Assignment

Martijn Koster, 6234119 Jurrian van de Kraats, 5961688
Tim Poorthuis, student nr

2023-02-15

1 Introduction

In this paper we will examine whether there is a causal effect from elderly people who have received an influenza vaccine and the likelihood of hospitalization. This will be examined by using the patient records dataset and different modeling methods using propensity scores, to account for confounders.

2 Methods

2.1 Examening the causal structure

Domain knowledge was used to create a DAG (Figure 1) that explains the causal structure present in the data. The variable 'contact with chiropractor (GP)' forms a proxy for the unobserved variable healthy lifestyle. Getting the influenza vaccine is connected to age and contact with GP. Having obtained a influenza vaccination was associated with a lower risk for adverse cardiovascular events [Behrouzi et al., 2022]. Having pulmonary disease and diabetes increases the chance for cardiovascular disease [Genootschap]. Sex forms a confounder in a healthy lifestyle [Loef and Walach, 2012] which in turn causes the afore mentioned diseases. The causal paths of the DAG should be examined to asses whether unbiased causal inference is possible. There is a flow of statistical information through open backdoor paths due to observed and unobserved confounders. The eventual model would need to adjust for these confounders in order to perform an unbiased causal inference.

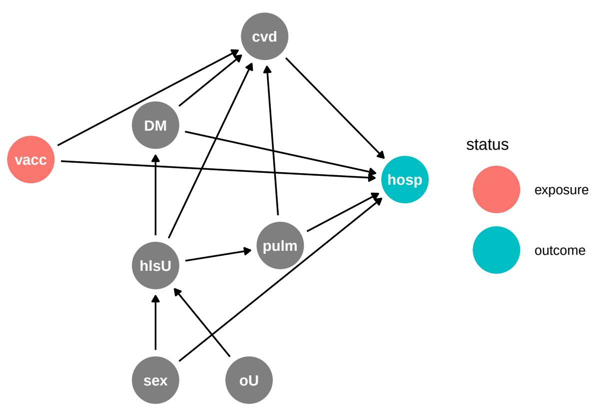

Figure 1: DAG model with Vaccine as exposure and hospitalization as outcome

2.2 Statistical Methods

2.2.1 Baseline Characteristics

The electronic patient records dataset consist of eight variables. The variables age and contact with a chiropractor were continues, the variables vaccination status, sex, cardiovascular disease, pulmonary disease, diabetes and hospitalization were binominal. Table 1 presents the baseline characteristics of 40000 individuals who were included in the study.

Baseline characteristics stratified by the study outcome indicate that 254 of the respondents were hospitalized. Respondents who were hospitalized were older (79.68 vs 75.63), had more contact with the GP (21.08 vs 14.71), were less often female (48.43% vs 61.99%), had more often cardiovascular disease (72.05% vs 49.25%) and more often Diabetes (11.42% vs 6.51%).

Table 1: Baseline Characteristics stratified by Influenza vaccination received and Hospitalisation

		Influenza vaccination received		Hospitalized	
Characteristics	Total	Yes	No	Yes	No
N	40000	29616	10384	254	39746
Age, mean (SD)	75.65 (6.97)	75.9 (6.83)	74.97 (7.32)	79.68 (7.2)	75.63 (6.97)
Contact, mean (SD)	14.75 (11.54)	15.85 (11.73)	11.64 (10.38)	21.08 (15.59)	14.71 (11.5)
Female, n (%)	24763 (61.91)	18022 (60.85)	6741 (64.92)	123 (48.43)	24640 (61.99)
Pulmonary disease, n (%)	4937 (12.34)	4244 (14.33)	693 (6.67)	60 (14.33)	4877 (12.27)
Cardiovascular disease, n (%)	19757 (49.39)	15702 (53.02)	4055 (39.05)	183 (72.05)	19574 (49.25)
Diabetes mellitus, n(%)	2618 (6.54)	2223 (7.51)	395 (3.8)	29 (11.42)	2589 (6.51)
Received Influenza Vaccination, n (%)				184 (72.44)	29432 (74.05)

2.2.2 Propensity Scores (PS)

In order to control for confounding, a PS was estimated by fitting a logistic regression. A PS gives the probability being vaccinated for the respondents. Based on the DAG (Figure 1) the variables: age, sex, cardiovascular disease, pulmonary disease, diabetis mellitus, and GP contact were used in the PS model. For the variables age and contact a spline is used [Tian et al., 2019].

In Figure 2, the PS for vaccinated and unvaccinated individuals appear to be well-balanced, supporting the positivity assumption, which means that both treatement groups have a chance to get the treatment given the covariates [Westreich and Cole, 2010].

2.2.3 PS as Covariate

The first adjusted model is to use the PS as a covariate. In a observational study the treated and untreated group have an equal distribution given that these are divided in groups of a constant propensity. The propensity score can be used as a baseline variable to account for the dimensional difference between groups since it is assumed that the treatment is unconfounded given this propensity score [Schafer and Kang, 2008].

2.2.4 Inverse Probability Weighting (IPW)

With the aforementioned propensity scores, IPW is calculated by $\frac{1}{PS}$ for the vaccinated group and $\frac{1}{1-PS}$ for the unvaccinated. IPW creates a pseudo-population by equaling the effect of the confounders mimicking a random control trial. [Shiba and Kawahara, 2021].

Two models were created, one with stabilized- and one with unstabilized weights. When using stabilized weights the numerator model also includes confounders, giving more stable estimates compared to the unstabilized weights [van der Wal and Geskus, 2011]. In both models bootstrapping was used to account for the inflated sample size of the pseudo population.

3 Results

Table 2 shows the crude association between vaccination status and hospitalization was examined using logistic regression, and the odds ratio was found to be 0.921 (95% CI: 0.699, 1.214), indicating a non-significant association ($p = 0.562$). The C-statistic, a measure of discrimination, was 0.508, suggesting poor predictive performance of the model.

Considering the second model in Table 2, which presents the PS score as covariate, the Odds Ratio suggests a significant negative association (adjusted OR: 0.635. 95% CI 0.478 to 0.843; $p <.001$). The

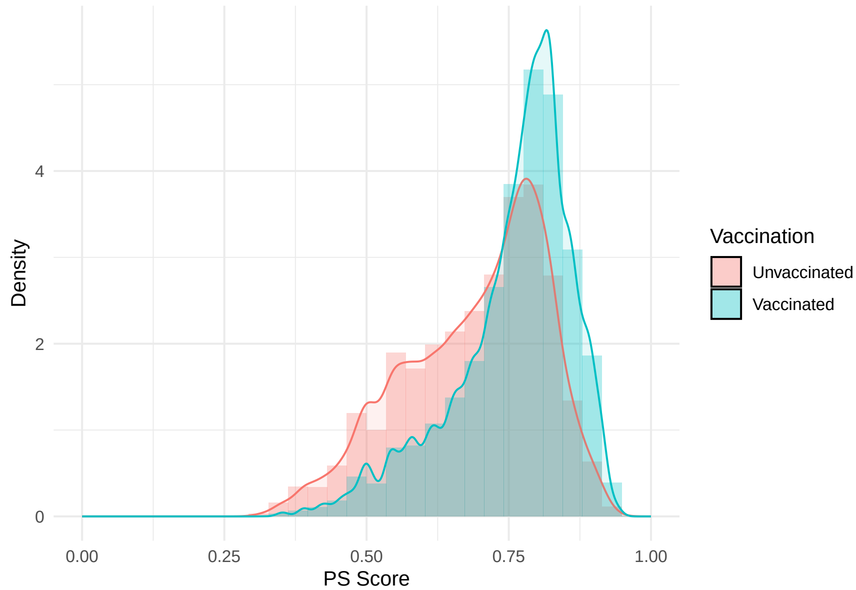

Figure 2: Distribution of the Propensity score for participants who received a vaccination compared with those who did not receive a vaccination

C-Statistic of 0.679 suggests that the model has moderate discriminatory power.

The IPW model with unstabilised weights yields significant negative association between the exposure and outcome variable (adjusted OR: 0.617, 95%CI 0.523 to 0.728; p <.001). The model presents moderate discriminatory power, where C = 0.573.

The last model in Table 2 is an IPW model with stabilised weights. This model also presents a negative association between vaccination and hospitalisation (Adjusted OR: 0.617, 95% CI 0.509 to 0.748; p <.001). The C-statistic suggests moderate discriminatory power (C= 0.573).

Table 2: Association between influenza vaccination and hospitalization (n=40000)

Model Specification	OR (95% CI)	P-Value	C-Statistic
Unadjusted	0.921 (0.699 to 1.214)	0.562	0.508
PS score as covariate	0.635 (0.478 to 0.843)	<.001	0.679
Unstabilised IPW	0.617 (0.523 to 0.728)	<.001	0.573
Stabilised IPW	0.617 (0.509 to 0.748)	<.001	0.573

4 Conclusion / Discussion

- Conclusions supported by data
- Other issues (both positive and negative) Maybe write something about matching here?

References

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