Assignment

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Introduction

Write here a short motivation with a RQ

- well articulated RQ

The aim of the study is to assess whether annual influenza vaccination reduces the risk of hospitalization among elderly (i.e., people aged >=65 years).

Methods

Selection of confounders

Based on the Directed Acyclical Graph (DAG) model in Figure 1 confounders were selected to adjust the statistical model.

Statistical Methods

Baseline Characteristics

Baseline characteristics are important, because they provide essential information on the participant and help to ensure that the study is conducted in a fair and unbiased manner. The baseline characteristics of the study were summarised. The categorical variables were summarised as frequencies and means, whereas the continuous variables as means SD. The baseline characteristics will be stratified by both the exposure as the outcome variable.

Propensity Score Model

In order to control for confounding (observed and unobserved), a propensity score score was estimated by fitting a logistic regression. The variables used to calculate the propensity score are derived from the aforementioned DAG, namely: age, sex, cardiovascular disease, pulmonary disease, diabetis mellitus, and GP contact in 12 months prior to start of study. For the variables age and contact a spline is used, because it has shown favorable performance compared to other propensity score methods (Tian, Baro & Zhang, 2019).

We will develop a propensity score model and calculate Inverse probability weighting

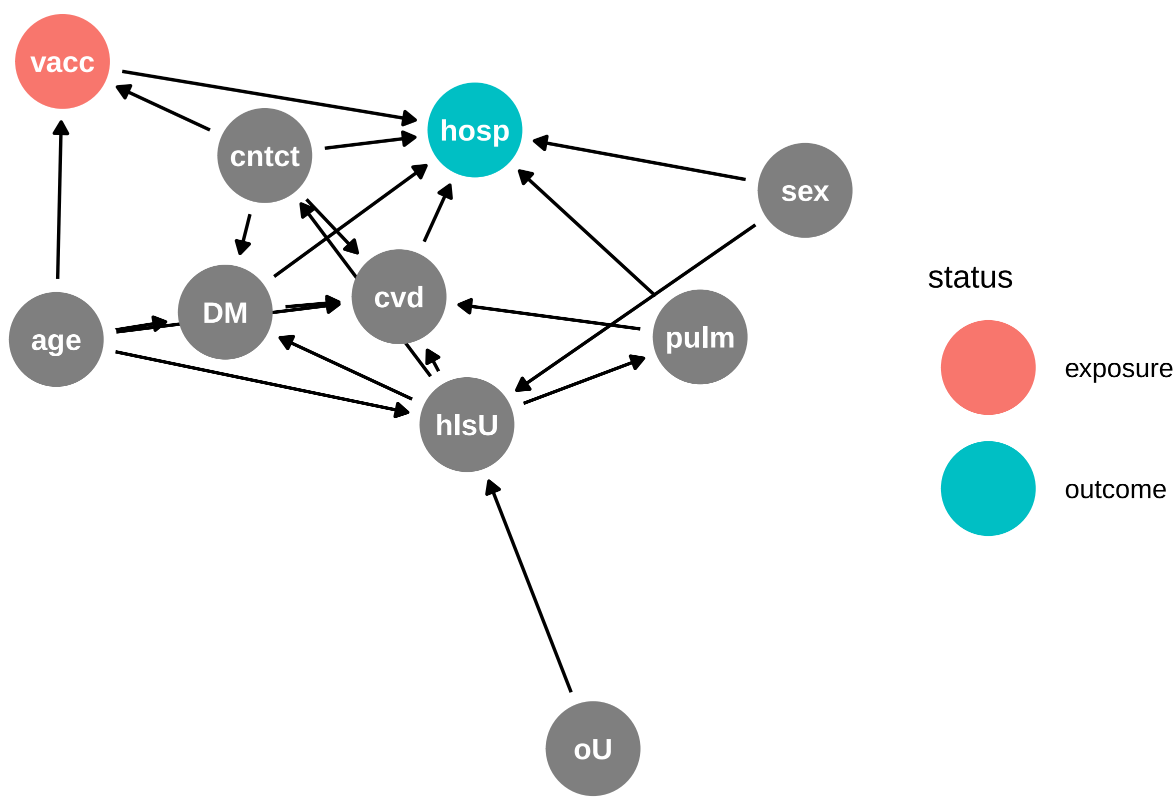

Figure 1: DAG model with Vaccine as exposure and hospitalization as outcome

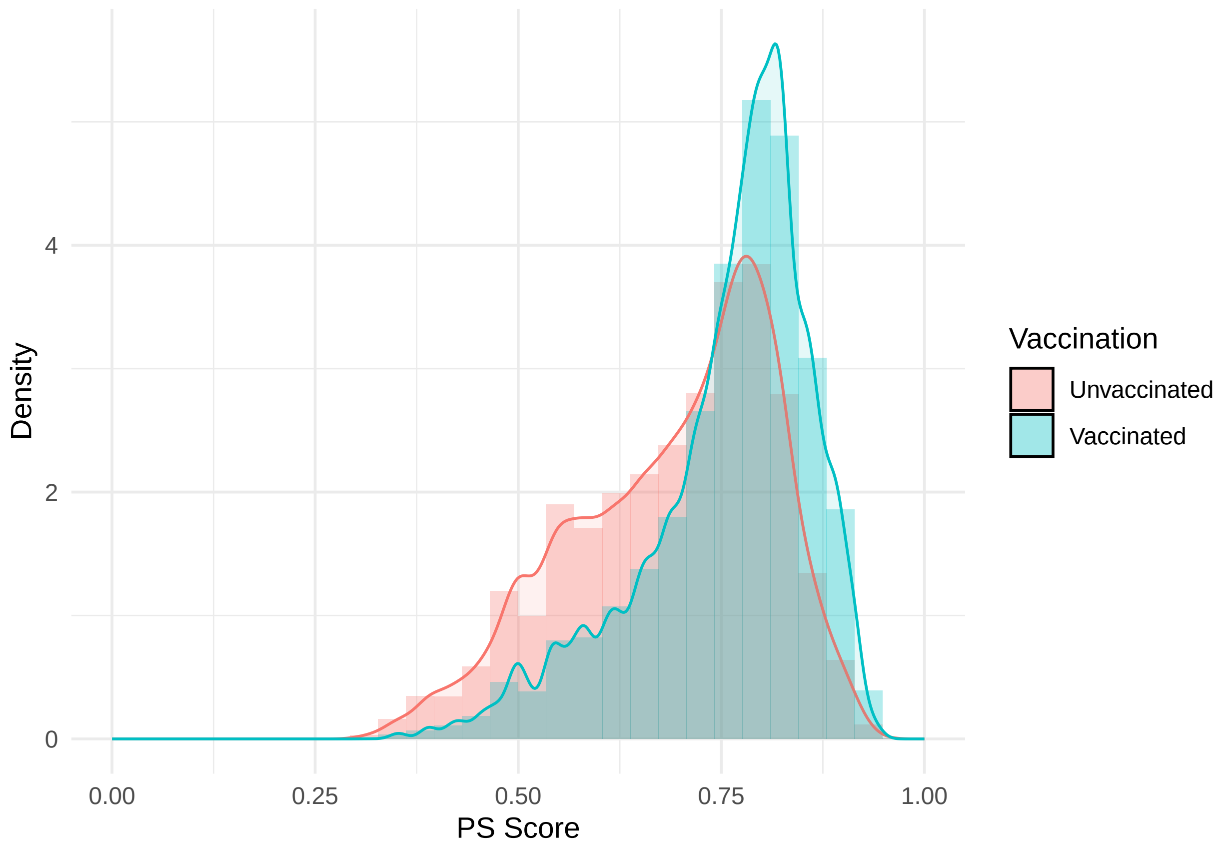

Figure 2: (#fig:ps_score)Distribution of the Propensity score for participants who received a vaccination compared with those who did not receive a vaccination

The confounders are moderately related with the exposure of interest (C=0.66) –> Add some interpretation here.

We see that the mean propensity score for the ones who are vaccinated is higher (As expected)

Assignment These are the unstabilised weights of the inverse probability score.

We can use stabilised weights as well

What's the difference compared to unstabilized weights? *The difference is in the numerator of the weights. Here, the results are equal, because the numerator is just a constant. However, the numerator model can include confounders too, in which case the stabilized weight yield more stable estimates.*

WE need to check for positivity:

The positivity assumption means that both exposed and unexposed individuals need to be present in all sub-populations defined by the combinations of covariate values –> Westreich, D., & Cole, S. R. (2010). Invited commentary: positivity in practice. American journal of epidemiology, 171(6), 674-677.

There is non-positivity

- Checking assumptions of method to control for confounding
- Implementation of methods to control for (observed/unobserved) confounding

Results

Baseline Characteristics

Table 1 presents the baseline characteristics of 40,000 individuals who were included in the study. The mean age 75.65 and the majority of the study population 61.91% were female. Approximately half of the respondent have Cardiovascular disease, whereas 12.34 percent have Pulmonary disease and 6.54% have Diabetes Mellitus.

A total of 29616 (74.04%) respondents were vaccinated, whreas 10384 (25.96%) were not vaccinated. People who received a vaccination had on average more often pulmonary disease (14.33% vs 6.67%), cardiovascular disease (53.02% vs 39.05%) and diabetes (7.51% vs 3.8%).

Baseline characteristics stratified by the study outcome indicate that 254 of the respondents were hospitalized as opposed to 39746 who were not. Respondents who were hospitalized were older (79.68 vs 75.63), had more often contact with the GP (21.08 vs 14.71), were on average less often a female (48.43% vs 61.99%), had on average more often cardiovascular disease (72.05% vs 49.25%) and on average 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)

- Reporting characteristics of study population
- Reporting crude/adjusted effect measures

Crude measures:

As shown in Table 2, 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 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).

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)	0.000	0.679
Unstabilised IPW	0.617 (0.523 to 0.728)	0.000	0.573
Stabilised IPW	0.617 (0.509 to 0.748)	0.000	0.573

Adjusted measures

Conclusion / Discussion

- Conclusions supported by data
- Other issues (both positive and negative)

References

Shiba K, Kawahara T. Using Propensity Scores for Causal Inference: Pitfalls and Tips. J Epidemiol. 2021 Aug 5;31(8):457-463. doi: 10.2188/jea.JE20210145. Epub 2021 Jun 12. PMID: 34121051; PMCID: PMC8275441.

Yuxi Tian, Elande Baro & Rongmei Zhang (2019) Performance evaluation of regression splines for propensity score adjustment in post-market safety analysis with multiple treatments, Journal of Biopharmaceutical Statistics, 29:5, 810-821, DOI: 10.1080/10543406.2019.1657138