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Modeling Impact of Social Determinants of Health on Disease Status

Abstract:

Social Determinants of Health (SDOH) include the economic and social conditions that influence health status. However, despite increasing recognition of the importance of SDOH, the relationship between SDOH and health outcomes is still not well understood. Additionally, to our knowledge, no model has been created that systematically attempts to represent the influence of multiple SDOH on the risk of developing multiple diseases. In this paper, we utilized ICD-10 to determine important SDOH to include within the model then used MeSH to systematically search PubMed to find relationships between SDOH and diseases. We then constructed a Bayesian Network relating SDOH and health outcomes. Next, we used bayesian problem-solving methods to create a tool that outputs a patient's risk of developing different diseases based upon the patient's unique SDOH. The final model included 9 SDOH, 78 diseases, and 135 probabilistic relationships between SDOH and diseases. Evaluation of the model on five sample cases by a physician on a scale from 1-5 found that the model provided reasonable output (3.2/5) and novel findings (3.4/5), but that accuracy of probabilities was not great (2.4/5). Overall, we found that, despite limitations, a model of SDOH could have clinical utility.

Background/Motivation:

Medicine does not exist in a vacuum. Healthcare professionals are increasingly acknowledging this truth as well as the pressing need to address a patient's Social Determinants of Health (SDOH). Social Determinants of Health (SDOH) are the economic and social conditions that influence health status. This includes the social and economic gradient influenced by a diverse set of conditions including availability of resources to meet daily needs, access to educational and occupational opportunities, availability of community-based resources, and the ability to access health care services, social support, and transportation options [1]. SDOH have received increased attention within the last few years as healthcare organizations recognize the economic and moral incentives to address these issues. In our current era of big data and our newfound propensity for combining together heterogeneous forms of data to make complex decisions within medicine, SDOH could become a topic of even greater importance.

Large-scale ontologies are also beginning to focus on SDOH as LOINC, ICD-10, and SNOMED-CT have all expanded their ontologies to include hierarchical relationships of different SDOH [2]. Each of these three efforts was pushed forward independently leading to little concordance between the three ontologies in relation to SDOH. Nonetheless, the existence of explicit specifications of SDOH within biomedical ontologies is an important step forward for the field. However, despite the recognition of the importance of SDOH and the explicit coding of SDOH within ontologies, the relationship between SDOH and health outcomes is still not well understood [3]. Additionally, this knowledge is dispersed throughout the literature and difficult to summarize to be of use to physicians. As a result, doctors often struggle to adequately address the myriad of ways in which SDOH can affect their patients [4]. Medical training is only beginning to recognize the importance of SDOH leaving many practicing physicians without the knowledge necessary to holistically address the varied needs of their patients.

To address many medical problems of prediction under uncertainty, probabilistic graphical models are employed. One prominent example within the medical field is Quick Medical Reference Decision-Theoretic (QMR-DT) [5]. QMR-DT takes as inputs a patient's physical symptoms and outputs a differential diagnosis. Using QMR as its knowledge base and incorporating probabilities for various diseases based on data from the National Center for Health Statistics, QMR-DT is a belief-network representation based upon bayesian reasoning [6].

Additionally, numerous models exist to determine the impact of SDOH on health outcomes including McDaniel 2018 and Llorente et al., 2018 [7,8]. However, these models either do not include multiple diseases or do not include multiple SDOH. To our knowledge, no model has been created that utilizes a systematic search of the literature to assess the influence of multiple SDOH on multiple health outcomes. We hence propose to do so utilizing an approach similar to QMR-DT but replacing symptoms with a patient's unique SDOH. In this project, we will systematically search the literature to find relationships between SDOH and health outcomes to create a Bayesian Network that, given a patient's social determinants of health, will output their relative risk of developing certain diseases. We will then have a physician perform a formative and summative evaluation of the model.

Methods:

a) Ontology:

To inform the design of our Bayesian Network, we first searched the literature for existing ontologies that model hierarchies of SDOH. We found that ICD-10, SNOMED-CT, and LOINC all have explicit specifications relating to SDOH. Using knowledge gleaned from a review covering the documentation of SDOH-related clinical activities using standardized medical vocabularies [2], we determined that ICD-10 contained the most usable documentation of SDOH. ICD-10 is the 10th revision of the medical classification list created by the World Health Organization and contains information upon a variety of diseases, conditions, and other data [9]. We utilized the ontological representation of SDOH within ICD-10 as the foundation for constructing our list of SDOH to include within our Bayesian Network. ICD-10 contains a certain section of codes from Z55-Z65 that all relate in some form to various SDOH. We used these codes to create our model and attempted to choose SDOH that were non-overlapping. Specifically, if we felt that two or more ICD-10 codes were directly related in a parent-child hierarchy, then we would only choose to include one of the SDOH. For instance, in cases such as "homelessness" and "unstable housing situation," we would only include the more general term "unstable housing situation" as a SDOH in our model.

To create our systematic searches to determine the impact of SDOH on health outcomes, we first searched the MeSH (Medical Subject Headings) controlled terminology to find MeSH term(s) corresponding to each individual ICD-10 code. MeSH is the NLM controlled vocabulary thesaurus that is used for indexing articles within PubMed. Hence, MeSH allowed us to link our ICD-10 terms to PubMeed articles.

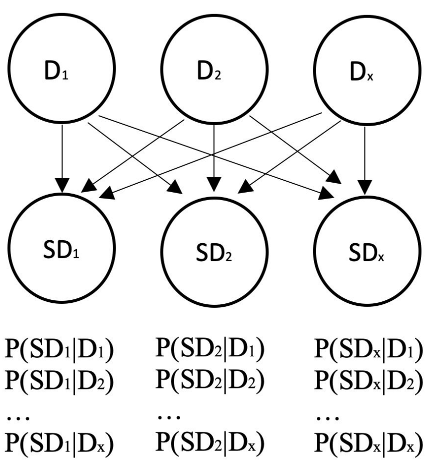
We then conducted a systematic search of PubMed for relationships between diseases and our SDOH. We did so by searching specifically for the MeSH term relating to our SDOH and the MeSH term “prevalence” indicating that we are concerned with the probability that the disease of interest will occur given the SDOH. Prevalence is formally defined to be the proportion of a particular population found to be affected by a medical condition [10]. To demonstrate our search strategy, our query for homelessness as a SDOH consisted of: "Homeless Persons" [Mesh] AND “Prevalence” [Mesh] AND United States.

With these search formattings, we then searched through the papers that our systematic search returned. We only included studies that were both written in English and examined either the whole United States or a subset of the United States. In studies that satisfied the above criteria and noted the prevalence of a disease given a SDOH or prevalence of a SDOH given a disease, the corresponding relationship was included in our model. In the problem-solving section, we will discuss how we dealt with probabilities given in the form of a disease given SDOH. Diseases were only added to the model as we discovered relationships between a certain disease and SDOH. After our systematic search informed the relationships to include in our model, we found the prior probability of social determinants of health in the US by utilizing data gleaned from scientific journal articles or governmental agencies. Additionally, we found the prior probability of diseases primarily from data from the National Center for Health Statistics though we utilized other data sources if the data required wasn’t present in this data source.

b) Problem-Solving Methods:

With the probabilities from our systematic searches above, we then created a Bayesian Network. The formulation of this Bayesian Network is founded upon the QMR-DT model, and the structure of our Bayesian Network is described below. The Bayesian Network consists of nodes D_x representing diseases and nodes SD_x representing SDOH with relationships modeled between diseases and SDOH. The structure is shown below in Figure 1.

Figure 1: Bayesian Network Structure



The list of SDOH nodes was created by including one SDOH for each ICD-10 code corresponding to a unique node for each social determinant. As corresponding relationships between SDOH and diseases were found during our systematic search, disease nodes included within the model were added, arrows were created between the corresponding diseases and SDOH, and the probabilities were stored in an excel file for later retrieval. In the absence of finding a relationship between the SDOH and a certain disease, no arrow exists connecting the two.

Some data from the literature was present in the form that we desired as the prevalence of a certain social determinant SD_x given the prevalence of a certain disease D_i. This relationship can be written as $P(D_i|SD_x)$ However, data from the literature often consisted of statistics in the form of prevalence of a certain disease D_i given a certain social determinant SD_x . This relationship can be written as $P(SD_x|D_i)$. In these cases, we needed to use Bayes Rule to obtain the correct probability. Hence, we used Bayes rule to calculate the needed value for the model:

$$P(SD_x|D_i) = \frac{P(D|SD_x)*P(SD_x)}{P(D)}$$

With the Bayesian Network created above, we used the assumptions implicitly present within the model as well as Bayes Rule as our problem-solving method. The assumptions of our model include the marginal independence of diseases, the conditional independence of SDOH given disease hypothesis, and that diseases and SDOH are binary. Although we recognize that these conditions certainly do not hold entirely true, these assumptions remain necessary for the model to be computationally tractable.

The math behind our implementation of Bayes rule is shown below for the probability of a single disease given two SDOH with defined values though the logic extends to multiple SDOH and any disease:

$$P(D_i|SD_1, SD_2, ..., SD_n) = \frac{P(SD_1, SD_2|D_i)*P(D_i)}{P(SD_1, SD_2)} = \frac{P(SD_1|D_i) * P(SD_2|D_i)*P(D_i)}{P(SD_1)*P(SD_2)}$$

Our problem-solving method then uses the formulation above to calculate the following values:

$$[P(D_1|SD_1, SD_2, ..., SD_n), P(D_2|SD_1, SD_2, ..., SD_n), ..., P(D_n|SD_1, SD_2, ..., SD_n)]$$

Then, our problem-solving method simply returns the 5 highest probabilities from the above list as part of its differential diagnosis of risk. Our problem-solving method was developed using Python, and the code for our implementation is provided in the appendix.

c) Evaluation

We evaluated our model by utilizing the expert opinion of a Stanford-trained physician for both a summative and formative evaluation. To assess the effectiveness of the model in a variety of use cases in a summative manner, we chose to use sample cases with 1,2,3,4, and 5 unique SDOH included. We then created these five cases by choosing the SDOH to include within the model uniformly at random. For each of these five sample cases, we then provided the physician with the patient's unique SDOH, the output from the model of the differential risk diagnosis of the five most likely diseases, and the prior prevalence of the diseases outputted within the top five.

Then, we asked the doctor to rate on a scale from 1-5 the following criteria:

1. To what extent does the differential disease risk profile match what you believe is a reasonable output based on your prior experience?
2. To what extent does the differential disease risk profile output diseases that you didn't consider or weren't aware are associated with the patient's unique SDOH?
3. How accurate do the probabilities appear?

After the physician had seen all five of the sample cases, we then performed the formative evaluation. For this aspect of the evaluation, we asked the physician to list any limitations that they observed with the model, ways in which they believed the model could be improved, and how they felt that the model could be incorporated into a clinical workflow. We hoped that this dual summative and formative evaluation would allow us to truly delve into the effectiveness of the model.

Results:

Searching through ICD-10, we found certain codes that related directly to SDOH and used these as a framework to determine which SDOH to include in the model. Below within Table 1, we have that each term represents a major subject area that we used to help construct the model where each subject area may be a superset of numerous SDOH:

Table 1: ICD-10 Codes and Associated SDOH

Term Description	**MeSH Term**	**ICD-10 Code**
Unemployment*	Unemployment	Z56.0
Mental strain related to work	Occupational Stress	Z56.6
Exposure to air pollution	Air Pollution	Z58.1
Exposure to water pollution	Water Pollution	Z58.2
Exposure to radiation	Radiation Exposure	Z58.4
Homelessness*	Homeless Persons	Z59.0
Lack of adequate food/water*	Food Supply	Z59.4
Social exclusion and rejection	Social Distance	Z60.4
Target of perceived adverse discrimination and persecution	Social Discrimination	Z60.5
Sexual abuse of child*	Child Abuse	Z61.4
Imprisonment*	Prisons	Z65.1
Exposure to disaster, war, and other hostilities*	War Exposure	Z65.5
Poverty*	Poverty	Z59.5
Abuse in Spousal Relationship	Spousal Abuse	Z63.0
Educational Issues*	Literacy; Academic Failure	Z55

*Associations between this SDOH and at least one disease found within the literature (total of 9)

Our literature search returned 4,085 search results. Combing through those results, we found 78 unique diseases with associations to 9 SDOH. Overall, we found 135 unique associations between SDOH and disease. There was a mean of 1.73 associations per disease and a mean of 15 associations for each SDOH. We also found that unemployment and homelessness had the most associations within the literature.

Information on the outputs for all five SDOH is included within the appendix though we have included the outputs for two of the sample cases.

Figure 2: Output of Model for Sample Patient with Two SDOH

```
P(Hypertension | No high school diploma, Lack of adequate food/water) = 0.668.
The prior P(Hypertension) is 0.29

P(cognitive impairment | No high school diploma, Lack of adequate food/water) = 0.638.
The prior P(cognitive impairment) is 0.046

P(periodontis | No high school diploma, Lack of adequate food/water) = 0.5.
The prior P(periodontis) is 0.5

P(Diabetes/Prediabetes | No high school diploma, Lack of adequate food/water) = 0.476784761904762.
The prior P(Diabetes/Prediabetes) is 0.105

P(Obesity | No high school diploma, Lack of adequate food/water) = 0.4.
The prior P(Obesity) is 0.4
```

Figure 3: Output of Model for Sample Patient with Four SDOH

```
P(traumatic brain injury | sexual abuse of child, Unemployment, Poverty, imprisonment) = 1.5075.
The prior P(traumatic brain injury) is 0.016

P(Alcohol abuse/dependence | sexual abuse of child, Unemployment, Poverty, imprisonment) = 1.255825.
The prior P(Alcohol abuse/dependence) is 0.08

P(bipolar disorder | sexual abuse of child, Unemployment, Poverty, imprisonment) = 0.96.
The prior P(bipolar disorder) is 0.028

P(Coronary Heart Disease | sexual abuse of child, Unemployment, Poverty, imprisonment) = 0.7057446808510637.
The prior P(Coronary Heart Disease) is 0.047

P(Mental Illness | sexual abuse of child, Unemployment, Poverty, imprisonment) = 0.7034920634920636.
The prior P(Mental Illness) is 0.189
```

From our results included in Figure 2, Figure 3, and the appendix, we can see that the model appears to work well for inputs with a smaller number of SDOH. However, some probabilities in the model begin to lose meaning when given inputs of a large number of SDOH when they become more than 1.

Finally, we performed our evaluation. For our formative evaluation results, the physician remarked that the biggest limitation with the model was that it outputted probabilities that weren't always bounded by one. The physician felt like the model did show relative differences given the variables tested but would want to see a statistical analysis of the differences of probabilities or general estimate of error to use this information clinically. Our overall summative evaluation results can be seen in Table 2 below.

Table 2: Summative Evaluation Results

Question	Mean Score
To what extent does the differential disease risk profile match what you believe is a reasonable output based on your prior experience?	3.2
To what extent does the differential risk profile output diseases that you didn't consider or weren't aware of are associated with this patient's unique SDOH?	3.4
How accurate do the probabilities appear?	2.4

Discussion/Future work:

To date, there is no model that systematically characterizes the influence of SDOH on patients' health outcomes. We created this tool to aid physicians in considering a patient's SDOH in order to holistically evaluate their patient's health. We hope this will help physicians take into account both their patients' symptoms as well as their patient's unique SDOH when diagnosing patients and creating treatment plans.

Our model incorporated information relating SDOH to a diverse set of diseases indicating its potential use in a primary care or general hospital setting where a variety of diseases are seen. Additionally, the model achieved solid marks from the physician who noted the reasonable output and relatively novel findings that the model provided.

We recognize that our model, as is, maintains certain limitations. The first major limitation is the assumption that the model makes in assuming that SDOH are conditionally independent of each other given the disease output. We attempted to pick SDOH that did not directly overlap, but the inherent relationships between SDOH, for instance between homelessness and food insecurity, make this assumption problematic. We believe that it is likely that this assumption not being valid leads to some probabilities being above one. This is because this assumption doesn't account for the fact that SDOH are associated and not accounting for this association could artificially raise the probabilities the model gives. A second major limitation of our model is that it did not include basic patient information such as demographics or chief complaint, limiting its use as a diagnostic aid. A third major limitation is that our model only included relationships reported in the literature which means that relationships not reported in the literature were not captured by this model. Related to the third assumption, our fourth major assumption is that the relationships were synthesized from studies that varied significantly in both their methodologies and study populations potentially hindering the generalizability of the model.

In the future, we hope to evaluate the suitability of the various assumptions made within our model. Doing so could greatly increase the generalizability of the model. We could do this by acquiring a large dataset that includes SDOH and patient diagnosis information to update the probabilities and the relationships in our Bayesian Network. Another important direction that could be pursued in the future would be to combine his Bayesian Network of SDOH and health outcomes with a Bayesian Network linking symptoms and demographics to health outcomes with the goal of creating a more robust diagnostic aid. In addition, we would like to test the validity and the utility of this model with more physicians. Despite limitations, we believe that incorporating SDOH into a diagnostic tool could provide clinical utility.

References

1. Daniel, Hilary, et al. “Addressing Social Determinants to Improve Patient Care and Promote Health Equity: An American College of Physicians Position Paper.” *Annals of Internal Medicine*, vol. 168, no. 8, 2018, p. 577., doi:10.7326/m17-2441.

2. Arons, Abigail, et al. “Documenting Social Determinants of Health-Related Clinical Activities Using Standardized Medical Vocabularies.” *JAMIA Open*, vol. 2, no. 1, 2018, pp. 81–88., doi:10.1093/jamiaopen/ooy051.

3. Braveman, Paula, and Laura Gottlieb. “The Social Determinants of Health: It's Time to Consider the Causes of the Causes.” *Public Health Reports*, vol. 129, no. 1_suppl2, 2014, pp. 19–31., doi:10.1177/00333549141291s206.

4. Andermann, Anne. “Taking Action on the Social Determinants of Health in Clinical Practice: a Framework for Health Professionals.” *Canadian Medical Association Journal*, vol. 188, no. 17-18, 2016, doi:10.1503/cmaj.160177.

5. Jaakkola, T. S., and M. I. Jordan. “Variational Probabilistic Inference and the QMR-DT Network.” *Journal of Artificial Intelligence Research*, vol. 10, 1999, pp. 291–322., doi:10.1613/jair.583.

6. Shwe, M. A., et al. “Probabilistic Diagnosis Using a Reformulation of the INTERNIST-1/QMR Knowledge Base.” *Methods of Information in Medicine*, vol. 30, no. 04, 1991, pp. 241–255., doi:10.1055/s-0038-1634846.

7. Mcdaniel, Jt. “Prevalence of Chronic Obstructive Pulmonary Disease: County-Level Risk Factors Based on the Social Ecological Model.” *Perspectives in Public Health,* vol. 138, no. 4, 2018, pp. 200–208., doi:10.1177/1757913918772598.

8. Llorente, José María, et al. “Variability of the Prevalence of Depression in Function of Sociodemographic and Environmental Factors: Ecological Model.” *Frontiers in Psychology*, vol. 9, 2018, doi:10.3389/fpsyg.2018.02182.

9. Hilton-Jones, David. “Application of the International Classification of Diseases to Neurology (ICD-NA).” *Neuromuscular Disorders*, vol. 10, no. 6, 2000, p. 464., doi:10.1016/s0960-8966(00)00097-3.

10. Noordzij, Marlies, et al. “Measures of Disease Frequency: Prevalence and Incidence.” *Nephron Clinical Practice*, vol. 115, no. 1, 2010, pp. c17–c20., doi:10.1159/000286345.

Division of Labor:

Ryan Crowley and Vardhaan Ambati shared the workload equally and often collaborated on the same aspect of the project. Ryan focused more on using ICD-10 to determine the SDOH to include within the model. Vardhaan focused more on performing systematic searches of the literature to find probabilities with which to populate the Bayesian Network. Both individuals worked to design and implement the Bayesian Network and problem-solving methods together.

Authorization to share:

If so desired by the teaching team, we authorize the sharing of this project as an example for future classes.

COVID-19 Situation:

Vardhaan's roommate was a close contact of the first Stanford undergraduate diagnosed with COVID-19. Vardhaan was under self isolation for 3 days until his COVID-19 test results came back negative. Although Ryan was not personally in contact with any undergraduate students diagnosed with COVID-19, he was forced to unexpectedly vacate his housing to return home.

Appendix/Program submission:

Appendix Figure 1: Code Used for Model and Instructions

```python
import csv

SODH = ["No high school diploma", "Unemployment", "Homelessness", "Lack of adequate food/water", "Poverty", "sexual abuse of child", "impriso
diseases = ['Depression', 'Hypertension', 'Coronary Heart Disease', 'Stroke', 'Heart Attack', 'Substance Use Disorder', 'Chronic Kidney Disea


priorDisease = [0.059, 0.29, 0.047, 0.0024, 0.002, 0.03, 0.14, 0.0765, 0.4, 0.189, 0.0033, 0.105, 0.056, 0.12, 0.044, 0.027, 0.08, 0.175, 0.0
priorSODH = [0.1, 0.036, 0.0017, 0.111, 0.118, 0.1, 0.0067, 0.076, 0.924]
D_SDH = []
SDH_D =[]

f = open("values.txt", "r")
for row in f:
    #print(row)
    arr = row.split()
    for i in range(len(arr)):
        if arr[i] != "nan":
            arr[i] = float(arr[i])
    D_SDH.append(arr)

SDH_D = D_SDH


for i in range(len(SODH)):
    for j in range(len(diseases)):
        if D_SDH[i][j] != 'nan':
            value = D_SDH[i][j] * priorSODH[i] / priorDisease[j]
            SDH_D[i][j] = value
        else:
            SDH_D[i][j] == 'nan'



print("Input the numbers of the SODH's you are interested in. Press 'q' to quit.")
for i in range(len(SODH)):
    print(str(i+1) + ". " +SODH[i])
print("")
quit = False
interest = []
while(not quit):
    num = input ("Enter number :")
    if num == 'q':
        quit = True
    else:
        interest.append(int(num) - 1)
print("")

probs = []
probSet = set()
diseaseDict = {}
for i in range(len(diseases)):
    prob = priorDisease[i]
    SDHs = ""
    denom = 1
    for j in range(len(interest)):
        if(SDH_D[interest[j]][i] != "nan"):
            prob *= SDH_D[interest[j]][i]
            denom *= priorSODH[interest[j]]
        if(j == 0):
            SDHs = SDHs + SODH[interest[j]]
        else:
            SDHs = SDHs + ", " + SODH[interest[j]]
    x = prob/denom
    probSet.add(x)
    if x in diseaseDict.keys():
        diseaseDict[x].append(diseases[i])
    else:
        diseaseDict[x] =  [diseases[i]]

for val in probSet:
    probs.append(val)


probs.sort(reverse=True)
for i in range(5):
    for j in range(len(diseaseDict[probs[i]])):
        print("P(" + diseaseDict[probs[i]][j] + " | " + SDHs + ") = " + str(probs[i]) + ".")
        print("The prior P("+diseaseDict[probs[i]][j]+") is " + str(priorDisease[diseases.index(diseaseDict[probs[i]][j])]))
        print("")
```

To run the program in terminal, go to the directory with the code file and type “python [filename].” Pick the SDOH desired, and then hit “q” when done. The program will give the disease risk output.

Appendix Figure 2: Model Output for Sample Cases

a)

```
P(periodontis | Poverty) = 0.654.
The prior P(periodontis) is 0.5

P(asthma | Poverty) = 0.46.
The prior P(asthma) is 0.078

P(Obesity | Poverty) = 0.408.
The prior P(Obesity) is 0.4

P(Hypertension | Poverty) = 0.39.
The prior P(Hypertension) is 0.29

P(Chronic Kidney Disease | Poverty) = 0.2992.
The prior P(Chronic Kidney Disease) is 0.14

P(hypercholesterolemia | Poverty) = 0.2992.
The prior P(hypercholesterolemia) is 0.12
```

b)

```
P(Hypertension | No high school diploma, Lack of adequate food/water) = 0.668.
The prior P(Hypertension) is 0.29

P(cognitive impairment | No high school diploma, Lack of adequate food/water) = 0.638.
The prior P(cognitive impairment) is 0.046

P(periodontis | No high school diploma, Lack of adequate food/water) = 0.5.
The prior P(periodontis) is 0.5

P(Diabetes/Prediabetes | No high school diploma, Lack of adequate food/water) = 0.476784761904762.
The prior P(Diabetes/Prediabetes) is 0.105

P(Obesity | No high school diploma, Lack of adequate food/water) = 0.4.
The prior P(Obesity) is 0.4
```

c)

```
P(Hypertension | nonveteran, Lack of adequate food/water, sexual abuse of child) = 0.7785655172413795.
The prior P(Hypertension) is 0.29

P(cognitive impairment | nonveteran, Lack of adequate food/water, sexual abuse of child) = 0.638.
The prior P(cognitive impairment) is 0.046

P(Alcohol abuse/dependence | nonveteran, Lack of adequate food/water, sexual abuse of child) = 0.526.
The prior P(Alcohol abuse/dependence) is 0.08

P(periodontis | nonveteran, Lack of adequate food/water, sexual abuse of child) = 0.5.
The prior P(periodontis) is 0.5

P(Obesity | nonveteran, Lack of adequate food/water, sexual abuse of child) = 0.4.
The prior P(Obesity) is 0.4
```

d)

```
P(traumatic brain injury | sexual abuse of child, Unemployment, Poverty, imprisonment) = 1.5075.
The prior P(traumatic brain injury) is 0.016

P(Alcohol abuse/dependence | sexual abuse of child, Unemployment, Poverty, imprisonment) = 1.255825.
The prior P(Alcohol abuse/dependence) is 0.08

P(bipolar disorder | sexual abuse of child, Unemployment, Poverty, imprisonment) = 0.96.
The prior P(bipolar disorder) is 0.028

P(Coronary Heart Disease | sexual abuse of child, Unemployment, Poverty, imprisonment) = 0.7057446808510637.
The prior P(Coronary Heart Disease) is 0.047

P(Mental Illness | sexual abuse of child, Unemployment, Poverty, imprisonment) = 0.7034920634920636.
The prior P(Mental Illness) is 0.189
```

e)

```
P(Coronary Heart Disease | nonveteran, Unemployment, sexual abuse of child, Poverty, Lack of adequate food/water) = 4.392933165098292.
The prior P(Coronary Heart Disease) is 0.047

P(Heart Attack | nonveteran, Unemployment, sexual abuse of child, Poverty, Lack of adequate food/water) = 4.386999999999999.
The prior P(Heart Attack) is 0.002

P(Stroke | nonveteran, Unemployment, sexual abuse of child, Poverty, Lack of adequate food/water) = 1.7937500000000004.
The prior P(Stroke) is 0.0024

P(traumatic brain injury | nonveteran, Unemployment, sexual abuse of child, Poverty, Lack of adequate food/water) = 1.5075.
The prior P(traumatic brain injury) is 0.016

P(Diabetes/Prediabetes | nonveteran, Unemployment, sexual abuse of child, Poverty, Lack of adequate food/water) = 1.4813943147392294.
The prior P(Diabetes/Prediabetes) is 0.105
```

Appendix Table 1: Full Summative Evaluation Results

	Question 1	Question 2	Question 3
Model w/ One SDOH	**3**	**3**	**2**
Model w/ Two SDOH	**4**	**4**	**3**
Model w/ Three SDOH	**4**	**2**	**3**
Model w/ Four SDOH	**3**	**4**	**2**
Model w/ Five SDOH	**2**	**4**	**2**