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Leveraging diagnosis and biometric data from the All of Us Research Program to uncover disparities in obesity diagnosis

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ABSTRACT

Background: Despite extensive efforts to standardize definitions of obesity, clinical practices of diagnosing obesity vary widely. This study examined (1) discrepancies between biometric body mass index (BMI) measures of obesity and documented diagnoses of obesity in patient electronic health records (EHRs) and (2) how these discrepancies vary by patient gender and race and ethnicity from an intersectional lens.

Methods: Observational study of 383,380 participants in the National Institutes of Health *All of Us* Research Program dataset.

Results: Over half (60 %) of participants with a BMI indicating obesity had no clinical diagnosis of obesity in their EHRs. Adjusting for BMI, comorbidities, and other covariates, women's adjusted odds of diagnosis were far higher than men's (95 % confidence interval 1.66–1.75). However, the gender gap between women's and men's likelihood of diagnosis varied widely across racial groups. Overall, Non-Hispanic (NH) Black women and Hispanic women were the most likely to be diagnosed and NH-Asian men were the least likely to be diagnosed.

Conclusion: Men, and particularly NH-Asian men, may be at heightened risk of underdiagnosis of obesity. Women, and especially Hispanic and NH-Black women, may be at heightened risk of unanticipated harms of obesity diagnosis, including stigma and competing demand with other health concerns. Leveraging diagnosis and biometric data from this unique public domain dataset from the All of Us project, this study revealed pervasive disparities in diagnostic attribution by gender, race, and ethnicity.

1. Background and significance

Health institutions define obesity as a "disease wherein an increase in body fat promotes adipose tissue dysfunction and abnormal fat mass physical forces, resulting in adverse metabolic, biomechanical, and psychosocial health consequences" [1]. Although imperfect, body mass index (BMI) remains a widely used and acceptable measure to classify obesity for its ease of use [2,3]. Clinical guidelines advise providers to screen all adult patients for obesity using BMI [4], where a BMI greater than or equal to 30 kg/m^2 indicates obesity [2,3]. Most electronic health record (EHR) systems even compute and/or display BMI, and many systems flag patients with abnormal BMI values [5]. Despite such institutional efforts to standardize clinical definitions of obesity and identify patients with obesity, there is little consensus among providers on how it should be diagnosed, when it should be treated [2,6–8], and whether it even constitutes a disease [8,9]. Many providers are also unaware of evidence-based guidelines and feel inadequately trained to identify and treat obesity [6,10–14]. As a result, the extent and ways in which patients are diagnosed with obesity in clinical settings vary widely [15–25]. Obesity is considered pervasive in the U.S, but

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infrequently diagnosed [15–24,26] or treated [27] in clinical settings.

Gendered constructions of body weight and its relationship with health may help explain who does and does not receive a diagnosis for obesity, independent of whether patients truly have obesity or not. Increased adiposity is seen as less normative [28,29] and less healthy [30] on women than men, and women are more likely to seek weight loss [31]. This could result in a higher likelihood of patients and/or providers [32] initiating conversations about weight loss among women [33], or a lower threshold used for diagnosis of obesity in women than men. The pervasive practice of visually assessing obesity [14,19] may also contribute to a gender gap in diagnosis. Visual assessments of excess adiposity underestimate obesity, but are less likely to underestimate obesity in women than men because they are affected by gender norms around body weight [34]. Abundant secondary analyses of EHR data find that, independent of BMI and comorbidities, women are more likely to be diagnosed with obesity than men [18–20,23,24,35]. Given data limitations in the collection of gender in EHRs and limited sample diversity, little is known about diagnostic variation in obesity among other minoritized gender identities.

Racial and ethnic understandings of obesity might further drive variation in obesity diagnoses. Clinical decisions tend to be attuned to prototypical cases for diseases [36] and obesity is especially prevalent in Black and Hispanic/Latino populations in the U.S [37]. Public health and news messaging around obesity also stresses its prevalence among these populations [38–40], further cementing patient prototypes. Black and Hispanic/Latino individuals are also more harshly judged for increased adiposity than are White individuals [29,40–44], perhaps because stereotypes around race and body fat coalesce (e.g., over-indulgence and noncompliance). Together, these factors may lead providers to disproportionality notice obesity for Black and Hispanic/Latino patients, driving up diagnosis rates for these patients. At the same time, some evidence suggests that Black individuals (especially women) are more likely to accept larger and curvier body types [45], and Black and Hispanic/Latino individuals are less likely to seek weight loss [46] than non-Hispanic Whites. This work predicts that these patients would be less likely to initiate conversations about weight loss in clinical settings, thus reducing their likelihood of obesity diagnosis. Limited scholarship examines cultural representations of obesity in other racial and ethnic groups. However, related research hints that body composition and health are evaluated differently for Asian individuals compared to other races and ethnicities: Asian individuals are evaluated as physically weaker than White or Black individuals, independent of their objective strength [47]. Additionally, perhaps the “model minority” stereotype extends to perceptions of Asian individuals’ health [48], leading to the underassessment of obesity among Asian patients. This prior work might predict lower rates of obesity diagnosis among Asian patients.

Prior empirical studies examining how obesity diagnosis (independent of BMI and comorbidities) varies by patients’ race and ethnicity yields mixed results [20,21,23,35,49,50]. These studies on obesity diagnostic practices are hampered by small sample sizes and limited diversity [16,17,22,23,50]. For instance, some of these studies include insufficient Asian and/or Hispanic/Latino participants in the sample for analysis [17,22,23,50], another has insufficient sample diversity for any statistical analysis of race/ethnicity [19], and another codes race and ethnicity as White versus non-White [16].

In addition, empirical research on obesity diagnostic practices examines patient characteristics in isolation [but see 22]. Meanwhile, social science highlights that identities are interconnected (i.e., “intersectionality”), especially in context of body weight and health [22,28,29,38,42,51]. For instance, as often stressed by media and public health messaging, obesity is especially prevalent among Black and Hispanic women [38]. Further, social judgments of body weight are particularly harsh for Black and Hispanic or Latina women [29,38,42,44,51]. Thus, it is crucial to consider how obesity diagnosis patterns vary jointly by gender and race and ethnicity.

We leverage data from the NIH *All of Us* Research Program to overcome prior methodological challenges in studying diagnostic variation in obesity. Unlike EHR records from single sites, *All of Us* includes a large sample size where minorities are well represented, and social identity is granularly coded. This offers the opportunity to detail how diagnostic attribution varies by social identity and account for interactions between social identities. Further, while much prior work in this area is constrained to data available in EHRs, *All of Us* offers EHR data enhanced through the incorporation of information from surveys and biometric data collection.

Two research questions are addressed: (1) How often are individuals with a BMI indicating obesity (BMI $\geq$30.0 kg/m^2) diagnosed with obesity by their providers? We hypothesize that obesity tends to be underdiagnosed compared to BMI measures. (2) How do obesity diagnosis rates, controlling for BMI, vary by gender and race? We hypothesize that women will be more likely to be diagnosed than men. We make no specific hypotheses for race/ethnicity, or interactions between race/ethnicity and gender.

2. Methods

2.1. Data and sample

This study draws from the *All of Us* dataset: a large, deidentified dataset of consented U.S. adults aged 18 and over [52]. Data about participants are combined from multiple sources including surveys, physical measurements, and EHRs. We first include participants in the Controlled Tier Dataset V7 (summer 2017 to July 1, 2022) with any demographic and basics survey information (N = 413,406). Participants who report pregnancy (or possible pregnancy) at the time of survey data collection or did not share their EHR data are excluded, leaving a final sample size of N = 383,380 (Fig. 1).

2.2. Measures

2.2.1. Clinical obesity diagnosis

Our core dependent variable is a provider’s clinical diagnosis of obesity at any time point (0/1) in patients’ EHR data. This variable is extracted from patients’ conditions list in their EHR data shared with *All of Us*, and is based on claims and diagnosis codes.

2.2.2. BMI

BMI is the most recently measured BMI based on personal measurements data in *All of Us*, collected at study intake. Outliers (BMI <9 or >90) are recoded to missing. We evaluate BMI as both a continuous and categorical variable, where BMI is coded as: underweight (<18.5), normal weight (18.5–24.9), overweight (25.0–29.9), or obesity ($\geq$30.0). In places, we further distinguish obesity class I (30.0–34.9), obesity class II (35.0–39.9), and obesity class III ($\geq$40.0). Notably, BMI is an imperfect anthropometric measure: it does not reflect comparative components of body composition and is based on normative values for mostly White individuals [53,54]. More accurate methodologies for assessing

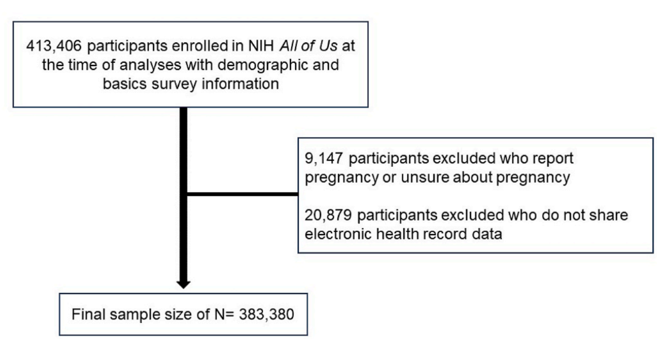

Fig. 1. Sampling data from the NIH *All of Us* research program dataset.

body composition (e.g., bioelectrical impedance and imaging methods) are generally not available for clinical use. Other clinic-based strategies to measure adiposity (e.g., body fat calipers, waist circumference, or waist-to-hip ratio measurements) can be cumbersome, time-consuming, and prone to poor reliability due to inter-operator variability and lack of formal training; hence they are not routinely performed in most clinical settings. BMI, therefore, remains the best and most widely used initial screening variable despite its limitations. Clinical decisions based on BMI are usually informed by other data, such as patient history, exams, and labs. Therefore, adjusting for BMI and comorbidities offers a clinically relevant and widely-accepted, if imperfect, analytic strategy to investigate the attribution of obesity diagnosis (rather than merely patterns of obesity morbidity) [18–20,23,24,35].

2.2.3. Gender, race, and ethnicity

Independent measures include gender identity, race, and ethnicity. Gender identity is collected as: "Woman", "Man", "Non-Binary," "Transgender" or "Additional Options." We summarize this variable as "Woman", "Man", or "Gender Minority," where the final category encompasses "Non-Binary," "Transgender" and "Additional Options." All of Us collects Hispanic/Latino ethnicity separately from race; however, all 59,342 (15.5 %) respondents who report "none indicated" for race also reported Hispanic/Latino ethnicity. Therefore, we code race/ethnicity as Hispanic/Latino (any race), "NH-White", "NH-Black or African American," "NH-Asian," "NH-Native Hawaiian or Pacific Islander," "NH-Middle Eastern or North African (MENA)" "NH-More than 1 racial population." As a tradeoff, this coding scheme obscures the 2.2 % (N = 5948) of respondents who report Hispanic/Latino and a specific race. *All of Us* does not make the Indigenous people data set available for general researchers and so this category was not included in compliance with NIH policy.

2.2.4. Covariates

Our covariates include age, health insurance, highest level of education, two measures for poverty, and several measures of health status. Age is calculated as the difference (in years) between the participants' date of birth and the date they took the basics survey for *All of Us*. Health insurance is coded as having health insurance or not. Highest level of education is coded as: "College graduate or advanced degree", "College 1–3 Years", "Grade 12 or GED", and "Less than a high school degree or equivalent". *All of Us* includes a variable for income, however there is too much missing data (N = 76,564; 20 %) to impute reasonably. Instead, we use two variables capturing poverty: 1) recent housing instability, coded as whether the participant had a concern about stable housing in the past 6 months or not; and 2) percent of people in the participant's zip code with an income below the poverty level. We include self-rated physical health, coded as "Excellent", "Very good," "Good," "Fair," or "Poor." We also include six comorbidities [18,35]: any lifetime diagnosis in EHRs of hypertension, sleep apnea, hyperlipidemia, type 2 diabetes, heart disease, or osteoarthritis.

Sensitivity analyses include a variable to capture recency of health service use, drawn from an optional survey with this question: "About how long has it been since you last saw or talked to a doctor or other health care provider about your own health?" and is coded here as: "Less than 6 months ago", "6 months to 1 year ago", "1–2 years ago", or "2 or more years ago." Only 47 % (N = 178,618) of participants took the survey and the sample is biased compared to our larger sample. Therefore, we re-run analyses to adjust for recency of health service use using this subsample where relevant for men or women. We do not run these sensitivity analyses for gender minorities due to low cell counts.

2.3. Statistical analysis

In this observational study, we hypothesized that obesity tends to be underdiagnosed compared to BMI measures, and that women will be more likely to be diagnosed than men. We made no specific hypotheses for race/ethnicity, or interactions between race/ethnicity and gender. Our final sample size was N = 383,380, as described in section 2.1. After computing sample characteristics, missing data were imputed using predictive mean matching as implemented in the Hmisc package in R [55]. Missing data are described in Table 1. We then used t-tests and chi-squared tests to assess bivariate relationships with obesity diagnosis. Finally, we used logistic regression to assess relationships between obesity diagnosis and gender, race and ethnicity, and BMI, adjusting for our covariates. To statistically test interactions between gender and race

Table 1
Sample characteristics (N = 383,380).

Variable	n (%) or Mean (SD)
Clinically Diagnosed Obesity	
Has a diagnosis of obesity	73,229 (19.1)
No diagnosis of obesity	310,151 (80.9)
BMI	29.8 (7.6)
BMI class	
Has a BMI indicating overweight (25.0–29.9)	97,054 (25.3)
Has a BMI indicating obesity (≥30.0)	130,643 (34.1)
Missing BMI	66,624 (17.4)
Gender	
Woman	225,420 (58.8)
Man	147,856 (38.6)
Gender Minority	2681 (0.7)
Missing	7423 (1.9)
Race	
NH-Asian	12,377 (3.2)
NH-Black or African American	73,147 (19.1)
NH-Middle Eastern or North African	2167 (0.6)
NH-Native Hawaiian or Pacific Islander	383 (0.1)
Hispanic/Latino	67,962 (17.7)
NH-More than 1 Population	6175 (1.8)
NH-White	206,175 (54.8)
Missing	14,994 (3.9)
Age (years)	52.1 (17.0)
Education	
Less than a high school degree or equivalent	34,868 (9.1)
12 or GED	72,330 (18.9)
College 1 to 3	97,075 (25.3)
College graduate or advanced degree	166,572 (43.4)
Missing	12,535 (3.3)
Poverty Rate in Participant's Zip Code	15.8 (5.2)
Missing	250 (0.07)
Stable Housing Concern	
Concerns about housing instability	62,643 (16.3)
No concerns about housing instability	311,519 (81.3)
Missing	9218 (2.4)
Health Insurance	
Has health insurance	344,253 (89.8)
No health insurance	25,349 (6.6)
Missing	13,778 (3.6)
Physical Health Status	
Poor	19,534 (5.1)
Fair	76,696 (20.0)
Good	131,441 (34.3)
Very good	103,174 (26.9)
Excellent	37,115 (9.7)
Missing	15,420 (4.0)
Hypertension	117,471 (30.6)
Sleep Apnea	45,680 (11.9)
Hyperlipidemia	108,669 (28.3)
Type 2 Diabetes	52,508 (13.7)
Heart Disease	33,354 (8.7)
Osteoarthritis	95,164 (24.8)
Most Recent Health Care Interaction[a]	
6 months ago or less	147,992 (82.9)
6 months to 1 year ago	18,387 (10.3)
1–2 years ago	6264 (3.5)
2 or more years ago	3771 (2.1)
Missing	2204 (1.2)

Notes: BMI= Body mass index (kg/m^2). There is no missing data for age or clinical diagnoses.

[a] Among individuals who answered the Healthcare Utilization Survey (N = 178,618).

and ethnicity we used logistic regression models with interaction terms. For easier interpretability, tables present results from stratified models. We used 95 % confidence intervals (CIs) and two-sided statistical tests using $\alpha = 0.05$ to assess statistical significance. Due to low cell counts, we did not statistically test patterns for race and ethnicity among gender minorities. The first author cleaned the data and performed the statistical analysis.

2.4. Ethics

This research involved secondary analysis of deidentified data from consenting individuals through the *All of Us* Researcher Workbench and was determined “exempt” by the Purdue University Institutional Review Board (IRB-2024-1534).

3. Results

3.1. Sample characteristics

Our sample includes 59 % (N = 225,420) women, 38.6 % men (N = 147,856) and 0.7 % (N = 2681) gender minority individuals. A total of 42 % (N = 162,211) of our sample is not NH-White. The mean BMI in our sample is 30 (SD = 8). While approximately a third of participants (34 %, N = 130,643) have a BMI indicating obesity, just under a fifth of participants (19 %, N = 73,229) have an obesity diagnosis in their EHR. See Table 1.

3.2. To what extent are individuals with an elevated BMI clinically diagnosed with obesity?

Among those with a BMI indicating obesity, 60 % (N = 93,261) had no documented obesity diagnosis in their EHR. Across increasing classes of BMIs indicating obesity, the proportion of undiagnosed patients decreased but remained substantial. Pairwise chi-squared comparisons between these obesity classes confirmed that these differences in the rate of diagnosis across obesity classes were statistically significant (each $p < 0.0001$). A higher BMI was associated with a significantly increased likelihood of a clinical diagnosis of obesity (OR = 1.17, 95 % CI = 1.17 to 1.17), even among those with a BMI indicating obesity and adjusting for health status and comorbidities. See Table 2.

3.3. How do obesity diagnosis rates vary by patients’ gender and race/ethnicity?

Women’s adjusted odds of obesity diagnosis were 71 % higher than men’s (95 %: CI: 66%–75 %), adjusting for all covariates. The effect of BMI was also significantly weaker for women than for men (Table 3). These two gender patterns remained in sensitivity analyses accounting for health care interaction. Gender minorities’ adjusted odds of obesity diagnosis were significantly less than women’s, but not significantly different than men’s adjusted odds (Table 3). As noted earlier, we do not run sensitivity analyses for results involving gender minorities due to limited sample size.

Accounting for race/ethnicity reveals additional nuance. (See Table 3 and Fig. 2). For all gender groups, there was a general ordering by which NH-Asian individuals were least likely to be diagnosed, followed by individuals identifying as NH-Native Hawaiian or Pacific Islander, NH and more than 1 race, NH-MENA, NH-White, NH-Black, and finally Hispanic or Latino individuals being the most likely to be diagnosed. When accounting for most recent healthcare interaction in sensitivity analysis, we observed a subtly different ordering: among both women and men, the ordering was reversed for NH-MENA individuals and NH-individuals identifying with more than 1 race.

The variation in likelihood of diagnosis by race/ethnicity was substantial. For example, the adjusted odds of NH-White women being diagnosed were 1.80 (95 % CI: 1.60–2.04) times that of NH-Asian

Table 2
Bivariate relationships with clinical obesity diagnosis ($N = 383{,}380$).

Variable	Obesity Diagnosis Present n (%) of row or mean (SD)
*BMI Class****	
BMI Indicating Obesity Class III (≥40.0)	19,106 (56.8)
BMI Indicating Obesity Class II (35.0–39.9)	18,342 (45.2)
BMI Indicating Obesity Class I (30.0–34.9)	23,469 (29.4)
BMI Indicating Overweight (25.0–29.9)	10,562 (9.9)
BMI Indicating Normal Weight (18.5–24.9)	1705 (1.6)
BMI Indicating Underweight (<18.5)	45 (1.3)
*Gender****	
Woman	49,511 (21.6)
Man	23,348 (15.5)
Gender Minority	370 (13.6)
*Race and Ethnicity****	
NH-Asian	743 (5.8)
NH-Middle Eastern or North African	293 (13.0)
NH-More than 1 Population	1035 (16.2)
NH-White	38,573 (18.0)
NH-Native Hawaiian or Pacific Islander	91 (22.4)
NH-Black or African American	17,419 (22.9)
Hispanic/Latino	15,075 (21.3)
*Age (years)****	54.9 (15.1)
*Education****	
Less than a high school degree or equivalent	7791 (21.3)
12 or GED	16,435 (21.8)
College 1 to 3	23,497 (23.4)
College graduate or advanced degree	25,506 (14.9)
*Poverty Rate in Participant’s Zip Code****	15.7 (5.2)
Stable Housing Concern	
Concerns about housing instability	12,131 (18.8)
No concerns about housing instability	61,098 (19.2)
*Health Insurance****	
Has health insurance	69,977 (19.6)
No health insurance	3252 (12.1)
*Self-Rated Health****	
Poor	6863 (33.9)
Fair	23,054 (28.9)
Good	28,146 (20.5)
Very Good	12,590 (11.7)
Excellent	2576 (6.6)
*Hypertension****	
No clinical diagnosis of hypertension	20,944 (7.9)
Clinical diagnosis of hypertension	52,285 (44.5)
*Sleep Apnea****	
No clinical diagnosis of sleep apnea	43,432 (12.9)
Clinical diagnosis of sleep apnea	29,797 (65.2)
*Hyperlipidemia****	
No clinical diagnosis of hyperlipidemia	27,036 (9.5)
Clinical diagnosis of hyperlipidemia	47,193 (43.4)
*Type 2 Diabetes****	
No clinical diagnosis of type 2 diabetes	43,070 (13.0)
Clinical diagnosis of type 2 diabetes	30,159 (57.4)
*Heart Disease****	
No clinical diagnosis of heart disease	57,846 (16.5)
Clinical diagnosis of heart disease	15,383 (46.1)
*Osteoarthritis****	
No clinical diagnosis of osteoarthritis	31,596 (11.0)
Clinical diagnosis of osteoarthritis	41,633 (43.8)
Most Recent Health Care Interaction[a]***	
6 months ago or less	30,199 (20.6)
6 months to 1 year ago	2352 (12.9)
1–2 years ago	608 (9.8)
2 or more years ago	335 (9.0)

Notes: BMI= Body mass index (kg/m^2). There is no missing data for age or clinical diagnoses. Statistical significance for associations between each variable and obesity diagnosis assessed using t-tests (for age and poverty rate in zip code) or chi-squared tests (for all other variables). ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

[a] Among individuals who answered the Healthcare Utilization Survey ($N = 178{,}618$).

Table 3
Factors associated with clinical obesity diagnosis in logistic regression models.

	Model 1	Model 2a (Among Women)	Model 2b (Among Men)
		AOR (95 % CI)	AOR (95 % CI)
BMI	1.17*** (1.16–1.17)	1.16*** (1.16–1.16)	1.19*** (1.18–1.19)
Gender (reference: Man)			
Woman	1.71*** (1.66–1.75)		
Gender Minority	1.14 (0.98–1.32)		
Race/Ethnicity (reference: NH-White)			
NH-Asian	0.56*** (0.51–0.62)	0.54*** (0.48–0.61)	0.61*** (0.53–0.71)
NH-Native Hawaiian or Other Pacific Islander	0.76 (0.55–1.04)	0.76 (0.50–1.13)	0.80 (0.48–1.30)
NH-More than 1 race	0.97 (0.88–1.06)	0.99 (0.89–1.11)	0.94 (0.78–1.12)
NH-Middle Eastern or North African	1.00 (0.84–1.17)	1.15 (0.92–1.42)	0.86 (0.67–1.10)
NH-Black or African American	1.07*** (1.04–1.11)	1.16*** (1.11–1.21)	0.95 (0.89–1.00)
Hispanic/Latino	1.29 ***(1.25–1.33)	1.35*** (1.30–1.41)	1.17*** (1.10–1.24)
Age (years)	0.97*** (0.97–0.97)	0.96*** (0.96–0.97)	0.98*** (0.97–0.98)
Level of Education (reference: Less than a high school degree or equivalent)			
College graduate or advanced degree	1.00 (0.95–1.04)	0.98 (0.93–1.04)	0.97 (0.90–1.05)
College 1–3 years	1.11*** (1.06–1.15)	1.09*** (1.03–1.14)	1.12** (1.03–1.20)
Grade 12 or GED	1.04 (1.00–1.09)	1.04 (0.99–1.10)	1.03 (0.96–1.11)
Health Insurance: No	0.74*** (0.70–0.78)	0.75*** (0.70–0.79)	0.75*** (0.69–0.82)
Poverty Rate in Participant's Zip Code	0.99*** (0.98–0.99)	0.98*** (0.98–0.99)	0.99*** (0.99–1.00)
Stable Housing Concern: Yes	0.92*** (0.89–0.95)	0.95* (0.91–0.99)	0.89*** (0.83–0.94)
Self-Rated Health (reference: Excellent)			
Poor	1.22*** (1.14–1.30)	1.20*** (1.10–1.30)	1.24*** (1.11–1.39)
Fair	1.38*** (1.31–1.45)	1.39*** (1.30–1.49)	1.36*** (1.24–1.48)
Good	1.40*** (1.33–1.48)	1.41*** (1.32–1.51)	1.40*** (1.28–1.52)
Very Good	1.34*** (1.17–1.30)	1.24*** (1.16–1.33)	1.22*** (1.12–1.33)
Hypertension: Yes	3.42*** (3.32–3.52)	3.44*** (3.33–3.57)	3.31*** (3.15–3.49)
Sleep Apnea: Yes	3.70*** (3.59–3.81)	3.84*** (3.70–4.00)	3.44*** (3.29–3.59)
Hyperlipidemia: Yes	3.08*** (2.99–3.17)	2.89*** (2.79–3.00)	3.53*** (3.35–3.72)
Type 2 Diabetes: Yes	2.15*** (2.09–2.22)	2.14*** (2.06–2.22)	2.15*** (2.05–2.25)
Heart Disease: Yes	1.10*** (1.06–1.14)	1.08** (1.03–1.13)	1.10*** (1.04–1.15)
Osteoarthritis: Yes	2.90*** (2.83–2.99)	3.42*** (3.30–3.54)	2.24*** (2.14–2.34)
N of observations	383,380	229,745	150,893

Notes: BMI=Body mass index (kg/m^2). AOR = Adjusted odds ratio. NH = Non-Hispanic. Bold font indicates that the 95 % confidence interval does not include 1.00. ***p < 0.001, **p < 0.01, *p < 0.05.

women and the adjusted odds of NH-Black women were 2.05 (95 % CI: 1.82–2.33) times that of NH-Asian women. The adjusted odds of NH-MENA women were 2.11 (95 % CI: 1.65–2.70) times that of NH-Asian women. Finally, the adjusted odds of Hispanic/Latina women were 2.44 (95 % CI: 2.16–2.76) times that of NH-Asian women. All these patterns remained when accounting for healthcare interactions in sensitivity analyses. Predicted values from our logistic regression model offered additional insight into the heterogeneity across gender, race, and ethnicity. Predicted values suggested that a typical NH-Asian man in our sample with a BMI of 30.0 kg/m^2 had a mere 11 % chance of being diagnosed with obesity. A similar NH-White man had a 18 % chance of diagnosis, a similar NH-Black woman had a 28 % chance, and a similar Hispanic or Latina woman had a 32 % chance of diagnosis. See Fig. 2.

In all but one racial and ethnic group (Pacific Islander and Native Hawaiian), women were significantly more likely than men to be diagnosed with obesity. Notably, this gender gap varied substantially and significantly across race/ethnicity groups. It was substantially and significantly larger among Hispanic/Latino, NH-Black, and NH-MENA individuals, relative to NH-White individuals. NH-Asian women's adjusted odds of diagnosis were 55 % higher than NH-Asian men's (95 % CI: 29%–87 %), and NH-White women's adjusted odds of diagnosis were 59 % higher than NH-White men's odds of diagnosis (95 % CI: 54%–64 %). Meanwhile, NH-Black women's adjusted odds of diagnosis were 90 % higher than NH-Black men's (95 % CI: 80%–201 %), and Hispanic or Latina women's adjusted odds of diagnosis were 85 % higher than Hispanic or Latino men's (95 % CI: 75%–95 %).

When accounting for healthcare interaction in sensitivity analyses, the gender gap was still significant and substantial among NH-Asian, NH-White, NH-Black, and Hispanic or Latino groups. It was still not significant for NH-individuals identifying as more than 1 race and or as Native Hawaiian or Pacific Islander. We also still observe that the gender gap was still significantly larger among Hispanic or Latino and NH-Black individuals, relative to NH-White individuals, but we no longer observe any differences in the gender gap between NH-MENA, relative to NH-White, individuals.

4. Discussion

This study leveraged the large, demographically diverse NIH *All of Us* dataset to examine variation in obesity diagnosis at unprecedented granularity. Our findings demonstrate a significant underdiagnosis of obesity in clinical settings when compared to BMI measurements, aligning with similar trends observed in other samples [15–21,26]. Across increasing classes of BMIs indicating obesity (i.e., class I vs II vs III), underdiagnosis remained common but less frequent. This pattern could reflect that providers often use appearance to assess adiposity [14,19] and visual assessments commonly underestimate obesity [34]. It might also reflect that providers tend to use a higher threshold of measured BMI for diagnosing and addressing obesity as compared to commonly accepted metrics for a BMI indicating obesity. Prior work suggests that underdiagnosis stems from incomplete medicalization of obesity among providers, despite its medicalization among health institutions [15]. Our results specify that obesity is more likely to be assessed by providers as a medical condition the larger the patients' objective body size. This pattern is independent of patients' health status, so we do not expect that it arises simply because patients with higher BMIs tend to have more health concerns.

Variation and subjectivity around obesity diagnosis in clinical settings is anticipated. Despite widespread standardization efforts, providers frequently deviate from clinical guidelines [56,57]. This deviation can reflect providers' crucial role to individualize care and/or balance the benefits and potential harms of diagnosis and treatment activities [58,59]. Obesity is particularly challenging to standardize. It is an underspecified condition and BMI cutoffs are imperfect attempts to standardize and classify the continuous and nuanced relationship between adiposity and illness [53,60]. BMI should not be used as the sole measure when making clinical decisions. However, objective assessments help mitigate influence from racialized and gendered subconscious conceptions of body size (and its relationship to health) on obesity diagnosis [34],see also [61]. Beyond the context of obesity, subjective assessments of other attributes [47,62] and conditions (e.g., pain [63]) are similarly vulnerable to gender, racial, and ethnic bias.

Our results reveal substantial variation in obesity diagnosis rates by patients' gender and race and ethnicity, even after adjusting for BMI,

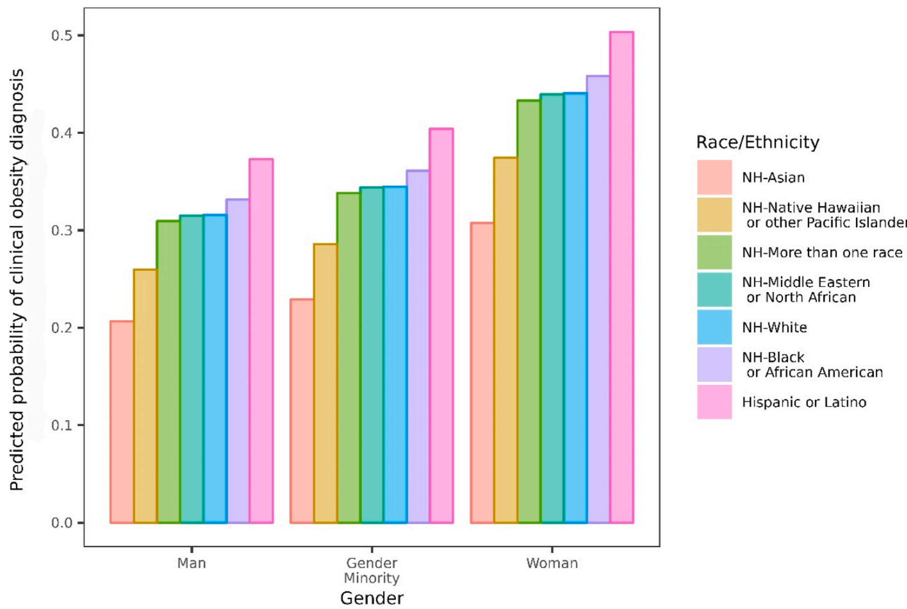

Fig. 2. Predicted probability of clinical diagnosis of obesity for individuals with a BMI indicating obesity (30.0 kg/m^2), by gender and race/ethnicity. These predicted probabilities are based on an individual with the median age in the sample (53.8 years), who is living in an area with the median poverty rate in the sample (15.3 %), a college graduate or has an advanced degree, has health insurance, has no recent housing instability, reports having "good" general health, does not have sleep apnea, diabetes, heart disease, or osteoarthritis, and does have hypertension and hyperlipidemia. NH=Non-Hispanic, BMI=Body Mass Index.

health status, and other covariates. Women were far more likely to be diagnosed with obesity than men, matching results from other samples [18–20,23,24,49], and theoretical scholarship [28]. We additionally find that measured BMI explains less of women's likelihood to have a diagnosis, compared to men's. For women, diagnosis depends less on objective body size and more on other factors (including factors unmeasured in this study, such as whether the patient or provider initiates conversations of weight management). Our results also offer insight into the effects of racial and ethnic and gender categories not yet examined in prior work on variation in obesity diagnosis. For instance, across all three gender groups, NH-Asian participants were the least likely to be diagnosed with obesity.

Our study further clarifies that the effect of patients' race and ethnicity on obesity diagnosis often depends on their gender. Among women, NH-Black participants are more likely to be diagnosed than NH-Whites, but there is no difference among men. Among both women and men, Hispanic or Latino patients were more likely to receive an obesity diagnosis compared to NH-White and NH-Asian women, but this difference is even greater among women. More broadly, accounting for intersectionality reveals that the gender gap in obesity diagnosis—-which is extensively documented in prior work [18–20,23,24,35]—is *amplified* among certain races/ethnicities and *nonexistent* in others.

Our findings suggest that NH-Black women and Hispanic women are least at risk of obesity underdiagnosis but might be most at risk of unanticipated consequences of obesity diagnosis in clinical settings. Consequences of diagnostic labeling and of providers' attention to body weight may include stigma, distraction from other health concerns, and patients' reduced trust in healthcare providers [64,65]. Meanwhile, men, and especially NH-Asian men, are at heightened risk of underdiagnosis of obesity. Underdiagnosis can put individuals at greater risk of obesity-related health problems in the future because they may not receive sufficient counseling on their risk and potential solutions.

One potential approach to improve accuracy in obesity diagnosis is to use EHR interventions, including clinical decision support and electronic forms of care pathways. Although there is controversy on how best to implement these strategies in the real world, various studies show the promise of flagging abnormal BMI values or offering a counseling template [21], but computing and presenting BMI alone may be insufficient for widescale improvements (e.g., increases in weight counseling) [66]. More generally, clinical decision support systems can increase adherence to clinical guidelines [67]. Additionally, EHR interventions and clinical decisions support systems offer opportunities to narrow disparities in diagnostic practices [68]. Indeed, in another context, EHR decision support demonstrated improvements in the management of ischemic vascular disease in diabetics to improve disparities for Black patients related to those who are offered amputation versus revascularization via stent and bypass [69]. In the case of obesity, future research could examine whether flagging abnormal BMI values or offering counseling templates reduces disparities in diagnostic practices.

Another potential approach to improve accuracy in obesity diagnosis and minimize disparities in diagnostic practices include improvements to curricula and training on obesity care. Prior work identifies several key tactics reducing the impact of cognitive and cultural biases on clinical decision-making through training. First, becoming aware of one's own susceptibility to bias [70]. Second, making conscious effort to focus on information relevant to the decision beyond information about social categories [70]. Third, being empathetic about another person's experience [71], such as imagining how much pain a patient is in regardless of their race [72]. In medical curricula on obesity, it may also be useful to incorporate learning about cultural norms around body weight, which may also have the broader benefit of mitigating weight-based stigma in healthcare [64].

4.1. Limitations

This study has several limitations. BMI measurement was taken at All of Us study intake, while the EHR data represents a longitudinal document. This implies that 1) underdiagnosis in our data is especially striking given that it reflects patients who have *never* been diagnosed with obesity, but 2) some overdiagnosis could reflect weight loss after study intake. Additionally, while the convenience sampling scheme used in *All of Us* enabled extensive representation of minoritized individuals, it inhibits generalizations to the broader U.S. population.

Our analyses were also hampered by several data quality issues in *All of Us*, underscoring calls for additional implementation science with *All of Us*. For instance, race was captured in a way that did not match many participants' own racial identities, there was too much missing information for income to use this variable, and only a limited subsample of respondents answered the survey with information about healthcare utilization. Previous work on EHR data quality and data bias may be applied to the *All of Us* data to offer a broader framework for documenting and addressing data quality.

Our study is also vulnerable to broader data quality issues in EHRs, including documentation bias. More specifically, it is possible that obesity was addressed during visits but not documented in claims or diagnosis codes (e.g., because other codes may be reimbursed at higher rates than obesity). Thus, findings about diagnosis rates do not directly translate to patterns in a provider's attention to obesity or treatment of obesity. Similarly, in the era of universal patient access to clinic notes, some healthcare professionals may be reluctant to document obesity for fear of stigmatizing their patients.

Our findings should also be contextualized in the limitations of BMI. First, as described earlier, BMI is a widely used but imperfect tool. We might observe different (and perhaps more accurate) rates of "underdiagnosis" if we were using another biometric measure (e.g., waist circumference) to compare to clinical diagnosis. Second, various research suggests using racially and ethnically specific cutoffs for BMI [54,73] (although the evidence is mixed, including inconsistent evidence on the direction that BMIs should be adjusted for some groups [74,75]). The strongest evidence is for the use of lower cutoffs for BMI's indicating obesity for Asian populations (27.5 kg/m^2 rather than 30 kg/m^2) [76]. Using this cutoff in our study would yield more NH-Asian participants with BMIs indicating obesity, suggesting even higher rates of underdiagnosis for these participants. That said, racially and ethnically specific cutoffs are not widely adopted by medical institutions and remain controversial. They conflate race and ethnicity with other correlated factors (e.g., access to nutrition and other social determinants of health) [77], which could be accounted for in assessments of obesity rather than race and ethnicity. They also naturalize and medicalize race and ethnicity [78], and depict racial and ethnic categories as unrealistically homogeneous groups [76].

Finally, the study period in the present analysis occurred before the widespread availability of highly effective anti-obesity medications for the treatment of obesity [79]. These medications are becoming extremely popular [80]. Because these anti-obesity medications require an obesity diagnosis, it is possible that a repeat analysis during this new era of highly effective treatment would render less, or different, variance between measured BMI and EHR diagnoses.

4.2. Conclusions

Diagnosing obesity can have critical consequences for patient well-being. A diagnosis can offer a key step towards engaging in shared decision making with clinicians and treatment [18,49]. However, diagnostic terminology such as "obesity" can also unduly pathologize body weight, yielding secondary unanticipated stigma or loss of trust, and can overshadow other health concerns [64]. Stigma against body weight can also compound with stigma from other minoritized statuses. Thus, both the potential for underdiagnosis and overdiagnosis are crucial to understand and mitigate in the context of obesity. This study revealed the striking variation in obesity diagnoses compared to BMI along the lines of patient gender and race/ethnicity.

Future work could expand the range of patient characteristics and contextual factors involved in diagnosis patterns of obesity. More generally, future work on diagnostic patterns could also continue the intersectional approach promoted in our study. Accounting for intersections between identities in a quantitative framework is not without challenges. Stratified models and interactions can be difficult to interpret, particularly when accounting for increasing numbers of interactions. An intersectional, quantitative analysis also requires large, diverse datasets to achieve sufficient sample sizes in granular and intersecting identity categories. Fortunately, sample size and inclusion are strengths of the *All of Us* program.

Three takeaway messages:

- Obesity is frequently underdiagnosed in clinical settings.
- Patients' likelihood of obesity diagnosis varies with their gender and race/ethnicity, independent of their body mass index, comorbidities, insurance status, and other key factors.
- Women are more likely to be diagnosed with obesity than men, independent of their body mass index, comorbidities, insurance status, and other key factors. However, the gender gap in obesity diagnosis is *amplified* among certain races/ethnicities and *nonexistent* in others.

Author contributions

AAK and AS conceptualized the study. AAK performed data analysis. AAK, AS, MTS and CWC reviewed results. AAK wrote the original draft and AAK, AS, MTS, EG, and CWC reviewed and edited the draft.

Disclosures

Amy Sitapati is a site PI for the All of Us Program.

Ethical adherence and ethical review

This research involved secondary analysis of deidentified data from consenting individuals through the *All of Us* Researcher Workbench and was determined "exempt" by the Purdue University Institutional Review Board (IRB-2024-1534).

Data availability statement

Data are available through the All of Us Researcher Workbench in the Controlled Tier V7, after approval from All of Us. Approved users may contact the first author for access to code and data in a workspace within the Researcher Workbench.

Declaration of Artificial Intelligence (AI) and AI-Assisted Technologies

During the preparation of this work the authors did not use AI.

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Competing interest statement

Amy Sitapati is a site PI for the All of Us Program. The other authors have no other competing interests or disclosures.

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