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Optimization Model: Resource Distribution for Risk Factors of Type 2 Diabetes Prevention

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Abstract

Type 2 Diabetes, a lifestyle disease, can be prevented/delayed by adopting a healthy lifestyle. Awareness of the same amongst the citizens can be one of the best ways to initiate a decline in the positive census of the disease. We use this paper to illustrate an optimization model where the budget can be distributed based on the census data of the risk factors involved. It uses a non-linear programming model and can easily be modified into a linear one. The alternative options and constraints too, are mentioned in the paper. The results show that the mid-western states need more share of the allocation based on risk factors. The model distributes the percentage of the budget allocated to different states based on a fixed risk factor constraint.

Keywords

Optimization, Algorithms, Application Based Solution, Diabetes, Resources, Solver, Excel, Objective Function

1. Introduction

We know that family history, obesity, and physical inactivity are risk factors for this condition, formerly known as adult-onset diabetes. NIH-funded research has shown that type 2 diabetes can be delayed or prevented [1]. Basic lifestyle interventions—modest weight loss and regular exercise—slash type 2 diabetes risk by 58% over 3 years in people with pre-diabetes [2]. Despite this good news, type 2 diabetes still accounts for 90% of diabetes cases nationwide and has been increasing at an alarming rate due to the rise in obesity and hypertension in the United States [3].

2. Stakeholder Analysis

Awareness with respect to the Diabetes program will primarily benefit the **citi-**

zens who suffer from it and the **government** by giving them an overview of which group of citizens should be targeted. Also, the **medical** industry will be benefit in terms that it will know where to direct its major resources and supplies promoting an overall healthy lifestyle in the nation. Drop in the number of citizens affected by diabetes in the next census.

Stakeholders in order of decreasing benefit will be patients, the government, and the medical industry. However, the results achieved will be dependent ultimately on the citizens. If the citizens implement and learn, then there definitely will be a positive result in the census.

We assume that the resources invested will be utilized completely for the benefit of educational awareness.

3. Objective

Diabetes is popularly also known as a lifestyle disease. The 5 major risk factors include high cholesterol, hypertension awareness, obesity, physical inactivity, and smoking [4].

The overall resource distribution maximizes the impact and creates awareness in the masses [5].

4. Critical Resources

The most critical resources and indicators which we will be using for our studies will be the data for the 5 risk factors [4]. We also take the self-diagnosed statistics for type II diabetes as a critical resource to identify the overall impact of diabetes across the states and as an additional indicator to our risk factor data.

Since working across all the states will be too cumbersome, we will target the states in different phases and run the optimization accordingly. We use the diagnosed diabetes data to narrow down the target states.

5. Data Sources and the Relation to the Proposed Model

Diagnosed Diabetes: The percentage of US adults who reported ever being told by a health professional that they had diabetes was estimated using data from the CDC's Behavioral Risk Factor Surveillance System (BRFSS) [6].

Risk Factors for Complications—Self-reported: The percentage of US adults with self-reported diabetes who also reported being current smokers was estimated using data from CDC's Behavioral Risk Factor Surveillance System (BRFSS). Similarly, obesity, Physical Inactivity, Hypertension Awareness, and High Cholesterol Awareness data has been reported [6].

The Risk Factor data enlists the percentage of each factor that contributes to the occurrence of diabetes on a self-reported basis [6]. The data is populated for each state, and we use it as an indicator of how prevalent a given risk factor is.

Using this information, we prepare a model where we find the number of resources that should be allocated to which risk factor and which state.

6. Formal Solution and the Algebraic Model

We begin with collating the data for all the states. Data for U.S. Virgin Islands is not available and hence it is removed.

The data is organized, and its statistical characteristics are tabulated as shown in Table 1 below.

We also apply conditional formatting and identify the states that have a higher index factor number. We use median as the benchmark to filter the states.

We notice that Hypertension, Obesity and High Cholesterol (we henceforth refer to these as the primary risk factors) conditions contribute more to diabetes than Physical Inactivity or Smoking (we henceforth refer to these as the secondary risk factors). Hence, we put a conditional statement to filter out the states which have any of the primary risk factors higher than the respective medians and have any of the secondary risk factors higher than the medians along with self-reported diabetes percentage higher than the medians.

We get the result as shown in Table 2 below.

We further model the whole solution to distribute the awareness budget/resource in the different states for different risk factors.

We create binary decision variables which will decide whether the money is supposed to be invested for a particular risk factor in the given state or not.

We also re-calculate the weights to get a standardized comparison result for each risk factor data.

Based on the overall average data from CDC [6], we recalculate the weights for each risk factor as shown in Table 3 below.

Based on these calculations we decide to allocate a definitive percentage of the budget/resource to each risk factor. The above numbers have been arrived based on the risk factor matrix. The distribution can be done based on one's chosen matrix or area of focus accordingly.

Next in the final optimization model, as shown in the figure below, we also put in an extra variable which determines what fraction of the maximum allowable budget/resource can be spent for the given risk factor. One can choose not to spend the complete amount on it. The model essentially becomes a non-linear model because of this assumption. The fraction variable can assume any value between 0 and 1 thus increasing the non-linearity of the model and giving an option to invest fractionally in some states. Thus, let us assume the following notations:

x_i: Fraction of the maximum budget/resource that can be invested

y_i: Decision variable

0: if it is decided not to invest in the state for the given risk factor.

1: if it is decided to invest in the state for a given risk factor.

z_{ij}: Individual Fractions for each state, i for each risk factor, j

A_{ij}: Amount invested in each state for each risk factor

We formulate the objective function/model as below:

$$\sum_j x_i y_i z_i = 100.00$$

Table 1. Percentage for risk factor or complication contribution to the occurrence of diabetes.

Std Dev	4.8	6.7	5.7	6.5	5.4
Median	59.8	61.1	57.1	32.9	21.2
Average	59.7	62.0	56.2	33.5	21.3
	High Cholestrol-2013	**Hypertension on Awareness-2013**	**Obesity-2014**	**Physical Inactivity-2014**	**Smoking-2014**
State	Percentage	Percentage	Percentage	Percentage	Percentage
All States Median	59.8	61.1	57.1	32.9	21.2
Alabama	63.4	68.2	59.1	37.5	21.2
Alaska	49.5	68.8	61.6	23.7	16.8
Arizona	61.1	66.8	62.9	31.3	19.2
Arkansas	58.8	69.2	63.2	54.4	30.2
California	63.4	61.2	45.1	28.2	13.6
Colorado	57.8	58.7	50.0	33.8	21.6
Connecticut	57.4	59.5	50.9	30.3	11.6
Delaware	60.3	59.4	59.2	38.0	23.9
District of Columbia	63.0	55.3	39.0	46.2	34.3
Florida	57.2	61.9	61.4	34.8	16.3
Georgia	58.0	62.9	50.3	29.3	23.4
Hawaii	57.7	58.9	49.0	26.9	16.8
Idaho	59.2	49.2	56.8	22.5	12.6
Illinois	60.6	57.3	60.7	45.0	16.5
Indiana	62.2	58.2	62.6	38.0	27.1
Iowa	63.1	52.8	63.7	21.7	25.3
Kansas	56.8	58.6	54.4	34.2	23.1
Kentucky	67.8	69.2	60.1	38.6	29.3
Louisiana	68.6	74.0	61.9	36.1	22.1
Maine	65.5	64.0	57.1	32.7	20.4
Maryland	52.6	58.0	65.8	35.0	23.5
Massachusetts	57.2	52.0	49.2	30.9	25.1
Michigan	58.2	60.8	60.5	29.0	17.4
Minnesota	63.9	53.8	54.1	30.0	17.9
Mississippi	66.3	76.4	57.1	38.0	24.0
Missouri	61.6	67.8	57.8	29.7	14.1
Montana	50.3	56.0	52.3	32.4	34.3
Nebraska	65.0	66.1	54.3	31.1	20.5

Continued

Nevada	57.5	61.0	52.3	29.0	15.8
New Hampshire	56.8	45.5	59.1	26.6	23.3
New Jersey	59.9	60.1	52.3	31.8	17.8
New Mexico	51.9	56.6	49.2	28.9	16.0
New York	55.3	63.9	56.4	35.8	19.6
North Carolina	60.1	61.7	61.7	32.9	16.7
North Dakota	59.0	68.1	55.3	22.8	17.2
Ohio	67.8	68.5	61.5	33.8	22.7
Oklahoma	58.8	69.7	62.4	39.4	21.4
Oregon	57.8	67.3	49.7	25.6	20.9
Pennsylvania	57.9	59.1	56.7	34.2	27.2
Rhode Island	61.7	63.4	60.2	25.3	25.3
South Carolina	64.8	69.6	61.9	37.1	22.6
South Dakota	59.8	61.4	58.0	29.6	18.1
Tennessee	64.3	61.1	53.1	37.9	35.6
Texas	63.8	60.7	56.2	43.3	15.6
Utah	56.2	50.4	54.7	28.7	15.2
Vermont	54.7	60.1	57.5	33.1	25.3
Virginia	63.8	64.4	56.6	34.2	21.1
Washington	48.9	58.9	57.2	31.5	23.1
West Virginia	62.7	72.5	59.5	40.7	25.6
Wisconsin	62.5	78.1	64.9	31.3	18.0
Wyoming	50.7	52.5	45.8	33.3	22.2
Guam	69.3	60.6	44.4	39.9	28.7
Puerto Rico	54.0	66.0	51.3	50.9	14.3

Table 2. Final list of states after filtering out conditional requirements.

	High Cholestrol-2013	Hypertension Awareness-2013	Obesity-2014	Physical Inactivity-2014	Smoking-2014	Diagnosed Diabetes-2014
State	Percentage	Percentage	Percentage	Percentage	Percentage	Percentage
Alabama	63.4	68.2	59.1	37.5	21.2	11.8
Arkansas	58.8	69.2	63.2	54.4	30.2	11.5
Delaware	60.3	59.4	59.2	38.0	23.9	9.7
District of Columbia	63.0	55.3	39.0	46.2	34.3	9.1
Florida	57.2	61.9	61.4	34.8	16.3	9.4

Continued

Georgia	58.0	62.9	50.3	29.3	23.4	11.0
Illinois	60.6	57.3	60.7	45.0	16.5	9.4
Indiana	62.2	58.2	62.6	38.0	27.1	9.7
Kentucky	67.8	69.2	60.1	38.6	29.3	11.3
Louisiana	68.6	74.0	61.9	36.1	22.1	10.4
Maryland	52.6	58.0	65.8	35.0	23.5	9.2
Mississippi	66.3	76.4	57.1	38.0	24.0	11.9
New York	55.3	63.9	56.4	35.8	19.6	9.2
North Carolina	60.1	61.7	61.7	32.9	16.7	9.8
Ohio	67.8	68.5	61.5	33.8	22.7	10.3
Oklahoma	58.8	69.7	62.4	39.4	21.4	10.9
Pennsylvania	57.9	59.1	56.7	34.2	27.2	9.6
South Carolina	64.8	69.6	61.9	37.1	22.6	10.7
Tennessee	64.3	61.1	53.1	37.9	35.6	11.7
Texas	63.8	60.7	56.2	43.3	15.6	10.8
West Virginia	62.7	72.5	59.5	40.7	25.6	12.0
Guam	69.3	60.6	44.4	39.9	28.7	11.6
Puerto Rico	54.0	66.0	51.3	50.9	14.3	14.2

Table 3. Average for each risk factor and their weighted contributions.

	Risk Factors	Average	Contribution
Calculated on the basis of average	High cholestrol	59.75	25.66%
	Hypertension awareness	62.00	26.63%
	Obesity	56.19	24.13%
	Physical nactivity	33.53	14.40%
	Smoking	21.35	9.17%

$$\text{S.t:}\quad y_i = 0,1 \tag{1}$$

$$\sum x_i y_i z_i < \text{Maximum Limit} \tag{2}$$

$$\sum_j A_{ij} = \text{Allocated Limit for } j \tag{3}$$

$$x \le 1 \tag{4}$$

The constraint (2) and (4) ensure that no state can be allocated more than its allocated budget/resources.

Constraint (3) ensures that the allocation for the given risk factor is achieved.

As a modification, we can also put a constraint on the minimum number of states covered in each risk factor category. For example, if we need to cover a minimum of 5 states in the Smoking risk factor, we can add an additional constraint as below:

$$\sum_j y_i = n$$

where n is the minimum number of states to be covered.

We first normalize the high cholesterol % across the states.

Figure 1 on the right gives a sample of how the constraints have been applied.

We randomly create the decision variable and assign values 0 or 1. Next we assign the maximum spend limits to the maximum investment amount ($z_i y_i$) in the last column.

We then go to MS Excel Solver Add-in and set out objective [7] [8]. See Figure 2 for reference. In this example, it's 25 for cholesterol contributions. We then tell it to change variables y_i and x_i. Next, we define constraints as mentioned above in the "Subject to the Constraints": box.

Since budget allocations cannot be negative, we also check the box below to make the unconstrained variables non-negative and then select the solving method to GRG Nonlinear. Once we click on Solve the Solver algorithm runs iterations and comes up with optimal assignments of budgets to the states. It picks which state needs to receive a budget and how much.

The format is attached in the report as an Appendix.

		z	y	x	A	<=
States to be targeted	High Cholestrol-2013		Yes/No	% to be invested	Amount Invested	Max Limit
Alabama	63.4	6.4	0	0.1	0.0	0.0
Arkansas	58.8	5.9	1	1.0	5.9	5.9
Delaware	60.3	6.0	0	0.3	0.0	0.0
Georgia	58.0	5.8	0	0.6	0.0	0.0
Illinois	60.6	6.1	0	0.7	0.0	0.0
Indiana	62.2	6.2	1	1.0	6.2	6.2
Kentucky	67.8	6.8	1	0.0	0.2	6.8
Mississippi	66.3	6.6	0	1.0	0.0	0.0
North Carolina	60.1	6.0	0	1.0	0.0	0.0
Ohio	67.8	6.8	0	1.0	0.0	0.0
Oklahoma	58.8	5.9	0	1.0	0.0	0.0
Pennsylvania	57.9	5.8	0	1.0	0.0	0.0
South Carolina	64.8	6.5	0	1.0	0.0	0.0
Tennessee	64.3	6.4	0	1.0	0.0	0.0
Texas	63.8	6.4	1	1.0	6.4	6.4
West Virginia	62.7	6.3	1	1.0	6.3	6.3
	997.6					

	No of states		Min States
	5	>=	5

	Tot Amt Inv		Max Limit
High Cholestrol	25.0	=	25

Figure 1. Snapshot of solution layout for high cholesterol resource optimization.

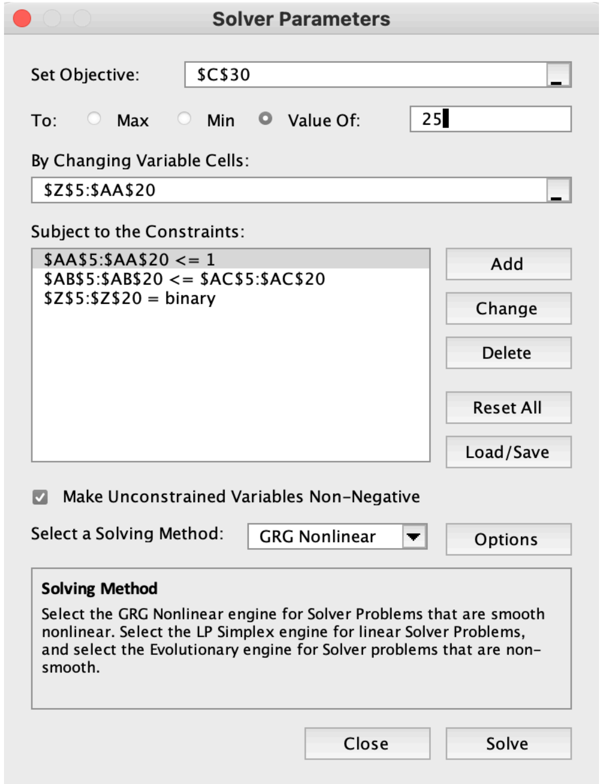

Figure 2. Solver parameters setting for non-linear optimization problem.

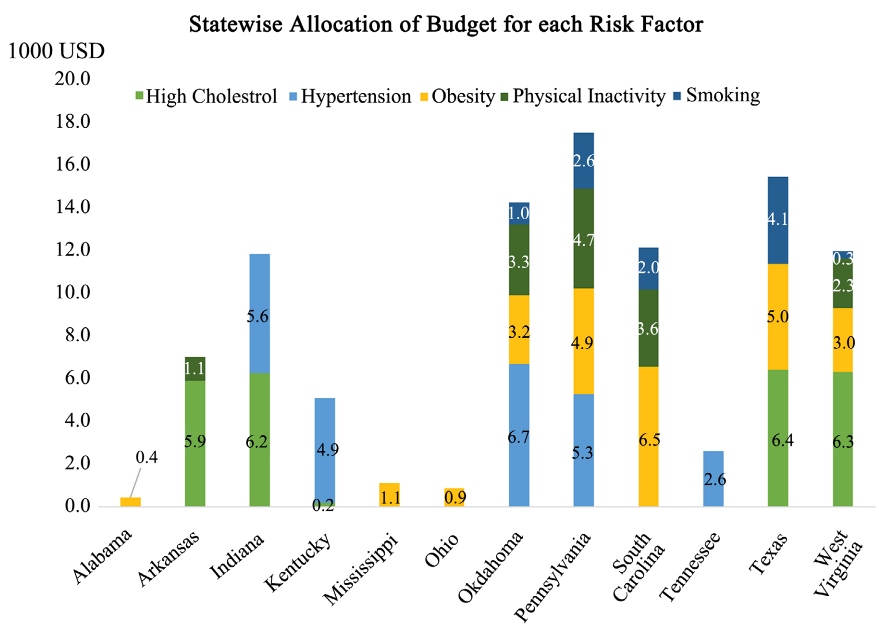

Figure 3. State wise allocation of budget for each risk factor after running the GRG Non-linear algorithm.

7. Conclusions & Results

We present the results in the form of a stacked bar chart shown in Figure 3. Each risk factor allocation is stacked up for the state it has been allotted to.

We notice that the states with the maximum share of the resource are Oklahoma, Pennsylvania, South Carolina, Texas, and West Virginia. We calculate this simply by summing the amount invested in each state over all the risk factors. The sample calculation is shown in the Appendix sheet attached.

We see that the model chooses to not allocate any resources to Delaware, Georgia, Illinois, and North Carolina. This model assumes a fixed allocation for each risk factor. Alternatively, we can also assume a fixed allocation for each state and re-model the whole optimization problem to maximize the objective function. This is particularly useful when we have a limited individual budget for different departments which in this case state. It becomes a maximization problem then.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix

https://docs.google.com/spreadsheets/d/13F9kSS--csqruyZoNuCxSWAhrXpZGWU8/edit?usp=sharing&ouid=116516128823988613493&rtpof=true&sd=true