High dose inactivated influenza vaccine inconsistently improves heterologous antibody responses in an elderly human cohort

**Authors**

* W. Zane Billings (ORCID: 0000-0002-0184-6134);
* Yang Ge (0000-0001-5100-0703);
* Jessica H. Knight (0000-0001-5764-7495);
* Hayley Hemme (0009-0002-6609-1390);
* Savannah M. Hammerton (0000-0003-2231-3510);
* Amanda L. Skarlupka (0000-0002-3654-9076);
* Wangnan Cao (0000-0002-6163-2760);
* Ye Shen;
* Justin Bahl (0000-0001-7572-4300);
* Paul G. Thomas;
* Ted M. Ross (0000-0003-1947-7469);
* Andreas Handel (0000-0002-4622-1146)

**Author affiliations**

1. College of Public Health, University of Georgia, Athens, GA, USA.
2. Center for the Ecology of Infectious Diseases, The University of Georgia, Athens, GA, USA.
3. School of Health Professions, University of Southern Mississippi, Hattiesburg, MS, USA.
4. National Cancer Institute, Bethesda, MD, USA.
5. School of Public Health, Peking University, Beijing, China.
6. St. Jude Children’s Research Hospital, Memphis, TN, USA.
7. Center for Vaccines and Immunology, University of Georgia, Athens, GA, USA.
8. Florida Research & Innovation Center, Cleveland Clinic, Port St. Lucie, FL, USA.

These authors (WZB and YG) contributed equally to this work.

Co-corresponding authors: WZB (wesley.billings@uga.edu), YG (Yang.Ge@usm.edu), AH (ahandel@uga.edu)

Disclaimer: This article was prepared while Amanda L. Skarlupka was employed at University of Georgia. The opinions expressed in this article are the author’s own and do not reflect the view of the National Institutes of Health, the Department of Health and Human Services, or the United States government.

# Abstract

**Background:** Older adults often mount a weak immune response to standard inactivated influenza vaccines. To induce a stronger response and better protection, a high-dose (HD) version of the inactivated Fluzone vaccine is recommended for individuals >65 years of age. While better immunogenicity and protection against the vaccine strain has been shown, it is not known if the HD vaccine also induces a better antibody response to heterologous strains.

**Methods:** We fit bayesian multilevel regression models to hemagglutination inhibition (HAI) antibody data from an influenza vaccine cohort spanning the 2013/14-2021/22 influenza seasons. We used this model to estimate the average causal effect (ACE) of obtaining the HD vaccine, relative to the SD vaccine.

**Results:** We show that while there is generally a benefit derived from the HD vaccine, the impact is small and inconsistent. For some strains, the HD vaccine might even result in less robust heterologous responses.

**Conclusions:** We suggest that further increases in dose might be worth investigating to help induce a stronger broad response.

**Keywords:** influenza, high-dose influenza vaccine, heterologous responses

# Introduction

Influenza vaccines are an important tool for reducing the burden of seasonal influenza, but the average effectiveness is often less than 50% [1]. Standard dose (SD) split inactivated vaccines, such as Sanofi Pasteur’s Fluzone, comprise the majority of vaccines licensed in the US [2], and are formulated to contain 15 micrograms of influenza hemagglutinin (HA) antigen protein for each strain of influenza included in the vaccine [3]. Influenza vaccines often induce a weak response in elderly individuals [4,5]. In response, Sanofi Pasteur developed a high dose (HD) formulation of the vaccine, Fluzone HD, which contains 60 micrograms of HA per strain in one dose [6,7].

In elderly individuals, HD vaccines induce a stronger homologous antibody response compared to SD vaccines to the influenza strains contained in the vaccine [7–13]. Additionally, HD vaccination is associated with reduced disease severity and reduced risk of complications in elderly individuals who contract influenza after vaccination [13]. HD vaccines also have the potential to elicit stronger immune responses in younger individuals [14], but younger individuals can develop protective immune responses with SD vaccine, and even fractional doses of SD vaccine [15,16]. Therefore, the HD vaccine is currently only recommended for elderly individuals.

While several studies have shown the ability of HD vaccines to induce stronger antibody responses to the HA contained in the vaccine, whether HD vaccines induce a stronger heterologous antibody responses (cross-reactive antibodies to strains not included in the vaccine formulation) is uncertain. [8,17] Since our ability to forecast which strains of influenza will circulate in the upcoming season is imperfect, it is important for influenza vaccines to induce both homologous and heterologous responses [18,19].

It is not obvious if HD vaccines are expected to have a positive, negative or no effect on heterologous responses. A higher dose might stimulate multiple diverse lineages of memory B-cells, and could enhance both the strength and breadth of protection. However, a higher amount of HA proteins to the homologous strains could induce a stronger homologous response, which might out-compete and immuno-dominate responses to any cross-reactive or novel antigens, resulting in less robust heterologous responses. The potential competition among HD vaccine-induced B-cells or T-cells might lead to more narrow protection from vaccination [20], making high-risk populations more vulnerable to vaccine mismatches.

Improving our understanding of the heterologous immune response to influenza vaccination remains a critical step in developing a broadly reactive influenza vaccine. In our study, we compare the antibody response between HD and SD vaccine recipients in a vaccine cohort study, using a panel of several historical influenza A strains. We found that while the HD response was higher for most strains, the impact was not consistent and the effect size was small, suggesting that HD vaccines could be further improved.

# Methods

## Data source

We used data from an ongoing human vaccination cohort study, which has been previously described in detail [21–23]. The study is a prospective open cohort which allows individuals to enroll in multiple years (potentially non-consecutively), and has been conducted across three study sites. Investigators annually recruited individuals who had not yet received an influenza vaccine in the current season. At intake, individuals provided demographic information, and investigators collected blood samples before administering a vaccine. Individuals aged 65 and older were given the choice between Fluzone SD and Fluzone HD, while individuals under 65 were given the SD vaccine. Individuals were asked to return for post-vaccination blood draws either 21 days (2013/14 through 2017/18 seasons) or 28 days (2018/19 season onward) after the initial visit. Investigators ran hemagglutination inhibition (HAI) assays the vaccine strains and several historical influenza strains for each serological sample.

For our analysis, we extracted previously deidentified records for individuals aged 65 and older from 2013/2014 influenza season through the 2021/2022 influenza season.

## Data processing

The raw data for our study were reciprocal HAI titer values produced by the HAI dilution assays described in the previous studies, along with limited demographic information for each participant (study site, season, age, sex, race, and a numeric identifier to track individuals across participation years). Since the SD vaccine was quadrivalent (containing two influenza B lineages) while the HD vaccine was trivalent (containing only a single influenza B lineage) for multiple years of the study, we elected to focus only on the heterologous response to influenza A virus strains, and excluded all data for influenza B strains.

The data represent a multilevel structure, where each study site recruited individuals, each individual could participate in multiple seasons, in each season an individual had a pre-vaccination and a post-vaccination serological sample, and investigators ran a panel of HAI assays to multiple strains on each serological sample. The HAI assays had a lower limit of detection (LoD) of 10 and an upper LoD of 20480. Values below the lower LoD were coded as 5 in the raw data. No values in our dataset were at the upper LoD. Following previous studies, [24,25] we conducted all analyses on the log scale, using the transformation

where is the titer variable we analyze. Using this transformation puts the titers on a scale of (values at the lower LoD) (values at the upper LoD).

## Outcome definitions

We calculated four common outcomes used in influenza vaccine studies [7,24]. The primary outcome we used for our study was titer increase, defined as the log (base 2) fold change between an individual’s post-vaccination and pre-vaccination titer. That is,

We present results for titer increase in the main manuscript. As a sensitivity analysis, we repeated our analysis using three additional outcomes: post-vaccination titer, seroprotection, and seroconversion. Seroprotection and seroconversion are binary outcomes, and this dichotomization leads to a loss of statistical power. However, these are commonly reported measures and can be useful for their clinical interpretation. We used standard definitions for seroprotection and seroconversion, with seroprotection defined as a post-vaccination titer greater than 1:40, that is,

where is the indicator function. The definition of seroconversion we used was seroprotection in addition to a titer increase of 2 or higher (i.e., a fold change of 4-fold or higher), that is,

Results for these three additional outcomes are included in the Supplement.

## Statistical analyses

For an initial descriptive analysis of the study population, we calculated summary statistics for the covariates we included in our models and for each of the model outcomes previously described. Summary statistics for the outcome variables, including analyses stratified by vaccine strain and assay strain, are shown in the Supplement. We conducted a crude analysis of the difference in fold change by dose for each vaccine strain and assay strain, also shown in the Supplement.

For our main results, we fit bayesian multilevel regression models for each of the outcomes [26,27]. Bayesian multilevel regression can estimate the average effect of dose in the population, while allowing the effect to vary across strata and flexibly controlling for nuisance confounders. We allowed the effect of dose to vary by vaccine strain and HAI assay strain, and effects for different groups were assumed to be correlated with a heterogeneous unstructured covariance matrix. We used random intercepts for subject and study site to control for baseline differences, and used smoothing splines to control for the effects of birth year, age, pre-vaccination titer, and season.

We used these models to estimate the effect of dose on each outcome of interest by calculating the posterior Average Causal Effect (ACE). To do so, we compared each individual’s predicted outcome under the dose received (HD or SD) to their predicted outcome for the counterfactual dose computed counterfactual HD and SD predictions for each individual, thereby estimating the individual causal effect (ICE) for each observation in the dataset. We estimated the ACE by summarizing the overall posterior distribution of ICEs using the mean point estimate with a 95% highest density credible interval (HDCI). We also computed conditional ACEs (cACEs) by summarizing the posterior distribution of ICEs in specific strata: within each season, within each vaccine strain, and within each assay strain and vaccine strain. In order to aid interpretation, we then base-2 exponentiated the ACEs and the limits of the HDCI. Each ACE represents the average difference in the model outcome across the full study sample between the high dose and standard dose vaccines, after controlling for confounders [28,29]. See the Supplement for additional details on cACE calculation.

Our study is a secondary data analysis, and the data were not collected with our specific research questions in mind. Therefore, a strict hypothesis testing framework using -values is not appropriate. Any statistical tests we conduct will have inflated false discovery rates and limited power. Therefore, we implemented models in a bayesian framework, and we focus on estimating the effect size and uncertainy as captured by credible intervals of the dose in our dataset, rather than testing hypotheses.

Details on model specification, outcome calculation, and details of implementation, including full data and code to reproduce results, are included in the Supplement.

## Implementation

We conducted all of our analyses using R version 4.4.1 (2024-06-14 ucrt) [30]. We used the tidyverse suite of packages for data cleaning, manipulation, and visualization [31], along with the packages tidybayes [32] and ggdist [33,34]. We used the packages here [35], renv [36], and box [37] for code management. We used ggplot2 for generating all figures [38]. We used the packages gtsummary [39] and flextable [40] for making all tables. We compiled our manuscript using Quarto version 1.5.43 [41] with the R packages knitr [42–44], and softbib [45]. We implemented our bayesian models using brms [46–48] and cmdstanr [49] with cmdstan version 2.34.1 [50] as the interface to the Stan probabilistic programming language [51,52]. More details on implementation are included in the Supplement, along with instructions for reproducing our results. The code and data are archived on Zenodo at this link: <https://doi.org/10.5281/zenodo.12666977>.

# Results

## Data description

Our data come from a prospective open cohort study and span the influenza seasons from 2013/14 through 2021/22, and included 254 unique individuals across all study sites and seasons, who provided 668 total observations. Participants aged 65 and older were vaccinated with either Fluzone SD or HD at one of three study sites (Stuart, FL and Pittsburgh, PA, from 2013–2016 and the University of Georgia (UGA) in Athens, GA from 2016–2021). [Table 1](#tbl-demographics) shows the distribution of observations, stratified by vaccine dose. The three study sites had similar distributions of demographic characteristics at both the observation and unique participant levels (see Supplement). Since we only include individuals 65 or older in our study, the age ranges and birth cohorts were similar for both dose groups. Throughout the course of the study, the recommended influenza vaccine composition was updated several times, encompassing 5 different H1N1 strains and 8 different H3N2 strains.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 1: Number of observations in our sample, stratified by the study site.   | **Characteristic** | **SD**, N = 234 | **HD**, N = 434 | **Overall**, N = 668 | | --- | --- | --- | --- | | Study, n (%) |  |  |  | | FL | 82 (35) | 41 (9) | 123 (18) | | PA | 73 (31) | 146 (34) | 219 (33) | | UGA | 79 (34) | 247 (57) | 326 (49) | | Season, n (%) |  |  |  | | 2013 - 2014 | 40 (17) | 16 (4) | 56 (8) | | 2014 - 2015 | 53 (23) | 39 (9) | 92 (14) | | 2015 - 2016 | 40 (17) | 58 (13) | 98 (15) | | 2016 - 2017 | 34 (15) | 77 (18) | 111 (17) | | 2017 - 2018 | 22 (9) | 16 (4) | 38 (6) | | 2018 - 2019 | 11 (5) | 8 (2) | 19 (3) | | 2019 - 2020 | 21 (9) | 69 (16) | 90 (13) | | 2020 - 2021 | 7 (3) | 76 (18) | 83 (12) | | 2021 - 2022 | 6 (3) | 75 (17) | 81 (12) | |

## Strain-specific effects reveal differences in vaccine response patterns

Our models allowed the effect of dose to vary by the assay strain used for HAI assays, so we first examined the strain-specific effects of dose.

For the H1N1 vaccine component, the titer increase was higher for HD in all of the H1N1 strains except for CA/09 ([Figure 1](#fig-all-strain-cates) A), where the point estimates for the heterologous responses were a mix of small positive and small negative values. MI/15 had positive point estimates for nearly all of the assay strains. Bris/18 showed a negative impact of dose for the single older strain used for testing, and positive impact for the other strains. GD/19 and Vic/19 had positive point estimates with almost all of the density of the interval estimate above 1 for the few strains they were tested against. The effect of the HD vaccine on the Chi/83 strain was negative for all three of the vaccines which it was tested against.

For H3N2, the effect of dose on heterologous responses showed patterns that varied based on vaccine strain ([Figure 1](#fig-all-strain-cates) B). For TX/12 and Switz/13, dose generally had a positive effect and this tended to increase as the year of isolation for the assay strain became more similar to the homologous strain. HK/14 showed an overall similar pattern, but with point estimates that suggested a negative dose effect for older strains. Nearly every assay strain for the Sing/16 and Tas/20 vaccines showed a negative effect of HD on heterologous and homologous responses. For KS/17 and HK/19, dose seemed to have an overall small positive impact.

|  |
| --- |
| Figure 1: Strain-specific ratio of HD over SD antibody responses of heterologous strains following vaccination with the indicated vaccine strain. Values above one indicate a better response for the HD vaccine, values below one indicate a better response for the SD vaccine. A) H1N1 vaccine strains. B) H3N2 vaccine strains. For more recent vaccines, only a subset of data for heterologous responses was available. |

## Most, but not all, HD vaccine formulations elicited a stronger overall response

After examining the strain-specific impact of the HD vaccine, we computed the overall impact of the dose on each vaccine strain, by essentially computing the difference in average response across all tested strains. We found a weakly positive overall effect of the HD vaccine for all H1N1 strains ([Figure 2](#fig-het-vex)). While the uncertainty in our parameter estimates is large, all of the HDCI estimates were consistent with a small positive benefit from the HD vaccine. For the H3N2 strains, the majority of vaccine strains showed a benefit for the HD vaccine. However, the HK/14, Sing/16, and Tas/20 vaccines all had negative point estimates.

|  |
| --- |
| Figure 2: Ratio of HD over SD average responses following vaccination with the indicated vaccine strain. |

## HD vaccines elicited stronger or equal responses in every influenza season.

For our final analysis, we pooled the H1N1 and H3N2 responses for a given vaccine and computed an overall effect of the dose for a given vaccine in each season (ignoring the influenza B components).

We found that an increase in dose had a positive but small impact for most seasons, while for a few seasons, we did not observe an impact ([Figure 3](#fig-season-cates)). On a vaccine-level basis, there was no indication of an overall detrimental effect of dose.

|  |
| --- |
| Figure 3: Ratio of HD over SD average responses across all influenza A strains for a given vaccine and all heterologous responses. |

# Discussion

We analyzed homologous and heterologous antibody responses to influenza A HD and SD vaccines across multiple years of influenza vaccinations.

While our estimates had high uncertainties and our secondary analyses should be interpreted as exploratory, our results preliminarily suggest a small but positive effect of the HD split-inactivated vaccine compared to the SD vaccine for inducing not only homologous (similar to prior results; see Supplement) but also better heterologous responses. However, this was not consistent and for some vaccine strains, there was a trend towards a negative impact for the HD vaccine. In general, both positive and negative effect sizes were small and most of the time the credible intervals included both a no-effect as well as positive and negative effect regions. Given that our analysis is a secondary data analysis of noisy observational data, and the effect sizes (increases in titer) for both SD and HD vaccines in our fairly heavily vaccinated population are not that large, the amount of uncertainty we observed is expected.

Our results suggest that the HD vaccine does induce both better homologous and heterologous responses for the majority of vaccine strains and thus should be a continued recommendation for older individuals.

Our results also suggest that the overall impact of the HD vaccine is very modest at inducing stronger antibody responses. Since we only examined the humoral immune response, if the mechanisms related to reduced disease severity are driven by cellular immune responses, there could be additional clinical benefits to the HD vaccine that cannot be learned from the data we used.

Finally, our results do not preclude a stronger beneficial effect of a higher vaccine dose. Assuming that a higher dose (higher than the current dose in the HD vaccine) would further enhance immunogenicity, we could see a stronger effect which is consistently elevated from the SD vaccine. Since the current HD vaccine seems to be tolerated well, further studies on optimal dosing in elderly individuals might open avenues for improved vaccine design using the relatively cheap split-inactivated vaccine vector.

# Acknowledgments

We would like to acknowledge Michael Carlock (Cleveland Clinic, Port St. Lucie, FL, USA) for assistance with obtaining data.

**Conflicts of interest**: None of the authors declare any conflicts of interest.

**Funding sources**: YG was supported by the Start-up Grant from the University of Southern Mississippi and NIH contract 75N93019C00052. TMR is supported by the Georgia Research Alliance as an Eminent Scholar. AH received partial support from NIH grants/contracts U01AI150747, R01AI170116, 75N93019C00052 and 75N93021C00018. YS received partial support from NIH grants/contracts R35GM146612, R01AI170116 and 75N93019C00052. The funders had no role in the study design, data collection and analysis, decision to publish, or preparation of the manuscript.

**Author contributions**:

* WZB: conceptualization, methodology, software, formal analysis, data curation, visualization, writing (original draft)
* YG: conceptualization, methodology, software, formal analysis, data curation, writing (original draft
* JHK: methodology
* HH: writing (review and editing), validation
* SMH: methodology, writing (review and editing), validation
* ALS: writing (review and editing), validation
* WC: writing (review and editing), validation
* YS: methodology, writing (review and editing)
* JB: writing (review and editing)
* PGT: writing (review and editing)
* TMR: data collection, data curation, writing (review and editing)
* AH: conceptualization, data curation, writing (review and editing), supervision, funding acquisition

**Data availability statement**: an archive containing all of the code files and data necessary to reproduce our results is located on Zenodo at this link: <https://doi.org/10.5281/zenodo.12666976>.

# References

[1] Centers for Disease Control and Prevention. Past Seasons Vaccine Effectiveness Estimates. Past Seasons Vaccine Effectiveness Estimates. https://www.cdc.gov/flu/vaccines-work/past-seasons-estimates.html; 2021.

[2] Centers for Disease Control and Prevention (CDC). TABLE. Influenza vaccines — United States, 2023–24 influenza season\* CDC. https://www.cdc.gov/flu/professionals/acip/2022-2023/acip-table.htm; 2023.

[3] Sanofi Pasteur. FluZone Quadrivalent [package insert]. 2023.

[4] Grohskopf LA. [Prevention and Control of Seasonal Influenza with Vaccines: Recommendations of the Advisory Committee on Immunization Practices, United States, 2021 Influenza Season](https://doi.org/10.15585/mmwr.rr7005a1). MMWR Recommendations and Reports. 2021;70.

[5] Robertson CA, DiazGranados CA, Decker MD, et al. [Fluzone High-Dose Influenza Vaccine](https://doi.org/10.1080/14760584.2016.1254044). Expert Review of Vaccines. 2016;15:1495–1505.

[6] Centers for Disease Control and Prevention (CDC). [Licensure of a high-dose inactivated influenza vaccine for persons aged or=65 years (Fluzone High-Dose) and guidance for use - United States, 2010](https://www.ncbi.nlm.nih.gov/pubmed/20431524). MMWR Morbidity and mortality weekly report. 2010;59:485–486.

[7] Falsey AR, Treanor JJ, Tornieporth N, et al. [Randomized, double-blind controlled phase 3 trial comparing the immunogenicity of high-dose and standard-dose influenza vaccine in adults 65 years of age and older](https://doi.org/10.1086/599790). The Journal of Infectious Diseases. 2009;200:172–180.

[8] Couch RB, Winokur P, Brady R, et al. [Safety and immunogenicity of a high dosage trivalent influenza vaccine among elderly subjects](https://doi.org/10.1016/j.vaccine.2007.08.042). Vaccine. 2007;25:7656–7663.

[9] DiazGranados CA, Dunning AJ, Jordanov E, et al. [High-dose trivalent influenza vaccine compared to standard dose vaccine in elderly adults: Safety, immunogenicity and relative efficacy during the 2009 season](https://doi.org/10.1016/j.vaccine.2012.12.013). Vaccine. 2013;31:861–866.

[10] DiazGranados CA, Dunning AJ, Kimmel M, et al. [Efficacy of High-Dose versus Standard-Dose Influenza Vaccine in Older Adults](https://doi.org/10.1056/NEJMoa1315727). New England Journal of Medicine. 2014;371:635–645.

[11] Lee JKH, Lam GKL, Shin T, et al. [Efficacy and effectiveness of high-dose influenza vaccine in older adults by circulating strain and antigenic match: An updated systematic review and meta-analysis](https://doi.org/10.1016/j.vaccine.2020.09.004). Vaccine. 2021;39:A24–A35.

[12] Chang L-J, Meng Y, Janosczyk H, et al. [Safety and immunogenicity of high-dose quadrivalent influenza vaccine in adults 65 years of age: A phase 3 randomized clinical trial](https://doi.org/10.1016/j.vaccine.2019.08.016). Vaccine. 2019;37:5825–5834.

[13] Chaves SS, Naeger S, Lounaci K, et al. [High-Dose Influenza Vaccine Is Associated With Reduced Mortality Among Older Adults With Breakthrough Influenza Even When There Is Poor Vaccine-Strain Match](https://doi.org/10.1093/cid/ciad322). Clinical Infectious Diseases. 2023;77:1032–1042.

[14] Gouma S, Zost SJ, Parkhouse K, et al. [Comparison of Human H3N2 Antibody Responses Elicited by Egg-Based, Cell-Based, and Recombinant Protein-Based Influenza Vaccines During the 2017-2018 Season](https://doi.org/10.1093/cid/ciz996). Clinical Infectious Diseases. 2020;71:1447–1453.

[15] Lunny C, Antony J, Rios P, et al. [Original research: Safety and effectiveness of dose-sparing strategies for intramuscular seasonal influenza vaccine: A rapid scoping review](https://doi.org/10.1136/bmjopen-2021-050596). BMJ Open. 2021;11.

[16] Schnyder JL, De Pijper CA, Garcia Garrido HM, et al. [Fractional dose of intradermal compared to intramuscular and subcutaneous vaccination - A systematic review and meta-analysis](https://doi.org/10.1016/j.tmaid.2020.101868). Travel Medicine and Infectious Disease. 2020;37:101868.

[17] Hilleman MR. [Antibody response in volunteers to Asian influenza vaccine](https://doi.org/10.1001/jama.1958.02990100022005). Journal of the American Medical Association. 1958;166:1134.

[18] Erbelding EJ, Post DJ, Stemmy EJ, et al. [A Universal Influenza Vaccine: The Strategic Plan for the National Institute of Allergy and Infectious Diseases](https://doi.org/10.1093/infdis/jiy103). The Journal of Infectious Diseases. 2018;218:347–354.

[19] Paules CI, Sullivan SG, Subbarao K, et al. [Chasing Seasonal Influenza The Need for a Universal Influenza Vaccine](https://doi.org/10.1056/NEJMp1714916). New England Journal of Medicine. 2018;378:7–9.

[20] Angeletti D, Yewdell JW. [Understanding and Manipulating Viral Immunity: Antibody Immunodominance Enters Center Stage](https://doi.org/10.1016/j.it.2018.04.008). Trends in Immunology. 2018;39:549–561.

[21] Nuñez IA, Carlock MA, Allen JD, et al. [Impact of age and pre-existing influenza immune responses in humans receiving split inactivated influenza vaccine on the induction of the breadth of antibodies to influenza A strains](https://doi.org/10.1371/journal.pone.0185666). Huber VC, editor. PLOS ONE. 2017;12:e0185666.

[22] Carlock MA, Ingram JG, Clutter EF, et al. [Impact of age and pre-existing immunity on the induction of human antibody responses against influenza B viruses](https://doi.org/10.1080/21645515.2019.1642056). Human Vaccines & Immunotherapeutics. 2019;15:2030–2043.

[23] Abreu RB, Clutter EF, Attari S, et al. [IgA Responses Following Recurrent Influenza Virus Vaccination](https://doi.org/10.3389/fimmu.2020.00902). Frontiers in Immunology. 2020;11:902.

[24] Beyer WEP, Palache AM, Lüchters G, et al. [Seroprotection rate, mean fold increase, seroconversion rate: Which parameter adequately expresses seroresponse to influenza vaccination?](https://doi.org/10.1016/j.virusres.2004.02.024) Virus Research. 2004;103:125–132.

[25] Ranjeva S, Subramanian R, Fang VJ, et al. [Age-specific differences in the dynamics of protective immunity to influenza.](https://doi.org/10.1038/s41467-019-09652-6) Nature communications. 2019;10:1660.

[26] Faraway JJ. Extending the Linear Model with R: Generalized Linear, Mixed Effects and Nonparametric Regression Models, Second Edition. 2016.

[27] McElreath R. Statistical rethinking: A Bayesian course with examples in R and Stan. 2nd ed. Boca Raton: Taylor and Francis, CRC Press; 2020.

[28] Holland PW. Statistics and Causal Inference. Journal of the American Statistical Association [Internet]. 1986 [cited 2024 Apr 23];81:945–960. Available from: <https://www.jstor.org/stable/2289064>.

[29] Naimi AI, Whitcomb BW. [Defining and Identifying Average Treatment Effects](https://doi.org/10.1093/aje/kwad012). American Journal of Epidemiology. 2023;192:685–687.

[30] R Core Team. R: A language and environment for statistical computing [Internet]. Vienna, Austria: R Foundation for Statistical Computing; 2024. Available from: <https://www.R-project.org/>.

[31] Wickham H, Averick M, Bryan J, et al. [Welcome to the tidyverse](https://doi.org/10.21105/joss.01686). Journal of Open Source Software. 2019;4:1686.

[32] Kay M. tidybayes: Tidy data and geoms for Bayesian models [Internet]. 2023. Available from: <http://mjskay.github.io/tidybayes/>.

[33] Kay M. [ggdist: Visualizations of distributions and uncertainty in the grammar of graphics](https://doi.org/10.1109/TVCG.2023.3327195). IEEE Transactions on Visualization and Computer Graphics. 2024;1–11.

[34] Kay M. ggdist: Visualizations of distributions and uncertainty [Internet]. 2023. Available from: <https://mjskay.github.io/ggdist/>.

[35] Müller K. Here: A simpler way to find your files [Internet]. 2020. Available from: <https://here.r-lib.org/>.

[36] Ushey K, Wickham H. Renv: Project environments [Internet]. 2024. Available from: <https://rstudio.github.io/renv/>.

[37] Rudolph K. Box: Write reusable, composable and modular r code [Internet]. 2023. Available from: <https://CRAN.R-project.org/package=box>.

[38] Wickham H. ggplot2: Elegant graphics for data analysis [Internet]. Springer-Verlag New York; 2016. Available from: <https://ggplot2.tidyverse.org>.

[39] Sjoberg DD, Whiting K, Curry M, et al. Reproducible summary tables with the gtsummary package. The R Journal [Internet]. 2021;13:570–580. Available from: <https://doi.org/10.32614/RJ-2021-053>.

[40] Gohel D, Skintzos P. Flextable: Functions for tabular reporting [Internet]. 2023. Available from: <https://ardata-fr.github.io/flextable-book/>.

[41] Allaire JJ, Teague C, Scheidegger C, et al. [Quarto](https://doi.org/10.5281/zenodo.5960048). 2024.

[42] Xie Y. Knitr: A general-purpose package for dynamic report generation in r [Internet]. 2023. Available from: <https://yihui.org/knitr/>.

[43] Xie Y. Dynamic documents with R and knitr [Internet]. 2nd ed. Boca Raton, Florida: Chapman; Hall/CRC; 2015. Available from: <https://yihui.org/knitr/>.

[44] Xie Y. Knitr: A comprehensive tool for reproducible research in R. In: Stodden V, Leisch F, Peng RD, editors. Implementing reproducible computational research. Chapman; Hall/CRC; 2014.

[45] Arel-Bundock V, McCrain J. [Software citations in political science.](https://doi.org/10.1017/S1049096523000239) PS: Political Science & Politics. 2023;April:1–4.

[46] Bürkner P-C. [brms: An R package for Bayesian multilevel models using Stan](https://doi.org/10.18637/jss.v080.i01). Journal of Statistical Software. 2017;80:1–28.

[47] Bürkner P-C. [Advanced Bayesian multilevel modeling with the R package brms](https://doi.org/10.32614/RJ-2018-017). The R Journal. 2018;10:395–411.

[48] Bürkner P-C. [Bayesian item response modeling in R with brms and Stan](https://doi.org/10.18637/jss.v100.i05). Journal of Statistical Software. 2021;100:1–54.

[49] Gabry J, Češnovar R, Johnson A. Cmdstanr: R interface to ’CmdStan’ [Internet]. 2024. Available from: <https://mc-stan.org/cmdstanr/>.

[50] Gabry J, Češnovar R, Johnson A. Cmdstanr: R interface to ’CmdStan’. 2023.

[51] Stan Development Team. Stan Modeling Language Users Guide and Reference Manual. 2022.

[52] Carpenter B, Gelman A, Hoffman MD, et al. [Stan: A Probabilistic Programming Language](https://doi.org/10.18637/jss.v076.i01). Journal of Statistical Software. 2017;76:1–32.