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Abstract

Objectives: Investigate whether combinations of sociodemographic factors, chronic conditions, and other health indicators pose barriers for older adults to access Annual Wellness Visits (AWVs) and influenza vaccinations. **Methods:** Data on 4999 individuals aged ≥65 years from the 2012 wave of the Health and Retirement Study linked with Medicare claims were analyzed. Conditional Inference Tree (CIT) and Random Forest (CIRF) analyses identified the most important predictors of AWVs and influenza vaccinations. Multivariable logistic regression (MLR) was used to quantify the associations. **Results:** Two-year uptake was 22.8% for AWVs and 65.9% for influenza vaccinations. For AWVs, geographical region and wealth emerged as the most important predictors. For influenza vaccinations, number of somatic conditions, race/ethnicity, education, and wealth were the most important predictors. **Conclusions:** The importance of geographic region for AWV utilization suggests that this service was unequally adopted. Non-Hispanic black participants and/or those with functional limitations were less likely to receive influenza vaccination.

Keywords

annual wellness visits, influenza vaccinations, preventive healthcare utilization, machine learning methods

Introduction

Aging of populations worldwide has intensified the focus on appropriate receipt of preventive health services for the promotion of good health and wellbeing in old age.[1-3] With the increasing prevalence of older adults living with multiple chronic conditions in the US,[4,5] access to medical care and supportive environments is essential to ensure health and quality of life for these older adults.[3] It is, thus, worrisome from a public health perspective that recommended preventive healthcare services are substantially underutilized among older adults in the US.[6] To improve health and access to care for this segment of the population, Annual Wellness Visits (AWVs) offered at no cost for eligible Medicare beneficiaries were introduced in 2011. The primary aim of this initiative was to increase access to preventive healthcare services for older adults.[7,8] Influenza vaccination is a critical part of these services as it is a high-impact and cost-effective strategy to maintain the health of older adults.[9] Following the introduction of AWVs, studies have elucidated favorable developments including increased referrals and use of preventive

healthcare services.[10-17] At the same time, primary care physician practices and geographical regions where AWVs are more frequently adopted do not deliver a higher amount of healthcare services overall.[18]

Despite a gradual increase in utilization of AWVs after their introduction in 2011,[17-21] less than a quarter of Medicare beneficiaries received an AWV in 2015.[19] Previous studies have identified underutilization of AWVs among older adults who are unmarried, members of a race/ethnic minority group,

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or living in rural or less affluent areas.[11,18,20,21] For influenza vaccinations, while findings are inconsistent with regard to age, sex, and single chronic conditions,[11,18,21] sociodemographic factors and number of chronic conditions have been consistently linked to influenza vaccination uptake among older adults in the US.[15,22-27]

None of the previous studies on AWVs and influenza vaccinations have focused on the interaction between individual characteristics, such as sociodemographic factors and health indicators. However, individual characteristics may converge to influence the receipt of AWVs and influenza vaccinations among Medicare beneficiaries. Better understanding of the relationship between these factors in the use of AWVs and influenza vaccinations will inform future prevention efforts to address potential inequities and barriers to accessing services among different demographic groups. This study was undertaken to explore the combinations of sociodemographic factors, chronic conditions, and other health indicators that characterize utilization of AWVs and influenza vaccinations among groups of older adults.

Methods

We used data from the 2012 wave of the Health and Retirement Study (HRS) linked through individual identification numbers with Centers for Medicare and Medicaid Services (CMS) claims. In brief, the HRS is a nationally representative survey of individuals aged ≥51 years. The survey has been conducted biennially since 1992 with refreshment samples added every 6 years.[28] The selection of participants (N=4999) for the study was based on enrollment in Medicare Part A and B for 12 consecutive months during the study period or until death, age ≥65 years, and complete information for predictors (Figure A1). At least 3 years of enrollment in the Medicare fee-for-service program was required to identify the conditions based on the Center for Medicare and Medicaid Services' Chronic Condition Data Warehouse (CCW) algorithms. The study protocol was approved by Oregon Health and Science University Institutional Review Board (STUDY00017034).

The main exposure variables consist of sociodemographic factors, chronic conditions, and other health indicators. Sociodemographic factors were identified in HRS and include: age categorized as 65 to 69 years (reference) with 5-year increments to ≥90 years; sex (male as reference); race/ethnicity categorized as non-Hispanic White (reference), Hispanic, and non-Hispanic Black; geographical region based on Census Divisions: New England (reference), Mid-Atlantic, East-North Central, West-North Central, South Atlantic, East-South Central, West-South Central, Mountain Division, and Pacific Division (see Online Appendix Figure A2 for more details); HRS validated measure of self-reported wealth (See Hurd et al for further details[29]) included as quintiles in US$ (1st: ≤4000

(reference), 2nd: >4000 to ≤150 000, 3rd: >150 000 to ≤327 500, 4th: >327 500 to ≤767 000, 5th:> 767 000); Medicare-Medicaid dual eligibility (no as reference); and education as years in school centered on 12 years (median).

Chronic conditions up to the time of HRS interview covered common chronic conditions in older adult populations as recommended by Goodman et al.[30] The chronic conditions were identified from linked Medicare beneficiary files and administrative claims using CMS Chronic Condition Data Warehouse (CCW) algorithms.[31,32] A description of the methodology to ascertain each chronic condition can be found at the CCW website.[31,32] Number of somatic conditions up until the time of the HRS interview was defined as a count of hypertension; congestive heart failure; coronary artery disease, coronary and ischemic heart disease; cardiac arrhythmias; hyperlipidemia; stroke; arthritis; asthma; cancer (breast, prostate, lung, colorectal, blood and endometrial); chronic kidney disease; chronic obstructive pulmonary disease; diabetes mellitus; and osteoporosis. Alzheimer's disease and related disorders of senile dementia (ADRD) and depression were included separately to address the presence of mental or neurodegenerative conditions. Additional health indicators from HRS included: activities of daily living and instrumental activities of daily living (ADL/IADL) limitations by a continuous score (0-11) (ADL: dressing, walking across a room, bathing, eating, getting in and out of bed, toileting; IADL: preparing hot meals, grocery shopping, using telephone, taking medication, and managing money); body mass index (BMI) categorized as underweight/normal: ≤25 (reference), overweight: >25-30, obese grade I: >30-35, obese grade II: >35-40, obese grade III: ≥40; and proxy interview (no proxy/self-interview as reference).

The two outcomes were identified by Current Procedural Terminology (CPT) codes in CMS during 2-years follow-up from HRS interview date: (1) AWVs (CPT codes: G0438 and G0439) and (2) influenza vaccinations (CPT codes 90630, 90653–90657, 90661, 90662, 90672–90674, 90685–90688, Q2035–Q2039, and G0008).[17] AWVs and influenza vaccinations were formulated as dichotomous variables.

Descriptive statistics were conducted using means with standard deviations for continuous variables and frequencies with percentages for categorical variables for each of the outcomes. Statistical analyses were conducted in 3 steps. First, Conditional Inference Tree (CIT) analyses, implemented in the R package 'partykit',[33] were performed to identify combinations of sociodemographic factors, chronic conditions, and other health indicators predicting AWVs and influenza vaccinations. CIT is a non-parametric machine learning method that performs recursive binary partitioning to examine the relationship between multiple explanatory variables and a single outcome. In this process, a decision tree is constructed by testing the null hypothesis of independence between each variable and the outcome. If the hypothesis cannot be rejected or no division can be

made without at least 60 individuals (1.2% of our sample) in each group, the algorithm was stopped. Otherwise, the variable with the greatest reduction of heterogeneity in the outcome is selected and a binary split of the variable is performed. The algorithm recursively repeats these steps until the stopping criteria are met. To build these models, we used 75% of the dataset for training and reserved 25% for testing. After constructing a CIT with the training data, we used the test dataset to identified the accuracy, sensitivity, and specificity of the CIT based on the cutoff point on the ROC curve closest to the optimal model based on Youden's Index, the cutpoint on the ROC curve that optimizes both sensitivity and specificity. We repeated the analyses three times with different random seeds to confirm the robustness of the results. Second, a Conditional Inference Random Forest (CIRF) algorithm was implemented using the R package 'party'[34] on the full dataset to test whether the CIT identified the most important variables for predicting the outcomes. This method uses bootstrapping aggregation to create multiple decision trees, each using a random sample of variables as split candidates, and collects their results. Each forest was created using 1500 trees. We reported the ranking of the variable importance identified in the CIRF analyses. Third, multivariable logistic regression analyses were conducted using the full dataset to identify risk estimates (adjusted odds ratios [aORs]) and 95% confidence intervals (95% CI) and quantify the association between all exposure variables and each of the two outcomes.

In the machine learning models, all count and continuous variables (age, educational level, BMI, ADL/IADL, and wealth) were included as continuous variables. The previously described variable categorizations were used in the logistic regression analyses. R code to run CIT and CIRF are provided in the Online Appendix.

Results

Baseline characteristics for the overall population as well as stratifications by AWV and influenza vaccination status are presented in Table 1. In total, 1139 (22.8%) older adults received an AWV and 3292 (65.8%) an influenza vaccination.

Figure 1A shows results from the CIT analysis of AWVs during the 2-year period following participants' HRS interview. It shows that combinations of geographical region, wealth, and education resulted in different proportions of AWV utilization. Individuals living in New England had the highest AWV utilization level of 40.4%. In the other geographical regions, individuals with ≤14 years of education and wealth ≤$159 000 had the lowest AVW utilization of 15.2%. The CIT for this analysis had an accuracy of 55.4% with a sensitivity of 52.8% and specificity of 56.2% in the testing data. Repeating the Conditional Inference Tree analyses with different seeds produced CIT that all selected

geographical region, wealth and education, but with different splits resulting in slightly different CIT structures. One CIT additionally included age and another included ADL/IADL limitations.

The CIRF results for AWVs are shown in Figure 2A. They support findings from the CIT analyses, identifying geographical region and wealth as the two most important predictors of AWVs.

Multivariable logistic regression results (Table 2) showed that relative to those living in New England, older adults living in all other regions had lower ORs of receiving AWVs. Residents in West-North Central (aOR: 0.32; 95% CI: 0.22, 0.45), West-South Central (aOR: 0.35; 95%CI: 0.24, 0.49), and Mid-Atlantic (aOR: 0.38; 0.26, 0.54) were associated with the lowest AWV utilization. A dose-response relationship was identified between quintiles of wealth and AWV utilization. Female sex, Hispanic ethnicity, and more years of education were also significantly associated with higher ORs of AWV utilization in the multivariable logistic regression analysis. The concordance statistic (C-statistic) for the multivariable logistic regression was 0.62.

Findings from the CIT analysis for receipt of influenza vaccinations during the 2-year period after HRS interview are presented in Figure 1B. These results show that various combinations of race/ethnicity, number of somatic conditions, educational level and partnership status differentially affected influenza vaccination uptake. The lowest levels of influenza vaccination uptake were among (1) Hispanic and non-Hispanic Black beneficiaries with ≤4 somatic conditions (42.1%) and (2) non-Hispanic White beneficiaries with ≤2 somatic conditions and no partner (43.8%). The highest level of influenza vaccination uptake was among non-Hispanic White beneficiaries with >9 somatic conditions (84.4%). The CIT had an accuracy of 64.4% with a sensitivity of 75.3% and a specificity of 43.2%. Repeating the CIT analysis with different seeds produced trees that selected the variables race/ethnicity, number of somatic conditions, and education yet with different splits. None of the other CIT included partnership status and one additionally incorporated ADL/IADL limitations.

The CIRF results for influenza vaccinations are shown in Figure 2B. As we found in CIT analyses, number of somatic conditions, race/ethnicity, educational level, and wealth were identified as the most important predictors of influenza vaccination uptake. In addition, the CIRF analysis identified partnership status as the 5th most important predictor.

Multivariable logistic regression results (Table 2) showed a dose-response relationship for somatic conditions (aOR: 1.19; 95%CI: 1.15, 1.22), years of education (aOR: 1.06; 95%CI: 1.03, 1.08), and wealth in quintiles. Non-Hispanic Black beneficiaries (aOR: 0.53; 95%CI: 0.44, 0.65 and aOR: 0.51; 95%CI: 0.37, 0.70) had lower

**Table 1.** Baseline Characteristics of Study Population, n (%).

			Annual wellness visits		Influenza vaccinations	
		All	No	Yes	No	Yes
All		4999 (100.0%)	3860 (77.2%)	1139 (22.8%)	1707 (34.1%)	3292 (65.9%)
Sociodemographic factors						
Age	65-69 years	746 (14.9%)	564 (14.6%)	182 (16.0%)	273 (16.0%)	473 (14.4%)
	70-74 years	1371 (27.4%)	1027 (26.6%)	344 (30.2%)	480 (28.1%)	891 (27.1%)
	75-79 years	1298 (26.0%)	999 (25.9%)	299 (26.3%)	457 (26.8%)	841 (25.5%)
	80-84 years	840 (16.8%)	667 (17.3%)	173 (15.2%)	265 (15.5%)	575 (17.5%)
	85-89 years	488 (9.8%)	390 (10.1%)	98 (8.6%)	146 (8.6%)	342 (10.4%)
	90+ years	256 (5.1%)	213 (5.5%)	43 (3.8%)	86 (5.0%)	170 (5.2%)
Sex	Male	1982 (39.6%)	1542 (39.9%)	440 (38.6%)	700 (41.0%)	1282 (38.9%)
	Female	3017 (60.4%)	2318 (60.1%)	699 (61.4%)	1007 (59.0%)	2010 (61.1%)
Race/Ethnicity	Non-Hispanic white	4080 (81.6%)	3115 (80.7%)	965 (84.7%)	1271 (74.5%)	2809 (85.3%)
	Hispanic	314 (6.3%)	242 (6.3%)	72 (6.3%)	127 (7.4%)	187 (5.7%)
	Non-Hispanic black	605 (12.1%)	503 (13.0%)	102 (9.0%)	309 (18.1%)	296 (9.0%)
Partnership status	No	2157 (43.1%)	1723 (44.6%)	434 (38.1%)	793 (46.5%)	1364 (41.4%)
	Yes	2842 (56.9%)	2137 (55.4%)	705 (61.9%)	914 (53.5%)	1928 (58.6%)
Geographical region	New England	218 (4.4%)	133 (3.4%)	85 (7.5%)	63 (3.7%)	155 (4.7%)
	Mid-Atlantic	473 (9.5%)	381 (9.9%)	92 (8.1%)	140 (8.2%)	333 (10.1%)
	East-North Central	855 (17.1%)	662 (17.2%)	193 (16.9%)	320 (18.7%)	535 (16.3%)
	West-North Central	550 (11.0%)	455 (11.8%)	95 (8.3%)	185 (10.8%)	365 (11.1%)
	South Atlantic	1281 (25.6%)	987 (25.6%)	294 (25.8%)	442 (25.9%)	839 (25.5%)
	East-South Central	352 (7.0%)	249 (6.5%)	103 (9.0%)	104 (6.1%)	248 (7.5%)
	West-South Central	612 (12.2%)	502 (13.0%)	110 (9.7%)	221 (12.9%)	391 (11.9%)
	Mountain division	225 (4.5%)	168 (4.4%)	57 (5.0%)	78 (4.6%)	147 (4.5%)
	Pacific division	433 (8.7%)	323 (8.4%)	110 (9.7%)	154 (9.0%)	279 (8.5%)
Education in years, mean (SD)		12.6 (3.2)	12.4 (3.2)	13.0 (3.1)	12.1 (3.3)	12.8 (3.1)
Wealth	1st quintile	1000 (20.0%)	845 (21.9%)	155 (13.6%)	427 (25.0%)	573 (17.4%)
	2nd quintile	1000 (20.0%)	803 (20.8%)	197 (17.3%)	394 (23.1%)	606 (18.4%)
	3rd quintile	1000 (20.0%)	766 (19.8%)	234 (20.5%)	329 (19.3%)	671 (20.4%)
	4th quintile	1000 (20.0%)	746 (19.3%)	254 (22.3%)	283 (16.6%)	717 (21.8%)
	5th quintile	999 (20.0%)	700 (18.1%)	299 (26.3%)	274 (16.1%)	725(22.0%)
Dual eligibility	No	4468 (89.4%)	3426 (88.8%)	1042 (91.5%)	1487 (87.1%)	2981 (90.6%)
	Yes	531 (10.6%)	434 (11.2%)	97 (8.5%)	220 (12.9%)	311 (9.4%)
Chronic conditions						
Somatic conditions, mean (SD)		5.3 (2.5)	5.3 (2.5)	5.2 (2.5)	4.7 (2.5)	5.5 (2.5)
Alzheimer's disease	No	4188 (83.8%)	3208 (83.1%)	980 (86.0%)	1,464 (85.8%)	2724 (82.7%)
	Yes	811 (16.2%)	652 (16.9%)	159 (14.0%)	243 (14.2%)	568 (17.3%)
Depression	No	3393 (67.9%)	2612 (67.7%)	781 (68.6%)	1222 (71.6%)	2171 (65.9%)
	Yes	1606 (32.1%)	1248 (32.3%)	358 (31.4%)	485 (28.4%)	1121 (34.1%)
Other health indicators						
Body mass index	Underweight/normal	1868 (37.4%)	1432 (37.1%)	436 (38.3%)	623 (36.5%)	1245 (37.8%)
	Overweight	1812 (36.2%)	1385 (35.9%)	427 (37.5%)	604 (35.4%)	1208 (36.7%)
	Obese grade 1	885 (17.7%)	696 (18.0%)	189 (16.6%)	333 (19.5%)	552 (16.8%)
	Obese grade 2	307 (6.1%)	249 (6.5%)	58 (5.1%)	104 (6.1%)	203 (6.2%)
	Obese grade 3	127 (2.5%)	98 (2.5%)	29 (2.5%)	43 (2.5%)	84 (2.6%)
ADL/IADL limitations, mean (SD)		0.8 (1.9)	0.8 (1.9)	0.6 (1.7)	0.8 (2.0)	0.7 (1.8)
Proxy interview	No	4793 (95.9%)	3691 (95.6%)	1102 (96.8%)	1631 (95.5%)	3162 (96.1%)
	Yes	206 (4.1%)	169 (4.4%)	37 (3.2%)	76 (4.5%)	130 (3.9%)
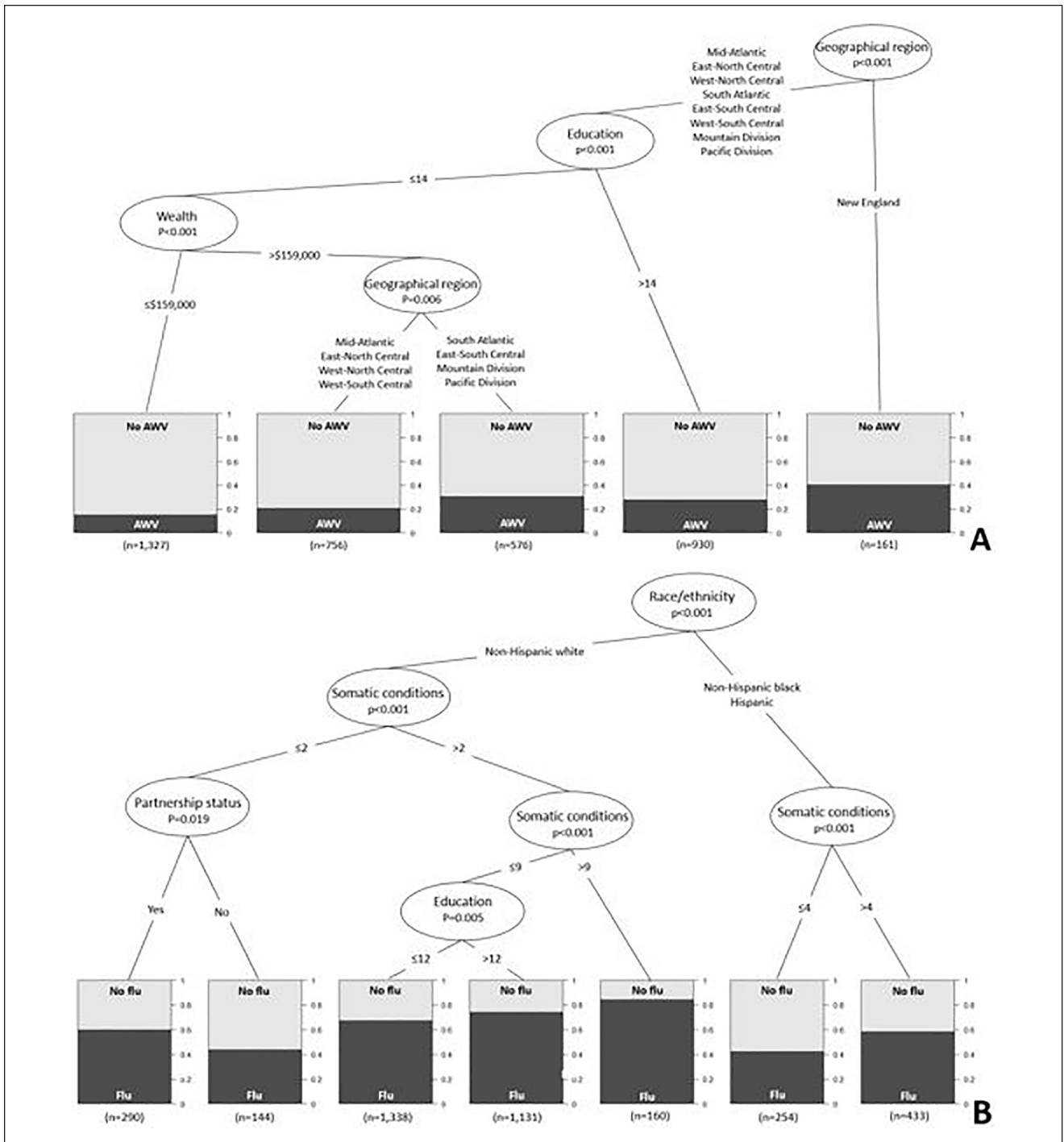
Figure 1. Conditional Inference Trees for (A) Annual Wellness Visits (AWV) and (B) Influenza vaccinations (Flu). Explanatory note: The circles (child nodes) show the characteristics (variables) for which the data is split into the final boxes (terminal nodes). The boxes show the proportion of individuals with these characteristics that receive (A) Annual Wellness Visits (AWV) and (B) Influenza vaccinations (Flu). The "n"s under the boxes provide the number of individuals in each terminal node.

adjusted odds of influenza vaccinations than non-Hispanic White and Hispanic beneficiaries, respectively. Influenza vaccination uptake did not vary between non-Hispanic White and Hispanic beneficiaries. Older adults with a partner had 19% (95% CI: 1.19, 1.37) higher odds of influenza vaccinations than those without. Female sex and ADL/IADL limitations were also significantly associated with higher adjusted odds of influenza vaccinations. The
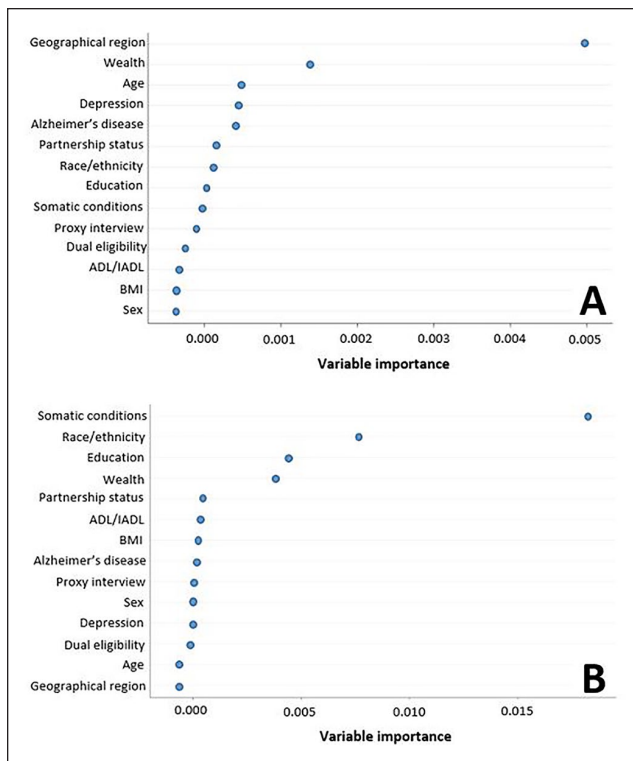
Figure 2. Conditional Inference Random Forest for (A) Annual Wellness Visits and (B) Influenza vaccinations. Explanatory note: The graphs illustrate the ranking of variable importance for predictors on the *y*-axis. The *x*-axis shows the mean decrease in accuracy if the specific variable is removed from a Conditional Inference Tree. The ranking of the variables are informative, whereas the variable importance value should not be interpreted.[35]

C-statistic for the multivariable logistic regression was 0.66.

Discussion

We conducted machine learning analyses to explore combinations of predictors for AWVs and influenza vaccinations among US Medicare beneficiaries. The most important predictors of receiving an AWV were geographical region and wealth, whereas number of somatic conditions, race/ethnicity, educational level, and wealth were the most important predictors of influenza vaccinations.

Utilization of AWVs has increased since its introduction in 2011.[17-21] In this study, 22.8% received at least one AWV within a 2-year period following their 2012 HRS interview, which is comparable to previous findings in a 5% national sample of Medicare beneficiaries in 2011 to 2013.[14] However, a recent report has shown that AWV uptake for Medical Advantage patients increased from 2011 to 2015, leading to 40% greater uptake in these patients compared to fee-for-service patients.[36] Furthermore, another study found

that healthcare practices with medically and socially complex patients provide less AWVs, whereas accountable Care Organizations and practices with higher rates of electronic health record incentive program participation provided more AWVs in 2015.[19] Yet, future studies are needed to determine whether the increase in AWVs since their introduction is explained by diffusion of recommendations from practice guidelines and policy to implementation in the healthcare practices and/or by incentives programs aimed at managed care beneficiaries.

We identified individuals living in New England to have the highest AWV utilization. Interestingly, we identified that no other characteristics were predictive of utilization within this region in the CIT analysis. For individuals living in the other geographical regions, AWV utilization was lowest among beneficiaries with fewer years of education (≤14) and lower levels of wealth ($\leq\$159\,000$). This illustrates that individual socioeconomic factors, which are related to uptake of other preventive healthcare like influenza vaccination,[24] may be important in geographical regions with lower AWV utilization. To ensure adequate provision and use of preventive services, it is essential that AWVs are equally available and accessible across all geographical regions of the country. When this is met, our findings suggest that socioeconomic factors may be important for utilization.

Our finding that geographical region is the most important predictor of AWVs with highest utilization in New England is supported by a study of a 20% random sample of 2015 Medicare beneficiaries. Ganguli et al. (2018) showed that 51.2% of primary care practices did not provide AWVs; those that provided AWVs were clustered in the Northeast and urban areas, had a more stable patient assignment and a slightly healthier patient mix. Practices with lower AWV rates more often provided care for underserved populations, such as racial minorities and Medicare-Medicaid dual eligibility patients.[19] We also identified that socioeconomic factors including wealth and education were important predictors of AWV utilization. This is indirectly supported in a number of other studies that identified residence in more affluent areas and non-rural metropolitan areas to have higher AWV utilization.[11,18,20,21]

Hispanic ethnicity and female sex were significantly associated with greater AWV utilization in the multivariable logistic regression analysis. Previous studies of sex are inconsistent.[11,21] Studies have shown lower AWV utilization among non-Hispanic Black and other race/ethnicity groups compared to non-Hispanic White Medicare beneficiaries.[11,18,20,21] One study that investigated utilization among Hispanic beneficiaries found lower utilization of AWVs in comparison to non-Hispanic White beneficiaries in univariable analysis, but no association in multivariable analysis.[20] The surprising finding from our analysis that AWV utilization was higher in Hispanic beneficiaries compared to

Table 2. Multivariable Logistic Regression Analyses of Annual Wellness Visits and Influenza Vaccinations.

Sociodemographic factors		Odds ratio (95% confidence interval)*	
		Annual wellness visits	Influenza vaccinations
Age	65-69 years	1.00 (reference)	1.00 (reference)
	70-74 years	1.04 (0.84;1.29)	0.95 (0.79;1.16)
	75-79 years	0.93 (0.74;1.16)	0.86 (0.70;1.06)
	80-84 years	**0.77 (0.59;0.99)**	0.89 (0.70;1.12)
	85-89 years	0.78 (0.57;1.06)	0.96 (0.73;1.27)
	90+ years	0.70 (0.46;1.04)	0.86 (0.61;1.21)
Sex	Male	1.00 (reference)	1.00 (reference)
	Female	**1.20 (1.03;1.39)**	**1.28 (1.12;1.46)**
Race/Ethnicity**	Non-Hispanic white	1.00 (reference)	1.00 (reference)
	Hispanic	**1.58 (1.14;2.18)**	1.04 (0.78;1.39)
	Non-Hispanic black	0.87 (0.68;1.11)	**0.53 (0.44;0.65)**
Partnership status	No	1.00 (reference)	1.00 (reference)
	Yes	1.11 (0.95;1.30)	**1.19 (1.03;1.37)**
Geographical region	New England	1.00 (reference)	1.00 (reference)
	Mid-Atlantic	**0.38 (0.26;0.54)**	0.94 (0.65;1.35)
	East-North Central	**0.47 (0.34;0.65)**	**0.72 (0.51;0.99)**
	West-North Central	**0.32 (0.22;0.45)**	0.82 (0.57;1.16)
	South Atlantic	**0.47 (0.34;0.64)**	0.85 (0.61;1.17)
	East-South Central	**0.67 (0.47;0.97)**	1.14 (0.77;1.67)
	West-South Central	**0.35 (0.24;0.49)**	0.85 (0.59;1.20)
	Mountain division	**0.48 (0.32;0.72)**	0.74 (0.49;1.12)
	Pacific division	**0.48 (0.34;0.69)**	**0.69 (0.48;0.99)**
Education in years		**1.04 (1.01;1.06)**	**1.06 (1.03;1.08)**
Wealth	1st quintile	1.00 (reference)	1.00 (reference)
	2nd quintile	**1.36 (1.07;1.74)**	1.11 (0.92;1.35)
	3rd quintile	**1.62 (1.27;2.09)**	**1.35 (1.09;1.66)**
	4th quintile	**1.71 (1.33;2.22)**	**1.66 (1.33;2.07)**
	5th quintile	**2.11 (1.62;2.75)**	**1.67 (1.33;2.10)**
Medicaid-Medicare dual eligibility	No	1.00 (reference)	1.00 (reference)
	Yes	1.07 (0.81;1.40)	1.10 (0.88;1.37)
Chronic conditions			
Number of Somatic conditions		1.03 (0.99;1.06)	**1.19 (1.15;1.22)**
Alzheimer's disease	No	1.00 (reference)	1.00 (reference)
	Yes	0.94 (0.75;1.16)	1.11 (0.92;1.35)
Depression	No	1.00 (reference)	1.00 (reference)
	Yes	1.02 (0.87; 1.19)	1.11 (0.96;1.28)
Other health indicators			
Body mass index	Normal	1.00 (reference)	1.00 (reference)
	Overweight	1.02 (0.87;1.20)	1.05 (0.91;1.21)
	Obese grade 1	0.89 (0.73;1.09)	0.87 (0.72;1.04)
	Obese grade 2	0.79 (0.57;1.08)	1.05 (0.80;1.39)
	Obese grade 3	1.05 (0.66;1.62)	0.97 (0.65;1.46)
ADL/IADL limitations		0.97 (0.93;1.02)	**0.95 (0.91;0.99)**
Proxy interview	No	1.00 (reference)	1.00 (reference)
	Yes	1.02 (0.67;1.51)	1.12 (0.80;1.58)

*Bold = statistical significant estimates.
Odds ratio and 95% confidence interval for non-Hispanic black vs. Hispanic: Annual Wellness Visits **0.55 (0.38, 0.80) and influenza vaccinations **0.51 (0.37, 0.70).**

non-Hispanic White and Black beneficiaries may not be representative of the full Medicare population. Our study only had 6.3% Hispanics, whereas Hispanics represented 10.7% of the population in the previous study.[20] Hispanic particpants in the present study may be a more selected group and, thus, possibly healthier than the general Hispanic population in the US, because they represent a smaller proportion of the final study population compared to other

studies. This may be explained by the strict selection criteria (Figure A1), which may have influenced the inclusion of this race/ethnic group more than non-Hispanic white and black participants.

This study elucidated that AWVs do not reach all Americans and utilization was especially low among beneficiaries with lower levels of wealth and education in geographical regions with overall low AWV utilization. This could lead to unforeseen negative consequences by increasing sociodemographic health disparities among older adults in the US. Due to the risk of increased health disparities, Tipirneni et al suggest implementation of a new version of AWVs that targets the root causes of poor health covering individual, social, and behavioral determinants of health in addition to addressing cognition, balance, and vision as predictors of poor health.[37] Our findings and those from previous studies suggest that a first step to increase access to and use of AWVs may be to increase incentives for healthcare providers throughout the US to administer AWVs.

Influenza vaccination coverage of 65.9% during the 2-year period in this study is in line with coverage (66.2% ± 0.8%) among adults aged ≥65 years in the US during the 2012-2013 season.[38]

We identified number of somatic conditions, race/ethnicity, educational level, and wealth as important predictors of influenza vaccination uptake. Uptake was highest among non-Hispanic White beneficiaries with >9 somatic conditions. By contrast, influenza vaccination uptake was low among all race/ethnic groups with few somatic conditions – that is, non-Hispanic White beneficiaries with ≤2 somatic conditions and no partner and Hispanic and non-Hispanic Black beneficiaries with ≤3 somatic conditions. This may suggest an interplay between somatic conditions and race/ethnicity for influenza vaccination coverage.

Previous studies have also identified chronic conditions as positive predictors of influenza vaccination uptake in the US;[26] however, findings for single chronic conditions such as dementia, diabetes, and asthma are inconsistent.[22,25,26] In this study, neither ADRD nor depression were identified as predictors of influenza vaccinations. Individuals with medical conditions are at the highest risk of complications including death from influenza infections;[39] hence, it is an important and positive public health finding that older adults with more somatic conditions have greater uptake.

In our multivariable logistic regression, we found that non-Hispanic Black beneficiaries had lower influenza vaccination uptake than both non-Hispanic White and Hispanic beneficiaries. Influenza vaccination, surprisingly, did not differ between non-Hispanic White and Hispanic beneficiaries, which may be explained by a healthy selection of Hispanics in our study population as previously discussed. Prior studies generally showed lower influenza vaccination uptake among race/ethnic minorities in the US. Two studies have shown that non-Hispanic Black and/or Hispanic older

adults had lower uptake than non-Hispanic White older adults,[15,23] and one study showed that non-Hispanic Black older adults more often refused influenza vaccination than non-Hispanic White older adults.[27] However, a fourth study showed that Hispanics had the lowest uptake of racial/ethnic groups examined and were less aware of recommendations, less informed about influenza virus and benefits of vaccination, and the least confident about the vaccine compared to both non-Hispanic Black and White older adults.[22] Lower influenza vaccination uptake in minority groups may be explained by differences in community-specific attitudes toward vaccination, inadequate access to care, marginalization, and lack of trust in the healthcare system.[24] The impact of sex on influenza vaccination coverage is mixed,[15,25,27] whereas Medicare-Medicaid dual eligible beneficiaries have been found to have lower coverage.[15]

A number of literature reviews have proposed mechanisms that may lead to underutilization of influenza vaccinations. In summary, a positive attitude toward influenza vaccination, high perceived utility and safety of vaccination, previous severe influenza experiences, cues to action including advice from health professionals and kin networks, habits (e.g., previous influenza vaccination uptake), and practical barriers including transport and access issues for the oldest older adults were identified as the major and most consistent factors influencing influenza vaccination uptake.[24,40-42] The largest of the systematic reviews (N = 470 studies) argued that sociodemographic factors are only indirectly related to influenza vaccination utilization.[41]

Our findings and those from previous studies show a continued need for the healthcare system and public health authorities to strive toward greater influenza vaccination coverage among older adults in the US. This is supported by a qualitative meta-analysis of 14 years of influenza-related communication research by U.S. Centers for Disease Control and Prevention (CDC). The qualitative meta-analysis showed that many people have an aversion toward influenza vaccinations and tend to overestimate the effect of other actions to decrease the risk of infection with influenza virus.[42] Further, the positive impact of AWVs on preventive healthcare utilization[10-17] may suggest that increased implementation of AWVs throughout the US may help improve influenza vaccination uptake.

This study has several strengths. Through linkage of HRS and CMS, we were able to identify a comprehensive number of potential predictors of AWVs and influenza vaccinations including sociodemographic characteristics, chronic conditions, and other health indicators. We included information on chronic conditions and use of preventive healthcare services from CMS, which are not subject to recall bias. We were able to explore our research questions and the impact of multiple predictors by leveraging machine learning models instead of restricting our hypothesis to *a priori* knowledge. In CIT analyses, we

obtained empirical information about the combinations of variables important for AWV utilization and influenza vaccination uptake, not restricted to a linear relationship. The differences in the two analytical approaches (logistic regression models versus machine learning models) resulted in slightly different findings, which is reasonable due to the different criteria for the two analytical approaches. The logistic regression model is a parametric model that builds on a specific form and estimates parameters based on the data. The logistic regression model is defined and the effects of the variables are quantified from the fitted data. On the other hand, the machine learning methods make predictions based on the data where there are no assumptions about specific functional forms or inferential models. Instead, an algorithm is presented with the training inputs and desired outputs and executes all steps to develop a rule to map inputs to outputs. These machine learning methods provide automated ways of assessing complex data for important patterns. In this study, the machine learning methods were applied to identify key predictors of the two outcomes, whereas the logistic regression model was used to quantify the relationships.

The generalizability of our results to all older Americans may be hampered by restricting the study population to Medicare FFS beneficiaries aged ≥65 years with ≥3 years of enrollment in the Medicare fee-for-service program at baseline. This was necessary to identify chronic conditions by the CCW algorithms[31,32] and subsequent preventive healthcare use (Figure A1). There were also insufficient numbers of American Indian/Native Alaskan or Asians in HRS to include in the models, limiting inference for these groups. Although these approaches provide insights to factors associated with AWV and influenza vaccination, they do not infer a causal relationship. Finally, the study did not elucidate potential mediating factors explaining the sociodemographic factors and morbidities as predictors of AWVs and influenza vaccination. Especially, healthcare utilization may be an important factor explaining the findings, which should be investigated in future studies.

Conclusion

AWVs and influenza vaccinations are underutilized among the US Medicare population. Applying CIT and CIRF analyses, we identified geographical region and wealth as important factors for AWV utilization, whereas number of somatic conditions, race/ethnicity, wealth and educational level were predictive for influenza vaccination uptake. The importance of geographic region for AWV utilization suggests that this service was unequally adopted. Non-Hispanic black participants and/or those with functional limitations were less likely to receive influenza vaccination.

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Supplemental Material

Supplemental material for this article is available online.

References

1. Christensen K, Doblhammer G, Rau R, Vaupel JW. Ageing populations: the challenges ahead. *Lancet*. 2009;374: 1196-1208.
2. Livingston G, Sommerlad A, Orgeta V, et al. Dementia prevention, intervention, and care. *Lancet*. 2017;390(10113): 2673-2734.
3. Beard JR, Officer AM, Cassels AK. The world report on ageing and health. *Gerontologist*. 2016;56(Suppl 2):S163-S166.
4. Akushevich I, Kravchenko J, Yashkin A, Yashin A. Multimorbidity time trends among older U.S. adults. *Innov Aging*. 2018;2(Suppl 1):711.
5. King DE, Xiang J, Pilkerton CS. Multimorbidity trends in United States adults, 1988-2014. *J Am Board Fam Med*. 2018;31:503-513.
6. Centers for Disease Control and Prevention, Administration on Aging, Agency for Healthcare Research and Quality, and Centers for Medicare and Medicaid Services. *Enhancing use of clinical preventive services among older adults* [Internet]. Washington, DC; 2011.
7. Koh HK, Sebelius KG. Promoting prevention through the affordable care act. *N Engl J Med*. 2010;363:1296-1299.
8. Colburn JL, Nothelle S. The medicare annual wellness visit. *Clin Geriatr Med*. 2018;34:1-10.
9. Maciosek MV, Solberg LI, Coffield AB, Edwards NM, Goodman MJ. Influenza vaccination health impact and cost effectiveness among adults aged 50 to 64 and 65 and older. *Am J Prev Med*. 2006;31:72-79.

10. Chung S, Lesser LI, Lauderdale DS, Johns NE, Palaniappan LP, Luft HS. Medicare annual preventive care visits: use increased among fee-for-service patients, but many do not participate. *Health Aff*. 2015;34:11-20.

11. Camacho F, Yao NA, Anderson R. The effectiveness of medicare wellness visits in accessing preventive screening. *J Prim Care Community Health*. 2017;8:247-255.

12. Galvin SL, Grandy R, Woodall T, Parlier AB, Thach S, Landis SE. Improved utilization of preventive services among patients following team-based annual wellness visits. *N C Med J*. 2017;78:287-295.

13. Chung S, Romanelli RJ, Stults CD, Luft HS. Preventive visit among older adults with Medicare's introduction of Annual Wellness Visit: closing gaps in underutilization. *Prev Med*. 2018;115:110-118.

14. Jiang M, Hughes DR, Wang W. The effect of Medicare's Annual Wellness Visit on preventive care for the elderly. *Prev Med*. 2018;116:126-133.

15. Shen AK, Warnock R, Selna W, MaCurdy TE, Chu S, Kelman JA. Vaccination among Medicare-fee-for service beneficiaries: characteristics and predictors of vaccine receipt, 2014-2017. *Vaccine*. 2019;37:1194-1201.

16. Simpson VL, Kovich M. Outcomes of primary care-based Medicare annual wellness visits with older adults: a scoping review. *Geriatr Nurs*. 2019;40:590-596.

17. Tao G. Utilization pattern of other preventive services during the US Medicare annual wellness visit. *Prev Med Rep*. 2018;10:210-211.

18. Ganguli I, Souza J, McWilliams JM, Mehrotra A. Trends in use of the US Medicare annual wellness visit, 2011-2014. *JAMA*. 2017;317:2233-2235.

19. Ganguli I, Souza J, McWilliams JM, Mehrotra A. Practices caring for the underserved are less likely to adopt Medicare's annual wellness visit. *Health Aff*. 2018;37:283-291.

20. Lind KE, Hildreth K, Lindrooth R, Crane LA, Morrato E, Perraillon MC. Ethnoracial disparities in Medicare annual wellness visit utilization: evidence from a nationally representative database. *Med Care*. 2018;56:761-766.

21. Hu J, Jensen GA, Nerenz D, Tarraf W. Medicare's Annual Wellness Visit in a large health care organization: who is using it? *Ann Intern Med*. 2015;163:567-568.

22. Nowak GJ, Cacciatore MA, Len-Rios ME. Understanding and increasing influenza vaccination acceptance: insights from a 2016 national survey of U.S. adults. *Int J Environ Res Public Health*. 2018;15:711.

23. Frick KD, Scanlon DP, Bandeen-Roche K, Kasper JD, Simonsick EM, Sullivan EM. Influenza vaccination by race among disabled community dwelling older women. *J Health Care Poor Underserved*. 2004;15:220-236.

24. Wheelock A, Thomson A, Sevdalis N. Social and psychological factors underlying adult vaccination behavior: lessons from seasonal influenza vaccination in the US and the UK. *Expert review of vaccines*. 2013;12(8):893-901.

25. Martinez-Baz I, Aguilar I, Moran J, Albeniz E, Aldaz P, Castilla J. Factors associated with continued adherence to influenza vaccination in the elderly. *Prev Med*. 2012;55:246-250.

26. Shah SM, Carey IM, Harris T, DeWilde S, Cook DG. The impact of dementia on influenza vaccination uptake in community and care home residents. *AgeAageing*. 2012;41:64-69.

27. Banach DB, Ornstein K, Factor SH, Soriano TA. Seasonal influenza vaccination among homebound elderly receiving home-based primary care in New York City. *J Community Health*. 2012;37:10-14.

28. Sonnega A, Faul JD, Ofstedal MB, Langa KM, Phillips JW, Weir DR. Cohort Profile: the Health and Retirement Study (HRS). *Int J Epidemiol*. 2014;43:576-585.

29. Hurd M, Meijer E, Moldoff MB. Rohwedder, S. *Improved Wealth Measures in the Health and Retirement Study: Asset Reconciliation and Cross-wave Imputation*. Santa Monica, CA: Rand Corporation and University of Southern California; 2016.

30. Goodman RA, Posner SF, Huang ES, Parekh AK, Koh HK. Defining and measuring chronic conditions: imperatives for research, policy, program, and practice. *Prev Chronic Dis*. 2013;10:E66.

31. Centers for Medicare and Medicaid Services. *Chronic Conditions Data Warehouse*. https://www2.ccwdata.org/web/guest/condition-categories. Accessed 2019.

32. Centers for Medicare and Medicaid Services. *CMS Chronic Conditions Data Warehouse (CCW) CCW Condition Algorithms Centers for Medicare and Medicaid Services*. https://www2.ccwdata.org/documents/10280/19139421/other-condition-algorithms.pdf. Accessed November, 2019.

33. Hothorn T, Hornik K, Van de Wiel MA, Zeileis A. *ctree: Conditional Inference Trees. Vignette R package partykit version 1.1-1*. https://cran.r-project.org. 2006.

34. Hothorn T, Hornik K, Strobl C, Zeileis A. *A Laboratory for Recursive Partytioning. Package 'party' version 1.3-3*. https://cran.r-project.org/. 2019.

35. Strobl C, Malley J, Tutz G. An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychol Methods*. 2009;14:323-348.

36. Lind KD, Carter EA, Noel-Miller CM. *Annual Wellness Visits among Medicare Advantage Enrollees: Trends, Differences by Race and Ethnicity, and Association with Preventive Service Use*. USA: AARP Public Policy Institute; 2019.

37. Tipirneni R, Ganguli I, Ayanian JZ, Langa KM. Reducing disparities in healthy aging through an enhanced Medicare annual wellness visit. *Public Policy Aging Rep*. 2019;29:26-32.

38. U.S. Center for Disease Control and Prevention. *Flu Vaccination Coverage*. USA: U.S. Center for Disease Control;2013.

39. Fiore AE, Uyeki TM, Broder K, et al. Prevention and control of influenza with vaccines: recommendations of the Advisory Committee on Immunization Practices (ACIP), 2010. *MMWR Recomm Rep*. 2010;59:1-62.

40. Yeung MP, Lam FL, Coker R. Factors associated with the uptake of seasonal influenza vaccination in adults: a systematic review. *J Public Health*. 2016;38:746-753.

41. Schmid P, Rauber D, Betsch C, Lidolt G, Denker ML. Barriers of influenza vaccination intention and behavior - a systematic review of influenza vaccine hesitancy, 2005 - 2016. *PLoS One*. 2017;12:e0170550.

42. Nowak GJ, Sheedy K, Bursey K, Smith TM, Basket M. Promoting influenza vaccination: insights from a qualitative meta-analysis of 14 years of influenza-related communications research by U.S. Centers for Disease Control and Prevention (CDC). *Vaccine*. 2015;33:2741-2756.