

The Relationship Between BMI Categories and Adult Diabetes Prevalence Across Countries With Different Income Classifications

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ABSTRACT

Type 2 diabetes mellitus (T2DM) is a growing global health concern, with obesity and socio-economic factors contributing to differences in disease prevalence between populations.

Body mass index has a strong relationship to diabetes and insulin resistance; in obese individuals, the amount of fatty acids, glycerol, and other substances involved in the development of insulin resistance is increased. This study investigated the relationship between country-level BMI categories and adult diabetes prevalence (as a proxy for T2DM prevalence) across countries with different income classifications. The findings statistically suggest that country-level BMI patterns and income classifications are associated with differences in diabetes prevalence, although the use of country-level data limits causal and individual interpretations.

Nevertheless, the findings suggest that the positive correlation between obesity and diabetes occurrence can be altered by socioeconomic factors, thus warranting further studies that explore the intersection of biological and socioeconomic factors in the likelihood of incurring chronic diseases.

INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder characterised by high blood sugar resulting from defects in insulin secretion, insulin action, or both (American Diabetes Association, 2012). It is estimated that diabetes mellitus affects 415 million people and is predicted to escalate to 642 million by the year 2040. Yet a further 193 million people with diabetes remain undiagnosed due to the often mild nature of this condition (Al-Lawati, 2017). The steady increase in the prevalence of diabetes is attributed to population growth and ageing (40%), rise in age-specific prevalence (28%) and interactions of the two (32%; Gojka, 2016). Diabetes mellitus places an unsustainable demand on individuals, their careers, health care systems and society. The complications of diabetes can affect any system in the body, and it is noted that relatively few diabetics escape them entirely. Research indicates that a high percentage of diabetic outpatients are

found with neurological abnormalities and arterial diseases (British Medical Journal, 1953). These lifelong complications could interestingly appear before the classic symptoms of diabetes are recognized. For instance, a study found that a notable percentage of diabetics presented with complications as their initial complaint rather than typical diabetic symptoms. In addition to that, its steady increase in low- and middle- income countries further demonstrates that the disease burden is not restricted to high-income populations, making differences in diabetes prevalence between countries an important area of investigation (Arokiasamy et al., 2021).

Diabetes mellitus can be divided into four categories : type 1, type 2, gestational and syndrome monogenic diabetes. Type 1 Diabetes mellitus (T1DM), also known as autoimmune diabetes, is a chronic disease characterized by insulin deficiency due to pancreatic- β -cell loss and leads to hyperglycemia (Katsarou et al., 2017). Gestational diabetes mellitus (GDM) is a serious pregnancy complication, in which most women without previously diagnosed diabetes develop chronic hyperglycemia during gestation (Plows et al., 2018). While GDM usually resolves during delivery, it can have long lasting health consequences including increased risk for T2DM, and future obesity, cardiovascular disease and/ or T2DM in the child (Feig and Moses, 2011). Monogenic disease is caused by specific gene mutations, and has features of severe insulin resistance without obesity; diabetes develops when β -cells do not compensate for insulin resistance (Adler et al., 2019). However, this investigation is going to be centred around Type 2 Diabetes mellitus (T2DM; also previously known as non-insulin dependent diabetes mellitus) because it accounts for nearly 90% of the approximately 537 million cases of diabetes mellitus worldwide (Ahmad et al., 2022) in addition to being closely linked to the epidemic of obesity (DeFronzo et al., 2015), making it the most reliable category for measuring weight-related chronic disease burden across different national incomes.

The biological basis of T2DM stems from a flawed feedback loop between defective insulin secretion by pancreatic β -cells and insulin resistance (Roden and Shulman, 2019). Insulin is a polypeptide hormone mainly secreted by beta cells in the islets of Langerhans of the pancreas which regulates glucose levels in the bloodstream and induces glucose storage in the liver, muscles and adipose tissue, resulting in overall weight gain (Rahman, 2021a). The literature shows that initially, there is a compensatory increase in insulin secretion, which maintains glucose levels in the normal range but inadequate insulin makes it impossible for cells to use glucose as an energy source (Vasiljević et al., 2020) ; consequently, high-glucose concentrations in the bloodstream lead to a condition known as hyperglycemia (Accili, 2018) which can cause diabetes mellitus and other health complications such as complications with the nervous system damage and dysfunction of the eyes and kidneys. Similarly, in muscles, insulin resistance reduces glucose uptake; in the liver, insulin fails to suppress gluconeogenesis leading to excessive hepatic glucose output; and in adipose tissue, obesity-related adipocyte enlargement promotes lipolysis, free fatty acid release, macrophage infiltration, and low-grade inflammation. These inflammatory and lipid-mediated signals worsen insulin resistance, further injuring β -cells. Initially, β -cells compensate by secreting more insulin but overtime they lose function and mass, resulting in inadequate insulin secretion (Galicja-Garcia et al., 2020). Obesity is particularly relevant to the development of T2DM because increased adiposity is associated with metabolic processes that contribute to insulin resistance ; in obese

individuals, the amount of fatty acids and glycerols and other substances involved in the development of insulin resistance is increased (Algoblan et al., 2014). Therefore, excess adiposity can contribute to a loop in which insulin resistance increases metabolic stress on β -cells, while progressive β -cell dysfunction reduces the body's ability to compensate for insulin resistance (Colditz, 1995) through various inflammatory mechanisms. This provides a biological basis for the established association between increasing adiposity and the risk of developing T2DM.

BMI is one of the most adapted ways of estimating people's body fat percentage and is used in the assessment of an individual's nutritional and health status (Bhurosy and Jeewon, 2013). Although BMI commonly applies to individual people, examining the prevalence of BMI categories at a country level allows investigations of population patterns of overweight and obesity to be compared with population-level diabetes prevalence. Thus, the biological association between excess adiposity and T2DM gives a basis for examining if countries with higher obesity prevalence also exhibit higher diabetes prevalence. Since obesity has become one of the most critical public problems worldwide with approximately 2.5 billion adults worldwide being overweight and over 890 million adults living with obesity in 2022 (Blüher, 2019), measuring BMI has increased in popularity and has been directly associated with health risks and death rates in many populations, irrespective of age, sex and ethnicity (Bhurosy and Jeewon, 2013). This investigation therefore considers BMI as a population-level measure than can be used to examine whether differences in obesity prevalence are associated with differences in adult diabetes prevalence across many countries but not as evidence that obesity causes diabetes in an individual.

The association between T2DM and high BMI brings us to the discussion if this same relationship could be expected everywhere. Even though both T2DM and BMI have risk factors that are likely to be multifactorial behavioural problems such as cigarette smoking, physical inactivity, intake of saturated fatty acids and sugar-sweetened beverages (Suwannaphant et al., 2017), the relationship could vary across countries with different income classifications because of structural and lifestyle differences. For example, in high-income countries, advanced healthcare access, high health expenditure, and widespread screening; lead to early preventative care and high diagnosis rates. While urbanisation and processed diets are more common, higher rates of education and public wellness campaigns help mitigate risks, making obesity and associated chronic health conditions manageable. Conversely, in low-to-middle-income regions, rapid urbanisation and shifting socioeconomic conditions have introduced high-calorie diets and lifestyles than the local healthcare systems can adapt. This could result in low diagnosis rates and limited preventative care, allowing T2DM to go undetected until severe complications arise. Consequently, differences in healthcare access and disease detection may mean that recorded or estimated diabetes prevalence does not necessarily reflect the same disease burden across all countries. A country may have high prevalence of obesity but lower recorded diabetes prevalence because diabetes is underdiagnosed. Similarly, a country with lower average BMI could still have a substantial diabetes burden due to differences in diet, urbanization or other metabolic risk factors. Whereas recent studies suggest that the rate of increase in overweight and obesity in high-income countries may be slowing, there is growing evidence that this epidemic has accelerated in low-and middle-income countries, where 2 out of 3 people

with diabetes now reside (Choukem and Dimala, 2021). This unprecedented increase has paralleled the alarming rise in diabetes mellitus in these regions of the world, such that 79% of the estimated 463 million people with diabetes reside in low-middle-income countries.

Although the association of obesity and T2DM has been extensively investigated, the extent to which this population-level relationship differs across countries with different income classifications provides a further area for investigation. Instead of assuming that the obesity and diabetes association is identical across all countries, this investigation analyzes how population-level BMI correlates with adult diabetes prevalence across countries of different national income classification. Therefore, it is hypothesized that countries with higher prevalence of obesity and overweight will have higher adult diabetes prevalence, and that the strength of this association will differ across countries in different income classifications. The investigation therefore asks: How does national obesity prevalence correlate with adult diabetes prevalence across countries with different income classifications?

METHODS

The study examined the relationship between population-level BMI and adult diabetes prevalence across countries classified into different World Bank income groups. I used the search string of “country income classification datasets” in google to obtain a dataset by the World Bank. The World Bank classifies 218 countries, which includes both its member nations and other small sovereign territories, into distinct income groups based on strict financial criterion : Gross National Income (GNI) per capita (Metreau et al., 2026). GNI measures the total income earned by a nation’s citizens and businesses, including income earned abroad, divided by its total population. The data was collected by compiling national economic statistics submitted by countries and international organisations. According to predefined GNI per capita thresholds, countries are assigned income classifications which are : low-income, lower-middle income, upper-middle income and high-income.

Following the same format, I obtained BMI and T2DM datasets from the Non-Communicable Diseases Risk Factor Collaboration (NCD-RisC). These datasets were produced by combining data from numerous nationally representative health surveys and epidemiological studies worldwide. The BMI dataset contains age-standardized BMI estimates for adult men and women across all countries worldwide from 1980 to 2024, BMI proportions and uncertainty intervals. Similarly, the diabetes prevalence dataset provides age-standardized prevalence for adult men and women by their counties as well as uncertainty intervals from 1990 to 2022.

Because the NCD-RisC diabetes dataset reports overall adult diabetes prevalence rather than separating the different categories of diabetes mellitus, overall adult diabetes prevalence was used as a proxy for T2DM prevalence. This was based on the large account for T2DM among diabetes cases; however, the proxy does not represent T2DM exclusively.

Data from NCD-RisC and the World Bank were combined to create an age standardized dataset containing International Organisation for Standardization (ISO) code, sex, prevalence estimates of diabetes as well as categories of BMI from 1990 to 2022. To prepare the datasets above for statistical analysis, I adapted an R script that was executed to clean and merge the datasets using the R packages *tidyverse*, *tidyr*, and *dplyr*. The resulting dataset contained 12,698 complete observations from 197 countries across 1990-2022, with separate observations for men and women.

Income classifications were assigned at the country-year level. The World Bank Income dataset provided a separate classification for each country in each year, which was converted into long format and merged with the BMI and adult diabetes datasets by country and year. This ensured that countries which changed income classification between 1990 and 2022 were assigned the classification corresponding to each specific year rather than a single, more recent classification being applied retrospectively.

The dependent variable in this study was age-standardized adult diabetes which was used as a proxy for T2DM. The independent variable was population-level prevalence within selected BMI categories. One of the primary reasons for the continued use of BMI is how accessible and simple it is as it only requires weight in kilograms to be divided by height in metres squared that can easily be measured by healthcare professionals, researchers and even individuals (Muscogiuri et al., 2023). In this investigation, the following categories were examined : overweight prevalence (BMI $25 < 30 \text{ kg/m}^2$), obesity prevalence (BMI $\geq 30 \text{ kg/m}^2$), BMI $30 < 35 \text{ kg/m}^2$, BMI $35 < 40 \text{ kg/m}^2$, and severely obese (BMI $\geq 40 \text{ kg/m}^2$). Of these, obesity prevalence was selected as the primary explanatory variable in the final statistical model because excess adiposity has an established biological role in the development of insulin resistance and β -cell dysfunction (Algoblan et al., 2014; Galicia-Garcia et al., 2020), making it the BMI category most directly linked to the risk of T2DM risk. Country income classification was also used as an independent categorical variable consisting of four groups: low income, lower-middle income, upper-middle income and high income. The final dataset also contained year and sex variables which were retained because their role in the final statistical models was considered when determining the most appropriate analytical approach.

Statistical analyses were conducted in R. Descriptive statistics were used to summarize the prevalence of adult diabetes prevalence and obesity prevalence across countries and income groups. Because the dataset had repeated observations for the same countries across many years, a linear mixed-effects model was used to account for the non-independence of observations within countries. An interaction between obesity prevalence and income classification was included to assess whether the relationship between obesity prevalence and adult diabetes prevalence differed across income groups.

Model residuals were assessed using the DHARMA package in R (Hartig, 2025), which simulates residuals for mixed-effects models so they can be inspected in a similar way to residuals from a standard linear regression. The dispersion test showed no evidence of over- or under- dispersion (dispersion=1.00, $p=0.83$). However, the residuals were not perfectly uniform, with a small excess of residuals clustering near the boundaries of the distribution (0 and 1), which produced a statistically significant

Kolmogorov-Smirnov test ($D=0.04, p<2.2 \times 10^{-16}$) and a slightly higher number of outliers than expected (1.9% observed vs. 0.8% expected, $p<2.2 \times 10^{-16}$). Because the dataset is large ($n=12,698$), these tests are very sensitive to even small deviations, so a statistically significant result does not necessarily mean that the model is a poor fit. This pattern is most likely because both adult diabetes and obesity prevalence are proportions bounded between 0 and 1, which can cause linear regression to behave slightly less accurately near these boundaries. Future studies could consider using beta regression or a logit-transformed outcome, which are designed specifically for proportion data.

RESULTS

Relationship between adult diabetes prevalence and income groups

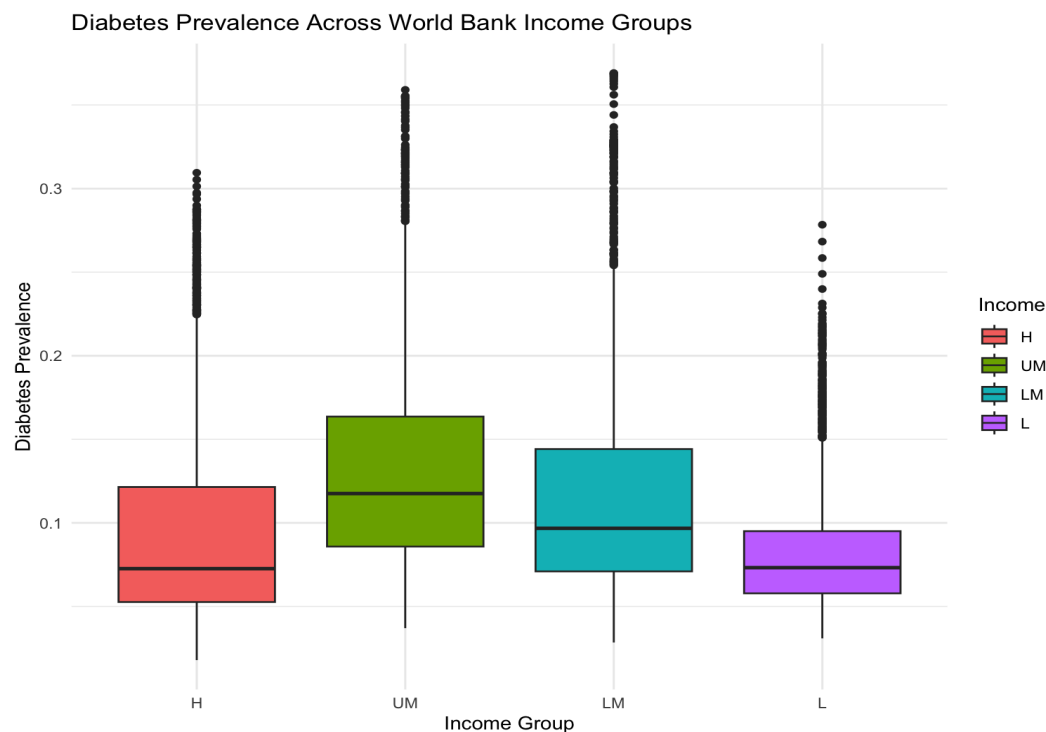


Figure 1. Distribution of adult diabetes prevalence across World Bank Income Classifications, 1990-2022.

Diabetes prevalence differed across income groups, with upper-middle- and lower-middle-income countries showing higher median prevalence than high- and low-income countries (Figure 1).

Table 1. Linear mixed-effects model examining the association between obesity prevalence and adult diabetes prevalence.

Predictor	Estimate	95% Confidence Interval
Obesity	0.2002	0.1898 to -0.2107
Upper-middle income	-0.0111	-0.0142 to -0.0080
Lower-middle income	-0.0136	-0.0169 to -0.0103
Low income	-0.0203	-0.0238 to -0.0167
Year	0.00088	0.000836 to 0.000926
Women	-0.0127	-0.0134 to -0.0119
Obesity x Upper-middle income	0.0499	0.0396 to 0.0602
Obesity x Lower-middle income	0.0458	0.0349 to 0.0566
Obesity x Low income	0.0827	0.0674 to 0.0979

A linear mixed-effects model was used to examine the association between obesity prevalence and adult diabetes prevalence, with country included as a random intercept and year, sex and income classification included as fixed effects, alongside an interaction between obesity prevalence and income classification (Table 1). The fixed effects of the model accounted for approximately 38.6% of the variance in adult diabetes prevalence (marginal $R^2=0.386$), while the full model, including the country random intercept, accounted for approximately 92.6% of the variance (conditional $R^2= 0.926$). This large difference indicates that most of the variance in adult diabetes prevalence lies between countries rather than being explained by obesity prevalence or income classification alone, reinforcing that the identified relationships should be interpreted as population-level associations rather than as measures of individual risk.

Obesity prevalence was significantly and positively associated with adult diabetes prevalence in high-income countries, the reference group ($\beta=0.2002$, 95% Confidence Interval:0.1898 to -0.2107). The interaction terms between obesity prevalence and income classification were all positive, indicating that the association between obesity and adult diabetes prevalence was in upper-middle-, and lower-middle-, and low-income countries than in high-income countries, with the steepest association observed in low-income countries.

Association Between Obesity and Adult Diabetes Prevalence by Income Group

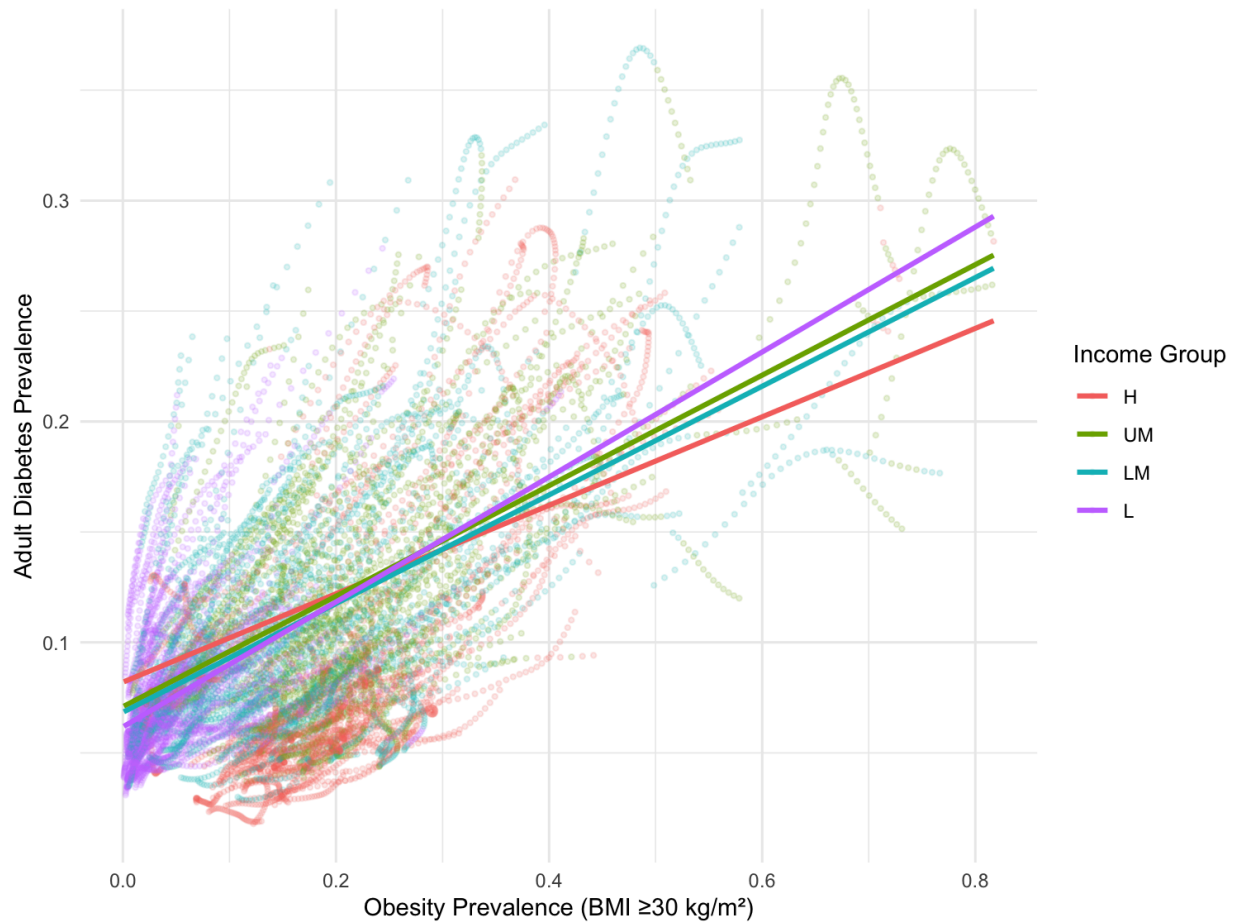


Figure 3. Predicted associations between obesity prevalence and adult diabetes prevalence and adult diabetes prevalence by income classification, based on fixed effects from a linear mixed-effects model.

High-income countries were used as the reference category for income classification, and men were used as the category for sex. Interaction coefficients therefore represent the difference between each income group's obesity-diabetes association and that of the high-income reference group.

The slope of the association between obesity prevalence and adult diabetes prevalence for each income group in Figure 3 differed by income classification: it was weakest in high-income countries and became progressively steeper in upper-middle-, lower-middle-, and low-income countries, with the steepest predicted association in low-income countries. This pattern is reflected in the significant positive interaction between obesity prevalence and income classification, indicating that a given increase in obesity prevalence is associated with a larger predicted increase in adult diabetes prevalence in lower-income countries than in high-income countries.

DISCUSSION

The linear mixed-effects model accounted for the non-independence of repeated observations within the same country over time, with country included as a random intercept and year and sex included as fixed effects. This approach was necessary because the dataset contained 12,698 observations from 197 countries across 1990-2022, meaning that individual country-year observations were not statistically independent of another.

The pattern seen in Figure 1 where upper-middle- and lower-middle income countries showed higher median diabetes prevalence than high-and low- income countries, suggesting that the relationship between national income and diabetes prevalence is not a simple linear one, and likely shaped by other factors associated with income, including healthcare access, urbanization, nutrition, physical activity, and differences in disease detection may contribute to these patterns. Therefore, income classification should be interpreted as an indicator of broader socioeconomic context rather than as a direct biological cause of diabetes prevalence.

The fixed effects of the model, comprising obesity prevalence, income classification, year, sex and their interaction, accounted for approximately 38.6% of the variance in adult diabetes prevalence (marginal $R^2 = 0.386$). Obesity prevalence was significantly and positively associated with adult diabetes prevalence in high-income countries. However, the interaction terms show this association was not consistent with different income groups: the obesity-diabetes association became progressively stronger moving from high-income to upper-middle-, lower-middle-, and low-income countries, with the steepest association found in low-income countries. This pattern suggests that at the population level, increase in obesity prevalence may be associated with disproportionately larger increases in diabetes prevalence in lower-income countries compared with high-income countries. This could possibly be explained by structural factors in lower-income settings such as limited access to healthcare, lower rates of early diagnosis, and different dietary or metabolic risk profiles. These may compound the biological relationship between the biological relationship between adiposity and insulin resistance, though this cannot be confirmed by an ecological, country-level design and would require further research using individual-level data.

This finding should be interpreted cautiously. The much larger conditional R^2 (0.926) compared with the marginal R^2 (0.386) shows that the great majority of variance in adult diabetes prevalence is explained by differences between countries themselves, rather than by obesity prevalence or income classification. This reinforces that country level identity; with many unmeasured factors such as diet, genetics, healthcare, infrastructure and diagnostic practices, plays a large role in explaining diabetes prevalence than the variables measured in this study, and that the obesity-income interaction, while statistically significant, explains a comparatively modest share of the overall variance.

These results are broadly consistent with prior work suggesting that the relationship between BMI and diabetes risk is not uniform across settings. Choukem and Dimala (2021) similarly found that the association between BMI and diabetes risk varied across low-and middle-income countries, supporting the view that this relationship is dependent on the context rather than fixed. Richards et al.(2022) also identified BMI as a significant country-level predictor of diabetes prevalence, consistent with the overall positive association found here. However, this study extends that literature by showing, using a model that accounts for repeated country-level observations, that the strength of the obesity-diabetes association may be greatest in lower-income countries. This pattern needs further investigation, ideally with individual-level data that can account for diagnostic and healthcare access differences directly rather than inferring them from income classification alone.

Limitations in methodology

A key limitation is that the diabetes prevalence dataset found from NCD-RisC reports diabetes prevalence rather than specifically adult diabetes prevalence. In this investigation, the overall adult diabetes prevalence was used as a proxy for adult diabetes because it accounts for $\cong 90\text{-}95\%$ of the diabetes mellitus cases (American Diabetes Association, 2011). However, this approach also means that there might be an intersection with type 1 diabetes mellitus or even gestational diabetes and cannot be interpreted as exclusively representing adult diabetes.

A further limitation is that the investigation uses country-level observations rather than individual-level data. The relationship identified cannot establish that individuals with higher BMI are necessarily the individuals contributing to the observed national diabetes prevalence, nor can it give a cause for individual-level diabetes.

The investigation did not account for other risk factors which may influence adult diabetes prevalence risk including physical activity, diet and socioeconomic factors such as healthcare access, health expenditure and diabetes prevalence education. This is especially important because these variables could act as confounding factors. For example, countries with higher obesity prevalence may also differ in dietary patterns, healthcare access and diagnostic practices.

BMI in itself is also an imperfect variable in terms of measurement of adiposity because it does not consider lean body mass, bone, fat proportions, nor metabolic health which are strong indicators of overall health (Romero-Corral et al.,). BMI's weight categories imply that there is a typical healthy body, a concept that oversimplifies health by disregarding the variety of human body types (Pischon, 2010). In addition to that, overinterpretation may lead to weight stigma, or discriminatory acts or perceptions based on height and weight (Shanks et al., 2025). However, BMI remains useful for this investigation because the NCD-RisC dataset provides standardized population-level BMI category prevalence across a very large number of countries and years, making it practical for international comparison even though it is not a perfect measure of individual adiposity. To address these issues, other cost-friendly and non-invasive measures are useful. For instance, waist circumference - while having its own strengths and weaknesses (such as being inexpensive, sensitive to health outcomes and changes in body composition, but prone to

inconsistencies in measurement) provides a more accurate measure of fat distribution and could complement BMI when used together (Ross et al., 2020).

CONCLUSION

This study investigated the relationship between population-level BMI category prevalence, adult diabetes prevalence and national income classification.

The findings demonstrated a statistically significant positive association between all BMI categories examined and adult diabetes prevalence and adult diabetes prevalence also differed significantly across World Bank income classifications. This association remained significant after accounting for income classification, and a significant interaction between obesity prevalence and income indicated that the strength of this association differed by income group; specifically, the association between obesity and diabetes prevalence was weakest in high-income countries and progressively stronger in upper-middle-, lower-middle-, and low-income countries.

This finding is consistent with the hypothesis that the relationship between obesity and diabetes prevalence is not uniform across income classifications, and suggests that structural or socioeconomic factors associated with lower national income may compound the relationship between adiposity and diabetes risk at the population level. However, the large gap between the model's marginal and conditional R^2 values indicates that most of the variation in adult diabetes prevalence lies between countries themselves, rather than being explained by obesity prevalence or income classification alone thereby underscoring that obesity and income are only part of a much larger and more complex set of factors driving national diabetes prevalence. Further research should investigate additional socioeconomic and behavioral risk factors such as physical activity, dietary patterns, and healthcare access, ideally using individual-level data that can better disentangle the mechanisms underlying these population-level associations.

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