Live Personalized Nutrition Recommendation Engine

Nitish Nag
University of California, Irvine
Irvine, California
nagn@uci.edu

Vaibhav Pandey
University of California, Irvine
Irvine, California
vaibhap1@uci.edu

Ramesh Jain
University of California, Irvine
Irvine, California
jain@ics.uci.edu

ABSTRACT

Dietary choices are the primary determinants of prominent diseases such as diabetes, heart disease, and obesity. Human health care providers, such as dietitians, cannot be at the side of every user at all times to manually guide them towards optimal choices. Automated adaptive guidance fused with expert knowledge can use multimedia data to technologically scale health guidance without human intervention. Addressing the correct granularity of recommendations (in this case meal dishes) is essential for effortless decision making. Thus we make a decision support system using multi-modal data relying on timely, contextually aware, personalized data to find local restaurant dishes to satisfy a user's needs. Algorithms in this system take nutritional facts regarding products, efficiently calculate which items are healthiest, then re-rank and filter results to users based on their personalized health data streams and environmental context. Our recommendation engine is driven by the primary goal of lowering the barriers to a personalized healthy choice when eating out, by distilling dish suggestions to a single contextually aware and easily understood score.

CCS CONCEPTS

• **Information systems → Mobile information processing systems**; • **Human-centered computing → Ubiquitous computing**; **Mobile computing**; **Ambient intelligence**; **Smartphones**;

KEYWORDS

Personalized Health; Cybernetics; Precision Medicine; Nutrition Science; Multi-modal data streams; Human Modeling; Resource-Needs Matching; Recommendation Engine

1 INTRODUCTION

Mobile phone sensor technologies have created a vast amount of quantitative and qualitative multimedia regarding personal health. The next step in advanced health systems will be to effectively utilize this data to provide guidance for users. Since these data streams have different granularity levels, integration in the context of an application is an approach to extract utility from the data. Synchronized data streams can power recommendations for users to effectively manage their health at all times, location, and contexts. We believe that recommendation systems, such as in Figure 1, that combine user personal information and context, along with local physical resources will drive the future of health behaviors. We dive into this principle by guiding users towards healthy food options that are personalized for their biological and contextual parameters.

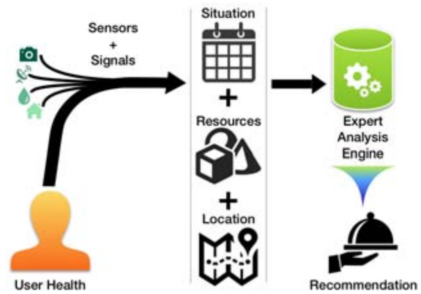

Figure 1: User data and context is expertly matched with local physical resources.

Improving health outcomes from lifestyle should be a normal part of life in every moment and place, not just medical intervention during illness. Health is essentially a product of our genome and lifestyle [24, 25] with lifestyle being the primary controllable aspect of our health.

Recent computational technology has rapidly advanced quantifying and personalizing services such as advertising, entertainment, and shopping. These advances have put customers at the center of power in driving commercial success, such as through reviews on Amazon products or likes on Facebook. Unfortunately consumers still lack personalized quantitative power in decision making regarding their health. Diet is the most dangerous aspect of health risk factors in most western countries [2]. Patients make better lifestyle choices that would combat diabetes if given guidance, and many health conscious consumers demand healthy food [23]. Human health service providers want their patients to access expert information at all times yet they cannot be at the patient side at all times. This problem exists due to the obvious difficulty of scaling human dissemination of knowledge, like in hospitals. Translating this expert knowledge into everyday life decisions needs to be in a live actionable form. For example, typically patients with diabetes who are supervised by nutrition experts meet once every three months. This is an inappropriate amount of support for a patient, who is choosing what to eat multiple times a day. The patient should have guidance at all times. Even if a nutritionist is available to guide a client, they don't usually have all information related to the appropriate nutrition in immediate context of the individual. This is

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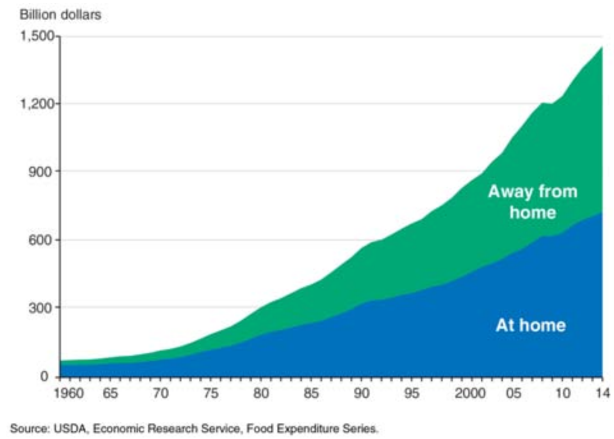

Figure 2: Consumer purchasing habits of spending on restaurant food continue to rise. The ratio of food spending at restaurants versus at home has continuously grown for the last 50 years. [27]

where personalized multi-modal data and resource databases can shine.

Consumers eat on average over 33 percent of their caloric intake from eating out at restaurants, which constitutes over half of their food expenditure as shown in Figure 2. In 1977, 18 percent of calories were from restaurants [14]. The future trend strongly points towards increasing food purchases made away-from-home. This is why assisting everyday lifestyle management for eating out must be inexpensive, scalable, and increase health transparency of consumer purchasing. This is especially important to reach all ends of the socioeconomic spectrum [17]. Companies like Amazon use quantitative measures like reviews or filters to help customers easily find what they are looking for at the correct granularity of the product. Nutrition facts on items are not very actionable by users and not personalized for their needs. They are too complex to analyze without expert knowledge, and are tedious to interpret. They are also static and are based on a population average. The main question we want to answer for every consumer is: "How will this product affect **my** health?". We quantitatively and independently judge the health metrics given product specifications. This way, a user can instantly know with transparency how a certain product may or may not fit their individual needs based on scientific expert knowledge. It has been shown, that with better knowledge about a decision, consumers make healthier choices [30].

A new era of health multimedia is ushering in expert knowledge and data resources with computational power to drive dynamic recommendations, alleviating the user of querying for their needs. Our inspiration is to provide the right guidance at the right time for users to best manage their health. Representing the spatio-temporal knowledge of food resources in a way for individual multi-modal health and environmental data to interact together is the fundamental problem in nutrition navigation. Ultimately, transforming data and knowledge to actionable lifestyle choices is the most promising, effective, and attainable method to improve human health. *We have developed an automated smartphone application that can place a personalized dietitian level of decision support for finding food with location and user context awareness.*

It is important to emphasize recommendations via expert knowledge as a potential key to unlock healthy diets for the world. Translating the multimedia work in this field from figures and statistics of past data to changing future behavior must be the eventual goal. Tracking diet is a very useful feature, but lacks the capability of giving actionable suggestions to improve health. The core problem at hand we are attempting to solve is real time needs-resource matching. Recommendations are essential to modern content and product consumption.

Improved dietary management is appreciated as a win-win-win factor by patients, providers, insurance, and government entities. Programs like the Diabetes Prevention Program (DPP) have been approved by the National Institute of Health in the United States for health insurance reimbursement codes. These programs use human face-to-face interaction to conduct dietary coaching. Similar preliminary efforts have shown technology interventions can improve clinical outcomes [4], such as doing these educational programs over video conference. DPP programs alone will be of relevance to over *100 million* patients in the United States. Accessibility to enough providers to address this population demand lags, hence the need for automated expert systems.

Access to human experts continue to stifle large scale dietary management improvements. Socioeconomic factors prevent most people from access to private dietitians. Education is also a large barrier. Furthermore, even those with health insurance are only reimbursed for nutrition consultation if they are at high risk or diseased, which is too late. Practicing nutritionists spend significant amounts of time trying to help recommend what their clients should eat in the clinical office, but are unable to connect to patients at the time when they are making nutritional choices.

2 RELATED WORK

Research efforts by nutrition researchers to grade the quality of food have addressed both qualitative and quantitative approaches. Qualitative approaches include the Healthy Eating Index and the Diet Quality Index are semi-quantitative [11]. From these methods, nutritionists have vocalized the need to translate expert recommendations into a usable platform for simple consumption by users [13] Given a certain budget, finding the best nutrition has also been explored [6]. Most of these studies use rudimentary methods that have not been able to integrate in daily life, or through the use of commonly available information like nutrition facts. Quantitative approaches with scoring mechanisms show weak associations with actual disease outcomes [28] [2]. Efforts in modeling expert knowledge are limited, for example, with linear correlations with a small panel of nutritionists [15]. Because nutrition facts are readily available for all major restaurant chains and for packaged items, algorithms that use this information are most promising for immediate consumer use and health impact. The North American derived Nutrient Rich Foods Index 6.3 (NRF) [10], French derived SAIN/LIM method [29], and British FSA [12] all are based more heavily on available nutrition facts, yet have not been established to capture expert knowledge of dietitians or utility for individual users [19]. Current mobile applications that use nutrition facts just offer filters on the data, such as less than 600 calories [22]. This still places the decision making burden of how to properly rank items available

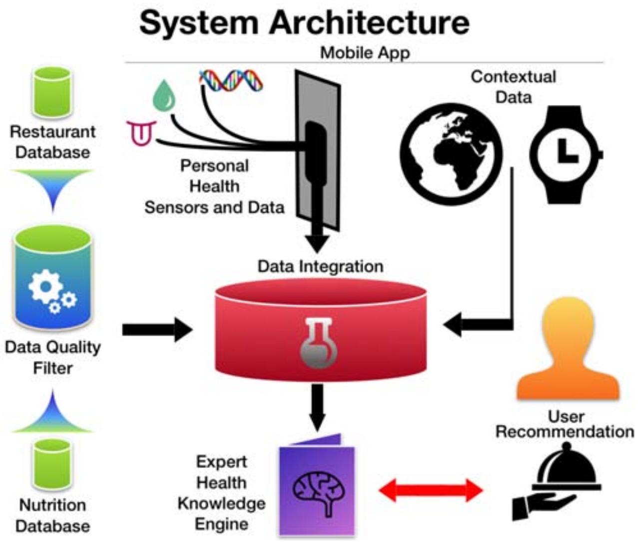

Figure 3: Block architecture of the live context aware personalized dietitian system.

for the user. Dietary decision support using algorithmic derivations to optimize health have been used in cattle feed analysis [9].

3 SYSTEM ARCHITECTURE

Figure 3 shows our core architecture. The person vector is defined by user's location and inherent health parameters such as weight, height, activity steps, altitude, and the entity vector is defined based on the nutritional analysis of each dish. The Daily Values (DV) of nutrients defines the interaction between the person vector and the entity vector.

3.1 Data Filter

We ensure basic data quality by doing numeric checks on ingredients and nutritional values. The filters include: 1.**Calories** filter ensures that the caloric value provided matches the nutritional value (carbohydrates, fat and alcohol) available with the dish. 2. **Carbohydrates** filter ensures that the total carbohydrates reported is less than the sum of sugar, fiber, and starch. 3. **Fat** filter ensures that the total fat reported with the meal matches with different sources of fat (such as saturated fat, trans fat etc.). 4. **Red meat filter** ensures that if a dish contains red meat then the quantity of saturated fat reported is not zero. Given the nutrition facts only from our database, these are the only filters that can be applied.

3.2 Multimedia Integration

Nutritional requirements of users change with their environment and their daily activity levels. Utilizing multi-modal contextual data including GPS location, barometer, and pedometer output, we can provide very accurate recommendations. We use these sensors to calculate a live estimate of the user's daily nutritional requirements (Algorithm 1). The calculated daily values are then used to rank the meals based on how well they fulfill the individual's nutritional needs in Algorithm 2).

3.3 Health Expert Knowledge Engine

Users also do not know quantitatively how their choices are affecting their health, which is why we have developed a ranking algorithm. The original concept of the algorithm is based on a ratio of healthy to unhealthy nutrients [7]. We assign a personalized health score (normalized from 1-100 with 100 being healthiest) to every physically local dish and food item based on the item nutritional facts and the user parameters (which includes their daily nutritional requirements and any dietary restrictions due to pre-existing medical conditions such as diabetes). Our system calculates the user parameters values as a function of real-time mobile phone sensor data and environmental parameters (Algorithm 1) [19]. Different macro nutrients are assigned a weight for calculating the score which depends on the dietary restrictions placed on or the health goals of the user. For example, the score for a sugar rich meal is less for a diabetic person as the increased weight for the sugar reduces the overall score for the meal. Similarly, protein rich food items attain a higher score if the person's goal is to gain muscle.

Algorithm 1 Adaptive daily value

```
Work = 9.8*Weight*HeightTraveled + (Weight*Steps)/(60*100)
if Gender = "Male":
    BMCal = Weight*10 + 6.25*Height - 5*Age + 5
else:
    BMCal = Weight*10 + 6.25*Height - 5*Age - 161
dailyCal = BMRatio*BMCal + Work
dailyCal = dailyCal*(1 + (85 - Temperature)/(8*100))
newDailyValues = DailyValues * dailyCal/2000

NaMultiplier =  1 + 0.015*((Temperature - 32)*0.56 - 23)
newDailyValues['Na'] = NaMultiplier*DailyValues['Na'] +
                       (Altitude/1000)^2.5
return newDailyValues
```

Algorithm 2 ELIXIR

procedure ELIXIR–SCORE(weights, DailyValues, Mult)
  $RecBN = (Protein, Fiber)$
  $RecAN = (VitA, VitC, Ca, Fe)$
  $RestBN = (Cal, Chol, Na, SatFat, TotFat, Sugar)$
  $RecBase = \sum_{i \in RecBase} weights[i] * \frac{dish[i]}{DailyValues[i]}$
  $RecBase = RecBase + weights[Fiber] * \frac{dish[Fiber]}{dish[Carb]} + weights[ComplexCarb] * \frac{(dish[Carb] - dish[Fiber] - dish[Sugar])}{dish[Carb]}$
  $RecAdd = \sum_{i \in RecAN} weights[i] * \frac{dish[i]}{DailyValues[i]}$
  $RestBase = \sum_{i \in RestBN} weights[i] * \frac{dish[i]}{DailyValues[i]}$
  $RestBase = RestBase + weights[Carb] * \frac{dish[Sugar]}{dish[Carb])} + weights[SatFat] * \frac{dish[SatFat]}{dish[TotalFat]} + weights[TransFat] * dish[TransFat]$
  $BaseElixir = \frac{(RecBase + Mult * RecAdd)}{((1 + Mult) * (RestBase))}$
  return $BaseElixir$
end procedure

Table 1: Nutrient weights for different health conditions. N=Normal, D=Diabetes, BP=Hypertension, MA=Muscle Atrophy, CVD=Cardiovascular Disease, O=Obesity

	Weight					
Nutrient	N	D	BP	MA	CVD	O
Calories	1.00	1.00	1.00	1.00	1.00	7.00
Protein	1.00	1.00	1.00	25.00	1.00	1.00
Sugar	1.10	4.25	1.10	1.10	1.10	1.10
Total Fat	1.10	1.10	1.10	0.70	1.10	1.10
Saturated Fat	1.70	1.70	1.70	1.00	4.70	1.70
Carbohydrate	1.00	1.00	1.00	1.00	1.00	1.00
Fiber	1.50	3.00	1.50	1.50	1.50	1.50
Sodium	1.00	1.00	9.00	1.00	1.00	1.00
Cholesterol	1.20	1.20	1.20	1.20	4.20	1.20
Vit A	1.00	1.00	1.00	1.00	1.00	1.00
Vit C	1.00	1.00	1.00	1.00	1.00	1.00
Calcium	1.00	1.00	1.00	1.00	1.00	1.00
Iron	1.00	1.00	1.00	1.00	1.00	1.00
Trans Fat	0.91	0.91	0.91	0.91	0.91	0.91
Complex Carb	0.10	0.10	0.10	0.10	0.10	0.10

This score evaluates the items in a much more relevant manner for consumers to make their dietary choices compared to raw nutrition facts [7]. There are standardized algorithms available for measuring the nutrient density in the food items but none have been used in any consumer applications or incorporate the personal context of the user. We are incorporating the expert dietary recommendations of the various health professional society guidelines such as the American Heart Association and the American Diabetes Association [1] [8]. For example, in the case of diabetes, sugars is not recommended in the diet, hence the weighting factor was tuned by an expert dietitian to reflect this fact as shown in Table 1. Additional human clinical studies on nutrient requirements during exercise and environment are also incorporated [5]. We call our algorithmic scoring system Environment and Life Integrated eXpert Individualized Recommendation System (ELIXIR)(Algorithm 2), which uses expert tuned weights from the professional health guidelines for a given set of diseases as shown in Table 1. Baseline DV is set from the USDA Guidelines [21].

3.4 User Interface

The user receives automatic recommendations from the system through a mobile application (Fig. 4). The user set their dietary restrictions and allergen information in their profile page, and we are able to filter items that do not match their criteria. The user's weight, height, gender, and health condition are all used to populate their custom daily values for each nutrient. This information is then used in combination with adjustment from the environmental temperature and altitude to show them the best available meals in the vicinity in form of a map view and a list view. The user also has the ability to search for a particular type of dish (eg. pizza) or a particular restaurant. The application would recommend the healthiest dish related to a manual query in the user local vicinity to take an actionable step.

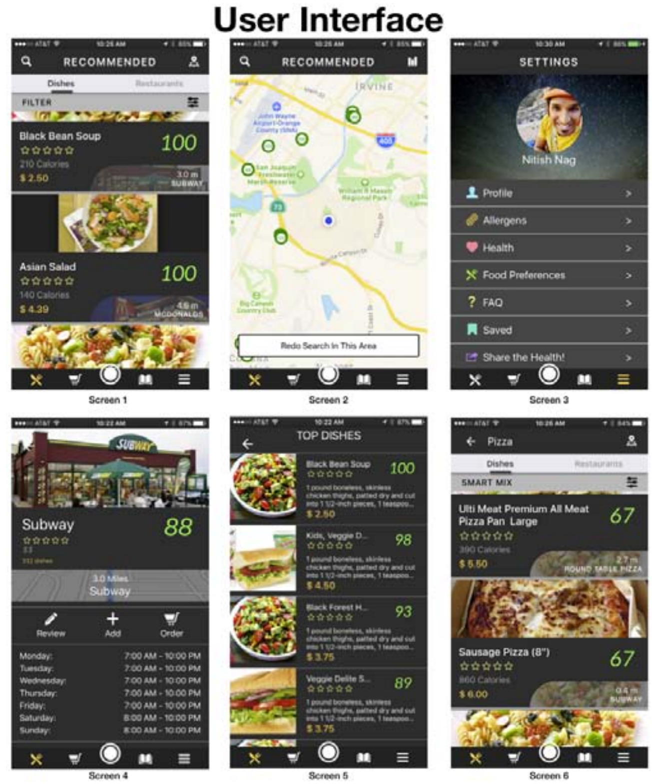

Figure 4: Mobile application front-end system.

4 DATASET

We use a combination of physical entity data crawled from Google Maps, web restaurant nutritional information, and government resources. Nutritional data contains the nutritional facts for different meals/dishes. We have collected this data from various publicly available sources. We have used two types of data sets for our experiments in the paper. United States Department of Agriculture has provided a food composition database which contains nutritional value and ingredients for 158,552 food items. In addition to the USDA dataset, we have also created a geo-tagged database of menu items from restaurants in California, United States. This dataset contains over 10 million geo-tagged dishes, which map the restaurant dishes to the location they are served at.

We have 6 synthesized users in our system with specific health parameters to show how recommendations change in the system. Synthetic data is generated for each user to address a particular health case study that is common (Table 2).

Mobile phone sensors from users that we consider as data streams at a given time point include accelerometer and barometer (which gives both floors climbed and altitude). The temperature data is pulled from the location via GPS mapping to current weather information from NOAA [20]. The user health condition, height, weight, and gender are entered into the app during the on-boarding process.

5 EXPERIMENTS AND RESULTS

The primary aim is to automatically answer this query in real-time: "What is the best meal for lunch around me?". We have three different scenarios that we test our six users in. The occasion in

Table 2: Simulated Users of System. N=Normal, D=Diabetes, BP=Hypertension, MA=Muscle Atrophy, AN=Anorexia Nervosa, O=Obesity

		Health Parameters					
		Height	*Weight*	*Gender*	*Health*	*Age*	*BMR*
Users	U_1	167 cm	125 lbs	Male	N	29	1.8
	U_2	190 cm	290 lbs	Male	O	37	1.5
	U_3	155 cm	85 lbs	Female	AN	18	1.9
	U_4	173 cm	155 lbs	Female	D	55	1.4
	U_5	163 cm	142 lbs	Female	HBP	62	1.2
	U_6	178 cm	139 lbs	Male	MA	42	1.3

Table 3: Personalized lunch recommendation scenarios.

Situation	Sensor Parameters			
	Steps	Floors	Altitude	Temp
Workday	2,400	12	20 feet	70 F
Hiking	30,650	207	10,700 feet	42 F
Beach Picnic	7,430	31	0 feet	92 F

each scenario is to find the best personalized lunch meal for each user / situation combination within a 32 kilometer radius.

5.1 Food Group Suggestions

The results of a nutrition based food ranking/recommender system should agree with the common accepted knowledge among dietitians. For example, among the meat based food items seafood is considered to be a healthier option as compared to poultry, beef and pork based products. Similarly, a person aiming to gain muscle or increase their weight should prefer protein and fat based meals as compared to vegetables and fruits. These trends can be seen in Fig. 7, where we have shown the average score for different food groups for each user. The Elixir algorithm has been previously evaluated to capture the general knowledge of food groups much better than internationally used food scoring algorithms, and with higher consistency than clinical human dietitians. Furthermore, Elixir has been shown to have the highest correlation to expert human dietitian recommendations relative to other ranking algorithms [19].

5.2 Adaptive Daily Value of Nutrients

The daily nutritional requirements depend on a multitude of factors that affect the person in a dynamic manner. Slowly changing or static data such as health conditions, body weight, height, and gender are used to modify the final ranking in Algorithm 2. This allows for separate systems to digest live sensor data versus slow changing clinical data. Although we do not consider activity other than steps, such as cycling or swimming, the concept for incorporating these activities is presented here. For example, the required amount of calories for an individual increases if they have been physically active during the day and a person may need more sodium than usual if they spent the whole day sweating at a hot beach. We obtain the environmental factors and activity levels from the user's smart phone and have incorporated in our system to provide an adaptive daily nutritional requirement (Algorithm 1). Fig. 5 and 6 display these values in a radar plot, and it can be seen that the nutritional

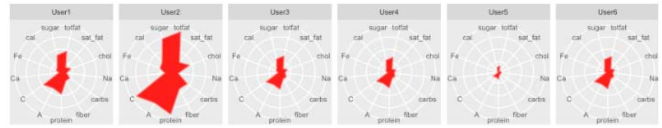

Figure 5: User nutritional profile in the workday context.

values vary with the user parameters and their environment. Physiological values to calculate calories burned from steps and stairs climbed, sodium needs based on temperature and altitude, were derived from established human clinical data [5] [18] [26] [3].

5.3 Meal Recommendations

The changes in the daily nutritional value must also be reflected in the recommendations generated by the system. The recommendations must change so that the nutrients with an increased daily value are given more weight in the recommendations. Fig. 6 displays the top 5 meal recommendations in a 20 mile radius for different users in our test scenarios along with their respective Elixir scores. Recommendations vary in different contexts to match the items that best fit (as measured by health score defined by Elixir) the Adaptive Daily Value for that user. Detailed nutrition facts for each item are available as artifacts of this article. The meal recommendations were verified to by a nutrition expert as healthy options to eat given each user's health condition and personal variables, with no top 5 recommendations that violate human nutritionist endorsement as healthy options for restaurant meals.

6 FUTURE WORK

6.1 Portion Size Recommendation

Meals are often comprised of multiple food items with very different nutritional values. We need to include the effect of portion sizes as a meal may still be considered healthy if the "unhealthy" items (for eg. chocolate cake for an obese person) are consumed in limited amount. Finding combinations of items which would satisfy a person's nutritional requirements and also be according to their preference is a computationally challenging task. Determining ideal portion sizes is out of scope for this paper and is a topic for future research that incorporates total diet tracking and recommendations.

6.2 Knowledge Base of Taste/Cuisine

Most people would not eat healthy food if it tastes bad. In order to enable people to make healthy lifestyle choices, we need to make sure that the recommendations are aligned with the user preferences while maintaining their health goals/status. This would involve using expert knowledge systems to classify dishes based on their taste profile and match this to contextual understanding why a user is satisfied with a certain dish. Following this, we can associate the dishes present in a user's search and purchase history to develop a taste and craving profile for the user. This challenge is non-trivial and will be addressed through a series of research efforts.

6.3 User Filtering System

We want to include capabilities of letting the users filter items at an ingredient level for their unique allergy needs. Food-drug interactions also cause over 100,000 unnecessary emergency room visits each year in the United states, which would involve enumerating all the ingredients in a dish and searching through about half a billion ingredient entries for filtering out the best dish for each person in real time for millions of users. It is clear that we need new revolutionary methods to solve this problem efficiently and especially to do this with a very high degree of precision. Users can enter in their medications and given the ingredient level data of dishes, we should filter out or highlight the dishes which have constituents that can react with their prescription.

6.4 Image Logging for Non-Purchased Meals

This constitutes a majority portion of an average individual's diet. Using the smart phone cameras to capture the food items to auto-populate a health diary is essential for total diet evaluation. We can use deep-learning image recognition techniques to give semantic data to the photos and auto generate tags that can be used to determine approximate nutritional value from the items in the picture. We can present the top suggestions from the image recognition system to the user to ensure that the images are labeled correctly. Efforts in this research field are rapidly becoming more robust [16] to give a better overview of an individual's diet.

7 CONCLUSION

Matching the healthiest food particular to a user's needs and resources is the key towards a healthier society. Using medical knowledge and personal data with situational awareness will be a fundamental paradigm in future health improvements to society. Humans have always resorted to asking for advice from experts, human or machine, which is the basis behind why recommendations are the most important factor in decision making. Ranking systems thus must be used to power these recommendations in the best way possible for each user. Our hope is to entice restaurants to deliver products that are inherently healthy. The presented research approach is only a single tool to develop healthier eating choices, and is not a holistic solution to solve poor diet. This amalgam of synergistic health multimedia fusion is a specific case in how to fuel health recommendation engines of the future.

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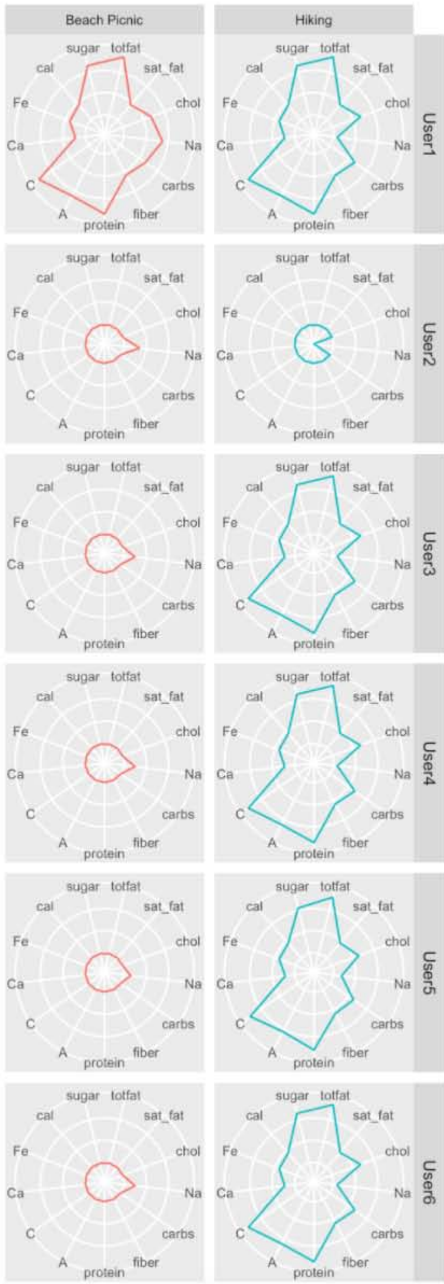
Nutrient Profiles and Recommendations



Workday		Hiking		Beach Picnic	
- Kabob Lunch	100	- Falafel	98.8	- Quinoa Vegetable Stew	100
- Veggie Bowl	100	- Tuscan Pesto Pasta Salad	87.9	- Kabob Lunch	93.5
- Aloo Gobi	99.9	- Hibachi Chicken	82.0	- Veggie Bowl	87.3
- Egg Noodles	99.7	- Penne With Marinara	80.0	- Egg Noodles	87.3
- Falafel	98.7	- Grilled Salmon	78.4	- Falafel	85.5
- Kabob Lunch	100	- Tuscan Pesto Pasta Salad	[illegible]	- Kabob Lunch	100
- Aloo Gobi	96.5	- Caesar Salad With Roasted Chicken	93.6	- Quinoa Vegetable Stew	93.4
- Bengan Bhartha	92.8	- Hibachi Chicken	93.3	- Lentil Burgers	90.5
- Salmon Steaks	92.2	- Tuna Salad	92.4	- Mediterranean Lentil Salad	85.7
- Seared Albacore Salad	88.8	- Grilled Salmon	90.2	- Tuscan Pesto Pasta Salad	83.5
- Ahi Tuna	100	- Falafel	100	- Ahi Tuna	100
- Halibut	100	- BLT Sandwich	96.6	- Halibut	100
- Falafel	100	- Chicken Caesar	96.5	- Falafel	99.8
- Seabass	100	- Tuna Salad	95.2	- Quinoa Vegetable Stew	98.2
- Swordfish	100	- Hibachi Chicken	92.2	- Seabass	97.2
- Veggie Bowl	100	- Falafel	99.3	- Quinoa Vegetable Stew	100
- Aloo Gobi	100	- Tuscan Pesto Pasta Salad	89.2	- Daphnes Kabob Lunch	90.4
- Kabob Lunch	100	- Tuna Salad	85.5	- Lentil Burgers	89.6
- Falafel	98.5	- Caesar Salad With Roasted Chicken	84.4	- Veggie Bowl	88.1
- Egg Noodles	98.4	- Hibachi Chicken	83.3	- Egg Noodles	86.0
- Falafel	100	- Falafel	100	- Quinoa Vegetable Stew	100
- Egg Noodles	100	- Chicken Caesar Salad	72.9	- Lentil Burger	97.0
- Veggie Bowl	100	- Pepperoni Pizza	69.0	- Falafel	96.2
- Aloo Gobi	100	- Oriental Chicken Salad	67.3	- Egg Noodles	94.2
- Seared Albacore Salad	92.6	- Hibachi Chicken	66.2	- Veggie Bowl	91.6
- Ahi Tuna	100	- Falafel	100	- Ahi Tuna	100
- Halibut	100	- BLT Sandwich	96.4	- Halibut	100
- Falafel	100	- Chicken Caesar	96.3	- Falafel	99.8
- Seabass	100	- Tuna Salad	94.2	- Quinoa Vegetable Stew	98.2
- Swordfish	100	- Hibachi Chicken	91.4	- Seabass	97.1

Scale:
Total Fat : 0 - 27, Sat. Fat : 0 - 27, Cholesterol : 0 - 270, Sodium : 0 - 2700, Carbohydrates : 0 - 270, Fiber : 0 - 27, Protein : 0 - 27, Vitamin A : 0 - 2700, Vitamin C : 0 - 27, Calcium : 0 - 2700, Iron : 0 - 27, Sugar : 0 - 27, Calories : 0 - 2700

Figure 6: User health data and context is matched with optimal local physical resources via automated and personalized expert knowledge. The plots represent the difference from the usual work day requirements (eg. Hiking - Work Day)

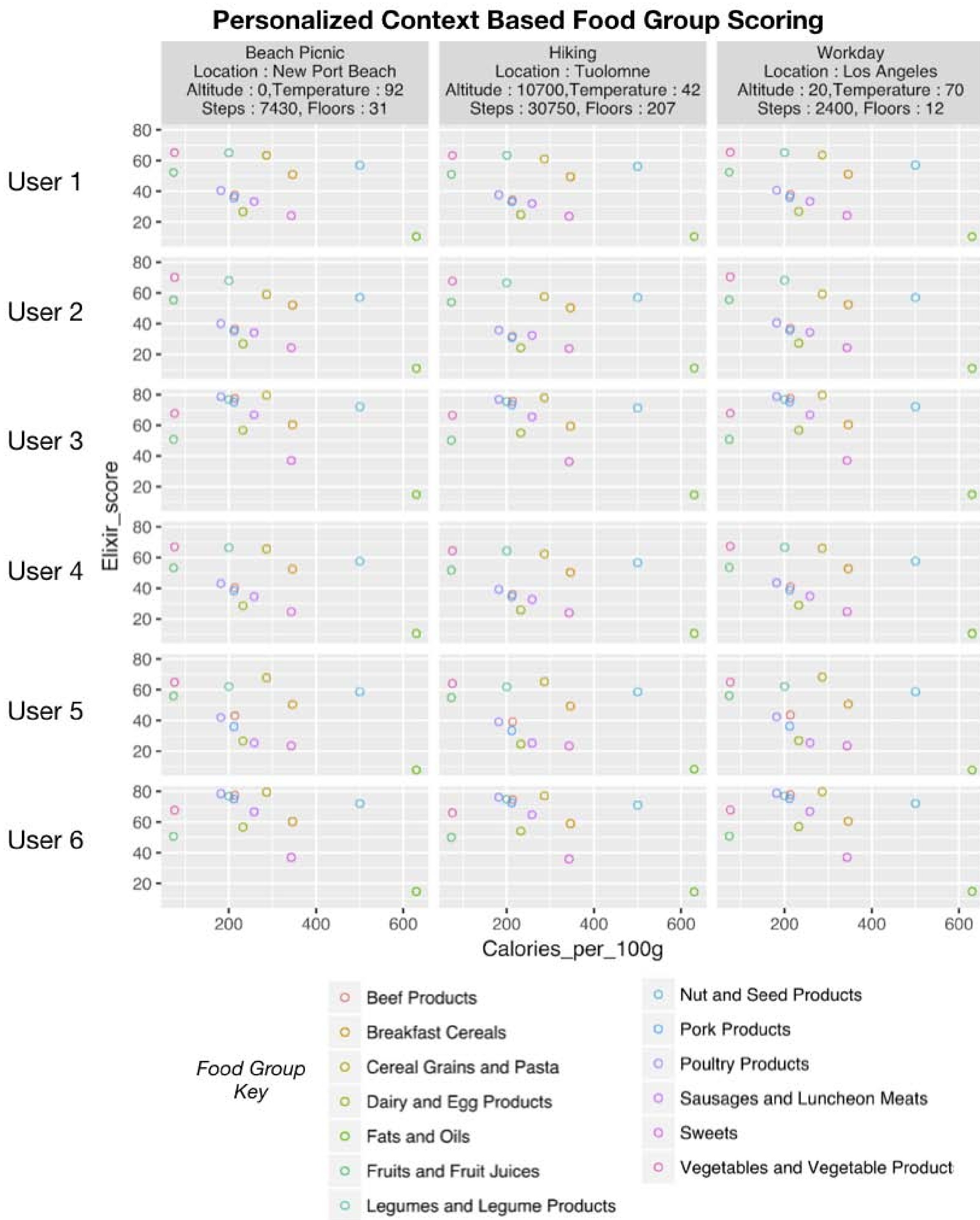


Figure 7: User health and context data creates unique individualized food group recommendations. This is important for context aware and precise personal recommendation engines.