Nutritional Analysis and Advanced Artificial Intelligence (AI) Predicts Weight Loss for People with Diabetes

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BACKGROUND

More than half of American adults (six in ten) are living with chronic conditions including diabetes and obesity (1). Healthy eating, as part of an overall healthy lifestyle to facilitate weight loss and weight loss maintenance, are of indisputable significance in reducing this burden (2,3)

The increasing prevalence of chronic conditions, combined with a worsening global shortage of health care professionals,(4) necessitates new approaches to diabetes-cardiometabolic care management to expand access to care, produce efficiencies, and improve outcomes (5).

Use of AI-powered digital health solutions to track one's dietary intake and health data creates opportunities to use this collected data to predict health outcomes and augment behavioral interventions. AI models and analysis techniques can prove useful to isolate those behaviors or factors that lead to better prediction of a health outcome.

SPECIFIC AIMS/PURPOSE

It is well established that keeping food records can help with achieving nutrition and weight loss goals (6) In this study, a machine learning (ML) model was used to determine if macro/micro-nutrient data (derived from multiple sources of dietary intervention data captured through a digital health solution) could aid in the prediction of weight loss, thus allowing registered dietitian nutritionists (RDNs) to make more personalized recommendations for weight loss in the future.

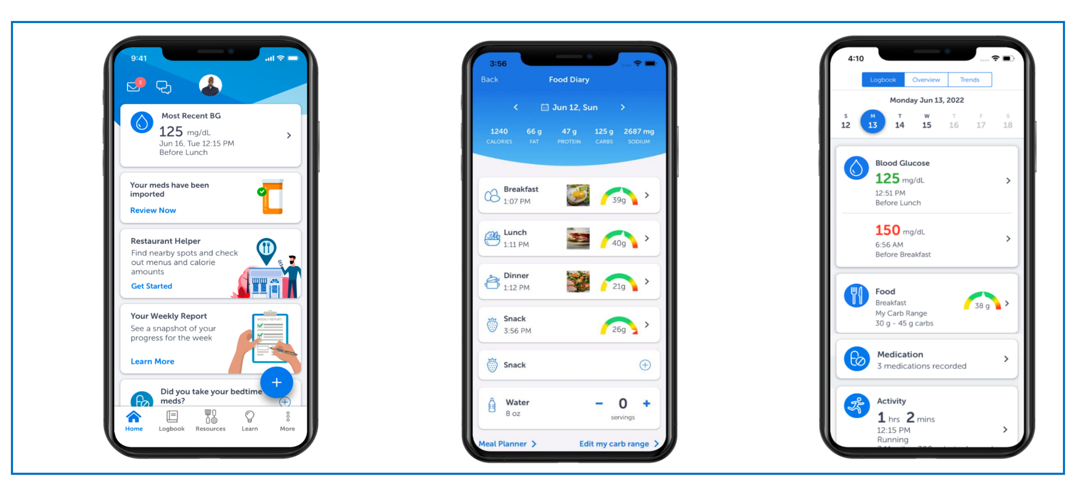
METHODS

1088 patients with T2D (60% female, 67% age 40-64, 27% age 65+) were enrolled in a digital health solution providing personalized coaching interventions to promote weight loss as a broader part of managing their diabetes.

Weight was captured at baseline and end of each person's engagement with the solution. Food, carbohydrate, meal planning and recipe entries were used as input sources to derive different macro and micro-nutrient content associated with each meal. These entries and nutrients for each meal were tabulated for each patient over their use period.

The nutrient data from the four food-related categories were used to train an XG-Boost ML model to predict weight loss. The Shapley method (SHAP) was used to evaluate the effect of different macro and micro-nutrients on the accuracy of the weight loss prediction.

Figure 1: Screenshots of the Digital Health Solution



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RESULTS

Figure 2: Population Demographics

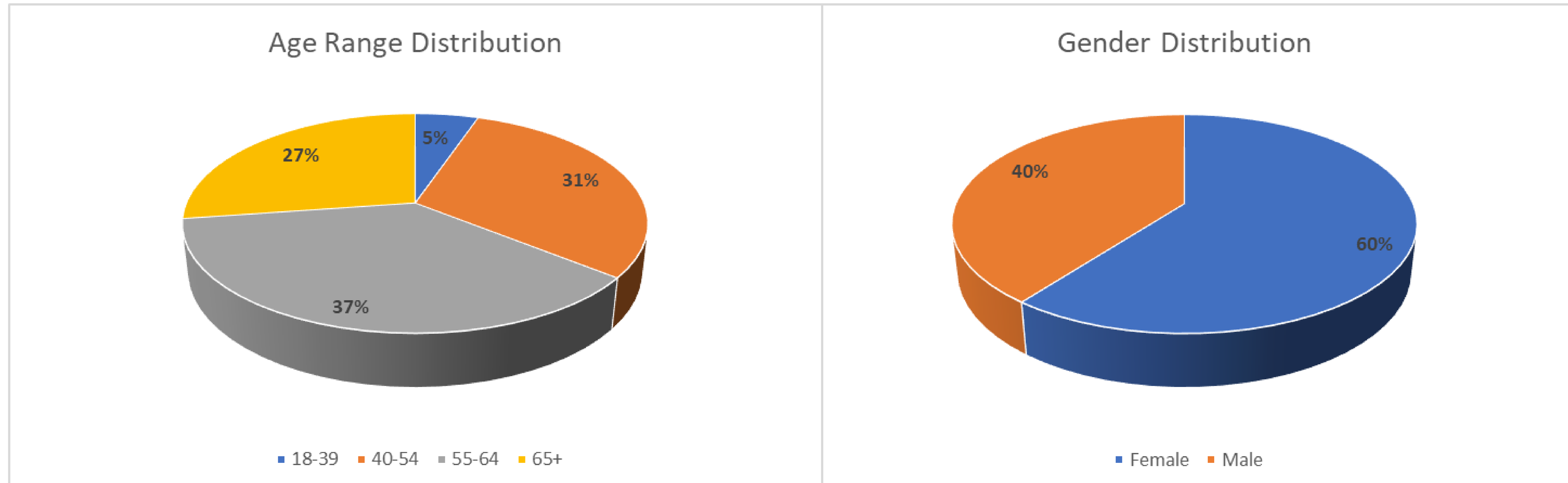
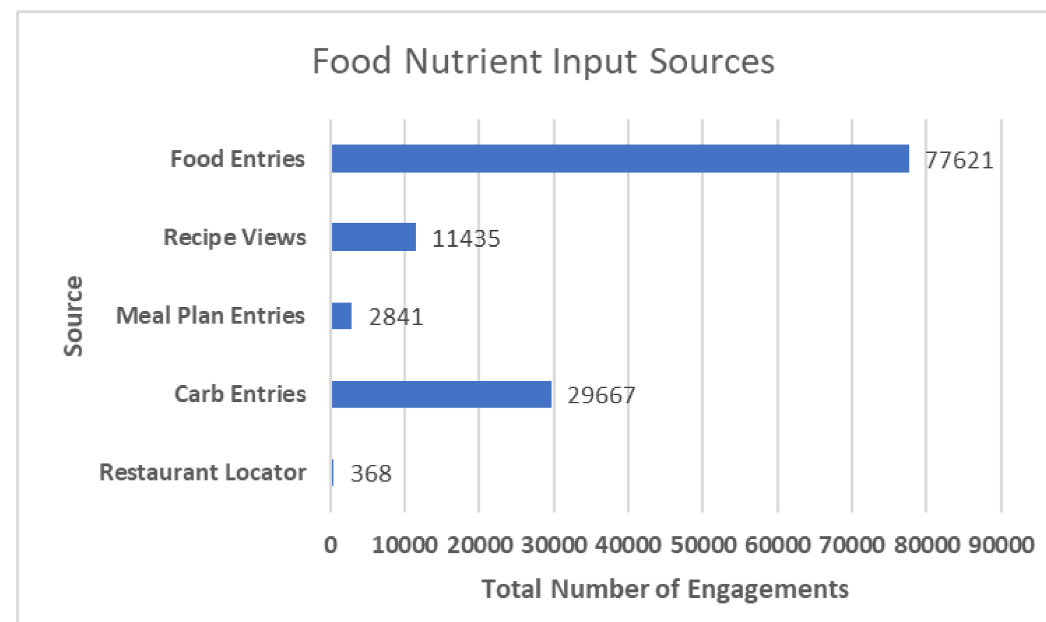


Figure 3: Engagement Data and Sources

Engagement Metric	Value
Average length of use	184 days
% of days with food-related engagements	55%
Direct food entries/person on days with food-related engagements	1.0



Figures 1 and 2 represent illustrative views of the digital health solution and demographic breakdown of the population respectively. Figure 3 depicts high-level engagement observations and the sources from which food nutrients were captured within the digital health solution. On average, participants engaged with the solution for 184 days and made food-related entries via five mechanisms on 55% of the total days spent using the solution. It was also observed that direct food entries were made each time a participant engaged with the food feature. The individual food-related engagements and a food-nutrient database were used to derive micro and macro-nutrient information to train our models.

We used the SHAP method (7) to evaluate the ability of a model to predict weight outcomes based on input variables which included micro and macro nutrient data. To note, SHAP is a method that explains the importance of individual input variables on the weight loss prediction outcome. SHAP deconstructs a prediction into a sum of contributions from each of the model's input variables[7]. Dependence plots are used to understand the relationship between a feature's values (in this case, the macro or micro-nutrient) and the model's predicted outcomes

Figures 4, 5, 6 and 7 show the Shapley (SHAP) dependence plots for each of the micro-nutrient variables for cholesterol, polyunsaturated fat, saturated fat and potassium. Future work can expand on the list of micro and macro-nutrients that can be used as inputs to the weight prediction model.

Figure 4 highlights a negative correlation between morning cholesterol records and its impact on weight loss prediction, suggesting that this variable can be used to more accurately to predict weight loss.

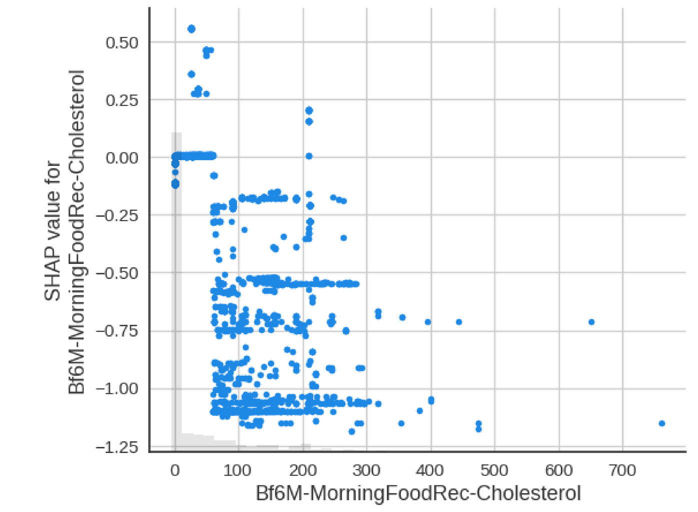


Figure 4: Cholesterol Effect

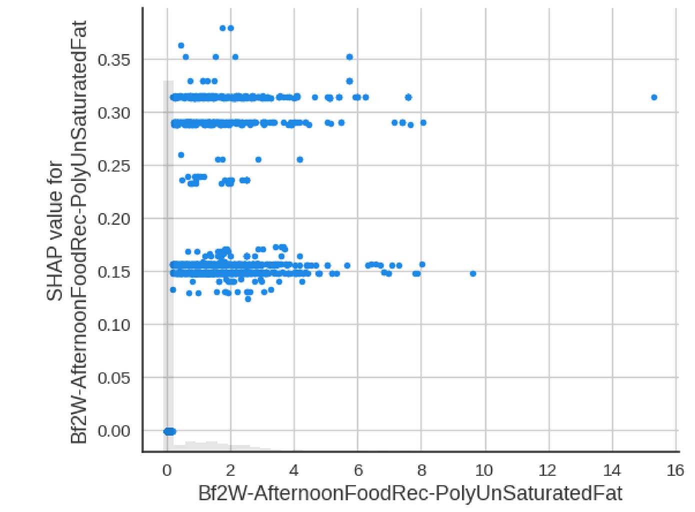


Figure 5: Polyunsaturated Fat Effect

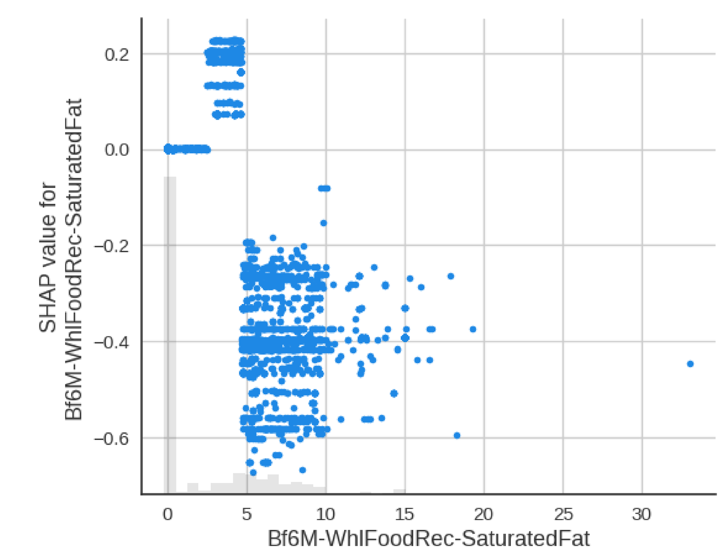


Figure 6: Saturated Fat Effect

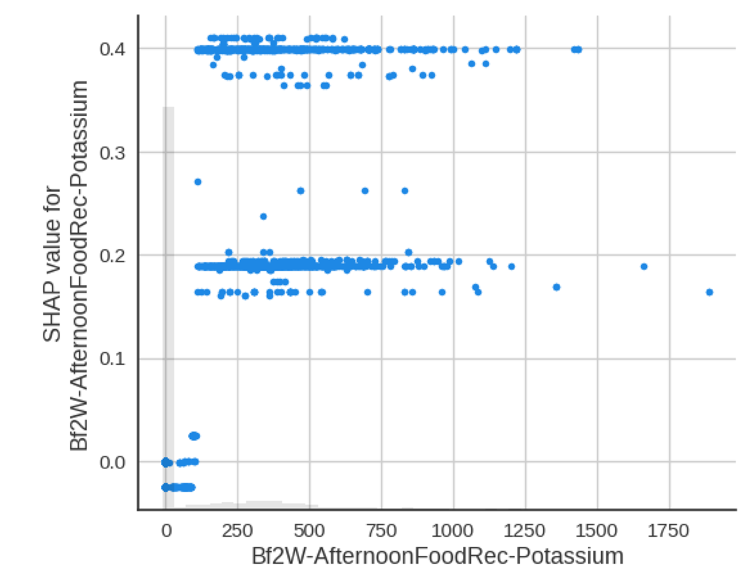


Figure 7: Potassium Effect

Figure 5 shows that a higher recording of polyunsaturated fats in afternoon meals 2 weeks prior to the prediction period is positively correlated with weight loss prediction. As such, there is importance in both the micro-nutrient content as well as the temporal aspect of when it's recorded. The different SHAP clusters also suggest that there are different possible effects for different cohorts on the weight of the polyunsaturated fat variable on prediction ability. We see the same effect in Figure 7 for afternoon potassium entries as a micro-nutrient that aids in the prediction of weight loss. Figure 6 shows that for most of the population, higher recording of saturated fats in the 6 months prior to prediction is negatively correlated with weight loss. Interestingly there is small cohort, where saturated fat is positively correlated with weight loss, which merits further research and investigation.

CONCLUSIONS

SHAP analysis, powered by a multitude of macro/micro-nutrient data, can be a useful tool for RDs to help optimize weight loss plans and time-of-day personalized nutrition guidance. Future work in this domain should expand the list of nutrients fed to the model during training to predict outcome variables such as weight loss.

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