Relations between Inflammation, access to care and Diabetes in two repesentative populations of China and Mexico.

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Author Note

List of group members ordered by alphabet.

Abstract

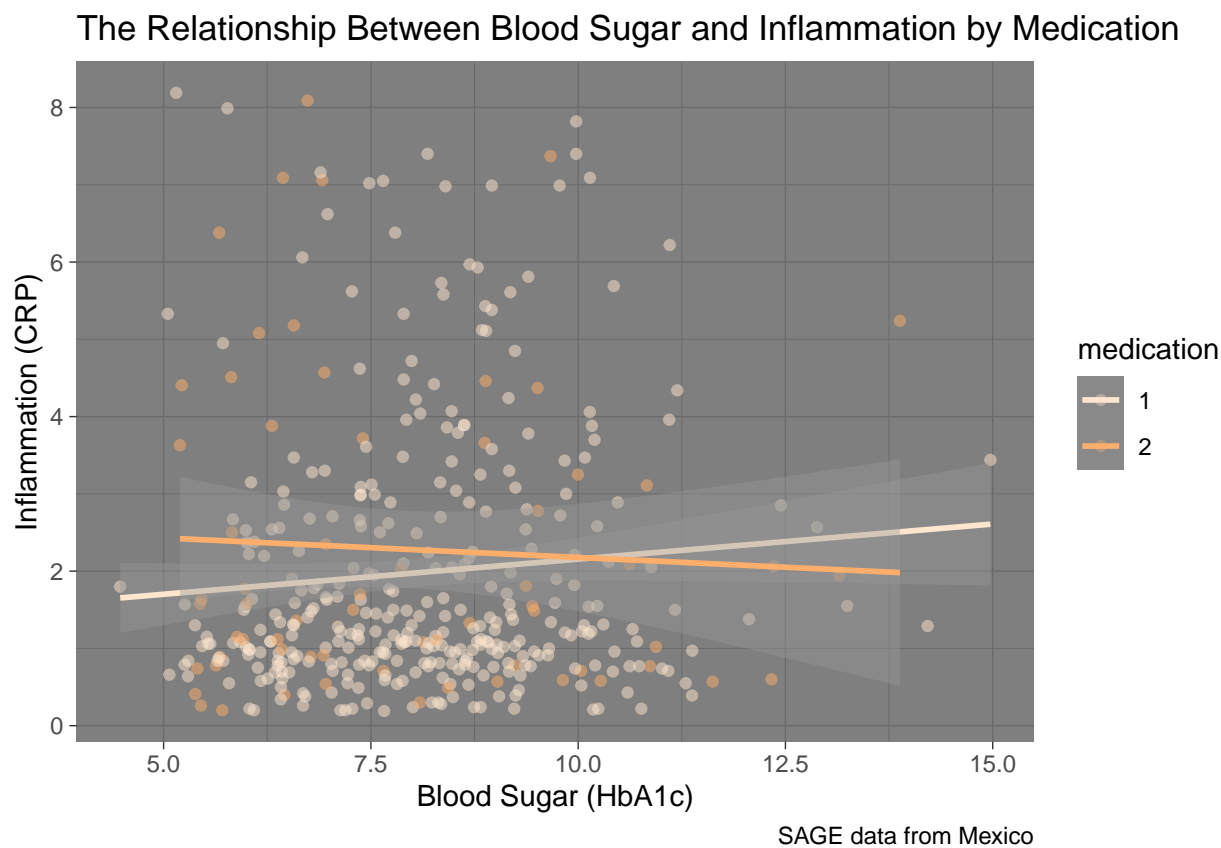*Background.* Background goes here. *Methods.* Methods go here. *Results.* Results here. *Conclusions.* Conclusions here.

Keywords: Diabetes, access to care, inflammation, health, Mexico, China

Word count: X (this cannot easily be done automatically, we can also just leave it out)

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```
## 
## Call:
## lm(formula = crp ~ hba1c * medication + age, data = RQ1_df)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -2.2772 -1.1663 -0.6781  0.7534  6.3926 
## 
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.19497    0.93370   2.351   0.0192 *
## hba1c              0.08034    0.05983   1.343   0.1800
## medication2        1.44670    0.96421   1.500   0.1343
## age               -0.01268    0.01061  -1.194   0.2330
## hba1c:medication2 -0.14441    0.11724  -1.232   0.2188
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 1.768 on 404 degrees of freedom
##   (1551 observations deleted due to missingness)
## Multiple R-squared:  0.01363,    Adjusted R-squared:  0.003864
## F-statistic: 1.396 on 4 and 404 DF,  p-value: 0.2347
```

The Relationship Between Blood Sugar and Inflammation by Medication

(figure: scatterplot of Inflammation (CRP) vs Blood Sugar (HbA1c) with regression lines by medication group 1 and 2)

SAGE data from Mexico

```
## 
## Call:
## lm(formula = crp ~ hba1c * dt_exrcse + age, data = data)
## 
## Residuals:
##    Min     1Q Median     3Q    Max
## -2.058 -1.190 -0.673  0.638  6.334
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.75378    1.06608   2.583   0.0101 *
## hba1c        0.02982    0.08539   0.349   0.7271
## dt_exrcse2  -0.31641    0.87926  -0.360   0.7191
```

```
## age                -0.01274    0.01063  -1.198    0.2315
## hba1c:dt_exrcse2  0.01552    0.10629   0.146    0.8840
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.772 on 404 degrees of freedom
##   (1551 observations deleted due to missingness)
## Multiple R-squared:  0.009143,   Adjusted R-squared:  -0.0006676
## F-statistic: 0.9319 on 4 and 404 DF,  p-value: 0.4452


## tibble [386 x 10] (S3: tbl_df/tbl/data.frame)
##  $ sex         : Factor w/ 2 levels "1","2": 2 1 2 1 2 2 1 1 2 1 ...
##  $ diagnosis   : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...
##  $ age         : int [1:386] 57 67 62 75 87 65 62 60 60 68 ...
##  $ hba1c       : num [1:386] 8.4 6.54 6.05 14.22 8.82 ...
##  $ crp         : num [1:386] 6.98 0.95 3.15 1.29 1.29 ...
##  $ medication  : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 2 ...
##  $ dt_exrcse   : Factor w/ 2 levels "1","2": 2 2 1 2 1 2 2 2 2 2 ...
##  $ med_dt_exrcse: Factor w/ 2 levels "1","2": 2 2 2 2 2 2 2 2 2 1 ...
##  $ access      : Factor w/ 2 levels "1","2": 2 2 2 2 2 2 1 1 1 2 ...
##  $ q5027       : int [1:386] NA NA NA NA NA NA 1 12 12 NA ...


## tibble [350 x 6] (S3: tbl_df/tbl/data.frame)
##  $ diagnosis: Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...
##  $ age      : int [1:350] 67 62 75 87 65 62 60 60 67 57 ...
##  $ hba1c    : num [1:350] 6.54 6.05 14.22 8.82 9.65 ...
##  $ crp      : num [1:350] 0.95 3.15 1.29 1.29 1 ...
##  $ dt_exrcse: Factor w/ 2 levels "1","2": 2 1 2 1 2 2 2 2 1 2 ...
```
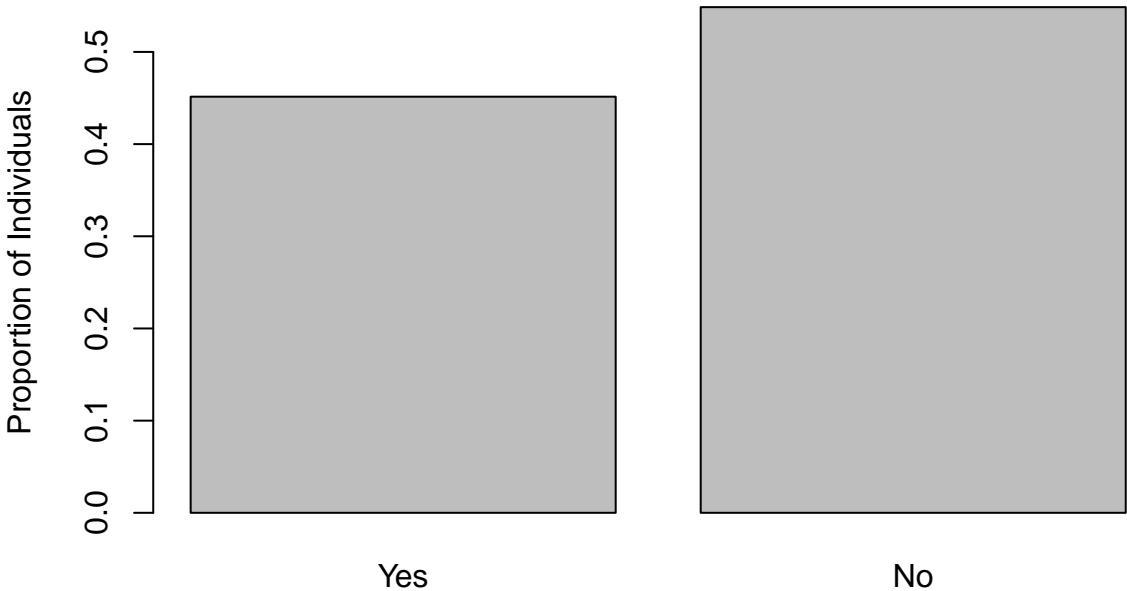
```
##  $ access   : Factor w/ 2 levels "1","2": 2 2 2 2 2 1 1 1 1 2 ...
```

```
##
## Yes  No
## 158 192
```


lividuals 50yo or older with Diabetes that partake in Diet&/Exercise and saw a Dr. in the L

The descriptive statistics for our sample look as follows:

Table 1

Descriptive statistics.

	Mexico
N_{total}	1960
Sex	
male	761 (38.80 %)

	Mexico
female	1198 (61.10 %)
unknown	1 (0.10 %)
Age	68.10 ($SD = 9.30$)
Diabetes	
diagnosed	449 (22.90 %)
undiagnosed	182 (9.30 %)

Introduction

Diabetes and its insidious complications continue to expand as a global health burden at an alarming rate. As of 2021, there were approximately 537 million adults living with diabetes in the world and this number is expected to jump to 783 million by 2045. A disproportionate percentage of these people live in low to middle income countries (LMICs). In light of the Covid pandemic, it is also of great import that we better understand the relationships between diabetes and infectious diseases as diabetes both increased the severity of Covid (in people with elevated a1c levels) and has increased in incidence during the Covid 19 pandemic (Yang et al., 2020) (Rohm, Meier, Olefsky, & Donath, 2022).

Additionally, diabetes is associated with a steep increase in cardiovascular disease risk and is a leading cause of death in many low to middle income countries (LMICs) including Mexico. Although the precise classification of diabetes remains controversial because of the complex nature of its pathogenesis, there are three universally acknowledged subtypes: type 1 diabetes, type 2 diabetes, and gestational diabetes. Diabetes is a progressive disease in that the longer one has it, the more complications ensue. Therefore, it is helpful to conceptualize diabetes as a process that can be stopped, but not reversed. Research that contributes to slowing down or stopping the process can be extremely valuable to global

health regardless of its contribution to cure and prevention because of the astronomical rates of diabetes in our world today.

Inflammation is a strong indicator of diabetes development and progression. Inflammation predicts the development of diabetes (Dilys J. Freeman et al., 2002) (Dilys J. Freeman et al., 2001) (Schmidt et al., 1999). Specifically, trials for drugs directed at inflammation among people with type 2 diabetes have indicated that drugs targeted at inflammation may be a therapeutic option for preventing diabetes (Agrawal & Kant, 2014).Retinopathy and focal neuropathy (Said, 2007) have also been linked to inflammatory processes. Additionally, the direct damage caused by high blood glucose leads to more inflammation and creates a nasty feedback loop wherein inflammation causes more insulin resistance which leads to high blood glucose.

Diabetes treatment and inflammation

The ability of cells to absorb insulin can be increased through diet, exercise, and oral pills.Increasing exercise and dieting can cause major decreases in inflammation. Some of the drugs for type 2 diabetes aimed at increasing insulin sensitivity also decrease inflammation (e.g., drugs that cause weight loss). In the opposite direction, insulin can cause severe low blood glucose levels that initiate a stress response causing more inflammation.

Methods

C-reactive protein and hba1c measured through dried bloodspots (minimally invasive biomarkers) [McDade, Williams, and Snodgrass (2007)).

Self-report surveys conducted by trained interviewers.

Data are from the World Health Organization's Study on Adult Health and Ageing (SAGE). Our data is from 1 of 5 countries where the data were collected.

Cite R packages here

Discussion

Limitations

We were not able to look at pills and insulin separately and some their effects have the potential to cancel each other out. The sex variable was established through interviewer discernment.

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