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Obesity, genomic ancestry, and socioeconomic variables in Latin American mestizos

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Abstract

Objectives: This article aims to assess the contribution of genomic ancestry and socioeconomic status to obesity in a sample of admixed Latin Americans.

Methods: The study comprised 6776 adult volunteers from Brazil, Chile, Colombia, Mexico, and Peru. Each volunteer completed a questionnaire about socioeconomic variables. Anthropometric variables such as weight, height, waist, and hip circumference were measured to calculate body indices: body mass index, waist-to-hip ratio and waist-to-height ratio (WHtR). Genetic data were extracted from blood samples, and ancestry was estimated using chip genotypes. Multiple linear regression was used to evaluate the relationship between the indices and ancestry, educational level, and economic well-being. The body indices were dichotomized to obesity indices by using appropriate thresholds. Odds ratios were calculated for each obesity index.

Results: The sample showed high percentages of obesity by all measurements. However, indices did not overlap consistently when classifying obesity. WHtR resulted in the highest prevalence of obesity. Overall, women with low education

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level and men with high economic wellness were more likely to be obese. American ancestry was statistically associated with obesity indices, although to a lesser extent than socioeconomic variables.

Conclusions: The proportion of obesity was heavily dependent on the index and the population. Genomic ancestry has a significant influence on the anthropometric measurements, especially on central adiposity. As a whole, we detected a large interpopulation variation that suggests that better approaches to overweight and obesity phenotypes are needed in order to obtain more precise reference values.

1 | INTRODUCTION

During the past decades, most of the world's population has experienced a progressive change in dietary habits and lifestyles that has had a great impact on the overall health condition. Overweight and obesity have become an increasingly widespread issue, to the point of being considered one of the main health challenges of the 21st century (WHO, 2017). This disease is characterized by an unwanted accumulation of fat, often accompanied by numerous outcomes that can be categorized into physical, psychological, and social complications. The most serious concerns are associated with a higher risk for diabetes, cardiovascular (CV) problems, metabolic syndrome, and acceleration of the aging process of many organs (Apovian & Gokce, 2012; Legler et al., 2015; Nakamura, Fuster, & Walsh, 2014).

Latin America has been no exception to the demographic and lifestyle changes that led to increased overweight and obesity throughout the world in recent years. Specifically, rapid urbanization was accompanied by a great demand for industrialization of food supplies, which resulted in increasing availability at the expense of quality. In Latin America, this worldwide process occurred in synchronicity with inherent regional characteristics, such as social inequality and genetic and nongenetic admixture, with varying patterns depending on country and locality.

It has been reported by several studies that obesity and overweight are influenced by socioeconomic variables, such as family economic income, place of residence (urban vs rural), education level (Acosta, 2013; Azar, Franetovic, Martínez, & Santos, 2015; Kurspahić-Mujčić & Zećo, 2017; Shang et al., 2013), and the interaction of these factors with gender. Some previous studies indicated that people in developing societies achieving high socioeconomic status (SES) were the most affected by overweight and obesity (Sobal & Stunkard, 1989). However, recent studies have shown that such gap has been closing, and reinforce the idea that overweight is no longer a disease typical of higher incomes. In this sense, Acosta (2013) noted that among men in Colombia, overweight is concentrated within the population at the upper part of the

income scale, whereas in women it is concentrated in the poorest population. In the United States, obesity has been found to be mainly concentrated in minority groups and among those with low socioeconomic levels (Zhang & Wang, 2004). Other variables such as eating and daily habits related to physical activity have been shown to be strongly related to obesity (Acosta, 2013; Azar et al., 2015; Garcia-Continente et al., 2015; Kurspahić-Mujčić & Zećo, 2017; Marín Cárdenas, Sánchez Ramírez, & Maza Rodríguez, 2013). For example, Pérez (2011) suggested a link between the consumption of industrialized foods in rural communities of Yucatan, Mexico, and an increase in the additional energy stored in fats and sugars and the consequent negative impact on health due to its association with the development of obesity.

Furthermore, previous evidence indicates some effect of population and ancestry on obesity incidence (Nettleton et al., 2015; Roy et al., 2015). It has been found that at a given level of body mass index (BMI), some Asian populations have a higher level of body fat and central fat, compared to populations of European origin (WHO, 2011). Some researchers have suggested that the greater susceptibility to obesity among some populations has a significant genetic basis that may be triggered when confronted with an obesogenic environment, like a westernized lifestyle. This hypothesis is known as the "thrifty genotype" (Neel, 1962). Evidence supporting this hypothesis is the higher rates of obesity and type 2 diabetes that have been observed among Native Americans and Polynesians, among others (Aguilar-Salinas et al., 2009; Lara-Riegos et al., 2015).

Regarding genetic risk factors, Latin American cosmopolitan populations are characterized by substantial genetic admixture, with predominant contributions from the Native American populations, Europe, and Africa (Morner, 1967). However, only a few studies (eg, Florez et al., 2009) have explored Latin American populations through an approach that includes the study of genetic ancestry, phenotypic variables, and the socioeconomic context.

The robustness and precision of anthropometric measurements used to quantify overweight and obesity are central to assessments of individual and population-level nutrition

status. For decades, epidemiologists and clinicians have identified persons with excess weight based on a widely used and easy-to-calculate index: BMI. However, although BMI is commonly used in public health, an obvious limitation is its inability to distinguish between fat and fat-free mass. In this sense, recent epidemiological studies have shown that abdominal obesity is increasing in western populations, irrespective of BMI categories, highlighting the importance of the distribution of body fat (Kabat, Kim, Hunt, Chlebowski, & Rohan, 2008; Koster et al., 2008; Ladabaum, Mannalithara, Myer, & Singh, 2014; Masala et al., 2008; Wang et al., 2008). An increasing number of studies have shown that other indexes, such as waist-to-hip ratio (WHR) and waist-to-height ratio (WHtR), are better predictors of CV risk than BMI (Ge et al., 2014; Hsieh & Muto, 2005; Motamed et al., 2015; Selvaraj et al., 2016; Yan et al., 2009).

In 1998, the WHO provided international BMI standards for classifying overweight and obesity in adults, based on the risk of obesity-related disease for Europeans at each BMI category. In recent years, the importance of selecting an adequate index and the need for specific cut-off points for each population, country, or geographical region has been emphasized. This information is beginning to be registered in regions such as Asia, Africa, and the Pacific Islands (WHO, 2011); however, there is less information regarding Latin American populations.

Considering the above, this article aims to test the agreement between several indexes developed to quantify overweight and obesity. Furthermore, and due to the complex and nonlinear nature of risk factors underlying the expression of overweight and obesity, including genetic and nongenetic effects and potential interaction effects, we aim here to estimate the contribution of both genetic ancestry and SES to weight gain, as estimated by BMI, WHR, and WHtR.

The detection of such effects requires using composite samples including, for each specimen, several indices aimed to measure overweight and obesity, estimations of socioeconomic (and other environmental) factors, and genetic ancestry data on populations of varying admixture composition. The Consortium for the Analysis of the Diversity and Evolution of Latin America (CANDELA) initiative has been successful in compiling such a metadata biobank (Ruiz-Linares et al., 2014), and these data are used here.

2 | MATERIALS AND METHODS

2.1 | Sample

The CANDELA initiative collected data from more than 7000 people from five countries in Latin America. A sample of 6776 adult volunteers from Brazil, Chile, Colombia,

Mexico, and Peru was included in this study. Recruitment took place mainly in five locations: México City (México), Medellín (Colombia), Lima (Perú), Arica (Chile), and Porto Alegre (Brazil). All participants provided written informed consent, and ethics committee's approval was obtained from: Universidad Nacional Autónoma de México (Mexico), Universidad de Antioquia (Colombia), Universidad Peruana Cayetano Heredia (Peru), Universidad de Tarapaca (Chile), Universidade Federal do Rio Grande do Sul (Brazil), and University College London (UK). For further sample details, see Ruiz-Linares et al. (2014).

A structured questionnaire was given to each volunteer. This included questions about education level, lifestyle variables, dietary patterns and information regarding salary, home appliances, domestic services, transportation and infrastructure, among others. From these variables, two indices of socioeconomic position were used: education, and an SES score, which is a wealth index constructed using the lifestyle and ownership questions. For further sample details, see Ruiz-Linares et al. (2014). Briefly, education level was assessed as a categorical variable containing three levels: (a) none/primary/technical, (b) secondary, and (c) university and postgraduate. Given the multifactorial and complex nature of economic wellness, the SES index was estimated from the information available in the CANDELA database on different lifestyle and ownership questions. A multivariate composite measure of SES was constructed using a principal component analysis approach, aggregating the scores from all such questions. This analysis is a validated method to describe SES differentiation within a population (Cahill & Sánchez, 2001; Vyas & Kumaranayake, 2006).

An anthropometric survey of each volunteer was carried out by the local research team using a standardized protocol and instruments, including height, weight, and hip and waist circumference (WC). All measurements were obtained twice, and the mean of the two measurements was retained for further analyses.

The following body indices were calculated: BMI, WHR, and WHtR. The body indices were dichotomized to obesity indices by using appropriate thresholds. Cutoff values of obesity for BMI and WHR were taken from the World Health Organization recommendations (WHO, 1998, 2011, respectively). Normal BMI values were established as 18.5-24.9 kg/m², and "obesity" after a BMI greater or equal to 30 kg/m². For WHR, values above 0.85 and 0.9 were considered not healthy for women and men, respectively. Regarding WHtR, "obesity" was taken to be values greater than 0.5, as suggested by Browning, Hsieh, and Ashwell (2010).

A certified phlebotomist collected blood samples and the DNA was extracted following standardized protocols (Ruiz-Linares et al., 2014). Samples were genotyped using the Illumina OmniExpress array (~730 K SNPs), and combined

with a global panel of reference samples. Supervised ancestry estimation using ADMIXTURE was performed, estimating three ancestry components: Native American, European, and African (Chacón-Duque et al., 2018).

2.2 | Statistical methods

The effect of genomic ancestry, age, education, and SES on the three body index phenotypes was evaluated by multiple linear regression. Each of the body indices (BMI, WHR, and WHtR) were regressed as the dependent variable onto five independent variables: age, Native ancestry, African ancestry, education, and SES. The analyses were performed separately for each combination of country and sex. With file independent variables being used, the significance threshold was adjusted using Bonferroni correction to allow for multiple testing. The significance threshold used was, therefore, 0.05/5 = 0.01.

We divided the sample by countries because there are variables that depend on public policies implemented by each state and only affect the population that receives such policies (Mussini & Temporelli, 2013). In this sense, and considering that income is an important factor to avoid deterioration of the nutritional status, Latin American countries have developed a series of state regulations and social policies aiming to eradicating hunger and poverty in the most vulnerable populations (Cash Transfer Programs), with different targets and goals depending on the region. The outcome of these programs has been positive in the reduction of hunger and poverty until recently, when some countries showed a turndown in the 2011-2013 period, after which an alarming increase in obesity has been observed (FAO & PAO, 2017).

It is relevant to note that the samples collected were convenience samples within each country and, therefore, do not represent the entire population of these countries. The recruitment was also biased to certain demographics, most commonly university students and staff. This presents another reason to perform the analysis separately within countries, and the results have to be interpreted cautiously with reference to these facts.

To estimate the relative risk of obesity associated with a high proportion of genomic ancestry, we used a multivariate logistic regression model. The body indices were transformed to binary variables (obese or nonobese), and these obesity indices were used as the outcome variable. The same set of independent variables were used as before. However, only the effects of Native ancestry on these obesity indices were investigated. Therefore, there was no need for Bonferroni correction for the *P* value threshold. The analyses were performed separately for each combination of country and sex. Note that for WHR, the cutoff values were different for the two sexes. All analyses were performed using the software Statistical Package for Social Sciences (SPSS) 20.2 and R 3.4.

As the distribution of the dependent and independent variables were non-normal, to better account for skewed distributions and possibility of outliers, robust versions of linear and logistic regressions were used, via the R package "robust."

3 | RESULTS

3.1 | General description

Table 1 shows the mean and SD of genomic ancestry according to country, along with the sample size and proportion of female participants. A more detailed description of the geographical variation of genetic estimates and an interpolated map based on coordinates for the participants' birthplaces can be found in Ruiz-Linares et al. (2014) and Chacón-Duque et al. (2018). The country with the highest Amerindian ancestry was Peru, followed by Mexico. The country with the lowest contribution to Amerindian ancestry was Brazil. Informative markers for African ancestry were higher in Brazil and Colombia (6.3% and 8.7%, respectively) than the rest of the countries, which stayed well below 3.1%. The Brazilian sample had the highest proportion of European ancestry (84.5%), followed by Colombia (62.2%) and Chile (49.5%).

A description of the obesity indexes (BMI, WHR, and WhtR) computed on a slightly larger sample (7236 individuals) with missing genomic data, using the recommended

			Europea	an	African		Native A	Native American	
Country	N	% Female	Mean	SD	Mean	SD	Mean	SD	
Brazil	682	68.3	84.5	15.8	6.3	8.9	9.3	11.6	
Chile	1858	39.7	49.5	15.8	2.2	2.3	48.3	16.1	
Colombia	1745	55.6	62.2	12.7	8.7	8.7	29.0	10.5	
Mexico	1233	61.2	39.6	18.8	3.0	2.7	57.5	19.4	
Peru	1258	58.7	30.8	17.5	3.1	4.6	66.1	18.6	

Note: These ancestry estimates are obtained from the subset of individuals who were chip-genotyped. Sample sizes and proportion of female volunteers, among the total sample of chip-genotyped individuals, are also provided.

TABLE 1 Mean and standard deviations (SD) of genetic ancestry by country

TABLE 2 Percentage of men and women classified as obese according to WHR, WHtR and BMI, by country and age class

		Women			Men			
Country	Age	WHR > 0.85	WHtR > 0.5	BMI > 30	WHR > 0.9	WHtR > 0.5	BMI > 30	
Colombia	18-30	(n = 538) 21.93	(n = 536) 28.80	(n = 812) 2.58	(n = 364) 12.08	(n = 366) 27.05	(n = 591) 4.56	
	31-40	(n = 48) 39.58	(n = 47) 46.66	(n = 112) 10.71	(n = 56) 33.92	(n = 56) 50.00	(121) 10.74	
	41-50	a	a	a	a	a	a	
	51-60	a	a	a	a	a	a	
	Total	(n = 588) 23.46	(n = 585) 34.52	(n = 926) 3.56	(n = 425) 14.82	(n = 427) 29.74	(n = 721) 5.54	
Brazil	18-30	(n = 722) 11.10	(n = 721) 16.88	(n = 723) 4.70	(n = 339) 13.86	(n = 339) 33.92	(n = 339) 8.55	
Brazil	31-40	(n = 151) 28.47	(n = 150) 37.59	(n = 151) 14.56	(n = 64) 40.62	(n = 64) 62.50	(n = 65) 13.84	
	41-50	(n = 88) 43.18	(n = 88) 65.06	(n = 88) 19.31	(n = 44) 68.18	(n = 44) 79.54	(n = 44) 15.90	
	51-60	(n = 47) 53.19	(n = 47) 71.11	(n = 47) 23.40	(n = 37) 89.19	(n = 37) 91.89	(n = 37) 35.13	
	Total	(n = 1044) 18.48	(n = 1042) 30.51	(n = 1045) 8.70	(n = 498) 29.11	(n = 498) 46.98	(n = 499) 13.02	
Chile	18-30	(n = 372) 7.28	(n = 369) 28.32	(n = 372) 9.67	$(n = 769) \ 26.00$	(n = 767) 60.76	(n = 775) 11.4	
	31-40	$(n = 78) \ 20.51$	(n = 78) 51.35	(n = 78) 23.07	(n = 135) 54.81	(n = 136) 85.29	(n = 137) 15.3	
	41-50	(n = 44) 45.45	(n = 44) 69.05	$(n = 44) \ 20.45$	(n = 70) 80.00	(n = 70) 94.28	(n = 70) 31.42	
	51-60	(n = 24) 41.66	(n = 24) 70.83	(n = 24) 25.00	(n = 53) 86.79	(n = 53) 94.33	(n = 53) 28.30	
	Total	(n = 518) 14.09	(n = 515) 40.97	(n = 518) 13.32	(n = 1027) 36.61	(n = 1026) 68.03	(n = 1035) 14.20	
México	18-30	(n = 686) 43.29	(n = 686) 43.41	(n = 687) 6.25	(n = 442) 38.00	(n = 442) 46.60	(n = 448) 12.3	
	31-40	(n = 115) 58.26	(n = 115) 67.57	(n = 115) 20.00	(n = 88) 64.77	(n = 89) 75.28	(n = 90) 25.53	
	41-50	(n = 70) 68.57	(n = 70) 85.30	(n = 70) 32.85	(n = 44) 81.81	(n = 44) 77.27	(n = 44) 29.54	
	51-60	(n = 82) 79.27	(n = 82) 93.75	(n = 82) 26.83	(n = 50) 92.00	(n = 50) 88.00	(n = 50) 28.00	
	Total	(n = 953) 50.05	(n = 953) 56.34	(n = 954) 11.63	(n = 624) 49.19	(n = 625) 56.16	(n = 632) 16.77	
Perú	18-30	(n = 259) 44.78	(n = 258) 52.52	(n = 514) 2.91	(n = 153) 37.25	(n = 152) 59.21	(n = 326) 6.70	
	31-40	(n = 16) 25.00	(n = 16) 80.00	(n = 29) 3.44	(n = 19) 52.53	(n = 19) 71.42	(n = 29) 31.03	
	41-50	a	a	a	a	a	a	
	51-60	a	a	a	a	a	a	
	Total	(n = 276) 43.84	(n = 275) 57.81	(n = 545) 2.93	(n = 176) 39.77	(n = 175) 61.71	(n = 360) 8.88	

Abbreviations: BMI, body mass index; WHR, waist-to-hip ratio; WHtR, waist-to-height ratio.

cutoff values, is shown in Table 2. The prevalence of obesity according to the BMI ranged from 16.8% in Mexican males to 2.9% in Peruvian females. BMI average (both sexes) values ranged from 4.6% in Colombia to 14.2% in Mexico. Peru, Brazil, and Chile were intermediate with 5.9%, 10.9%, and 13.8%, respectively. Taking all individuals together, the overall prevalence of obesity (>30 kg/m²) was 9.9% for BMI, 31.9% for WHR, and 48.3% for WHtR. In this sense, the incidence of obesity measured by indexes that included WC was higher than the incidence measured by BMI. Indexes showed a different distribution depending on the subsample, although in general WHtR resulted in the highest proportions. As

expected, obesity increased with age. Therefore, cross-country differences were greater among young people and tended to homogenize in later stages of life. Indexes were moderately to highly correlated with each other. WHtR was highly correlated with BMI ($r_p = .87$) and with WHR ($r_p = .728$), whereas the least correlated variables were BMI and WHR ($r_p = .480$). Figure 1 shows a Venn diagram comparing the number of people classified as obese according to the different indices. In accordance to correlation, indices did not fully agree on assigning obesity. Individuals who were simultaneously classified as obese or not healthy by the three indices comprised just 6.8% (493/7236) of the sample. Only one

^aIt indicates the category where the sample size was less than 20.

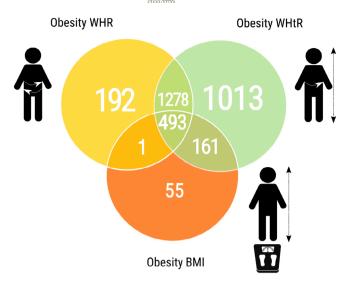


FIGURE 1 Prevalence of obesity according to each index

individual was classified as obese according to both BMI and WHR. Chilean women, for instance, displayed the highest proportion of obesity among people below the age of 30 years for BMI, but at the same time, they had the lowest percentage of obesity among women for WHR (Table 2). On average, Chilean women had a tendency for a peripheral distribution of fat, which is characterized by accumulation of weight in the lower half, near the hips and gluteus, while women in Mexico and Peru had a tendency for a central distribution of fat, characterized by excess weight around the midsection. In this sense, women from Peru and Mexico showed the highest percentage of obesity as measured by WHR. These results indicate a disparity regarding the ability of several indexes to classify persons as obese vs nonobese.

3.2 | Linear regression

The results of the multiple linear regression models (coefficients and *P* values) are depicted in Table 3. Each model had a relatively low percentage of explained variance and the number of significant predictors varied with regard to each population. European ancestry was excluded from the models because it could be linearly predicted from the American and African ancestries (ie, multicollinearity).

As seen in the table, the influence of genomic ancestry showed some trends in the regression models derived from all the indexes. Although the contribution to total variance was relatively low in these models, Amerindian ancestry was positively correlated with obesity, irrespective of the index used as a dependent variable. In addition, Amerindian ancestry showed significant relationships to WHR and WHtR in more subsamples than BMI, suggesting that indexes that included waist and/or hip circumference are more influenced by genomic ancestry than BMI. In the case of African ancestry, only

one subsample was associated with obesity: in Colombian males, high prevalence of African markers was associated with low values of WHR ($\beta = -.005$, P value < .004).

SES and educational level showed an interesting pattern with regard to their association with the indexes. Even when Bonferroni corrected P values resulted in mostly nonsignificant associations, there is a clear trend, and significant associations using P < .05, indicating that increasing obesity is associated with low levels of education among women, and with high levels of SES among men (Table 3).

Obesity indices were used via a logistic regression model to assess the effect of Native ancestry on obesity status. Odds ratio, confidence intervals, and P values are presented in Table 4. When we ran the models without adjusting for SES and education, the OR values did not vary significantly with respect to the model adjusted for education and economic well-being. As seen in the linear regression, European and Amerindian ancestry variables were highly collinear; therefore, the first parental population was excluded from the analysis for simplicity. In general, higher proportions of Amerindian ancestry were associated with higher ORs, independent of the obesity index used; in several of the subsamples, the association was statistically significant. Mexico, a sample with a high proportion of Amerindian ancestry, had elevated and significant ORs for almost every sex/obesity index comparison (OR = 7.49 and 12.76 for WHR in males and females, respectively, OR = 7.87 for BMI in males, and OR = 5.15 and 11.15 for WHtR in males and females, respectively). The Brazilian sample results should be taken with caution due to its low percentage of Native American ancestry (see Table 1). When the remaining countries were explored, the subsample of Peruvian females (WHtR) exhibited the highest OR, whereas the lowest value was observed in Colombian males (BMI). As a whole, these results suggest that individuals with Amerindian ancestry are at higher risk of obesity, when adjusting for age, sex, country, and socioeconomic level.

4 | DISCUSSION

The cultural, genetic, and phenotypic characteristics of Latin American populations are a result of an ongoing admixture process that began with the arrival of the European conquerors to the American continent in the 15th century and continues to this day. Although the health problems associated to overweight and obesity are a serious concern affecting human populations worldwide, these diseases affect Latin America populations in a particular way due to their distinctive genetic, social, economic, and historic-cultural background (FAO & PAO, 2017).

Our sample presented a high percentage of obesity, independent of the index used to quantify it. However, obesity prevalence and its distribution differed across subsamples

TABLE 3 Multivariate linear regression results for each index

		BMI					WHR					WHtR				
Country	Sex	Age	Native ancestry	African ancestry	SES	Education	Age	Native ancestry	African ancestry	SES	Education	Age	Native ancestry	African ancestry	SES	Education
Brazil	M	0.918	0.464	0.383	0.817	0.072	0.027	0.003	0.002	0.005	0.000	0.026	0.007	0.007	0.01	-0.003
		(0.005)	(0.187)	(0.248)	(0.013)	(0.823)	(<0.001)	(0.452)	(0.686)	(0.311)	(0.995)	(<0.001)	(0.17)	(0.153)	(0.05)	(0.601)
	ч	1.174	0.349	0.452	0.229	-0.437	0.024	0.012	0.000	-0.003	-0.017	0.025	0.009	0.007	0.000	-0.011
		(<0.001)	(0.038)	(0.014)	(0.172)	(0.011)	(<0.001)	(0.001)	(0.965)	(0.437)	(<0.001)	(<0.001)	(0.001)	(0.02)	(0.934)	(<0.001)
Chile	M	1.082	0.113	0.071	0.155	-0.171	0.022	0.003	0.002	0.004	0.002	0.019	0.005	0.001	0.004	-0.001
		(<0.001)	(0.307)	(0.519)	(0.172)	(0.133)	(<0.001)	(0.031)	(0.264)	(0.012)	(0.142)	(<0.001)	(0.003)	(0.356)	(0.027)	(0.69)
	ഥ	0.781	0.158	60.0	-0.05	-0.254	0.025	0.008	-0.004	-0.005	-0.005	0.022	0.008	-0.001	-0.002	-0.006
		(<0.001)	(0.34)	(0.593)	(0.755)	(0.12)	(<0.001)	(0.001)	(0.17)	(0.066)	(0.033)	(<0.001)	(0.001)	(0.772)	(0.336)	(0.01)
Colombia	Σ	0.753	0.248	0.03	0.462	0.207	0.014	0.004	-0.005	9000	0.000	0.011	0.005	-0.001	0.008	0.003
		(<0.001)	(0.053)	(0.822)	(0.001)	(0.143)	(<0.001)	(0.018)	(0.004)	(<0.001)	(0.939)	(<0.001)	(0.013)	(0.679)	(<0.001)	(0.217)
	ц	0.29	0.144	-0.038	0.175	0.043	0.004	0.005	-0.003	-0.002	-0.002	0.006	0.006	-0.003	0.002	-0.001
		(0.009)	(0.142)	(0.691)	(0.076)	(0.698)	(0.035)	(0.003)	(0.065)	(0.32)	(0.354)	(<0.001)	(<0.001)	(0.047)	(0.203)	(0.443)
Mexico	M	1.277	0.749	0.326	0.222	0.097	0.021	0.013	0.000	0.001	0.000	0.022	0.014	0.004	0.001	0.001
		(<0.001)	(<0.001)	(0.102)	(0.253)	(0.632)	(<0.001)	(<0.001)	(0.97)	(0.856)	(0.898)	(<0.001)	(<0.001)	(0.202)	(0.648)	(0.804)
	Щ	0.735	0.369	-0.06	-0.081	-0.209	0.022	0.018	-0.002	-0.005	-0.005	0.023	0.015	-0.001	-0.003	-0.006
		(<0.001)	(0.017)	(0.674)	(0.564)	(0.157)	(<0.001)	(<0.001)	(0.458)	(0.035)	(0.051)	(<0.001)	(<0.001)	(0.776)	(0.265)	(0.029)
Peru	\mathbf{Z}	0.724	0.421	-0.1	0.27	0.082	0.019	0.009	-0.002	0.002	0.001	0.015	0.009	-0.003	0.004	0.001
		(<0.001)	(0.026)	(0.58)	(0.12)	(0.657)	(<0.001)	(0.001)	(0.503)	(0.515)	(0.827)	(<0.001)	(0.001)	(0.221)	(0.113)	(0.688)
	ഥ	0.285	0.586	0.128	-0.046	0.078	0.003	0.014	-0.001	-0.005	0.003	0.000	0.014	0.000	-0.004	0.003
		(0.051)	(0.051) (<0.001)	(0.321)	(0.717)	(0.59)	(0.247)	(<0.001)	(0.746)	(0.019)	(0.266)	(0.016)	(<0.001)	(0.922)	(0.095)	(0.229)

Note: Each index variable is regressed via a multivariate linear regression model on age, Native and African ancestries, socioeconomic status (SES), and education. Regression coefficients and P values (in brackets) are presented. The regressions were done separately for each country and each gender. Significant associations (at 0.01 level, Bonferroni adjusted) are shown in bold, significant associations (at 0.05 level, without Bonferroni adjustment) are shown in italics, while nonsignificant results are shown in plain text.

TABLE 4 Multivariate logistic regression results for each obesity index against Native ancestry

		BMI			WHR			WHtR		
Country	Sex	OR	CI	P value	OR	CI	P value	OR	CI	P value
Brazil	M	3.83	(0.13-113.86)	.438	5.09	(0.29-89.47)	.266	87.70	(2.75-2792.97)	.011
	F	19.42	(1.20-315.61)	.037	16.67	(1.58-176.04)	.019	46.38	(4.95-434.35)	.001
Chile	M	2.12	(0.61-7.33)	.236	2.15	(0.81-5.68)	.123	2.71	(0.94-7.78)	.064
	F	1.03	(0.30-3.56)	.968	3.10	(1.03-9.33)	.044	5.82	(2.38-14.24)	<.001
Colombia	M	0.99	(0.04-22.59)	.995	2.84	(0.47-17.13)	.254	3.60	(0.84-15.43)	.084
	F	14.26	(0.44-457.62)	.133	8.84	(1.89-41.32)	.006	10.54	(2.57-43.20)	.001
Mexico	M	7.87	(1.73-35.79)	.008	7.49	(2.51-22.38)	<.001	5.15	(1.76-15.02)	.003
	F	1.30	(0.30-5.68)	.724	12.76	(5.30-30.75)	<.001	11.15	(4.68-26.57)	<.001
Peru	M	2.90	(0.41-20.37)	.285	6.53	(2.01-21.15)	.002	9.12	(2.91-28.53)	<.001
	F	1.55	(0.14-17.21)	.722	8.30	(3.32-20.74)	<.001	17.43	(6.96-43.65)	<.001

Note: Each index variable is converted into a dichotomous obesity index by the following threshold: BMI > 30, WHtR > 0.5, and WHR > 0.85 for women but WHR > 0.9 for men. The multivariate regression model is same as Table 3—the obesity index is regressed via a multivariate logistic regression model on age, Native and African ancestries, socioeconomic status (SES), and education. Regression results are shown only for Native ancestry. Odds ratios (OR), 95% confidence intervals (CI), and P values are presented. The regressions were done separately for each country and each gender. Significant association values (at 0.05 level) are given in black while nonsignificant result values are given in bold.

and according to the observed index. For instance, Chilean women had the largest percentage of obesity according to BMI, an observation that was accentuated in the youngest age groups. In contrast, they had the lowest percentage of central obesity according to WHR. Mexican and Peruvian women showed the highest levels of central obesity measured by both WHR and WHtR, but not by BMI. Using WHR usually results in a higher estimate of obesity compared to BMI, as previously reported in a study focused on obesity in developing countries (Dinsa et al., 2012).

These results show that a single index is not enough for a reasonable description of a complex phenotype such as body fat distribution. Even when using two different indices to measure obesity, one person can be normal weight according to an index and obese according to the other. Unfortunately, research studies have to be confined to a few standardize markers, but advances in new technology like 3D scanning may lead to better measurements and improvements in the screening of large populations. This will likely allow a rapid and precise quantification of the human body (Daniell, Olds, & Tomkinson, 2014; Jaeschke, Steinbrecher, & Pischon, 2015), with noninvasiveness and high accuracy (Medina-Inojosa, Somers, Ngwa, Hinshaw, & Lopez-Jimenez, 2016). Various types of handheld scanning systems are available in the market, which have progressively reduced the costs and installation complications, making it an accessible technology (Knoops Paul et al., 2017; Soileau et al., 2016). However, improvements in cameras and computer processing power allow the development of scanning software systems on smartphone technologies (Navarro et al., 2018).

As described above, the studied indexes show different aspects of obesity across subsamples and seem to be sensitive to several biological and nonbiological factors. A simple explanation could be found in the design of each index. The WHR and WHtR quantify abdominal obesity, while the BMI does not address the accumulation of central fat, which is a problem when trying to distinguish how adiposity is distributed. In addition, the differential coverage may be exacerbated by the underlying differences in the body shape of each population. This contrast can be clearly observed in our sample. Most women from Mexico and Peru exhibited an android body shape, a pattern characterized by central obesity, while women from Chile tended more to a gynoid body shape. Participants from Brazil and Colombia showed a mixed or intermediate pattern. It is necessary to mention that the current WHtR and WHR cutoffs have been defined after studies based on predominantly European-derived populations. Several authors have stated that these cutoffs may not be appropriate for other ethnic groups. For example, some studies have found that Asian samples tend to have a higher percentage of adipose tissue than their European counterparts when low BMI values are considered, (Deurenberg, Yap, & van Staveren, 1998); and a similar trend is observed for higher WHRs in Native Australians when compared to European Australians (Piers, Rowley, Soares, & O'Dea, 2003). In South America, reported cutoffs for WHR ranged wildly across studies, with no determined reference standards (Berber, Gómez-Santos, Fanghänel, & Sánchez-Reyes, 2001; Lear, James, Ko, & Kumanyika, 2009).

Currently, there is no consensus about the best adiposity measure. Some studies tend to find WHtR a better predictor

for health risk (Browning et al., 2010; Janssen, Katzmarzyk, & Ross, 2004). Others show better correlations for WHR criteria when assessing CV disease risk (Browning et al., 2010; Feldstein et al., 2005). Conversely, two large studies support WC as a strong predictor of high blood glucose and related conditions (Huerta et al., 2013; Mamtani et al., 2013; Schneider et al., 2007). However, WC does not consider height, potentially under- or overestimating risk in short or tall people. Despite all controversies, a prospective report on 4000 adults in the United States (Reis et al., 2015), two studies of 46 024 and 244 266 Chinese adults (Hou et al., 2013; Zeng et al., 2014), and a study of 1891 Singapore subjects (Lam, Koh, Chen, Wong, & Fallows, 2015) concluded that a combination of BMI and abdominal obesity (WC/WHR) are better predictors of CV disease than BMI or WC/WHtR/ WHR alone.

The role of SES in relation to diet underlies a complex interplay woven between the macroeconomic and microsocial spheres. In the first scale, trade policies have a direct role in the food chain by controlling food availability through imports and production. Policies influence competition, price changes, income, occupation, services, and to some extent the characteristics of dietary patterns by promoting the presence of certain foods over others and increasing the convergence of food habits (social facilitation) (Aguirre, 2004; FAO & PAO, 2017). In the microsocial sphere, the factors that determine the access to food in the household setting change across the regions. Families need accessibility to supplies and the ability to obtain food to fulfill their overall needs (FAO & PAO, 2017).

In a systematic review of SES and obesity, Dinsa, Goryakin, Fumagalli, and Suhrcke (2012) observed that in middle-income countries, such as those in our study, the association becomes largely mixed for men and mainly negative for women. Even though Bonferroni correction indicates nonsignificance for many of the regression tests we performed, least conservative P values (P value = .05) indicate a positive relationship between some obesity indexes and SES in men (eg, Brazil, Chile, Mexico), but largely undetermined relationships when exploring the female subsample. Conversely, and using the same criteria, our results suggest an inverse relationship between education level and obesity in women. Previous work has shown that education is the variable more strongly associated with body dissatisfaction and may have implications in the perception of society standards of attractiveness or health. This observation indicates that it is plausible that women with high education value a thinner body, which is a feature seen in studies performed in developed countries (McLaren, 2007). Another putative reason for the negative association between education and obesity may be part of a residual feature of the traditional role that women have in selecting and buying the food for all the family, despite the changes in gender roles of the last decade (Dinsa et al., 2012; McLaren, 2007).

Regarding genomic ancestry, Native American and European markers were inversely correlated in the CAN-DELA sample. People carrying a high Native American signature were associated with more abdominal fat than people with low Native American ancestry. When quantifying this influence, BMI was the least influenced index. Since our multiple regression models included education and economic wellness as covariates, our results suggest that genomic ancestry would have a significant effect on obesity, independent of economic status, or education. We did not find interaction effects among variables, with the sole exception of an attenuated influence of Amerindian ancestry on education in Mexican Women. However, there are other factors that can influence such relationships. For instance, recent studies on the UK Biobank sample found that the effect of genetic variants on BMI is modified by several lifestyle risk factors such as alcohol consumption, sleep patterns, diet, and physical activity (Rask-Andersen, Karlsson, Ek, & Johansson, 2017).

Another potentially confounding variable is access to health care. Perreira and Telles (2014) observed that individuals who self-reported as indigenous people have lower self-rated health than nonindigenous people in Latin America. Several studies confirm these observations and suggest that access to obesity treatments is not equally available to some specific social subgroups such as Native American descendants living in isolated or marginal conditions (Montenegro & Stephens, 2006), or people of low incomes (Bastos et al., 2014; Ortiz-Hernández, Pérez-Salgado, & Tamez-González, 2015).

Excess body fat in Latin America could be generally explained by shifts in lifestyle and diet patterns, but also by a susceptibility component with a genetic basis. The "thrifty genotype" hypothesis tries to explain why Native American groups exhibit alarming rates of obesity and diabetes. This postulates that populations exposed to inadequate or fluctuating food consumption generate adaptive methods to achieve a high level of efficiency in the use of energy and deposition of fats. If these mechanisms are conserved after the group succeeds in obtaining food regularly, there may be an increase in the prevalence of overweight and type II diabetes. This hypothesis could be applied to Native American populations that made recent contact with the western way of life (Burrows, Geiss, Engelgau, & Acton, 2000; Chakraborty et al., 1986; Williams, Long, Hanson, Sievers, & Knowler, 2000). For instance, there is a significant effect of Native American ancestry on the effect of B-cell function in the Colombian population, one of the leading drivers of type II diabetes (Caro-Gomez et al., 2018). In this sense, genetic association studies have identified a set of genes (over 30) linked to obesity, such as FTO (fat mass and obesity-associated protein), the first gene discovered by GWAS, MC4R (melanocortin 4 receptor), LEPR (leptin receptor), and NEGRI (Neuronal Growth Regulator I) (Speakman, Loos, O'Rahilly, Hirschhorn & Allison, 2018). However, it has been observed that the loci that promote obese phenotypes vary from population to population. depending on their genetic architectures. According to these results, each gene has a low effect of penetrance and the sociocultural variables take a preponderant role as predictive factors for obesity risk, for example, mainly daily caloric intake and the level of physical activity. In addition, the effect of other factors on the nutritional status, such as the action of the intestinal microbiota (Baothman, Zamzami, Taher, Abubaker and Abu-Farha, 2016) and epigenetic information (Rosen et al., 2018; Van Dijk, Tellam, Morrison, Muhlhausler, & Molloy, 2015), has been proposed by growing lines of research.

Due to this complexity, monitoring overweight and obesity is the foundation strategy for confronting the increased rate of chronic diseases associated with the current epidemiological transition. However, the classical anthropometric approach is not free of problems, since each index emphasizes a certain aspect of body shape but disregards others. Furthermore, interpopulation variation indicates that reference values of obesity should be revised and adapted to the admixed Latin American populations. Further studies using more flexible methods instead of the predefined categories are necessary for a better understanding of the nutritional status across several contexts and populations. This is more valuable in the surveillance field, where efficient, massive, and safe methods are being developed. Methods such as three-dimensional (3D) scanning based on smartphone technologies can help to implement fast, accurate, and cheap surface data (Medina-Inojosa et al., 2016; Navarro et al., 2018). Due to the nature of raw data (eg, meshes that can be stored in digital platforms), such solutions not only solve the problem of reducing a complex 3D shape phenotype to simplistic indexes, but facilitate the development of massive, population-specific databases that can be used to provide better reference values.

5 | CONCLUSIONS

Genomic ancestry is positively associated with obesity in most studied Latin American subsamples and is a reliable predictor of body shape. Furthermore, we suggest that education and economic wellness have significant but different roles with regard to gender. Women with a high educational level tend to display lower levels of obesity, while overweight in men is related to higher economic status. These results indicate that the pattern and magnitude of obesity among several countries of Latin America reflect the complex interrelation between cultures, social factors acting at large-scales, and genetics.

Unless a successful program is developed and sustained to stimulate people to remain physically active throughout their lives, it is expected that the proportion of sedentary people will continue to increase, and concomitantly, the prevalence of obesity and associated conditions. Under this scenario, novel methodological and technical devices need to be developed in order to achieve a better capture of body shape, larger databases, and population-based reference values.

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AUTHOR CONTRIBUTIONS

A.R., O.P., V.R., and R.G.J. designed the study; V.R., C.G., G.B., M.C.B., S.C.Q, F.R., and A.R.L. managed data acquisition and curation; A.R., O.P., P.N., V.R., and R.G.J performed the analyses; A.R.L., acquired funding; A.R., O.P., and R.G.J. wrote the original draft with assistance of all authors.

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