The source matters: Agreement and accuracy of race and ethnicity codes in Medicare administrative and assessment data

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ABSTRACT

Background: Errors in racial and ethnic classification of Medicare beneficiaries limit health services research on minority health and health disparities among priority populations, including American Indians and Alaskan Natives.

Objective: To compare the agreement and accuracy of three sources of race and ethnicity information contained in the Medicare data warehouse: 1) the Enrollment Database (EDB) which originate from Social Security data; 2) the Research Triangle Institute (RTI) imputed data based on name and geography; and 3) self-reported race and ethnicity data collected during routine home health care assessments as part of the Outcome and Assessment Information Set (OASIS).

Subjects: Medicare beneficiaries over the age of 18 who received home health care in 2015 (N = 4,243,090).

Measures: Percent agreement, sensitivity, specificity, positive predictive value, and Cohen's kappa coefficient.

Results: Compared to self-reported race/ethnicity data from OASIS, the RTI race code is more accurate than the EDB race code. Non-Hispanic whites and blacks were correctly classified by the RTI race code with 97% accuracy. However, more than half of American Indians/Alaskan Natives, one-fourth of Asian American/Pacific Islanders, and nearly one-tenth of Hispanics were misclassified by the RTI race code. Misclassification of race/ethnicity occurred less often for men, compared to women.

Discussion: These findings highlight the strengths and limitations of using race/ethnicity classifications contained in Medicare administrative data. Health services and policy researchers should consider using self-identified race/ethnicity information to augment administrative data sources. This is especially important for research that aims to include Asian Americans/Pacific Islanders and American Indians/Alaskan Natives.

INTRODUCTION

Improving minority health and reducing health disparities is a national priority.^{1,2} Recent attention has been placed on addressing confounding of observational data and the use of sophisticated causal modeling methods in health disparities research.³ However, monitoring and reducing disparities requires accurate data on race and ethnicity that is not consistently available.⁴⁻⁶ Administrative data sources of race/ethnicity data are limited with regards to completeness and accuracy, making self-reported data the preferred source and gold standard.⁷ Despite this, even when self-reported race/ethnicity data is available, an administrative data source is frequently used in research on disparities in healthcare quality and outcomes.⁸⁻¹⁰ The completeness and accuracy of race/ethnicity data is especially problematic for Asian Americans and Pacific Islanders (AAPI), as well as for American Indians and Alaskan Natives (AIAN).¹¹⁻¹³ As a result, incomplete and inaccurate race/ethnicity data limit our understanding of the sources of disparities in healthcare access, quality, and outcomes as well as evaluation of changes in minority health over time.

Administrative data, including insurance plan enrollment and demographic information, is contained in the Medicare Beneficiary Summary File (MBSF). The MBSF contains two separate race variables. The first is from the Medicare enrollment database (EDB), and originates from Social Security Administration records. The EDB race variable is known to severely undercount Hispanics, Asian Americans/Pacific Islanders, and American Indians/Alaskan Natives.¹⁴ Due to these limitations, analyses using race/ethnicity data from the enrollment file (EDB) are generally restricted to the identification of differences between black and white patient populations.^{9,15} The second race variable was created a decade ago by researchers at the Research Triangle Institute (RTI) to improve classification of Hispanics and Asians/Pacific Islanders.^{16,17} The RTI race imputation algorithm utilizes lists of Hispanic and Asian/Pacific Islander names from the U.S. Census, and simple geography (residence in Puerto Rico or Hawaii) to improve on the EDB race code.¹⁶ The RTI race variable is used by the Centers for Medicare & Medicaid Services' in reports on health disparities in the Medicare population and in studies which include focus on Hispanic and Asian/Pacific Islander populations.^{18,19}

In contrast to administrative data sources, national surveys of Medicare beneficiaries include self-reported race and ethnicity. Examples of survey datasets that contain self-reported race/ethnicity include the Medical Expenditure Panel Survey (MEPS), the Medicare Current Beneficiary Survey (MCBS), and the Health and Retirement Survey (HRS). Additionally, the Consumer Assessment of Healthcare Providers and Systems (CAHPS) patient experience datasets contain self-reported race/ethnicity data. Finally, self-reported race/ethnicity data is collected as part of post-acute and long-term care assessments including the Outcome and Assessment Information Set (OASIS) used in home health care, the Minimum Dataset (MDS) used in nursing homes, the Inpatient Rehabilitation Facility-Patient Assessment Instrument (IRF-PAI), and the Medicare Health Outcomes Survey (HOS) used in Programs of All-Inclusive Care of the Elderly and with a random sample of Medicare Advantage plan subscribers.

While patient experience survey data (CAHPS) has been used to validate race/ethnicity variables contained in administrative sources, the use of self-reported race/ethnicity data collected as a routine part of healthcare delivery has received less attention. The main objective of this analysis

is to compare the agreement and accuracy of three sources of race and ethnicity information contained in the Medicare data warehouse: 1) the Enrollment Database (EDB) race variable which originates from Social Security Administration data; 2) the Research Triangle Institute (RTI) race variable imputed from name and geography; and 3) self-reported race and ethnicity data collected by Registered Nurses and Physical Therapists during routine home health care assessments as part of the Outcome and Assessment Information Set (OASIS).²⁰ For added context, the accuracy and agreement measures are stratified by sex, patterns of misclassification errors are explored, and we compare our findings with earlier studies using survey data as the gold standard.

METHODS

Data Source and Patient Population

Two sources of race/ethnicity data for Medicare beneficiaries were combined for calendar year 2015: The Medicare Beneficiary Summary File (MBSF) containing the Enrollment Database (EDB) and Research Triangle Institute (RTI) race variables, and the Outcome and Assessment Information Set (OASIS) containing demographic data on all home health care patients. Demographic information on the OASIS is collected during the initial home health care visit by a registered nurse or licensed physical therapist. Race/ethnicity data is obtained by self-report (a caregiver may answer if the patient is unable) and allows for multiple answers to be recorded. The vast majority (99.7%) of home health beneficiaries had only a single race/ethnicity recorded, and we restricted our study to this population.

The study population included all Medicare beneficiaries, 18 years and older, who received home health care, and self-identified with only one race/ethnicity on the home health. Details of the 11,720 people (0.3% of study population) who identified with two or more racial/ethnic groups are included for the interested reader as a brief Appendix. The final study population consisted of 4,231,370 adult Medicare beneficiaries who received home health care in 2015. The study was approved by the Institutional Review Board of Rutgers, The State University of New Jersey.

Statistical Analyses

We performed three sets of analyses. All analyses were performed using SAS statistical software (version 9.4). First, we used the self-reported OASIS race as the validation standard to assess the agreement and accuracy of the EDB and RTI race variables, contained in linked Medicare administrative data. Datasets were linked at the patient level using a unique beneficiary identification code assigned for this purpose by CMS. Analyses of sensitivity, specificity, positive predictive value (PPV), and Cohen's kappa coefficient were calculated for the full sample and for each sex separately (**Table 1**). Sensitivity indicates the proportion of beneficiaries identified in the OASIS data in a specific race/ethnicity category who are correctly identified on the MBSF. Specificity is the probability that someone who is truly not in a specific race/ethnicity category in the MBSF will be classified as not affiliated with that race/ethnicity in the OASIS data. Positive predictive value is the proportion of beneficiaries identified by the MBSF in a specific race/ethnicity category who are self-identified in the same category on the OASIS data.

The Cohen kappa coefficient²¹ is a widely used measure of interrater reliability, ranging from 1 (complete agreement) to -1 (complete disagreement). As a point of reference, Landis and Koch suggest excellent agreement is indicated by a kappa coefficient greater than 0.81.²²

In the second set of analyses, the pattern of race/ethnicity misclassification are shown for both EDB and RTI race variables (**Table 2**). These analyses augment the accuracy and agreement statistics and highlight the more nuanced differences between the pattern of racial/ethnic misclassification errors in the EDB and RTI race variables.

In the third set of analyses, differences in race/ethnicity categorization of RTI compared to OASIS race/ethnicity are compared for a subset of beneficiaries with dementia or diabetes (**Table 3**). We determined dementia or diabetes diagnosis status for our subset study population from the Medicare Beneficiary Summary File (MBSF) chronic conditions warehouse flags. This analysis highlights one aspect of race/ethnicity variable choice on study design and the resulting differences in frequency and prevalence of chronic disease burden within subpopulations.

RESULTS

Agreement and accuracy of Enrollment Data Base (EDB) and Research Triangle Institute (RTI) race variables with self-reported race/ethnicity from OASIS.

Both the EDB and RTI race variables have mutually exclusive categories, meaning that a person who is categorized as white or black is considered to be non-Hispanic. In our analyses, using OASIS race as the validation standard, the specificity of EDB race for non-Hispanic whites was 79.5 compared to 95.5 for the imputed RTI race variable (**Table 1**). In other words, there is one in five chance that someone who is not white will be misclassified as white using the EDB race variable, but only a 4.5% chance of misclassification as white when using the RTI race variable. Among people who self-identified as non-Hispanic black, both the EDB and RTI race variables perform similarly, with high specificity (99.2-99.4) and high sensitivity (96.6-97.0).

As the EDB race variable originates from social security records, an Afro-Cuban naturalized U.S. citizen would be classified as Hispanic, based on country of birth, and this classification would be retained in the (imputed) RTI race variable. In our analyses, for people who self-identified as Hispanic, the original EDB variable had high specificity (99.8) but low sensitivity (36.2). In contrast, the RTI race variable had both high specificity (98.7) and good sensitivity (90.8), undercounting fewer than one in ten Hispanics.

Among people who self-identified as Asian, Hawaiian Native, or other Pacific Islander (AAPI), specificity of both the EDB and RTI race variables was high (99.6-99.7). However, the RTI race variable had better sensitivity (74.7) compared to the EDB race variable (65.0). Meaning, one in four people who self-identified as AAPI were undercounted using the RTI race variable, compared to the EDB race variable which undercounted one in three Asian American/Pacific Islanders.

Among people who self-identified as American Indian or Alaskan Native (AIAN) the specificity of the EDB and RTI race variables was high (99.8), however the sensitivity was low (43%). The

EDB classification of AIANs using tribal membership records resulted in fewer than half of AIANs were correctly classified in Medicare administrative race/ethnicity data (**Table 1**).

Sex differences in accuracy and agreement of race/ethnicity variables

The EDB race variable, originating from Social Security Administration records, is slightly more accurate for women compared to men among Hispanics ($k = 0.50$ vs. 0.49), AAPIs ($k = 0.72$ vs. 0.69), and whites ($k = 0.82$ vs. 0.80) (**Table 1**). In contrast the RTI race variable, imputed from U.S. Census name lists and residence in Hawaii or Puerto Rico, is less accurate for women compared to men among Hispanics ($k = 0.85$ vs. 0.89) and AAPIs ($k = 0.76$ vs. 0.78).

Patterns of over-classification and misclassification by race/ethnicity variables

The pattern of misclassification errors in the EDB and RTI race variables compared to self-reported race/ethnicity from the OASIS dataset are shown in **Table 2**. Using the original EDB race variable 190,434 people were misclassified as non-Hispanic white, with the majority (88%) self-identifying as Hispanic. In contrast, the RTI race variable mistakenly classifies a much smaller fraction of minorities as being non-Hispanic white. However, using the RTI race variable non-Hispanic whites are misassigned as Hispanic more than five times as often compared to the original EDB race variable, accounting for 78% of people misassigned to Hispanic ethnicity. Similarly, non-Hispanic whites comprise 80% of people misassigned by the RTI race variable as black, 77% of people misassigned as Asian/Pacific Islander, and 84% of people misassigned as American Indian/Alaskan Native (**Table 2**).

Dementia and diabetes frequency and prevalence by race/ethnicity variables

To illustrate the potential impact of race/ethnicity misclassification on estimated size of health disparities and disease prevalence we calculated the number of beneficiaries with dementia and diabetes using each of the three race/ethnicity variables. When comparing the numbers of people with a diagnosis of dementia or diabetes the largest net differences were among the Hispanics, Asians/Pacific Islanders, and American Indians/Alaskan Natives (**Table 3**). The net difference is important for study designs that draw their sampling frame from administrative data sources.

Using the RTI race variable (compared to OASIS) resulted in an overestimation of the number of Hispanics with dementia by a net difference of 4,283 (4.8%) and diabetes by a net difference of 10,477 (5.4%) (see **Table 3**). In contrast, the EDB race variable underestimated the number of Hispanics with dementia by a net difference of 48,407 (-54.8%) and diabetes by a net difference of 114,003 (-59.0%). However, the EDB race variable also produced falsely high estimates of the prevalence of dementia (34.1%) and diabetes (67.9%) in Hispanics (see **Figure 1**). The RTI and OASIS race variables produced similar estimates of the prevalence of dementia (29.0%-29.6%) and diabetes (63.9%-64.9%) among Hispanics.

Among AAPIs, the number of people with dementia was underestimated by a net difference of 1,853 (-6.4%) using the RTI race variable and by 6,032 (-21.1%) using the EDB race variable. The pattern was similar for diabetes in AAPIs, which was underestimated by a net difference of 4,391 (-8.2%) using the RTI race variable, and 12,113 (-22.6%) using the EDB race variable

(**Table 3**). When the prevalence of dementia and diabetes were calculated for AAPIs using each of the race/ethnicity variables the pattern was similar to that seen for Hispanics, with EDB race overestimating chronic disease burden (**Figure 1**). Using the RTI and OASIS variables the prevalence of dementia among Asians/Pacific Islanders was 32.1%-32.6%, and 34.1% using EDB race. For diabetes, the prevalence among AAPIs was 59.9%-60.2% using the RTI and OASIS race variables, and 62.7% using EDB race.

DISCUSSION

Consistent with prior studies, we found the race variables contained in Medicare administrative data undercount Hispanics, Asians/Pacific Islanders, and American Indians/Alaskan Natives.^{17,23,24} While advances have been made in Medicare Bayesian Improved Surname and Geocoding (MBISG) algorithm used to calculate racial and ethnic differences in Healthcare Effectiveness Data and Information Set (HEDIS) measures,²⁵⁻²⁷ the accuracy and agreement statistics of the MBISG 2.0 have not, to our knowledge, been published. As a benchmark for our findings we briefly summarize published accuracy and agreement statistics for EDB and RTI race/ethnicity variables using different ‘gold standard’ survey data sources in **Table 4**. From a methodological standpoint, the choice of race/ethnicity data source is essential at the study design stage for health disparities research. The impact of race/ethnicity variable selection on estimates of disease prevalence is of special concern, as we found in the case of dementia prevalence among Hispanics shown in **Figure 1**. When using the EDB race variable, the prevalence of dementia among Hispanics is 18% higher compared to when the RTI race variable is used, with an absolute difference of just over 5 percentage points (see **Figure 1**). A smaller difference (1.5 percentage points) is seen for AAPIs, with virtually no difference for non-Hispanic whites, blacks, and American Indians/Alaskan Natives (AIANs). Compared to the EDB race variable, if the RTI variable was a “race-specific” anti-dementia drug for Hispanics it would be a blockbuster.

For AAPI populations, our study findings have additional significance. Asian Americans/Pacific Islanders are the fastest growing population in the U.S., while being the most heterogeneous. Certain AAPI subgroups, such as Filipinos, may be more prone to misclassification using surname based imputation methods due to the long history of Spanish colonization in the Philippines. Similarly, the Republic of China (Taiwan) was colonized by the Dutch and Spanish; India was colonized by the Portuguese, Dutch, and British; and Vietnam, Laos, and Cambodia were colonized by the French. In addition, interracial/intercultural marriages frequently result in women changing their last name to that of their husband’s family, such that a woman who marries a Filipino-American man might be classified as Hispanic using name-based race algorithms.

While the self-reported race/ethnicity data should always be the first choice, we found the RTI race variable to be very accurate for identifying Hispanics ($k = 0.89$ for males; $k = 0.85$ for females), and non-Hispanic whites ($k = 0.90$) or blacks ($k = 0.96$) of either sex (**Table 1**). For more granular analyses, and especially research that aims to disentangle race/ethnicity and socioeconomic status, a higher level of accuracy may be desired. Researchers who are working with linked administrative and assessment datasets should report racial/ethnic differences based on the self-reported race variable. Reviewers and journal editors should question the source of

race/ethnicity data and critically examine the rationale for research which uses the EDB race variable, especially when reporting on black/white disparities. Additionally, future advances in race/ethnicity imputation algorithms should augment and include all self-reported race/ethnicity data from both survey (MCBS, HOS, CAHPS) and assessment (OASIS, MDS) data sources.

This study has several limitations. First, the study population consisted only of Medicare beneficiaries who utilized home health care in calendar year 2015. Compared to all Medicare beneficiaries, people who utilize home health care are older and have a higher burden of chronic disease. Second, blacks are slightly overrepresented in the home health care population compared to the full Medicare population (estimated with the RTI race variable). Third, some older adults, especially AAPIs and Hispanics, may retire or seek supportive care outside of the U.S., limiting their access and use of the Medicare home health care benefit, and the generalizability of findings for these individuals. Finally, AIANs who live on tribal reservations may be underrepresented, in contrast to people who identify as American Indians but are not tribal members.

In conclusion, administrative datasets are commonly used in reports and studies of minority health and health disparities. Our study highlights the potential for bias and error introduced during the selection of race/ethnicity data source. Our work confirms the advantages of using the RTI race variable compared to EDB race variable. We also show that further reductions in error and bias can be gained by using self-reported race/ethnicity contained in assessment datasets. These findings have important implications for the design of future studies and the interpretation of prior published research. Future work to improve imputation algorithms for race/ethnicity should be used to supplement existing sources of self-reported race/ethnicity data.

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FIGURE 1 Prevalence of Chronic Disease within a Defined Population, Conditional on Choice of Race/Ethnicity Variable

TABLE 1 Accuracy and Agreement of the Enrollment Data Base (EDB) and RTI Race/Ethnic Classifications Using the Home Health Care Outcome and Assessment Information Set (OASIS) for Comparison: 2015

Reference = OASIS race	True positive	False negative	False positive	True negative	Sensitivity	Specificity	PPV	Kappa
EDB race variable								
<i>Hispanic</i>	107,753	190,052	9,079	3,924,486	36.2	99.8	92.2	0.50
Male	43,047	77,852	3,406	1,525,418	35.6	99.8	92.7	0.49
Female	64,706	112,200	5,673	2,399,068	36.6	99.8	91.9	0.50
<i>AAPI</i>	52,616	28,364	13,683	4,136,707	65.0	99.7	79.3	0.71
Male	20,491	11,705	5,836	1,611,691	63.6	99.6	77.8	0.69
Female	32,125	16,659	7,847	2,525,016	65.8	99.7	80.4	0.72
<i>White</i>	3,229,553	69,983	190,434	741,400	97.9	79.5	94.4	0.81
Male	1,259,106	32,469	76,300	281,848	97.5	78.7	94.3	0.80
Female	1,970,447	37,514	114,134	459,552	98.1	80.1	94.5	0.82
<i>Black</i>	513,158	15,630	28,042	3,674,540	97.0	99.2	94.8	0.95
Male	188,826	6,204	10,786	1,443,907	96.8	99.3	94.6	0.95
Female	324,332	9,426	17,256	2,230,663	97.2	99.2	95.0	0.95
<i>AIAN</i>	6,892	9,080	8,061	4,207,337	43.1	99.8	46.1	0.44
Male	2,846	3,700	3,018	1,640,159	43.5	99.8	48.5	0.46
Female	4,046	5,380	5,043	2,567,178	42.9	99.8	44.5	0.43
RTI race variable								
<i>Hispanic</i>	270,370	27,435	48,592	3,884,973	90.8	98.7	84.8	0.87
Male	111,779	9,120	16,089	1,512,735	92.5	98.9	87.4	0.89
Female	158,591	18,315	32,503	2,372,238	89.6	98.6	83.0	0.85
<i>AAPI</i>	66,696	22,573	15,594	4,126,507	74.7	99.6	81.0	0.77
Male	27,207	8,466	6,086	1,607,964	76.3	99.6	81.7	0.78
Female	39,489	14,107	9,508	2,518,543	73.7	99.6	80.6	0.76
<i>White</i>	3,196,880	102,656	41,878	889,956	96.9	95.5	98.7	0.90
Male	1,249,568	42,007	14,562	343,586	96.7	95.9	98.8	0.90
Female	1,947,312	60,649	27,316	546,370	97.0	95.2	98.6	0.90
<i>Black</i>	511,064	17,724	21,699	3,680,883	96.6	99.4	95.9	0.96
Male	188,307	6,723	7,953	1,446,740	96.5	99.4	95.9	0.96
Female	322,757	11,001	13,746	2,234,143	96.7	99.4	95.9	0.96
<i>AIAN</i>	6,872	9,100	7,852	4,207,546	43.0	99.8	46.7	0.44
Male	2,839	3,707	2,928	1,640,249	43.4	99.8	49.2	0.46
Female	4,033	5,393	4,924	2,567,297	42.8	99.8	45.0	0.44

Abbreviations: AAPI = Asian American/Pacific Islanders/Native Hawaiians; AIAN = American Indians/Alaskan Natives.

TABLE 2 Beneficiaries with race misclassified by EDB or RTI compared to OASIS;
N = 4,231,370

OASIS race						
EDB race – 318,177 (7.5%) misclassified						
		Hispanic	AAPI	White	Black	AIAN
Hispanic	9,079	-	753 8.3%	6,695 73.7%	1,481 16.3%	150 1.7%
AAPI	10,462	1,124 10.7%	-	7,786 74.4%	728 7.0%	824 7.9%
White	190,434	167,495 88.0%	8,532 4.5%	-	8,376 4.4%	6,031 3.2%
Black	28,042	8,167 29.1%	1,155 4.1%	17,524 62.5%	-	1,196 4.3%
AIAN	8,061	517 6.4%	439 5.5%	6,614 82.1%	491 6.1%	-
Other/ Unknown	72,099	12,749 17.7%	753 8.3%	31,364 43.5%	4,554 6.3%	879 1.2%
RTI race – 179,488 (4.2%) misclassified						
		Hispanic	AAPI	White	Black	AIAN
Hispanic	48,592	-	6,214 12.8%	37,670 77.5%	4,175 8.6%	533 1.1%
AAPI	15,594	1,373 8.8%	-	11,948 76.6%	1,160 7.4%	1,113 7.1%
White	41,878	21,941 52.4%	6,589 15.7%	-	7,682 18.3%	5,666 13.5%
Black	21,699	2,298 10.6%	960 4.4%	17,265 80.0%	-	1,176 5.4%
AIAN	7,852	446 5.7%	362 4.6%	6,570 83.7%	474 6.0%	-
Other/ Unknown	43,873	1,377 3.1%	8,448 19.3%	29,203 66.6%	4,233 9.6%	612 1.4%

Abbreviations: AAPI = Asian American/Pacific Islanders/Native Hawaiians;
American Indians/Alaskan Natives.

AIAN =

TABLE 3 Number and ratio/net difference of Medicare beneficiaries from each racial/ethnic group who have a dementia or diabetes flag in the Medicare Chronic Conditions Warehouse using RTI race and EDB race compared to OASIS race.

Dementia sample; n = 1,195,145 / 4,231,370							
	OASIS	RTI	Ratio	Net difference	EDB	Ratio	Net difference
Hispanic	88,272	92,555	1.05	+ 4.9%	39,865	0.45	- 54.8%
AAPI	28,653	26,800	0.94	- 6.4%	22,621	0.79	- 21.1%
White	932,097	918,955	0.99	- 1.4%	966,390	1.04	+ 3.7%
Black	142,112	143,526	1.01	+ 1.0%	145,651	1.01	+ 1.5%
AIAN	4,011	3,662	0.91	- 8.7%	3,721	0.93	- 7.2%
Other/Unknown		9,647			16,897		
Diabetes sample; n = 2,018,686 / 4,231,370							
	OASIS	RTI	Ratio	Net difference	EDB	Ratio	Net difference
Hispanic	193,274	203,751	1.05	+ 5.4%	79,271	0.41	- 59.0%
AAPI	53,705	49,314	0.92	- 8.2%	41,592	0.77	- 22.6%
White	1,435,215	1,406,189	0.98	- 2.0%	1,516,959	1.06	+ 5.7%
Black	326,941	329,158	1.01	+ 0.8%	334,490	1.02	+ 2.3%
AIAN	9,551	8,902	0.93	- 6.8%	9,050	0.95	- 5.2%
Other/Unknown		9,647			37,324		

Abbreviations: AAPI = Asian American/Pacific Islanders/Native Hawaiians; AIAN = American Indians/Alaskan Natives. Note: Denominator for prevalence of chronic illness is based on the racial/ethnic subgroup population specific to each race variable (OASIS, EDB, RTI).

TABLE 4 Comparison of accuracy and agreement measures for EDB and RTI race with prior studies.

Waldo EDB 1998-2001 (n = 32,038) Reference: MCBS 1998-2001					Eicheldinger & Bonito EDB 2003 (n = 830,728) Reference: CAHPS 2000-2002				[Authors – this paper] EDB 2015 (n = 4,231,370) Reference: OASIS 2015			
Sensitivity	Specificity	PPV	Kappa		Sensitivity	Specificity	PPV	Kappa	Sensitivity	Specificity	PPV	Kappa
<i>Hispanic</i>	35.7	99.9	97.5	0.50	29.5	99.9	92.7	0.43	36.2	99.8	92.2	0.50
<i>AAPI</i>	54.0	99.8	70.0	0.61	54.7	99.8	84.5	0.66	65.0	99.7	79.3	0.71
<i>White</i>	96.5	88.2	98.2	0.81	99.3	61.7	91.7	0.71	97.9	79.5	94.4	0.81
<i>Black</i>	95.6	99.6	96.5	0.96	97.4	98.8	86.3	0.91	97.0	99.2	94.8	0.95
<i>AIAN</i>	20.6	99.9	69.5	0.32	35.7	99.9	59.9	0.45	43.1	99.8	46.1	0.44
					Bonito, Bann, Eicheldinger, et al. RTI NEWRACE 2003 (n = 830,728) Reference: CAHPS 2000-2002				[Authors – this paper] RTI 2015 (n = 4,231,370) Reference: OASIS 2015			
					Sensitivity	Specificity	PPV	Kappa	Sensitivity	Specificity	PPV	Kappa
	<i>Hispanic</i>				76.6	99.2	84.5	0.79	90.8	98.7	84.8	0.87
	<i>AAPI</i>				79.2	99.7	81.5	0.80	74.7	99.6	81.0	0.77
	<i>White</i>				-	-	-	-	96.9	95.5	98.7	0.90
	<i>Black</i>				-	-	-	-	96.6	99.4	95.9	0.96
	<i>AIAN</i>				-	-	-	-	43.0	99.8	46.7	0.44

Abbreviations: AAPI = Pacific Islanders; AIAN = American Indians/Alaskan Natives.