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Abstract
Obesity disproportionately affects socially marginalized populations, but traditional analyses often fail to capture the complexity of intersecting social determinants. To address this limitation, we applied Intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) to examine how combinations of different systems of power shape obesity prevalence in Brazilian adults. Data from 71,896 individuals in the 2019 Brazilian National Health Survey (PNS) were analyzed. Obesity was defined as BMI ≥ 30 kg/m². Individuals were categorized into 162 intersectional strata based on five dimensions (race, gender, age, income, and education). Two logistic multilevel models were estimated to account for additive and multiplicative effects of these dimensions, and predicted obesity prevalences across different social strata were examined. The prevalence of obesity varied significantly within and across intersectional strata, with the highest prevalence concentrated among women from Brown and Black groups with lower income and education. The explanatory effect of the intersectional strata decreased from 3.08% to 1.67% after including the social dimensions into the model. With a proportional change in variance of 46%, the analysis showed that the interaction effects are needed to capture the observed inequities between groups. . While additive effects account for part of the variance in obesity, persistent intersectional disparities highlight the limitations of traditional models. These findings underscore the importance of intersectional frameworks in revealing how systems of oppression are embodied in health outcomes.

Keywords: obesity, intersectionality theory, MAIHDA, health inequalities, social determinants of health

1. Introduction

Obesity is recognized as a disease of pandemic proportions, given its widespread and increasing prevalence worldwide. Projections estimate that by 2050, one in three adults over the age of 25 will be living with obesity [1]. In Brazil, the prevalence of obesity has grown rapidly, affecting 26% of the adult population in 2019 [2]. This figure is expected to rise to 29.6% by 2030 [3]. Its health burden is considerable: in 2019, high body mass index (BMI) was responsible for a collective 2,404 disability-adjusted life years (DALYs), comprised of 658 years lived with disability (YLDs), and 1,746 years of life lost due to premature death (YLLs), and 76 deaths per 100,000 inhabitants in the country [4].

The excessive accumulation of body fat characterizes obesity and results from a complex interplay of factors influencing energy balance, including biological, behavioral, psychological, social, political, and commercial determinants [5–6]. Although the social determinants of obesity are increasingly recognized in academic and policy discourse, most empirical studies struggle with adequately addressing these dimensions methodologically. Research on obesity often relies on individual-level frameworks that emphasize behavioral and biomedical risk factors, neglecting the broader structural and systemic drivers that shape population health. As a result, public policies and health interventions still tend to reproduce narratives that individualize responsibility for obesity, focusing predominantly on personal choices such as diet and physical activity [7]. This individualistic approach not only overlooks the complex social and economic contexts in which obesity develops but also risks reinforcing stigma and blame, particularly among marginalized populations who are disproportionately affected.

Obesity does not affect all populations equally. In OECD countries, research has shown that obesity disproportionately affects socially and economically disadvantaged groups [8]. In Brazil, similar patterns of inequality are observed and previous studies demonstrated that the prevalence is disproportionately higher among women, racial-ethnic minorities, and individuals with lower socioeconomic status [9].

Intersectionality as a critical and analytic framework has increasingly been applied in epidemiological research, particularly in the study of health outcomes [10–12].

At its core, it posits that individuals are situated within complex and interlocking systems of power that shape their lived experiences through mechanisms of oppression or privilege [13-16]. Within social epidemiology, intersectionality allows for a reconceptualization of individual-level categories, such as gender, race/ethnicity, income, age, and/or sexuality as proxies for broader social and structural systems of power, like sexism, classism, ageism, and heteronormativity. The intersection of these different categories may give rise to distinct intersectional social strata that reflect cumulative and multiplicative exposures to such systems of power.

Recently, multilevel approaches have enabled researchers to operationalize these theoretical premises in population-level studies. The Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA), introduced by Evans et al. (2018), incorporates an intersectional lens by nesting individuals (level 1) within more abstract groupings, intersectional strata (level 2). Each individual is thereby nested within a unique social position formed by combinations of key social variables (e.g., gender-race-class) [17–18].

This study builds on previous research applying MAIHDA to assess intersectional inequalities in obesity and nutrition-related outcomes in other populations [19-23], demonstrating the relevance of considering an intersectional quantitative approach to measure social gradients in health outcomes. In our study, this modelling strategy allowed us to: (1) estimate the prevalence of obesity within each stratum; (2) assess variance between and within strata; and (3) examine the influence of intersecting social identities on obesity rates among Brazilian adults. These objectives are essential to elucidate the role of structural systems of power in shaping obesity [17, 24–26].

2. Data and Methods

2.1. Data source

This study uses data from the 2019 Brazilian National Health Survey (*Pesquisa Nacional de Saúde*, PNS), a country-wide survey with sampling carried out in three stages: selection of the census tracts as the primary sampling units (PSU), selection of households, and selection of residents aged 15 and over. The questionnaire was divided into household and individual data. The microdata is available for the public at ftp://ftp.ibge.gov.br/PNS/2019/Microdados/. The survey protocol was approved by the Brazilian National Research Ethics Committee (process number 3.529.376). Participants were informed about relevant information following the 466/12 Resolution of the Brazilian National Health Council and were asked to sign a written consent agreement. More information on the survey methodology can be found elsewhere [27].

The initial sample comprised over 94,114 individuals who completed the interviewer-administered questionnaire. We excluded 17,307 individuals under 18 and over 65 years of age, as well as 738 pregnant women, as these groups may exhibit distinct obesity dynamics or may not accurately reflect adiposity. From this sample, 3,017 had no height or weight recorded, and 52 respondents had implausible BMI values (defined as BMI ≤ 15 kg/m2 and ≥ 60 kg/m2) [28]. Individuals who self-identified as Yellow (n=523) and Indigenous (n=552) were excluded due to an insufficient number of observations to construct corresponding intersectional strata. Considering an additional loss of 21 participants who did not have data on household income, our final analytical sample comprised 71,896 individuals with complete data.

2.2. Outcome

Obesity was defined as the outcome of interest. We first calculated the body mass index (BMI) as self-reported weight in kilograms divided by the square of self-reported height in meters (kg/m^2). Individuals with BMI greater than or equal to $30kg/m^2$ were classified as individuals with obesity [29].

2.3. Social strata dimensions

This study selected five sociodemographic variables to construct the social intersectional strata: age, gender, race, income level, and education level. Age was partitioned into tertiles: 'Younger adults' (18-34 years), 'Middle-aged adults' (35-48 years), and 'Older adults' (49-65 years). Gender was assessed through self-reported sex, with response options as 'Male' and 'Female', and subsequently classified as 'Man' and 'Woman' to reflect binary gender expressions. Self-reported race was assessed using the five categories of the Brazilian Institute of Geography and Statistics: 'White', 'Black', 'Yellow', 'Brown', and 'Indigenous', with final categories 'White', 'Black', and 'Brown' considered in the analysis. Household income per capita was measured, excluding the income of individuals identified as pensioners, domestic workers, or relatives of domestic workers. This variable was assessed in reference to the minimum wage (MW) at the time of the survey (R$ 998,00; R$ - Brazilian reais) and subsequently categorized into 'Low income' (0-1 MW), 'Middle income' (1-3 MW), and 'High income' (greater than 3 MW). Educational attainment was also grouped into 'Low education' (no schooling to incomplete primary education), 'Middle education' (complete primary to complete secondary education), and 'High education' (incomplete higher education or more).

All possible combinations of the selected social variables resulted in 162 intersectional strata, with individuals nested within categories of age (3 categories), gender (2 categories), race (3 categories), income (3 categories), and education (3 categories). Each stratum was labelled using a concatenated string that identified the specific combination of social positions – for example, 'Middle-age Male Brown Low Income Low Education'. Three intersectional strata had no observations: 'Younger Women Brown High income Low education', 'Younger Women Black High income Low education', and 'Middle-aged Women Brown High income Low education'.

It is important to stress that the composition of the social strata variable does not imply a biological perspective at any level. Instead, this variable maps the social location of individuals in specific systems of power that shape privilege or oppression for different social groups, such as women and men, or white and black individuals. They serve as proxies for social and structural interpretations, such as racism and patriarchy, enabling interpretations of these systems and their association with obesity and other health disparities [15,16,30]. It is also important to highlight that while age has an undeniable biological dimension, it is not solely a biological factor. The experience of aging is shaped by social contexts, giving rise to systems of power that can privilege or oppress individuals based on their age group. For instance, younger individuals may benefit from opportunities denied to older individuals due to ageism, while older adults may experience structural and cumulative discrimination in the workforce or healthcare.

2.4. Analytical approach

As a first step in the analytical process, we described the relative frequencies of each social dimension according to the overall analytical sample, along with the prevalence of obesity and corresponding 95% confidence interval (95% CI), accounting for the survey's complex sampling design and sampling weights. We then conducted logistic MAIHDA, given the binary nature of the outcome. Over the past five years, this method has gained increasing prominence and is currently considered a 'gold standard' for describing health inequities both between and within intersectional strata across a range of different health outcomes, including BMI [19,20,23]. Since its introduction, several limitations and methodological concerns [31] have been raised, but these have been increasingly addressed through clarification and support for its use [32].

First, we fitted the unadjusted null model (or variance component model), which serves as a simple intersectional model that estimates the total variance in the outcome between and within all 159 intersectional strata. Second, we specified the full model (or main effects model), incorporating the individual-level social variables used to construct the intersectional strata (age, gender, race, income, and education) as fixed parameters. This model allows us to assess the extent to which the total variance can be explained by the additive or interactive contributions of these social dimensions. For both models, we assigned second-order penalized quasi-likelihood estimates (PQL2) to define initial starting values and subsequently fitted the models using Markov chain Monte Carlo procedures (MCMC) [33].

We also specified three key measures to understand the relationship between intersectional strata and the outcome, which is one of the main goals of the MAIHDA approach [17]. The Variance Partition Coefficient (VPC) was the first measure of discriminatory accuracy employed considered. In the null model, VPC indicates the proportion of total variance in obesity that is attributable to differences between intersectional strata. In the full model, while the VPC retains the same interpretation, it also reflects the extent to which the additive effects of the social dimensions included in the intersectional strata explain the variation between intersectional strata. Theoretically, a VPC close to zero in the full model would suggest that inequities in obesity are predominantly additive (i.e. driven by each social dimension rather than the interaction of those dimensions). Thus, the VPC serves as a global measure to assess whether MAIHDA framework is necessary or whether traditional regression methods would suffice to estimate marginal effects and predict inequities in this sample. The Proportional Change in Variance (PCV) was also assessed as it measures the extent to which the between-strata variance is explained while controlling for the additive main effects included in the full model. A PCV close to 100% suggests that the additive social dimensions fully account for the variance between strata, thereby minimizing interaction effects. Finally, we also examined the Area Under the Receiver Operating Characteristic Curve (AUC) as it reflects the probability that an individual with obesity belongs to a stratum with higher predicted prevalence of obesity than an individual without obesity. It ranges from 0.5 (no discriminatory ability) to 1.0 (perfect discrimination) [17].

All analyses were performed using Stata 18.0 (Stata Corporation, College Station, USA), and MAIHDA models using MLwiN software (MLwiN 3.07) in Stata through the *runmlwin* function.

3. Results

The analytical sample was equally distributed across age groups (Table 1), with a mean age of 40.44 years (sd 13.32), in which over 50% were made up of women (52.06%), self-ascribed as Brown (45.57%) or Black (11.83%) participants, with lower income (52.49%), and with over three quarters being in low or middle levels of education (77.54%). The overall prevalence of obesity was 21.59% (95% CI: 20.80–22.40), and higher prevalences were observed in middle-aged and older adults, women, Brown and Black individuals, and in those with lower levels of education.

Results from both MAIHDA logistic models (null and main effects models) are presented in Table 2. In the null model, the VPC for obesity was estimated at 3.08%, suggesting that 3% of the total variance in obesity prevalence is attributable to differences between intersectional strata. When the social dimensions used to define the intersectional strata were added as fixed effects (full model), the VPC declined to 1.65%. Although the reduction in VPC indicates that part of the between-stratum variance in obesity prevalence is explained by the additive main effects of these social dimensions, the persistence of a non-negligible VPC in the full model suggests that intersectional (non-additive) effects remain. This interpretation is supported by the PCV, which was estimated at 46.42%. The fixed-effect regression coefficients from the full model (Table 2) help illustrate the additive (non-interactive) and unilateral influence of broader social dimensions on the prevalence of obesity. For example, compared to younger adults, middle-aged individuals (OR = 1.56; 95% CI: 1.41–1.73) and older adults (OR = 1.53; 95% CI: 1.35–1.69) had significantly higher odds of obesity. Black individuals (OR = 1.15; 95% CI: 1.02–1.29) also had higher odds compared to White individuals, while no significant differences were observed for Brown individuals. Although not statistically significant, women (OR = 1.11; 95% CI: 1.00–1.21) showed slightly higher odds of obesity than men . Regarding education and income levels, no clear pattern emerged.

The predicted probabilities of obesity across intersectional strata following the full model are presented in Figure 1A and highlights are presented in Table 3. The lowest predicted prevalence of obesity was observed in Younger Men White High income High education (10.18%, 95% CI 7.66-13.42) and the highest in Middle Women Brown Low income Low education (33.48%, 95% CI 27.55-39.97). Figure 1B shows that both groups had statistically significantly different values from the overall predicted prevalence (21.55%, 95% CI 16.65-27.48). The five strata with the lowest predicted prevalence of obesity (ranging from 10.18% to 12.72%) predominantly consist of younger individuals with high levels of education, particularly among women. Yet, younger Black men in low income and lower educational levels are also among these lower top five strata. On the other end, the five strata with the highest predicted prevalence (ranging from 29.63% to 33.48%) are exclusively composed of women, middle-aged or older, from Brown and Black groups, all of whom are in low or mid-income and levels of education.

4. Discussion

This study aimed to analyze the extent to which different and mutually reinforcing systems of oppression and privilege (age, gender, race, class, and education) shape unequal population-level patterns of obesity and the magnitude of inequality across strata in a representative sample of Brazilian adults. By implementing Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) within an intersectional framework, we estimated obesity prevalence across intersectional social positions and calculated global measures to assess the contribution of interactive social effects. Our findings reveal stark intersectional inequalities in the prevalence of obesity, with the predicted prevalence of middle-aged Brown women with low income and low education three times higher than that of younger White women with high income and high education. We found the prevalence of obesity varied significantly within and across intersectional strata, with the highest prevalence concentrated among women from Brown and Black groups with lower income and education.

Since the 2010s, studies have increasingly adopted broader theoretical frameworks from social epidemiology to understand trends in malnutrition worldwide, including political and social determinants of health [34–38]. These frameworks consider not only individuals' socioeconomic position, but also the structure and dynamics of food systems, such as food security, the existence of food deserts, public policies, and the implementation of the human right to adequate food [6]. In this perspective, structural and systemic factors provide greater explanatory power than individual choices, even if such relationships are more indirect and interactive. This aligns with a growing consensus that rejects biological determinism and individualistic or culturally stereotyped explanations for disparities in obesity rates [39]. Instead, ecosocial and social epidemiological theories emphasize that health inequalities reflect how individuals and social groups embody intersecting systems of privilege and oppression over the life course [36–38,40]. These theoretical frameworks gain further support when we examine empirical findings from Brazil, which demonstrate how structural inequalities shape obesity patterns across intersecting social markers. Findings from both Canella et al. (2020) and Araujo et al. (2018), based on data from the 2008–2009 Brazilian Household Budget Survey, provide consistent evidence of associations between socioeconomic positions (such as age, gender, race/ethnicity, income, and education) and overall higher obesity rates [9,41]. Araujo et al. (2018) highlight that the association between obesity and race among Brazilian adults is significantly modified by sex and socioeconomic status (SES). The authors found that obesity prevalence was highest among Black women (20.6%) and lowest among Brown men (11.8%). Among men, obesity increased with higher SES across all racial groups, with Black men showing the steepest increase. Among women, however, White and Brown women showed decreasing odds of obesity with increasing SES, while Black women exhibited the opposite pattern—having three times greater odds of obesity at high SES levels compared to their low-SES peers. Canella et al. (2020) observed a high overall prevalence of overweight and obesity among adult women from lower-income, lower-educated, and self-identified as Black or Brown compared with women from privileged social positions.

In our study, we assessed the influence of intersectional strata on obesity prevalence, considering each variable (age, gender, race, income, and education) as distinct axes of power that are structurally and systematically embedded within social and political institutions (as articulated by Crenshaw (1991) and Collins (2019) and Collins and Bilge (2016), among others). Our MAIHDA models indicate that differences between intersectional social strata exert a modest influence on disparities in obesity prevalence. The results initially showed that only 3.08% of the total variance in predicted obesity prevalence is attributable to differences between intersectional strata defined by gender, race, class, education, and age. As emphasized in the literature, the VPC captures both between-strata variability and residual heterogeneity within strata. Values below 5% suggest that most of the observed variation in obesity occurs among individuals within the same stratum rather than between strata [32]. However, while the low VPC suggests limited discriminatory accuracy of intersectional strata alone, it does not preclude the presence of meaningful interaction effects between individual-level social positions. Recent scholarship has shown that even modest between-strata variance can coexist with substantively important within-strata heterogeneity, especially when social categories intersect in non-additive and structurally embedded ways [18,42]. In this view, MAIHDA models are not primarily intended to maximize predictive accuracy, but rather to reveal patterns of social inequality that emerge from the intersection of systems of power and privilege [18]. Consequently, low VPC values should not be interpreted as evidence against the relevance of intersectional effects, but rather as a reflection of the complex and diffuse ways in which structural determinants operate across and within social groups.

When focusing on the five intersectional strata with the highest predicted prevalence of obesity, a salient pattern emerges. Afro-Brazilian women are the only group consistently represented among these strata, especially those aged 35 to 48 years with low or intermediate income and education. The two strata with the highest obesity prevalence include middle-aged and older Brown and Black women with both low income and lower to mid levels of education. Conversely, at the other end of the spectrum, the five strata with the lowest predicted obesity prevalence are less homogeneous. They predominantly include younger White and Black men with varying income levels but consistently high levels of education. Younger White women with both high income and high education also appear in this group. While no single group dominates, these strata share characteristics of youth and higher socioeconomic positioning. These last findings demonstrate how systems of power may generate similar patterns while being driven by entirely different mechanisms and dynamics, such as the formation of structures of oppression or, conversely, of privilege.

These disparities may be partially explained by the chronic activation of stress-related physiological systems in response to intersecting forms of discrimination, including racism, sexism, and classism. As shown in prior research [43], experiences of social exclusion and discrimination can activate the hypothalamic-pituitary-adrenal (HPA) axis, elevating levels of cortisol and related hormones. In turn, this biological response is linked to increased visceral fat accumulation, dysregulation of appetite-related hormones, and a greater propensity to consume calorie-dense, highly palatable foods. From an ecosocial perspective, these processes reflect the embodiment of oppression, whereby adverse social conditions are biologically internalized and contribute to health disparities [35,37,38]. At a structural level, institutional racism and other political determinants of health shape food environments and access to adequate nutrition [44]. Discriminatory policies and unequal urban planning contribute to food deserts and limit the availability of fresh, minimally processed foods in predominantly Black and poor neighborhoods [45–47]. Additionally, targeted marketing of ultra-processed foods and the erosion of traditional food practices reinforce unhealthy dietary patterns. Rather than being random or isolated, these patterns reflect historically produced and structurally maintained inequities in living conditions, access to resources, and exposure to stressors. This intersectional analysis underscores the importance of moving beyond additive explanations to identify the compounding effects of systemic social oppression on health outcomes.

Strengths and limitations

This study presents four main strengths. First, it draws on data from the 2019 Brazilian National Health Survey (PNS), a large, nationally representative sample of Brazilian adults, enabling national-level estimations of obesity prevalence across diverse social strata. Second, the analysis incorporates sampling weights and accounts for the survey's complex design, thereby increasing the validity and generalizability of the results. Third, the implementation of the MAIHDA approach represents a significant methodological and theoretical innovation in Brazilian nutritional epidemiology. This model allows for the simultaneous consideration of multiple and intersecting dimensions of social identity, capturing both their additive and interactive effects on health outcomes and providing a more fine-grained understanding of social inequality in obesity.

Furthermore, by adopting an intersectional perspective, MAIHDA enables the reconceptualization of traditionally individual or biological variables as markers of social position, thereby expanding the scope of social and ecosocial epidemiological research in nationwide Brazilian studies. Fourth, the study highlights specific high-risk groups (e.g., low-income, middle-aged Black and Brown women), offering actionable insights for targeted public health interventions and equity-oriented policies.

Nonetheless, the study has some limitations. The intersectional strata were constructed using self-reported categorical variables (age, sex, race, income, education) as proxies for larger structural forces, which may fail to fully capture the complexity of these interwoven systemic oppressions (such as sexism or racism). Second, despite the use of a large sample, small cell sizes in some strata limited statistical power and necessitated the exclusion of Indigenous and Yellow individuals, thereby reducing inclusivity and hiding inequalities faced by these populations. Third, gender was inferred from binary sex categories, restricting the capacity to represent non-binary and transgender individuals, whose experiences with health and social systems may differ substantially. Sexual orientation was also not possible to include in our model due to a too restrictive sample size from the thematic model from PNS-2019. Fourth, while obesity was estimated using BMI, this measure is subject to misclassification bias and does not account for body composition, fat distribution, or sociocultural meanings of body size. Fifth, the VPC and AUC values were low, indicating limited discriminatory accuracy of the intersectional strata, which may result from residual confounding, sparse data in specific groups, or unmeasured contextual variables. Finally, while the study adopts an intersectional and ecosocial lens, the models do not directly incorporate meso- or macro-level variables (e.g., neighborhood food environments, regional policy differences), which could help elucidate structural pathways linking social position and obesity. We suggest that future studies address these limitations, when possible.

Taken together, the study provides an important methodological and theoretical contribution to the field of nutritional epidemiology in Brazil, highlighting the structural embodiment of inequalities intersection of race, gender, age, income, and education. Despite the modest discriminatory accuracy of intersectional strata, our findings reveal clear patterns of vulnerability, with Black and Brown women from lower socioeconomic backgrounds consistently facing higher predicted obesity rates. These results reinforce the limitations of traditional analytical approaches and underscore the need to adopt intersectional and ecosocial frameworks.

Policymakers should prioritize intersectional strategies that address the upstream social and structural drivers of obesity, including combating racialized poverty, food deserts, and improving the accessibility to healthy foods for marginalized communities. In addition, in the context of Brazil's ongoing nutrition transition, marked by increasing consumption of ultra-processed foods, it is essential to monitor social inequalities in the occurrence of obesity through intersectional approaches.

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Table 1. Distribution of the analytical sample and prevalence of obesity (BMI≥30kg/m2) according to social strata dimensions. Brazilian National Health Survey, 2019.

	Sample distribution		**Obesity**
	n	**% (95% CI)**	**% (95% CI)**
Age groups			
Younger adults	26,278	36.55 (35.85-37.26)	16.13 (15.11-17.21)
Middle-aged adults	22,964	31.94 (31.32-32.57)	25.16 (23.75-26.64)
Older adults	22,654	31.51 (30.92-32.10)	24.28 (23.34-25.25)
Gender			
Men	34,467	47.94 (47.28-48.59)	19.81 (18.84-20.82)
Women	37,429	52.06 (51.41-52.72)	23.22 (22.33-24.13)
Race			
White	30,628	42.6 (41.82-43.39)	21.11 (20.00-22.26)
Black	8,505	11.83 (11.39-12.29)	23.96 (22.40-25.59)
Brown	32,763	45.57 (44.84-46.30)	21.42 (20.52-22.34)
Minimum Wage (MW*)			
Low (≤1 MW)	37,738	52.49 (51.62-53.36)	21.24 (20.31-22.19)
Middle (1 – 3 MW)	26,350	36.65 (35.91-37.40)	22.58 (21.39-23.81)
High (> 2 MW)	7,808	10.86 (10.25-11.49)	19.91 (18.47-21.44)
Level of education			
Low	21,245	29.55 (28.87-30.24)	23.48 (22.52-24.47)
Middle	34,503	47.99 (47.27-48.71)	21.41 (20.19-22.69)
High	16,148	22.46 (21.68-23.27)	19.46 (18.40-20.57)
Total	**71,896**	**100.00**	**21.59 (20.80-22.40)**

* In 2019, the minimum wage in Brazil was R$998,00.

Table 2. Parameters estimates from the multilevel logistic regression models of obesity (BMI≥30kg/m^2) considering an analytical sample (n=71,896) from the 2019 Brazilian National Health Survey.

Parameters	Null model OR (95% CI)	Full model OR (95% CI)
Fixed-effect parameters		
Age groups		
Younger adults		Ref
Middle-aged adults		1.56 (1.41-1.73)
Older adults		1.53 (1.35-1.69)
Gender		
Men		Ref
Women		1.11 (1.00-1.21)
Race		
White		Ref
Brown		1.01 (0.91-1.12)
Black		1.15 (1.02-1.29)
Minimum Wage (MW*)		
Low (≤1 MW)		Ref
Middle (1 – 3 MW)		1.07 (0.96-1.20)
High (> 2 MW)		0.98 (0.85-1.11)
Level of education		
Low		Ref
Middle		1.00 (0.90-1.13)
High		0.90 (0.79-1.02)
Model intercept (β_0)	0.27 (0.26-0.29)	0.18 (0.16-0.22)
Random-effects parameters		
Between-strata variance (sd)	0.10 (0.08-0.14)	0.05 (0.04-0.08)
Summary statistics		
VPC (%)	3.08	1.65
PCV (%)		47.02
AUC	0.59	0.59
Bayesian DIC	72958.59	72951.10

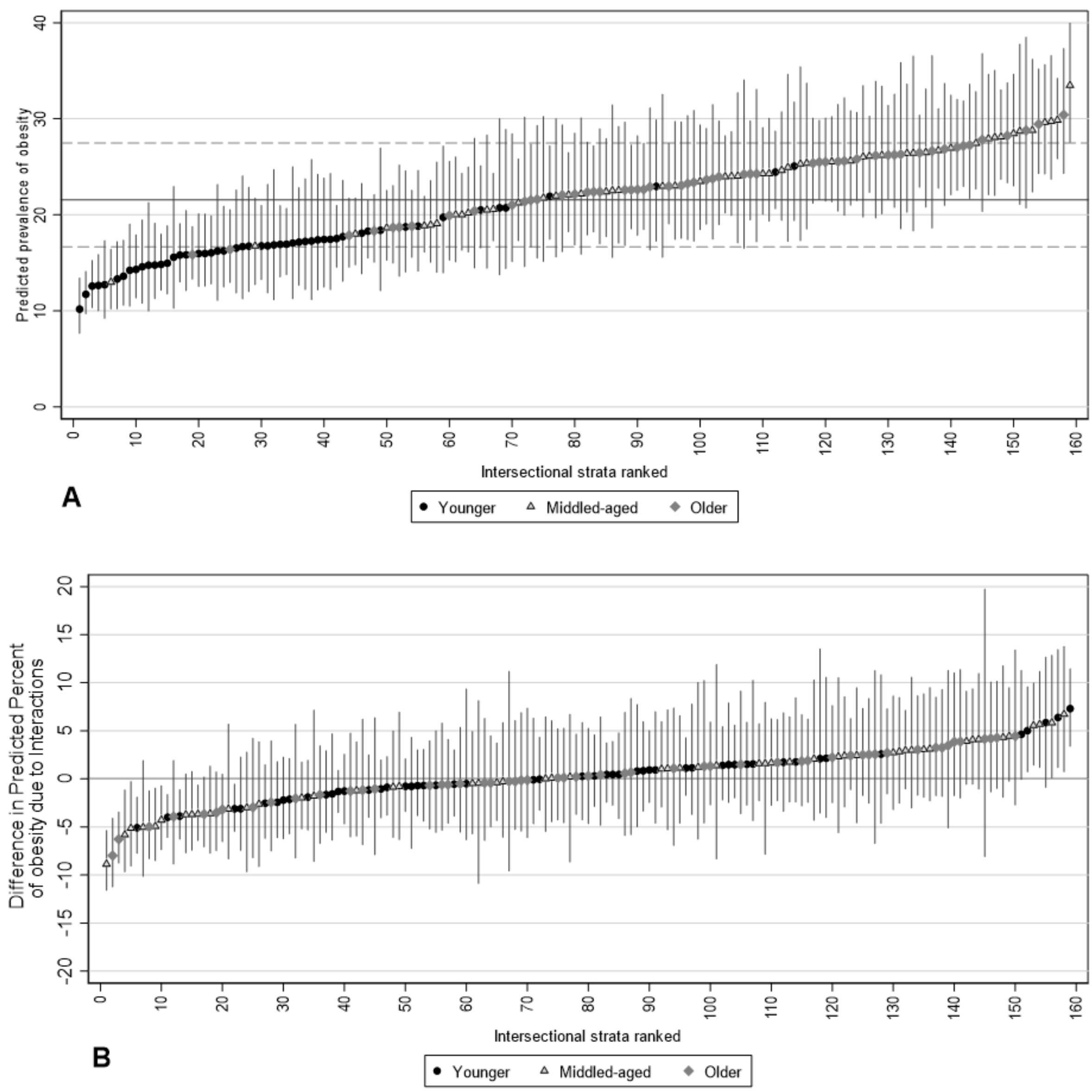
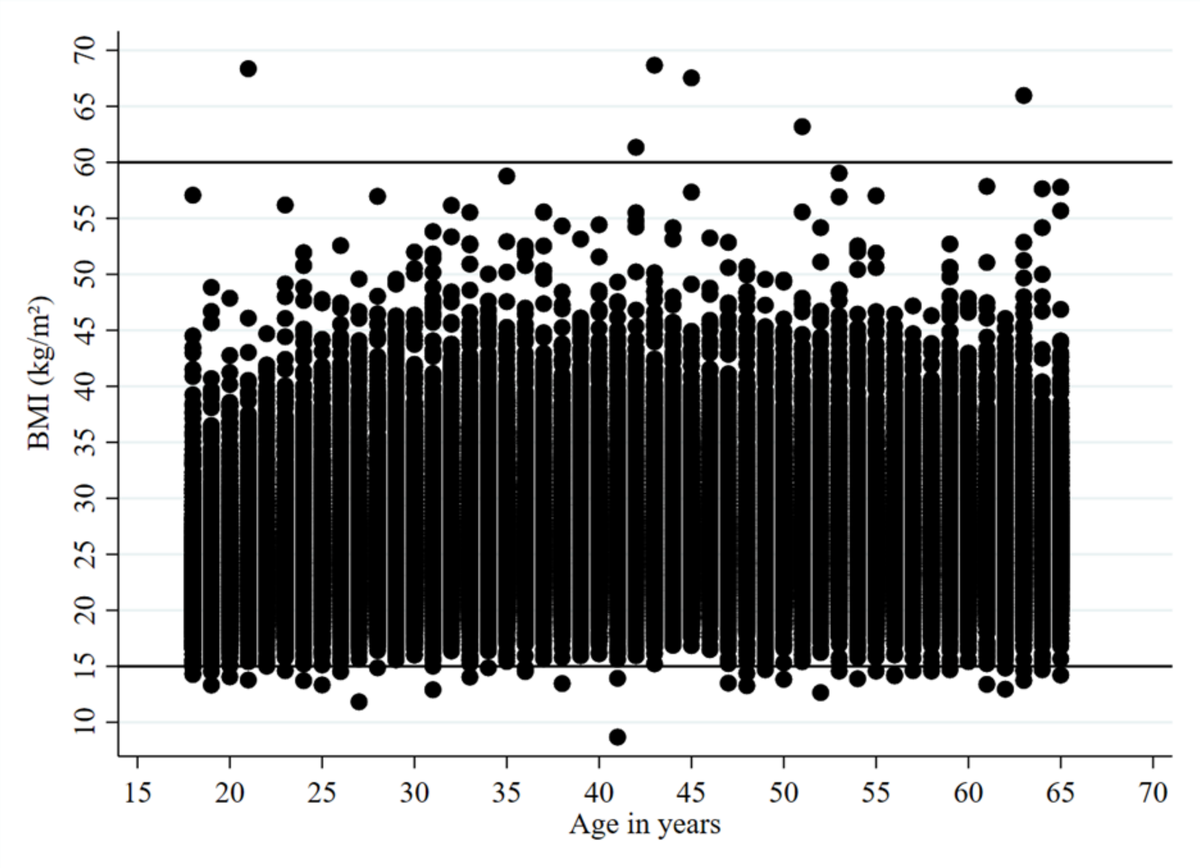


Figure 1. Predicted prevalence of obesity (BMI≥30kg/m2) (A) and residuals from the random-effects (B) of the full model across intersectional strata considering an analytical sample (n=71,896) from the 2019 Brazilian National Health Survey.

Table 3. Description of the intersectional strata of the predicted prevalence of obesity and residuals following results from the full model.

Strata	Obesity %	Obesity 95% CI	Position in Figure 1A
Five Lowest ranked strata of predicted prevalence of obesity			
Younger Women White High income High education	10.18	7.66-13.42	1
Younger Men Black Low income Mid education	11.72	9.69-14.11	2
Younger Men Black Low income Low education	12.58	10.32-15.26	3
Younger Women White Mid income High education	12.65	10.01-15.86	4
Younger Women Black High income High education	12.72	9.21-17.32	5
Five Highest ranked strata of predicted prevalence of obesity			
Middle Women Brown Low income Mid education	29.63	24.25-35.64	155
Middle Women Black Mid income Low education	29.74	23.70-36.58	156
Middle Women Black Low income Low education	29.86	25.83-34.22	157
Older Women Brown Low income Mid education	30.41	24.29-37.31	158
Middle Women Brown Low income Low education	33.48	27.55-39.97	159
Below the lowest predicted 95% CI (Lower dashed line in Figure 1A - 16.65)			
Younger Women White High income High education	10.19	7.66-13.43	1
Younger Men Black Low income Mid education	11.73	9.70-14.11	2
Younger Men Black Low income Low education	12.59	10.32-15.26	3
Younger Women White Mid income High education	12.65	10.01-15.86	4
Middle Women White High income High education	13.00	10.21-16.42	6
Above the highest predicted 95% CI (Higher dashed line in Figure 1A - 27.48)			
Middle Women Brown Low income Low education	33.48	27.56-39.97	159
	Residuals		**Position in Figure 1B**
Below the reference line (zero)			
Middle Women White High income High education	-8.85	-11.60;-5.36	1
Older Men Brown Low income Low education	-7.98	-11.24;-4.10	2
Older Men Black Low income Low education	-6.27	-8.76;-3.44	3
Middle Men Brown Low income Low education	-5.81	-9.67;-1.14	4
Middle Women Black High income High education	-5.13	-9.07;-0.28	5
Younger Women White High income High education	-5.08	-7.74;-1.90	6
Older Men Black Mid income Low education	-4.99	-8.31;-1.24	8
Middle Women White Mid income High education	-4.94	-8.51;-0.96	9
Middle Men White Low income Low education	-4.27	-7.36;-0.71	10
Younger Men Black Low income Mid education	-3.99	-6.11;-1.62	11
Younger Women White Mid income High education	-3.87	-6.27;-1.12	13
Middle Men Black Low income Low education	-3.67	-6.42;-0.64	16
Younger Men Black Low income Low education	-3.11	-5.47;-0.55	22
Above the reference line (zero)			
Younger Women White Low income Low education	5.02	0.73;9.58	152
Middle Women Black Low income Low education	5.55	1.43;9.98	153
Middle Men Black Mid income High education	5.67	1.18;11.19	154
Middle Men White High income Mid education	5.85	0.09;12.86	156
Younger Women Brown Low income Low education	6.39	1.18;13.45	157
Middle Women Brown Low income Low education	6.72	0.74;13.78	158
Younger Women Black Low income Low education	7.31	3.39;11.45	159

Supplemental materials



Supplemental Figure 1. Relationship between BMI (kg/m^2) and age in years. Brazilian National Health Survey, 2019.

CONTRIBUIÇÃO DOS AUTORES:

Marcos Fanton (autor de correspondência): Conceitualização; Supervisão; Metodologia; Redação (manuscrito original, revisão de literatura e revisão).
Helena M. Constante: Conceitualização; Supervisão; Metodologia; Redação (manuscrito original, revisão de literatura e revisão).
Raquel Canuto: Conceitualização; Supervisão; Metodologia; Redação (manuscrito original, revisão de literatura e revisão).

DECLARAÇÃO DE CONFLITO DE INTERESSES:

Os autores desse manuscrito declaram que não existem conflitos de interesses financeiros, pessoais, acadêmicos ou institucionais que poderiam ter influenciado de maneira inapropriada na realização ou na apresentação dos resultados.