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Short Communication

Risk factors associated with multiple correlated health outcomes in the 500 Cities Project

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ABSTRACT

Reducing chronic disease is a major health challenge. Risk factors for chronic diseases are often studied at the individual level, even though interventions and policies may be implemented at the city level. We use an ecologic study design with city-level data, to simultaneously assess the relative impact of unhealthy behaviors and preventive care measures on multiple chronic disease health outcomes. We analyze a newly available, large national dataset called the 500 Cities Project. We examine the associations between city-level prevalence of unhealthy behaviors, clinical preventive service use, and all chronic disease health outcomes in 500 of the largest U.S. cities for year 2014. After adjusting for age and demographic characteristics, using MANOVA we found that the top three risk factors for all health outcomes are smoking (Pillai's trace = 0.95, approx. F = 688.7, p-value $<$ 0.0001), lack of physical activity (Pillai's trace = 0.91, approx. F = 380.0, p-value $<$ 0.0001) and binge drinking (Pillai's trace = 0.91, approx. F = 348.8, p-value $<$ 0.0001), which are statistically significant after adjusting for multiple comparisons. Higher prevalence of an annual dental checkup, a preventive service use measure, is correlated with lower prevalence of several chronic diseases such as diabetes (correlation coefficient $r = -0.88$), poor physical health ($r = -0.91$), stroke ($r = -0.85$), cardiovascular disease ($r = -0.83$) and poor mental health ($r = -0.82$). Identifying important chronic disease risk factors at the city-level may provide more actionable information for policymakers to improve urban health.

1. Introduction

Reducing chronic disease is a major health challenge. Nearly half of Americans have at least one chronic disease, while a quarter of Americans have multiple chronic conditions (Ward et al., 2014). These conditions can have detrimental impacts on many aspects of daily life, including health, work, quality of life and function. It is known that several risk factors related to unhealthy behaviors, collectively termed the SNAP (Smoking, Nutrition, Alcohol and Physical activity) risk factors (Fine et al., 2004; Noble et al., 2015), are strongly associated with preventable causes of morbidity. Meanwhile, several clinical preventive services, such as an annual physical checkup, cholesterol screening and colon screening, can be protective against chronic conditions. However, risk factors for chronic diseases are often studied at the individual level, not at the city level, even though interventions and policies may be implemented at the city level.

In this article, we use an ecologic study design with city-level data to explore the relationship between prevalence measures of unhealthy behaviors, clinical preventive service use and health outcomes using the 500 Cities Project. The 500 Cities Project is a newly available dataset that provides city-level small area estimates for 497 of the largest U.S. cities for year 2014 (Scally et al., 2017; https://www.cdc.gov/500cities/, 2016), plus 3 other smaller cities to ensure inclusion of cities from all 50 states. Together, these cities have a total population of 103,020,808, representing approximately 33.4% of the total U.S. population. The populations of the different cities range from 42,417 in Burlington, Vermont to 8,175,133 in New York City, New York. Prevalence measures for these 500 cities are based on information from their corresponding census tracts (> 28,000 in total) (https://www.cdc.gov/500cities/, 2016). There are between 8 and 2140 census tracts per city, and in general, census tracts average about 4000 individuals (https://www.census.gov/geo/reference/gtc/gtc_ct.html, 2018). The CDC chose a set of thirteen health outcomes to be included in the 500 Cities Project, because they believe these outcomes represent chronic disease public health priorities, and are the most common, costly, and preventable health outcomes (https://www.cdc.gov/500cities/, 2016). It is possible that these health outcomes may have potentially contrasting etiology, and that unhealthy behaviors and

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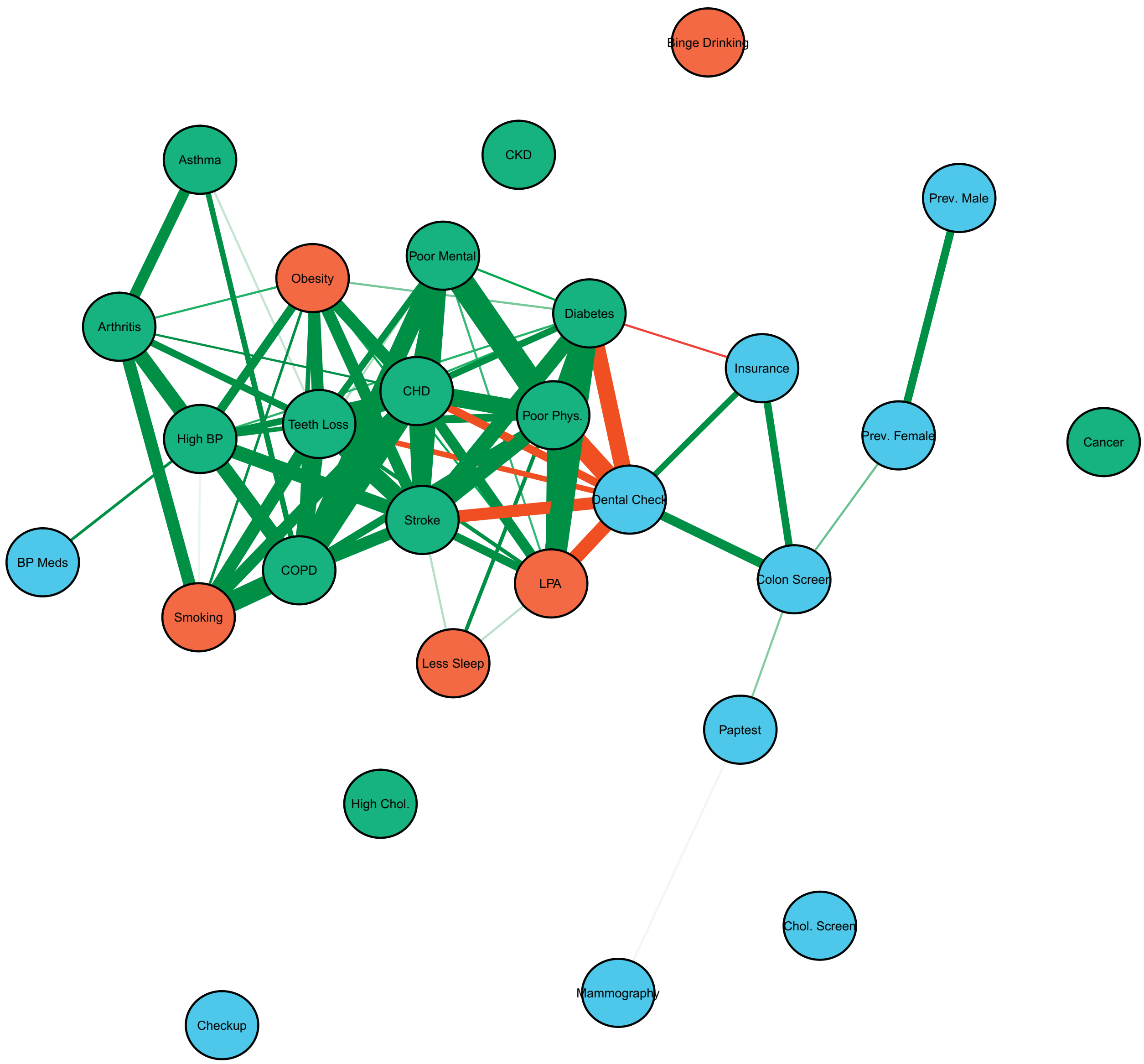

Fig. 1. Associations between unhealthy behaviors, prevention measures and health outcomes. Only $|r| > 0.75$ is plotted; thicker lines indicate stronger correlation; green indicates a positive association; red, negative association. Unhealthy behaviors are colored in red circles; prevention measures, in blue circles; health outcomes, in green circles. Data is from the 500 Cities Project, which contains US city-level data from 2014. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

preventive care factors may affect each health outcome differently. However, our goal is to show at the city level, the potential impact of unhealthy behaviors and preventive care towards the overall burden of chronic disease health outcomes.

A key difference between our approach and that of previously reported literature on risk factors of chronic disease, is that we investigate these associations at the city-level, not the individual-level. Specifically, we seek to simultaneously assess the relative impact of different unhealthy behaviors and different clinical preventive service use measures on multiple chronic disease health outcomes. We use network analysis to visualize the correlation between prevalence of unhealthy behaviors, clinical preventive service use, and health outcomes at the city level. We also use multivariate analysis to identify risk factors associated with all health outcomes.

2. Methods

2.1. Sample

Data from the 500 Cities Project contains city-level adjusted prevalence of unhealthy behaviors, clinical preventive service use, and health outcomes. City-level prevalence is adjusted for age, race/ethnicity, sex, education, and county-level poverty (https://www.cdc.gov/500cities/, 2016). Data from the 500 Cities Project is based on adult samples (age ≥ 18 years, unless otherwise noted) from the Behavioral Risk Factor Surveillance System (BRFSS), a nationally representative self-reported health surveillance survey (https://www.cdc.gov/500cities/, 2016).

2.2. Unhealthy behavior covariates

We include five measures on unhealthy behaviors (Scally et al., 2017; https://www.cdc.gov/500cities/, 2016): *Binge drinking* (≥5

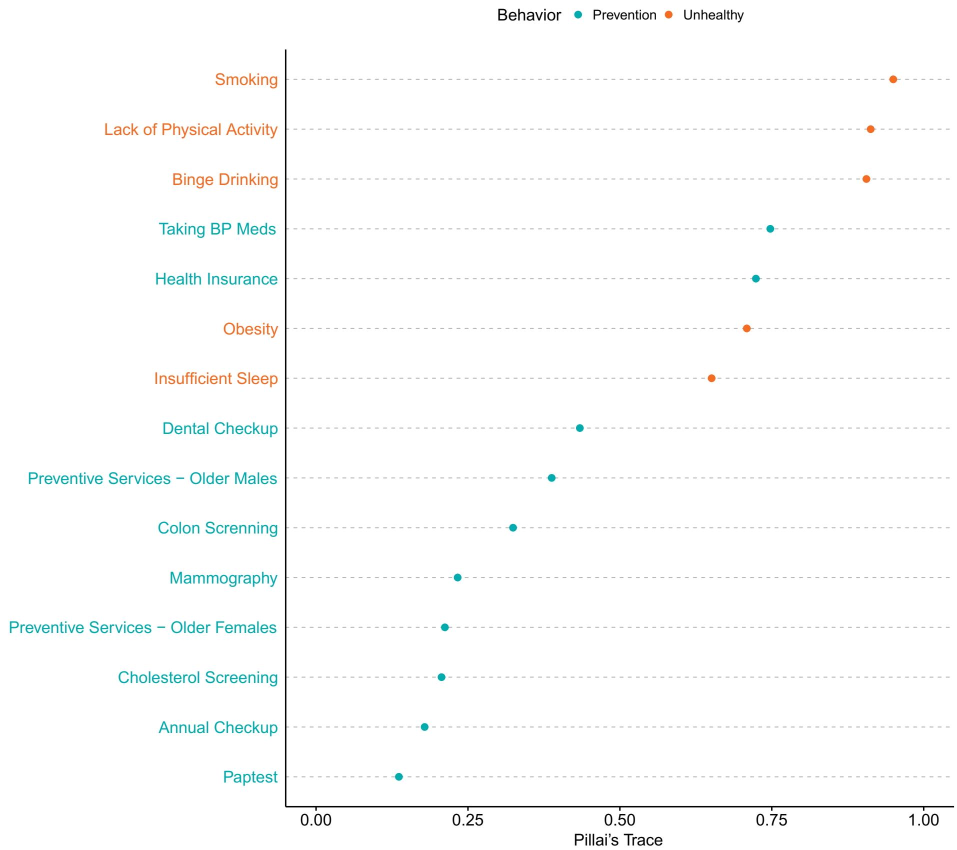

Fig. 2. Relative importance of unhealthy behaviors and prevention measures associated with all health outcomes. Relative importance is quantified by Pillai's Trace. Data is from the 500 Cities Project, which contains US city-level data from 2014.

drinks for men, or ≥ 4 drinks for women at a specific occasion in the last 30 days); *current smoking* (lifetime smoking of ≥ 100 cigarettes and currently smoking); *no leisure time physical activity* (no physical activities or exercises in the last 30 days); *obesity* (*BMI* ≥ 30), and *insufficient sleep* ($<$ *7 hour sleep*).

2.3. Clinical preventive service use covariates

We include ten measures on clinical preventive service use: *current health insurance*, *routine checkup*, *dental checkup*, *taking blood pressure medication*, *cholesterol screening*, *mammography use*, *Papanicolaou smear use*, *colon screening*, and *preventive service use among older adult males and females* (Scally et al., 2017; https://www.cdc.gov/500cities/, 2016).

2.4. Health outcomes

Lastly, we include thirteen measures on health outcomes (Scally et al., 2017; https://www.cdc.gov/500cities/, 2016). The variables *arthritis*, *current asthma*, *high blood pressure*, *cancer*, *high cholesterol*, *chronic kidney disease*, *chronic obstructive pulmonary disease*, *stroke*, *coronary heart disease* and *diabetes* are defined as respondents who report ever having been told they have that condition by a doctor, nurse or other health professional. *Poor mental health* and *poor physical health* were defined as reporting that for fourteen or more days in the last month. Teeth loss was defined as the loss of all natural teeth due to tooth decay or gum disease and was only reported for adults at or above 65 years of age.

2.5. Statistical analyses

We first analyzed the correlation among all the variables (prevalence of unhealthy behaviors, prevention measures and health outcomes). For ease of comparison, we first took the logarithm of all variables, and then centered and scaled all the variables. Using the R package '*qgraph*' (Epskamp, 2017), in R version 3.3.3, we visualized the correlation matrix among all the variables as a network.

We next used multivariate analysis of variance (MANOVA) to test if unhealthy behaviors and prevention measures are associated with all health outcomes simultaneously. In our model, we include all unhealthy behaviors and prevention measures, to simultaneously model their association with all health outcomes. We conducted hypothesis testing using Pillai's trace, and we report the F test statistic for each independent variable as a measure of its effect, using a Bonferroni adjustment to account for multiple testing. A p-value was considered statistically significant if it was less than $\alpha = 0.0033 = 0.05/15$, which is the significance level adjusted for 15 hypothesis tests. The analyses were performed in R version 3.3.3.

3. Results

Fig. 1 presents a network plot of the correlation matrix between prevalence of different unhealthy behaviors, prevention measures and unhealthy outcomes. In this network plot, each variable is represented by a node, or circle, while the lines, or edges, between the nodes depict the strength of the correlation. The thickness of the line indicates the strength of the association; for example, a thicker line depicts a larger correlation. Furthermore, red lines depict a negative correlation between two variables, while green lines depict a positive correlation between two variables. We only plot correlations with absolute value above 0.75.

We see that annual dental checkup is the prevention measure most strongly correlated with many poor health outcomes. The results show that prevalence of annual dental checkup is strongly negatively associated with prevalence of diabetes (correlation coefficient $r = -0.88$), poor physical health ($r = -0.91$), lack of physical activity ($r = -0.87$), stroke ($r = -0.85$), poor mental health ($r = -0.82$), cardiovascular disease ($r = -0.83$), teeth loss ($r = -0.81$) and lack of insurance $r = (-0.85)$. The results also show that prevalence of insufficient sleep is positively correlated with prevalence of diabetes ($r = 0.76$), lack of physical activity ($r = 0.76$) and stroke ($r = 0.80$). Prevalence of lack of physical activity is positively associated with prevalence of several chronic conditions, including diabetes ($r = 0.93$), poor physical health ($r = 0.85$), poor mental health ($r = 0.77$), stroke ($r = 0.83$), cardiovascular heart disease ($r = 0.84$), teeth loss ($r = 0.80$).

Fig. 2 presents the relationship between unhealthy behaviors and prevention measures with all health outcomes simultaneously. Here, we are interested in the relative importance of the unhealthy behaviors and prevention measures, so we use Pillai's trace to quantify the variable importance, which ranges from 0 to 1. The figure shows that out of all possible unhealthy behaviors and preventive clinical services used, three unhealthy behaviors have the strongest associations with all poor health outcomes. Specifically, the top three risk factors are smoking (Pillai's trace = 0.95, approx. F = 688.7, p-value < 0.0001), lack of physical activity (Pillai's trace = 0.91, approx. F = 380.0, p-value < 0.0001) and binge drinking (Pillai's trace = 0.91, approx. F = 348.8, p-value < 0.0001), which are all statistically significant after adjusting for multiple comparisons.

4. Discussion and conclusion

This study examined the associations between city-level prevalence of unhealthy behaviors, clinical preventive service use, and health outcomes in 500 of the largest U.S. cities. Using data from the 500 Cities Project, we found that among all unhealthy behaviors and clinical preventive service measures, prevalence of three unhealthy behaviors—smoking, lack of physical activity and binge drinking—are the most strongly associated with higher prevalence of chronic disease health outcomes. We note that although Fig. 1 shows that binge drinking does not have a strong ($|r| > 0.75$) correlation with individual health outcomes, it was still found to be an important predictor of overall chronic disease outcomes. We also found that higher prevalence of an annual dental checkup, a preventive service use measure, is associated with lower prevalence of several chronic diseases. This is likely a complex relationship - the literature has shown that dental check-ups are associated with factors such as SES (Thomson et al., 2010), dental insurance (Gnanamanickam et al., 2018), better mental health (Teng et al., 2016). Our analysis differs from traditional cohort studies which report associations at the individual level. By analyzing city-level data, our findings can help public health policymakers design systemic and structural intervention policies at the city-level to improve population health.

While previous studies have reported that the top three risk factors—smoking, binge drinking and lack of physical activity—are associated with most preventable causes of morbidity, we have now been able to show this result in the current urban population. Notably, we find that even when accounting for many preventive clinical services, it is still the prevalence of modifiable lifestyle factors that is most strongly associated with poor health. The findings can facilitate the identification of vulnerable cities for intervention strategies in order to decrease the prevalence of chronic conditions in these cities.

There are several limitations to our analysis. First, as the small area estimates of the 500 Cities Project are based on BRFSS, a self-reported sample survey, there may be limitations due to measurement bias, non-response or non-coverage (https://www.cdc.gov/500cities/, 2016). Second, while prevalence data from the 500 Cities Project is adjusted for age and socio-demographic characteristics, we are limited by the lack of other confounder information, such as additional variables related to socio-economic status, which may help explain health and screening behaviors (Scally et al., 2017). Third, while our analysis shows associations between higher prevalence of certain measures (e.g., smoking, lack of physical activity) and higher prevalence of chronic diseases, we cannot interpret these findings as a causal relationship. Many of the health outcomes are complex and interrelated, and arise from a combination of environmental, genetic and other factors, for which we do not have data. While other studies at the individual level may better differentiate these mechanistic causes of disease, our goal in this analysis is to study - at a population level - the main lifestyle factors that are associated with chronic disease. Our study encompasses a large population which accounts for approximately one third of the U.S. population. Therefore, we have identified proxy variables—particularly binge drinking, smoking, lack of physical activity, and annual dental checkup—as indicators of prevalence of thirteen chronic disease health outcomes in the population.

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