natural communication modality and it is easy to use without any technical background. In addition, the communication and recommendation provided by the system are personalized based on each user's physical, social, and cultural profile. Therefore, it would be easy to be accepted by the target audience. The proposed virtual assistant has been implemented on the Amazon Alexa platform. Preliminary experiments have demonstrated the usefulness of the virtual assistant.**

Keywords- Native Americans; diabetes; Voice-based technology, Alexa

I. INTRODUCTION

Native Americans (NAs), including American Indians and Alaska Natives, have a greater chance of having diabetes than any other US racial group [1]. Appropriate food and nutrition are integral components of diabetes management and diabetes self-management education [2]. However, it's not easy for patients to remember all the health guidelines, constraints and manually count calories. Although there are lots of websites and mobile apps available for nutrition coaching, meal planning and calorie counting (e.g., [3][4]), they are not well accepted by NA patients because of two major reasons: (1) These tools are not targeted specifically for NAs who are experiencing lower rates of health literacy, cultural differences, poverty, and social determinants of health. (2) The complexity of these digital tools makes them intimidated for NA users especially seniors who struggle to use a computer or smartphone because of poor vision and/or lack of familiarity with the computer interface.

To overcome the problems of existing digital tools, we propose an Artificial Intelligence-powered virtual agent to assist diabetes self-management specifically for NA users. Based on a recent report, more than 35 million Americans are using voice-enabled technologies such as Google Home, Amazon Alexa, and Microsoft Cortana. Among these technologies, the most popular one is Amazon Alexa that alone has dominated 70.6% share of the market [5]. Alexa is capable of voice interaction, music playback, making to-do lists, setting alarms, streaming podcasts, playing audiobooks, and providing weather, traffic, sports, and other real-time information, such as news [6]. Alexa can also control several smart devices using itself as a home automation system. Currently, interaction and communication with Alexa are only available in English, German, French, Italian, Spanish, and Japanese [7].

Since Amazon launched its Alexa skill store (like Apple's App Store and Android's Play store) in 2015, third-party skill developers all over the world have created over 10,000 skills for various uses [8]. These skills enable users to interact with their Alexa-enabled devices using natural language in a variety of ways ranging from gaming and shopping to gathering news, weather, travel, health, and fitness information.

With an increase in the use of voice-enabled devices, researchers have started to developed voice applications to innovate the healthcare domain. For example, some voice applications help elderly people, people with age-related disabilities or people with motor and vision impairments to enjoy doing the most usual works such as making a shopping list, playing music[9]. Also, voice-based healthcare education provides people with medically related information such as immunizations, colorectal cancer screenings [10] [11]. There are even research attempts to answer patient's questions about their condition, symptoms, medications and upcoming appointments to provide updates to health personnel if required [12].

In this paper, we propose an Artificial Intelligence - powered virtual agent to assist diabetes intervention for NAs in a culturally appropriate way. The patient-centered virtual health assistant will interact with NA users through Amazon's voice-activated technology, Alexa. It gives patients 24/7 access to useful information about food, nutrition and recommends food/meal to patients specific to their disease, age, social setting, preferences, tastes, financial ability, literacy, and culture. Voice is the most common way of communication in our daily life, thus providing a natural way of engaging with technology that requires minimal training. Our virtual agent-based intervention will remove NA patient's access barriers, increase patient literacy, patient engagement, thus sustainably improving the state of healthcare.

The rest of the paper is organized as follows. Section II surveys related work on meal recommendation system and Alexia Skills in Healthcare domain. Section III describes our proposed methodology in detail. Section IV presents our evaluation through five use case studies. Finally, in Section V, we provide conclusions and future work directions.

II. Related Work

A. Meal-and Nutrition Recommendation Systems

A multitude of mobile apps and online websites have been developed to make meal planning and food nutrition recommendation for maintaining a healthy lifestyle and losing weight. For example, the mobile app Mealtime [13] offers recipes tailored to the user's diet need and preference. Similarly, PlateJoy [14], Yummly [15] and PlanToEat [16] are also recipe manager including menu planning features.

With the epidemic of diabetes, more and more apps have been designed for diabetes patients to make healthy eating plans. MyFitnessPal [17] is one of the most popular health apps for diabetes diet management. It has a food database, including many restaurant foods. It also supports bar-code scanning to locate foods at the stores. My Diet Diary Calorie Counter [18] works as a digital diary for users to record their meals and physical activity. It helps users track carb intake and other nutrients and total calories. There are many other similar apps (e.g. [19] [20]) to assist diabetes patients in maintaining their healthy eating lifestyle.

Although these systems have been used in the general population, they are not popular among NA users because they do not consider NA users' special condition, such as low health literacy, low income, and cultural differences. Also, the interface is too complex for people without too many experiences with the digital device.

B. Alexa Skills for Healthcare

The potential of the voice-enabled devices in the field of healthcare has been noticed. Recently, Amazon has launched HIPAA compliant health care skills. 'KidsMd' is an Alexa skill developed by Boston Children's Hospital to allow parents to know their child's health symptoms [21]. This helps parents to decide whether they can treat their child or it's better to visit the professionals. Similarly, Boston Children's Hospital has worked on 'MyChildren's Enhanced Recovery After Surgery' Skill that allows parents to update the care team in the hospital about the recovery progress after a child has gone through heart surgery, It can also remind parents of their child's scheduled appointments [22]. 'Answers By Cigna' is another Alexa skill developed with the goal to reduce the existing gap between people and healthcare professionals. It can explain the meaning of the vocabularies

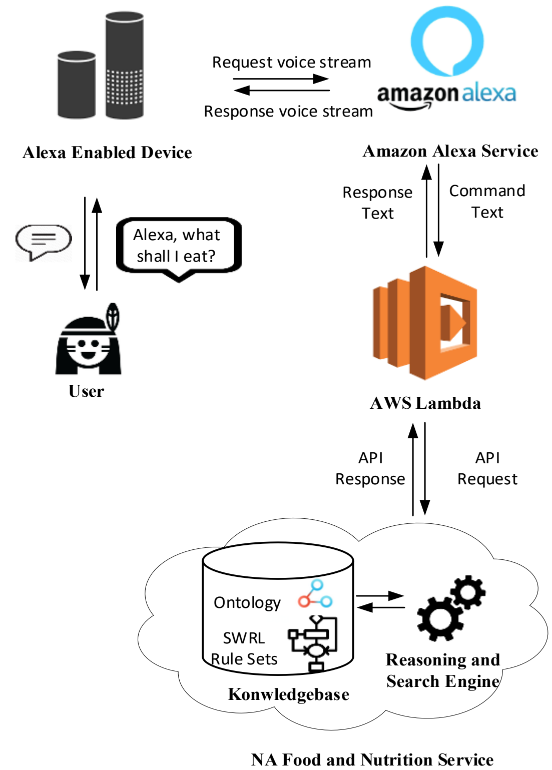


Fig. 1. Architecture of the system

that one may find unfamiliar with [23]. Alexa skill 'Livingo' allows the user to ask their last blood sugar reading [24]. Skills such as 'Express Script' [25] and 'Swedish Health Connect' [26] are helping people to order their medicines and set the next appointment with the health service provider. "Libertana Home Health Care" is a skill that helps nurses to assist their elderly patients [27]. Using this skill, nurses can quickly check if the patients have taken their medication. It also enables family members of elderly patients with the same access.

More and more skills are being developed to help people manage their health every day. To the best of our knowledge, there are no Skills developed specifically for NA diabetes patients to manage their disease.

III. System Design

The goal of the system is to design an Amazon Skill to extend the capability of Amazon Alexa to support diabetes management for NA users. The system is designed based on Amazon Alexa Software Development Kit (SDK), through which we can leave the Automatic Speech Recognition (ASR) and Natural Language Understanding (NLU) functionality to Amazon services and focus on the application logic.

Our skill defines a number of request types called "intents" in Alexa terms. Each intent represents a call to a food and nutrition service we implemented at the backend server for NA diabetes management. One intent represents a call/function interface to a particular service (e.g., a meal recommendation, a nutrition explanation); each intent can be mapped to several utterances (natural language phrases) for example ("what shall I eat", "recommend diner"). An utterance can refer to one or more slots (request parameters).

Fig. 1 shows the interaction flow of the proposed skill. Our skill takes a user's voice input from Amazon Alexa. Alexa converts speech input into text using Automatic Speech Recognition and Natural Language Understanding. Based on the schema we defined, Alexa can match with the intent defined in the AWS Lambda. AWS lambda and Alexa work together to collect all the data (slots) required from the user using the dialog management. To link the dialogue with a particular user's profile, context, and diabetes diet medical guidelines, we propose an ontology-based backend service layer. This layer bridges the gap between high-level application logic and low-level dialogue specifications. It allows the dialogue to be dynamically adapted according to the current high-level context. Once all the required slots are filled up, then lambda calls the API of our backend services. The backend service is mainly supported by a semantics-based reasoner working on the user's input, facts, and rules in the local knowledge base. Finally, AWS lambda sends text response from the backend service to Alexa which speaks it out to the user.

A. Knowledgebase to Extend Alexa's Domain Knowledge

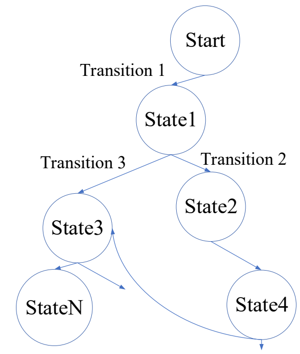
Most current digital voice assistants (e.g., Apple Siri, Amazon Alexa) cannot provide satisfying responses for healthcare questions due to their lack of domain knowledge. In addition, in order to provide a voice assistant that customized for the NA population, their specific needs and requirements also need to be embedded.

1) Knowledge in the form of ontology

We propose an ontology-based, semantic-oriented infrastructure for the fusion of heterogeneous related information and knowledge for this purpose. We extend Alexa's knowledgebase with new customized knowledge – an ontology focusing on concepts, relations, constraints, and rules about diabetes, diabetes-care guidelines, NA profile, food, and nutrition. An ontology explicitly represents a domain of discourse including a set of things, the properties of the things, and the relationships between the things. It semantically defines domain knowledge in standard ways that allow computer programs to understand and query the knowledge intelligently [37]. We have used an ontology defined in our previous work [38]. The ontology includes two major parts (a) a user profile ontology which captures NA user's social, economic, cultural and physical properties and provides evidence for personalization; and (b) the ontology of diabetes self-management support and education, which captures essential knowledge in an NA-friendly language for healthy eating. Food and nutrition ontology defined from other sources have been reused.

2) Semantic Rules

Besides facts and relationships defined in the ontology, the knowledge base also includes rules based on professional medical guidelines related to diabetes management. We have collected diabetes management general guidelines, food and nutrition guidelines and NA-related healthcare guidelines such as guidelines defined in American Diabetes Association



(ADA) [28], Nutritional Recommendations for Individuals with Diabetes [29], the prevention and control of the type-2 diabetes by changing lifestyle [30], and Dietary Guidelines for Americans (USDA) [31]. Indian Health Services (IHS) [32], American Indian and Alaska Health [33] and the National Indian Health Board [34]. The collected rules were further verified by physicians in our research team and then converted to rules that computers can "understand". Recommendations then can be automatically generated using reasoning over the ontology of patient profile, context, and the rules. We use the Semantic Web Rule Language (SWRL), an expressive W3C standard OWL-based rule language to present the generated rules.

B. Dialog and Context Modeling

We propose a structured state-based dialog model to enable a conversation between users and Alexa. To create an engaging conversation between users and Alexa, we need to incorporate flexibility and responsiveness. We model the dialog flow as a state graph, which can help the system to track context and different dialog states, and corresponding transitions to maintain the dialog flow. In our dialog model. In each dialog state, we define a discrete set of interaction types, a historical context memory for previous conversation content.

Incoming messages from the user will set the conversation to a new state and corresponding response. As shown in Fig. 2, the state graph includes the following components: (1) an initial state representing the start of the conversation, (2) a set of possible input messages, (3) a set of potential states that may result from the input messages, and (4) a set of possible actions or output events that result from a new state. This graph can help the system produce coherent responses in an on-going multi-turn conversation. It also guides the conversation direction towards the predefined schema instead of letting the topic drift randomly or completely controlled by the user.

We propose a hierarchical architecture with one high-level Dialog Manager (DM) and multiple low-level DMs corresponding to specific tasks, topics, or contexts. The high-level DM manages the conversation process as a whole, while the low-level DMs manage conversation segments for particular interactions. This hierarchical DM architecture makes adding new skills or updating existing skill easier. This is especially useful for processing high-level conversation that needs to be updated frequently. We utilize the dialog management service built in Alexa ASK [35], to help the system maintaining the conversation with the end user. With dialog management, we can control what Alexa might tell the user and possible response from the user in return. We can keep track of the state of the conversation when a conversation starts under certain context, control the conversation based on the state (STARTED, INPROCESS, COMPLETED), and give a required response through Alexa.

In a dialog session, some information should be saved for the whole dialog session, some be saved for a few following sessions, while some others be saved permanently. These types of information are called session context or long-term context. For example, a user's age, height, allergy info is long-term context; while the meal she chose for lunch can be session context. Different context information may have different expire time. The topic of the last conversation and the last conversation state in the dialog state graph are also stored in the session context. After a response is sent to the user, the context information is stored in the backend database for future uses.

C. *Response Generation*

At each turn of conversations between the user and Alexa, the DM module performs a series of steps aiming to find a response which can address the user's request/query and meets the constraints of the conversation topic and context. In most cases, this process requires retrieving content from back-end services. The processed user request is then sent to a response-generation component at the backend server to produce responses. The major part of the response generation if a semantics-based reasoning engine and search engine. They are built to make context-aware personalized recommendations or question answering. The reasoning engine is built based on the knowledge base we created (Section III.A). The knowledgebase maintains a profile for each user. The profile contains the following sub-profiles: (1) basic profile which stores each user's basic information including user's age, gender, education background, (2) health profile with user's diabetes type, level, medication, allergy, (3) social profile with user's religion, income, and (4) preference profile. The user profile also tracks certain dynamic information, such as user's blood glucose level, time and amount of last meal (breakfast, lunch, dinner), or today's physical activities. All the dynamic information will be updated frequently through communication with the user.

We use forward-chaining (can be backward-changing too) to do automatic reasoning. The reasoning engine takes rules (in SWRL format [36]) from the rule set and facts from food, nutrition ontology, and user profiles information from the patient profile ontology in the knowledgebase. When a user query or request is received from the Alexa interface, the query/request is passed to this reasoning engine, the contextual information, and auxiliary information such as intent and sentiment, are fed into the reasoning/search engine together with the rules and facts to control the generation of responses. The reasoning engine will determine if the premises of any rule is available, and the corresponding rule will be fired. The newly generated facts then can be used for firing other rules. In this way, the forward chaining-based reasoner can consider user's profile (including health, preference, capability, socioeconomic status), and other context information/event to provide an appropriate personalized recommendation. The results from the reasoner will be further refined by a personalization module based on the user's general intents, interests, and preferences.

D. *Error Handling*

Our skill handles two kinds of errors, namely software error and comprehension error. Software errors are caused by software problems, such as bugs and exceptions. Comprehension errors are caused by a misunderstanding of user's intents. For software errors, we use a high-level exception handler to catch and process the error. Basically, we record the error in the log, and then we restart the conversation by resetting the dialog states. For comprehension errors, the DM cannot match the user's input to related intents or cannot find required slots for an intent. When that is detected, the system will acknowledge that the conversation is beyond its comprehension, and then it will provide suggestions to the user for continuing the conversation.

IV. EVALUATION

The product of our project is an Amazon skill "Diet Helper" that fulfills all the goals mentioned above while maintaining a certain quality and efficiency. We have performed a set of preliminary evaluations on the skill.

A. *Execution Environment*

The backend ontological server is configured as follows:

- Processor: Intel® Core™ i-7-4770 CPU @ 3.40 GHz (8 CPUs), ~ 3.4 GHz
- RAM: 32 GB
- OS: Windows 10 Home 64-bit (10.0, Build 17763)
- Programming Language: Java 8, JDK 1.8

The Amazon Lambda service:

- Runtime: Node.js 8.10
- SDK to communicate with Alexa: ask-SDK
- Logging service: Amazon CloudWatch Logs

B. *Example Case*

Based on the backend services, our skill can support a variety of food and nutrition recommendation and education cases. In particular, we have tested on the following cases: (1) meal suggestion, which includes suggesting a meal based on user's context, or commenting on a meal user come up, (2) local restaurant and restaurant menu recommendation, (3) recipe recommendation, (4) food nutrition explanation, (5) daily/weekly diet history recall, (6) adding food and recipe to user's favorite list (for future use), (7) daily/weekly diet summary and comments. These cases are not independent, based on the conversation flow and user's intents, multiple cases can be integrated and used in one conversation.

Fig. 3 demonstrates one example of a conversation. The user is a 41-year-old Native American male. He is a Type 2 diabetic patient with high blood pressure and is overweighed.

1) *User: Hi Alexa, open Diet Helper.*
2) *Alexa: Welcome to Diet Helper. What can I do for you?*
3) *User: How many calories are in 2 eggs and 4 slices of bacon?*
4) *Alexa: 2 large boiled eggs have about 156 calories, and 4 slices bacon have about 178 calories, so all together it's 334 calories.*
5) *User: Is it good for a breakfast?*
6) *Alexa: It is fine. But I would suggest adding some food rich in fiber.*
7) *User: What do you mean fiber?*
8) *Alexa: Dietary fiber is the part of food from plants that cannot be digested. Foods rich in fiber slows the absorption of sugar and regulates insulin response. Fiber can help lower blood cholesterol and prevent diabetes and heart disease. High fiber foods include: whole grain breads and cereals, brown rice, fresh fruits and vegetables.*
9) *User: Oh, I see, thank you.*
10) *Alexa: Is there anything else I can help?*
11) *User: No, thanks.*

Fig. 3. An example fragment of conversation about food and nutrition education and meal suggestion

In this conversation, the user asks Alexa to count his calories, and also get food and nutrition education information from Alexa. Utterance (1) shows the user asks Alexa to start our skill. Utterance (3) shows how a user asks Alexa to count calories. Utterance (4) is Alexa's answer. After receiving Alexa's response, in the utterance (5), the user changes the conversation context for meal recommendation. Utterance (7) shows that the user wants Alexa to clarify the meaning of some terms he doesn't understand. And utterance (7) shows how Alexa reacts by re-phrasing and elaborating the question the user asked.

Underneath this conversation, the backend server will make decisions by considering the user's food availability, cooking time, preference. Most importantly, it will extract the user's profile, context, and health guideline to get all the constraints for choosing the recipe. For example, below we list a few examples of healthy eating guidelines the system follows. Based on the U.S. Department of Health and Human Services 2010 Dietary Guidelines, if a person consumes three meals per day, one meal should contain 800 to 850 calories for a man. According to the American Diabetes Association, a person's protein intake should be in the range (20 - 30) % of the meal energy according. All these guidelines will be checked in our backend reasoning engine.

C. Qualitative Evaluation

Preliminary qualitative evaluations were performed by the research team. In the experiment session, a total of 150 conversations were attempted. For each conversation, one purpose was randomly chosen from three purposes, namely meal recipe recommendation (Purpose 1), food and nutrition education (Purpose 2), and daily nutrition summary (Purpose 3).

TABLE I
DIALOG PERFORMANCE TEST

Metrics\Purpose	Purpose 1	Purpose 2	Purpose 3
Dialog Successful Rate	76%	87.0%	80.0%
Avg Dialog time	69.4s	43.8s	45.3s
Time Per Turn	6.1s	8.4s	8.57s
Number of Turns per Dialog	11.0	5.2	5.6
Recommendation Accuracy (success conversation)	100%	100%	100%

Table I illustrates the experiment results in terms of several metrics. In this experiment, we define a threshold of the maximum number of dialog turns. If a conversation exceeds this threshold and the user still does not get the desired answer/suggestion/recommendation, it is regarded as a failed conversation. In this experiment, we set the threshold of maximal dialog turns as 30. Also, in our experiments, we only test conversation with one intent (no nested intents and context switching). Using that threshold, the conversation success rate can be defined as success rate, is defined as shown in Equation (1).

$$\text{conversation success rate} = \frac{\#of\ successful\ conversations}{\#\ of\ total\ conversations} \quad (1)$$

Recommendation/suggestion accuracy (or correctness) is defined in Equation (2). It is evaluated by manually checking if the recommended content is correct based on the medical guidelines and consistent with the artificially generated user profile.

$$\text{Accuracy} = \frac{\#\ of\ correct\ recommendations}{\#\ of\ total\ recommendations} \quad (2)$$

Table I demonstrates that the conversation success rate ranges from 76%-87%. Most of the failed conversations happened when Alexa could not identify user's intents or details of the intents, i.e., matching user's utterance with intents and filling in the slots. This happens more when the tester is new to the system without knowing too much of the service scope of the system. We have proposed several strategies to improve this performance: (1) Provide more hints and guidance during the conversation with the user, then the user will have a better idea of how to use the skill. (2) Define more utterances and synonyms for each intent to improve the matching rate. (3) Use machine learning, such as a deep neural network, to identify/classify users intents.

Table I also shows a 100% accuracy. The accuracy is manually verified by checking each recommendation to see if it is consistent with the user's physical and socioeconomic conditions and follows all constraints and guidelines. These experiments have confirmed the correctness of the recommendations.

V. CONCLUSIONS

In this paper, we present the design, development, and evaluation of our Alexa Skill on food and nutrition management for NA users. Voice is the most natural and effective communication morality. Voice-based healthcare intervention is convenient and natural. It does not require users to have any background on using complex digital computing devices. Our current research result is preliminary. We are planning to extend the skill to support more expressive patterns for different types of questions and requests.

In our future work, we will deploy the system to NA users in a real setting and more comprehensive user studies will be performed to evaluate the usability of the system, the satisfaction of the users to this system, and the health improvement outcome of using this system on the target NA populations.

ACKNOWLEDGMENT

This work was supported by the National Science Foundation (NSF) under Div. Of Information & Intelligent Systems (IIS) with award number: 1722913.

REFERENCES

[1] C. Centers for Disease Control and Prevention, "National Diabetes Statistics Report: Estimates of Diabetes and Its Burden in the United States. Atlanta, GA: Centers for Disease Control and Prevention; 2017," US Dep. Heal. Hum. Serv., no. Cdc, pp. 2009–2012, 2017.

[2] "Nutrition Recommendations and Principles for People With Diabetes Mellitus," Diabetes Care, vol. 20, no. Supplement 1, p. S14 LP-S17, Jan. 1997.

[3] GoMeals. [Online]. Available: http://www.diabetesincontrol.com/gomeals/.

[4] "CalorieKing," [Online]. Available: https://www.calorieking.com/

[5] C. Franzese and M. Coyne, "The promise of voice: Connecting drug delivery through voice-activated technology," ONdrugDelivery, vol. 2017, no. 81, pp. 34–37, 2017.

[6] Amazon Alexa - Wikipedia [Online]. Available: https://en.wikipedia.org/wiki/Amazon_Alexa

[7] globalme, "Language Support in Voice Assistants Compared," 2018. [Online]. Available: https://www.globalme.net/blog/language-support-voice-assistants-compared.

[8] S. Perez, "The numbers of Alexa skills in the U.S. more than doubled in 2018," 2019. [Online]. Available: https://techcrunch.com/2019/01/02/the-number-of-alexa-skills-in-the-u-s-more-than-doubled-in-2018/.

[9] F. Capan, "Why Amazon device is a gift for healthcare What WWE taught me about EHR promotion," no. January, p. 2016, 2016.

[10] M. Parfitt, "Voice interfaces in home healthcare How AI driven tech is being used to assist older people," pp. 2–5, 2019.

[11] T. Morrow, E. Savitz, and F. Staff, "How Virtual Health Assistants Can Reshape Healthcare," pp. 1–9, 2013.

[12] M. Technologies, "Amazon ' s Alexa Voice Service in Healthcare Why Alexa for Healthcare ? Potential Uses of Alexa in Healthcare IT," pp. 1–8, 2019.

[13] "Mealime." [Online]. Available: https://www.mealime.com/.

[14] "Platejoy." [Online]. Available: https://www.platejoy.com/.

[15] "Yummly." [Online]. Available: https://www.yummly.com/.

[16] "Plan to eat." [Online]. Available: https://www.plantoeat.com/.

[17] "My fitness pal." [Online]. Available: https://www.myfitnesspal.com/.

[18] "My diet dairy calorie counter." [Online]. Available: https://play.google.com/store/apps/details?id=org.medhelp.mydiet&h.

[19] "Dario blood glucose management system." [Online]. Available: https://mydario.com/.

[20] "Glucose buddy." [Online]. Available: https://www.glucosebuddy.com/.

[21] B. C. Hospital, "KidsMD brings the clinical expertise of Boston Children's Hospital beyond the walls of Boston Children's to provide parents and caregivers trusted guidance on how to care for the symptoms of their child." [Online]. Available: https://accelerator.childrenshospital.org/portfolio/kidsmd/.

[22] B. C. Hospital, "My Children's Enhanced Recovery After Surgery (ERAS) Alexa Skill," 2019. [Online]. Available: https://www.voice.health/news/my-childrens-enhanced-recovery-after-surgery-eras-alexa-skill.

[23] Cigna, "'Answers by Cigna' Skill for Amazon Alexa Simplifies, Personalizes Health Care Information," Cigna, 2018. [Online]. Available: https://www.cigna.com/about-us/newsroom/innovation/answers-by-cigna-personalizes-healthcare.

[24] Livongo, "Livongo for Diabetes Program Releases HIPAA-Compliant Amazon Alexa Skill," Cision, 2019. [Online]. Available: https://www.prnewswire.com/news-releases/livongo-for-diabetes-program-releases-hipaa-compliant-amazon-alexa-skill-300824462.html.

[25] E. Scripts, "Alexa, Open Express Scripts," 2019. [Online]. Available: http://lab.express-scripts.com/lab/insights/industry-updates/alexa-open-express-scripts.

[26] Swedish, "Providence St. Joseph Health Makes Same-Day Express Care Appointment Scheduling Available on Amazon Alexa," 2019. [Online]. Available: https://www.swedish.org/about/swedish-news-blog/2019/04/same-day-express-care-scheduling-with-amazon-alexa.

[27] "Libertana." [Online]. Available: https://www.libertana.com/.

[28] D. Care and S. S. Suppl, "Introduction: Standards of medical care in Diabetes 2018," Diabetes Care, vol. 41, no. Supplement 1, pp. S1–S2, 2018.

[29] M. Alison Gray, RD, "Nutritional recommendation for people with diabetes," NCBI, 2015.

[30] M. Asif, "The prevention and control the type-2 diabetes by changing lifestyle and dietary pattern," PMC.

[31] O. of D. P. and H. Promotion, "2015–2020 Dietary Guidelines for Americans." [Online]. Available: https://health.gov/dietaryguidelines/2015/.

[32] U.S. Department of Health and Human Services, "Indian Health Service." [Online]. Available: https://www.ihs.gov/.

[33] I. H. Service, "Diabetes." [Online]. Available: https://www.ihs.gov/forpatients/healthtopics/Diabetes/.

[34] N. I. H. Board, "National Indian Health Board and Public Health." [Online]https://www.nihb.org/public_health/public_health.php.

[35] A. Kumar et al., "Just ASK: Building an Architecture for Extensible Self-Service Spoken Language Understanding," pp. 1–13, 2017.

[36] M. O. Connor, "Chapter - The Semantic Web Rule Language," 11th Intl. Protégé Conf., 2009.

[37] Guarino, N., Oberle, D. and Staab, S., 2009. What is an ontology?. In Handbook on ontologies (pp. 1-17). Springer, Berlin, Heidelberg.

Li, J. and Alian, S., 2018, September. Design and Development of a Biocultural Ontology for Personalized Diabetes Self-Management of American Indians. In 2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom) (pp. 1-7). IEEE.