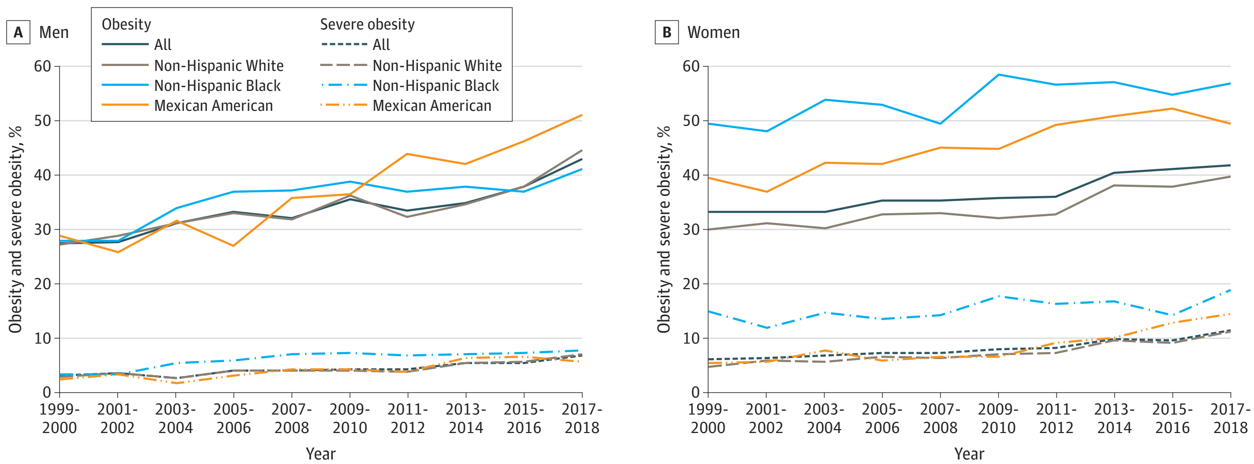
Figure. Age-Adjusted Prevalence of Obesity and Severe Obesity in US Adults[a]



[a] National Health and Nutrition Examination Survey data, prevalence estimates are weighted and age-adjusted to the projected 2000 Census population using age groups 20-39, 40-59, and 60 or older. Some estimates are potentially unreliable, due to CI width of more than 5% and relative CI width of more than 130% (severe obesity, non-Hispanic White men 2011-2012; severe obesity, Mexican American men 2001-2002, 2017-2018, and women 2001-2002) or due to fewer than 10 individuals with severe obesity (Mexican American men 2003-2004). The estimate for severe obesity in Mexican American men 2003-2004 was potentially unreliable due to the number of individuals with severe obesity being fewer than 10. Sample size ranges are non-Hispanic White men 879-1395; non-Hispanic Black men 374-662; Mexican American men 266-538; non-Hispanic White women 860-1447; non-Hispanic Black women 422-702; and Mexican American women 237-567. Significant linear trends ($P < .001$) for all groups except for (1) obesity among non-Hispanic Black men, which increased from 1999-2000 to 2005-2006 (slope, 3.4; 95% CI, 1.8-5.0; $P < .001$) and then leveled after 2005-2006 (slope, 0.3; 95% CI, −0.6 to 1.2; $P = .46$; difference in slopes, $P = .007$); (2) severe obesity among non-Hispanic Black women ($P = .02$); and (3) severe obesity among Mexican American women, which was level 1999-2000 to 2009-2010 (slope, 0.1; 95% CI, −0.5 to 0.6; $P = .81$) and increased after 2009-2010 (slope, 2.1; 95% CI, 1.1-3.1; $P < .001$; difference in slopes, $P = .004$).

Author Affiliations: National Center for Health Statistics, Centers for Disease Control and Prevention, Hyattsville, Maryland (Ogden, Fryar, Martin, Carroll, Gu, Hales); National Center for Chronic Disease Prevention and Health Promotion, Centers for Disease Control and Prevention, Atlanta, Georgia (Freedman).

Corresponding Author: Cynthia L. Ogden, PhD, National Center for Health Statistics, Centers for Disease Control and Prevention, 3311 Toledo Rd, Hyattsville, MD 20782 (cogden@cdc.gov).

Accepted for Publication: July 21, 2020.

Published Online: August 28, 2020. doi:10.1001/jama.2020.14590

Author Contributions: Dr Ogden had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.
Concept and design: Ogden, Hales.
Acquisition, analysis, or interpretation of data: All authors.
Drafting of the manuscript: Ogden.
Critical revision of the manuscript for important intellectual content: All authors.
Statistical analysis: Fryar, Martin, Freedman, Carroll.
Supervision: Ogden, Hales.

Conflict of Interest Disclosures: None reported.

Disclaimer: The findings and conclusions in this report are those of the authors and not necessarily the official position of the Centers for Disease Control and Prevention.

Additional Contributions: We thank Deanna Kruszon-Moran, MSPH, National Center for Health Statistics, Centers for Disease Control and Prevention, for statistical assistance and Joseph Afful, MS, Peraton Corp, for programming assistance. No compensation was provided.

1. CDC National Center for Health Statistics. NHANES response rates and population totals. Last reviewed August 4, 2020. Accessed August 4, 2020. https://wwwn.cdc.gov/nchs/nhanes/ResponseRates.aspx

2. Grummer-Strawn LM, Reinold C, Krebs NF; Centers for Disease Control and Prevention (CDC). Use of World Health Organization and CDC growth charts for children aged 0-59 months in the United States. *MMWR Recomm Rep*. 2010;59(RR-9):1-15.

3. Kelly AS, Barlow SE, Rao G, et al; American Heart Association Atherosclerosis, Hypertension, and Obesity in the Young Committee of the Council on Cardiovascular Disease in the Young, Council on Nutrition, Physical Activity and Metabolism, and Council on Clinical Cardiology. Severe obesity in children and adolescents: identification, associated health risks, and treatment approaches: a scientific statement from the American Heart Association. *Circulation*. 2013;128(15):1689-1712. doi:10.1161/CIR.0b013e3182a5cfb3

4. Ingram DD, Malec DJ, Makuc DM, et al. National Center for Health Statistics guidelines for analysis of trends. *Vital Health Stat 2*. 2018;2(179):1-71.

5. Parker JD, Talih M, Malec DJ, et al. National Center for Health Statistics data presentation standards for proportions. *Vital Health Stat 2*. 2017;2(175):1-22.

6. CDC National Center for Health Statistics. An investigation of nonresponse bias and sample characteristics in the 2017-2018 National Health and Nutrition Examination Survey. Accessed August 20, 2020. https://wwwn.cdc.gov/nchs/data/nhanes/analyticguidelines/17-18-sampling-variability-nonresponse-508.pdf

Association Between Number of In-Person Health Care Visits and SARS-CoV-2 Infection in Obstetrical Patients

A major concern that has emerged from the coronavirus disease 2019 pandemic is patient avoidance of necessary medical care.[1] Data regarding how in-person visits to medical facilities influence the risk of contracting severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection are limited. Obstetrical patients are a unique group who have required frequent in-person health care visits during the pandemic. The aim of this analysis was to examine whether the number of in-person health care visits was associated with the risk of SARS-CoV-2 infection.

Table. Association Between Each Additional In-Person Health Care Visit and Odds of SARS-CoV-2 Infection

	Cases		Control observations		
	No.	Clinic visits, mean (SD)	No.	Clinic visits, mean (SD)	OR (95% CI)
Primary analysis[a]					
Unadjusted[b]	93	3.1 (2.2)	372	3.3 (2.3)	0.93 (0.80-1.07)
Adjusted[c]	93	3.1 (2.2)	372	3.3 (2.3)	0.93 (0.80-1.08)
Sensitivity analyses[d]					
Assessing No. of clinic visits after March 24, 2020	90	2.5 (2.2)	357	2.6 (2.1)	0.91 (0.76-1.09)
Analyses excluding patients who					
Had a household member with known SARS-CoV-2 infection	68	3.5 (2.2)	270	3.6 (2.3)	0.97 (0.82-1.14)
Tested positive for SARS-CoV-2 infection antenatally	53	4.2 (2.2)	201	4.3 (2.4)	0.97 (0.82-1.15)
Complete case analysis	82	3.1 (2.2)	318	3.2 (2.4)	0.91 (0.78-1.07)

Abbreviations: OR, odds ratio; SARS-CoV-2, severe acute respiratory syndrome coronavirus 2.

[a] Assessing the number of in-person visits for patients from March 10, 2020, which was 2 weeks prior to the closure of nonessential business in Massachusetts.

[b] After matching on the gestational age of the cases and controls based on the date the case tested positive for SARS-CoV-2 infection (±6 days), race/ethnicity, insurance type (Medicaid vs commercial), and SARS-CoV-2 infection rate in the patient's zip code.

[c] Adjusting for age, body mass index, and essential worker occupation.

[d] All estimates were matched for the same covariates as in the primary analysis and were also adjusted for age, body mass index, and essential worker occupation.

Methods | Mass General Brigham institutional review board approval was obtained for this study and the need for informed consent waived. The study population included all patients delivering at 4 hospitals in the Boston, Massachusetts, area between April 19, 2020, and June 27, 2020, a period during which all obstetrical patients were tested for SARS-CoV-2 infection at the time of admission. All SARS-CoV-2 testing was performed on nasopharyngeal swabs using reverse transcriptase-polymerase chain reaction assays.

We performed a nested case-control study in which we used risk set sampling to match patients who tested positive for SARS-CoV-2 infection either during pregnancy or at the time of admission for labor and delivery with up to 5 control patients. The control matches were based on the gestational age of the cases and controls on the date the case tested positive for SARS-CoV-2 infection (±6 days), race/ethnicity (recorded in the patient's medical record; Black vs Hispanic vs Asian or White), insurance type (Medicaid vs commercial), and SARS-CoV-2 infection rate in the patient's zip code (divided in 20 groups by ventile).[2]

Based on electronic medical record data, we assessed the number of in-person visits for patients from March 10, 2020 (2 weeks prior to the closure of nonessential business in Massachusetts when community transmission was likely), to the date of the cases' SARS-CoV-2 infection diagnosis. The association between the number of in-person visits and the odds of SARS-CoV-2 infection diagnosis was assessed using conditional logistic regression with adjustment for age, body mass index (BMI; calculated as weight in kilograms divided by height in meters squared), and essential worker occupation.[3] We used multiple imputation to account for missing regression covariates (0.6% were missing BMI and 11.6% were missing essential worker occupation).

The odds ratios with corresponding standard errors were obtained from each of 10 imputed data sets and combined using the rules of Rubin[4] to produce pooled estimates with 2-sided 95% CIs. We performed sensitivity analyses assessing the number of clinic visits after March 24, 2020 (the date of closure of nonessential businesses), excluding patients with a household member with known SARS-CoV-2 infection, patients testing positive for SARS-CoV-2 infection antenatally, and patients with incomplete covariate information. Precision around the measures of association is provided using 2-sided 95% CIs. Statistical analyses were performed using SAS software version 9.4 (SAS Institute Inc).

Results | The study population included 2968 deliveries; 5 patients were not tested for SARS-CoV-2 infection and were excluded. There were 111 patients (3.7% [95% CI, 3.1%-4.5%]) who tested positive for SARS-CoV-2 infection. Of these 111 patients, 45 tested positive for SARS-CoV-2 infection antenatally and 66 tested positive at the time of admission for labor and delivery.

We excluded patients residing outside Massachusetts (2.2%) and those missing data required for matching (0.8%). We then matched 93 cases with 372 control observations. The mean number of in-person visits was 3.1 (SD, 2.2; range, 0-10) for cases and 3.3 (SD, 2.3; range, 0-16) for controls. For the association between the number of in-person health care visits and SARS-CoV-2 infection, the odds ratio was 0.93 (95% CI, 0.80-1.08) per additional visit. Sensitivity analyses yielded similar results (**Table**).

Discussion | There was no meaningful association between the number of in-person health care visits and the rate of SARS-CoV-2 infection in this sample of obstetrical patients in the Boston area. Massachusetts had the third highest SARS-CoV-2 infection rate in the country during the spring 2020 surge, and the Boston area was particularly affected.

The findings from this obstetrical population who had frequent in-person visits to a health care setting and underwent universal testing for SARS-CoV-2 infection suggest in-person health care visits were not likely to be an important risk factor for infection and that necessary, in-person care can be safely performed. Limitations of this study include the restriction to obstetrical patients. Future studies are needed to determine whether these findings extend to other populations and health care settings.

Sharon C. Reale, MD
Kara G. Fields, MS
Mario I. Lumbreras-Marquez, MBBS, MMSc
Chih H. King, MD, PhD
Stacey L. Burns, MD, MBA
Krista F. Huybrechts, MS, PhD
Brian T. Bateman, MD, MSc

Author Affiliations: Department of Anesthesiology, Perioperative and Pain Medicine, Brigham and Women's Hospital, Boston, Massachusetts (Reale, Fields, Lumbreras-Marquez, King, Burns, Bateman); Division of Pharmacoepidemiology, Brigham and Women's Hospital, Boston, Massachusetts (Huybrechts).

Corresponding Author: Sharon C. Reale, MD, Brigham and Women's Hospital, 75 Francis St, CWN L1, Boston, MA 02115 (screale@bwh.harvard.edu).

Accepted for Publication: July 28, 2020.

Published Online: August 14, 2020. doi:10.1001/jama.2020.15242

Author Contributions: Dr Reale and Ms Fields had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.
Concept and design: Reale, Lumbreras-Marquez, Huybrechts, Bateman.
Acquisition, analysis, or interpretation of data: Reale, Fields, Lumbreras-Marquez, King, Burns, Bateman.
Drafting of the manuscript: Reale, Bateman.
Critical revision of the manuscript for important intellectual content: Reale, Fields, Lumbreras-Marquez, King, Burns, Huybrechts, Bateman.
Statistical analysis: Reale, Fields, Burns, Huybrechts, Bateman.
Administrative, technical, or material support: Reale, Lumbreras-Marquez, Burns, Bateman.
Supervision: Reale, Bateman.

Conflict of Interest Disclosures: None reported.

Additional Contributions: We thank Julian Robinson, MD (Department of Obstetrics and Gynecology, Brigham and Women's Hospital), and Ilona Goldfarb, MD (Department of Obstetrics and Gynecology, Massachusetts General Hospital), for comments on an earlier version of the manuscript. Neither of these individuals was compensated for their contributions.

1. Baum A, Schwartz MD. Admissions to Veterans Affairs hospitals for emergency conditions during the COVID-19 pandemic. *JAMA*. 2020;324(1):96-99. doi:10.1001/jama.2020.9972

2. Massachusetts Department of Public Health. Archive of COVID-19 cases in Massachusetts. Accessed May 18, 2020. https://www.mass.gov/info-details/archive-of-covid-19-cases-in-massachusetts#march-2020-

3. Commonwealth of Massachusetts. COVID-19 essential services FAQs. Accessed May 18, 2020. https://www.mass.gov/info-details/covid-19-essential-services-faqs

4. Rubin DB. *Multiple Imputation for Nonresponse in Surveys*. Wiley; 1987. doi:10.1002/9780470316696

Geographic Distribution of US Cohorts Used to Train Deep Learning Algorithms

Advances in machine learning, specifically the subfield of deep learning, have produced algorithms that perform image-based diagnostic tasks with accuracy approaching or exceeding that of trained physicians. Despite their well-documented successes, these machine learning algorithms are vulnerable to cognitive and technical bias,[1] including bias introduced when an insufficient quantity or diversity of data is used to train an algorithm.[2,3] We investigated an understudied source of systemic bias in clinical applications of deep learning—the geographic distribution of patient cohorts used to train algorithms.

Methods | We searched PubMed for peer-reviewed articles published online or in print between January 1, 2015, and December 31, 2019, that trained a deep learning algorithm to perform an image-based diagnostic task and benchmarked performance against (or in tandem with) physicians across 6 clinical disciplines: radiology, ophthalmology, dermatology, pathology, gastroenterology, and cardiology. Search terms included *deep learning* and the clinical specialties of interest, along with Medical Subject Heading synonyms. Results were supplemented by searching reference lists of relevant publications and reviews. Studies that used at least 1 US patient cohort for algorithm training were included. All authors gave input to the search strategy. One author (A.K.) performed the search, screened articles, and extracted data, then repeated the process a second time after a washout period. The final set of included articles and extracted data was reviewed by all authors.

For each state, the number of studies that used at least 1 patient cohort from that state was determined. Patient cohorts provided by a hospital or health system were attributed to the home state of the institution unless an alternate method for assembling the cohort was described. If cohorts were ambiguous, we communicated with corresponding authors for clarification. Cohorts used only for testing or validation of an algorithm were not included.

Some patient cohorts were intrinsically geographically heterogeneous or ambiguous, such as cohorts from large studies from the National Institutes of Health (NIH) or clinical trials (spanning 5 or more states) and data from industry repositories. These cohorts were labeled "multisite" and their number and type were characterized separately.

Results | Of the 2606 studies identified by the search, 74 met inclusion criteria: radiology (n = 35), ophthalmology (n = 16), dermatology (n = 11), pathology (n = 8), gastroenterology (n = 2), and cardiology (n = 2). (The list of studies is available from the authors on request.)

Fifty-six studies (76%) trained algorithms using at least 1 geographically identifiable cohort. Cohorts from California appeared in 22 of the 56 studies (39%), cohorts from Massachusetts in 15 (27%), and cohorts from New York in 14 (25%) (**Table**). Forty of 56 studies (71%) used a patient cohort from at least 1 of these 3 states. Among the remaining 47 states, 34 did not contribute any patient cohorts, and the remainder contributed between 1 and 5 cohorts (Table).

Eighteen of 74 studies (24%) used multisite cohorts exclusively; across all studies, 23 multisite cohorts were identified. Thirteen (57%) of 23 were from existing NIH studies or consortia, 7 (30%) were from industry trials or databases, 2 (9%) were from online image atlases, and 1 (4%) was from an academic second opinion service.

Discussion | In clinical applications of deep learning across multiple disciplines, algorithms trained on US patient data