

NCAER NATIONAL DATA INNOVATION CENTER  
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NDIC FELLOWS PROGRAMME

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# Age-Specific BMI Cut-Offs for Older Adults Aged 60 and Above in India



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## What is the measurement challenge?

**B**ody mass index (BMI) helps predict/identify diseases in adults, such as cardiovascular diseases and diabetes. Although there are more accurate body composition measures such as Dual Energy X-ray Absorptiometry (DEXA) imaging, BMI remains the easiest measure to assess the body composition and nutritional status. With the older adult population in India expected to become about 20% of the total population by 2050 (India Aging Report, 2017) and the prevalence of both overweight and undernutrition affecting this population (IIPS, 2021), it will be useful to understand how current BMI thresholds will associate with their diagnosis and treatment and whether new BMI thresholds would be better.

The current WHO body mass index (BMI) thresholds were created using data from adults aged 18 and above and then generalising these cut-offs to all adults. This method is not reliable because body composition changes with age. Studies show that current BMI thresholds do not accurately portray health risks in older adults (Adams et al., 2006; Pischon et al., 2008; Zhu et al., 2003). In addition, while the association between high BMI/obesity and risk of diseases is well established, there are conflicting findings on the relationship between low BMI and cardiovascular diseases (CVDs). A J- or U-shaped relationship has been observed between BMI and all-cause mortality as well as CVD-related mortality. Thus, it is important to see whether BMI at either extremes of the continuum is associated with CVDs and whether new cut-offs would offer improved diagnosis and classification.

Figure 1 shows the relationship between BMI and mortality for different categories of diseases. The re-

lationship between BMI and all-cause mortality is U-shaped. This means that all-cause mortality is higher both at low and high BMI. Similar patterns are observed for communicable diseases, non-communicable diseases and injuries. This establishes that BMI, while being a predictor of health status, is also associated with mortality and it will be helpful to re-evaluate BMI cut-offs for better diagnosis and disease prevention.

## Data and Methodology

To create new BMI thresholds, we used data from an ageing study in India, the *Longitudinal Ageing Study of India (LASI) Wave 1*. This is a nationally representative survey of adults aged 45 and above across all states and union territories of India that collects information on disease, health and healthcare, and socio-economic well-being of older adults. The data was collected between April 2017 and December 2018.

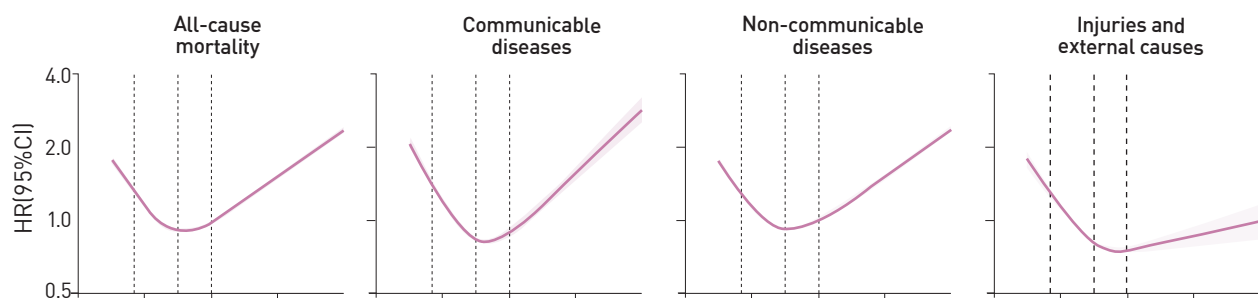
### Outcome Variable

The outcome variable was BMI. It was calculated from weight and height information of individuals provided in LASI data. It was calculated as follows:

$$\frac{\text{Weight in kilograms}}{\text{Height in metres}^2}$$

The BMI (calculated from the above formula) was used to assess nutrition status among the older adults. This was done by categorizing the individuals into three categories (underweight, normal and overweight/obese) using World Health Organization (WHO) cut-offs as follows:

**Figure 1: Relationship between mortality and BMI and mortality for different diseases**



Source: Bhaskaran et al. (2018).

- i.  $< 18.5 \text{ kg/m}^2$  (underweight)
- ii.  $18.5\text{--}24.9 \text{ kg/m}^2$  (normal weight)
- iii.  $>25.0 \text{ kg/m}^2$  (overweight/obese)

### Selection of health measures: Cardio-metabolic outcomes

A list of chronic diseases was prepared from available literature and the list was narrowed down to three diseases: heart diseases, hypertension, and diabetes. In LASI, the following questions were asked to collect data about these three conditions:

- Ever diagnosed with chronic heart diseases?
- Ever diagnosed with hypertension?
- Ever diagnosed with diabetes?

The composite cardio-metabolic (CM) outcome was then formed based on these three variables. A respondent was considered as having the composite cardiovascular outcome if they indicated 'yes' to any one of the above questions and not having the outcome otherwise.

## Statistical Analyses

### 1. Main analysis

#### *Description of the CART model and logistic regression model*

First, an age-stratified classification and regression tree (CART) analysis was conducted to determine appropriate BMI thresholds for adults aged 60 years and above using cardio-metabolic outcomes as the health indicator. This CART model was used to derive the new BMI cut-offs based on cardio-metabolic outcomes.

Next, logistic regression model was constructed to assess the magnitude and direction of relationship between the WHO and the new BMI thresholds and health status.

#### *Validation of the CART model*

Overfitting is a common issue in machine learning. It occurs when the predictive model is fitted too closely to the data. In order to avoid overfitting of the CART model, the comprehensive dataset was split into training and testing subsets. The training dataset was used to derive BMI cut-offs using CART analysis. 80% of cases from the comprehensive dataset were randomly selected to generate the training dataset

### 2. Confirmatory analysis

#### *Sensitivity and specificity of CART-derived thresholds*

A Receiver Operating Characteristic (ROC) curve was calculated to compare the performance of the newly derived thresholds from the WHO BMI cut-off points. Area under the curve (AUC), sensitivity, and specificity for both the newly derived cut-offs and the WHO cut-offs were computed. The AUC is a measure of diagnostic and/or predictive accuracy of the logistic regression model and assesses the model's performance in distinguishing between positive and negative outcomes. It lies between 0 and 1, with higher values suggesting better predictive ability. Through our analysis, we expect to see an improvement in AUC with CART derived outcomes as compared to WHO cut-offs.

#### *Validation of CART derived cut-offs: Agreement with waist circumference*

Waist circumference (WC) is a commonly used alternative to BMI for predicting disease risk among diverse populations as it is correlated highly with BMI (Flegal *et al.*, 2009). The World Health Organization recommends the following WC cut-offs:  $>94 \text{ cm}$  (men)/ $80 \text{ cm}$  (women), which corresponds to an increased risk of metabolic complications, and  $>102 \text{ cm}$  (men)/ $88 \text{ cm}$  (women), which corresponds to a substantially increased risk. Data for WC was taken from LASI, which reports WC at the individual level. For the purposes of this analysis, WC was thus categorized as such: Low risk ( $\leq 94 \text{ cm}$  (men) or  $80 \text{ cm}$  (women)), Increased Risk ( $>94 \text{ cm}$  (men)/ $80 \text{ cm}$  (women) to  $\leq 102 \text{ cm}$  (men)/ $88 \text{ cm}$  (women)), and Substantially Increased Risk ( $>102 \text{ cm}$  (men)/ $88 \text{ cm}$  (women)). The agreement statistic reported for assessing the agreement with waist circumference was the weighted Cohen's kappa, which takes into account the ordering of the categories used and accordingly assigns a weight to the degree of disagreement.

## Results

### 1. Main analyses

Table 1 compares the age-stratified cardiovascular BMI cut-offs (henceforth referred to as new cut-offs) with the WHO-BMI groups. These grouping were

**Table 1: Comparison of New BMI Thresholds Derived by CART Analysis with CM Outcomes (new BMI cut-offs)**

Category (Ref. Normal)	60-74 years old	75+ years	75+ years old
Increased Risk (-) <sup>1</sup>	<=17.4	<=13.3	Underweight (<18.5)
Low Risk 1	>17.4 to <=19.9	>13.3 to <=20.0	Normal (>=18.5 to <25.0)
Low Risk 2	>19.9 to <=22.9	>20.0 to <=21.5	
Low Risk 3	>22.9 to <=28.8	>21.5 to <=22.8	
Increased Risk (+) <sup>2</sup>	>28.8 to <=33.7	>22.8 to <=28.7	Overweight (>=25.0 to <30.0)
Substantially Increased Risk	>33.7	>28.7	Obese (>=30.0)

1 Increased risk (-) corresponds to an increased health risk due to lower BMI  
 2 Increased risk (+) corresponds to an increased health risk due to higher BMI

used to create six final New BMI cut-offs, derived directly from decision trees.

Within the BMI-CM-Risk groupings, new group names were given to focus on the pattern of disease risk (Table 1) in line with the research of Javed et al. (2022). The grouping comparable to “Underweight” was renamed “Increased Risk (-)”, “Normal” to “Low Risk”, “Overweight” to “Increased Risk (+)”, and “Obese” to “Substantially Increased Risk”.

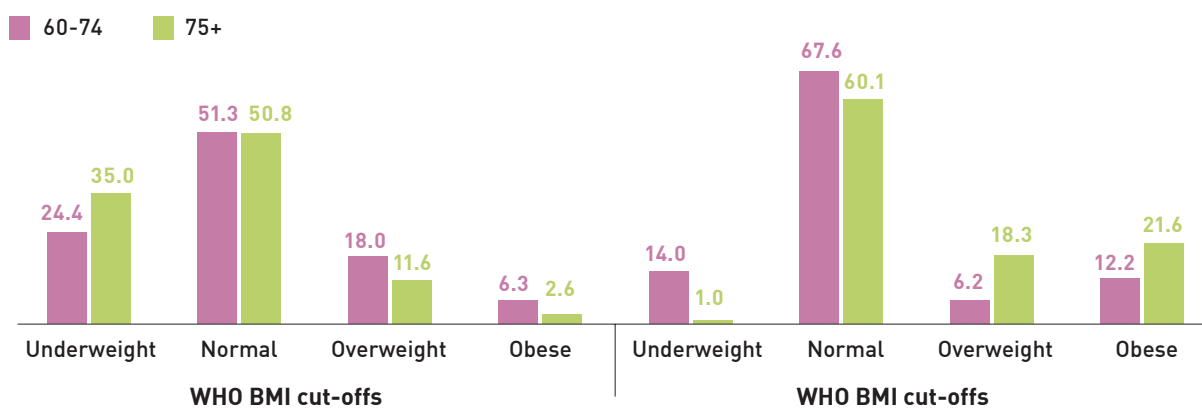
Figure 2 shows the distribution of older adults aged 60-74 years and 75 years across different WHO BMI cut-offs and New BMI cut-offs. The data shows that as adults age, there is a shift toward lower BMI categories. For example, the proportion of underweight individuals increases from 24.4% in the 60-74 age group to 35% in those aged 75 and above. This shift reflects age-related changes in body composition, such as muscle mass loss, which can result in a lower BMI. An increasing number of underweight individuals in older age groups could indicate a heightened risk of

frailty, malnutrition, and other related health issues.

The new BMI cut-offs result in a higher proportion of older adults being classified as having a normal BMI- 68% for those aged 60-74 and 60% for those aged 75 and above. This suggests that the CART cut-offs may be more lenient or better tailored to the physiological changes that occur with ageing. The higher classification of “Normal” BMI could lead to a reassessment of what is considered healthy weight in older populations. If the CART cut-offs are more reflective of older adults’ health status, they may help avoid over-diagnosis of underweight or overweight conditions, leading to more appropriate health interventions.

Using the WHO cut-offs, a significant proportion of older adults are classified as underweight or overweight, which could lead to interventions that may not be necessary or could be misaligned with the health needs of older adults. Misclassification can lead to inappropriate treatment plans. For instance, those classified as underweight might be subjected to inter-

**Figure 2: Distribution of Older Adult Population Across BMI Categories**



Source: Longitudinal Ageing Study of India (LASI) Wave 1 (2017-18)

**Table 2: Logistic Regression with WHO-BMI Cut-Offs as Predictor Variables**

Category (Ref. Normal)	60-74 years old	75+ years old
Underweight	0.86** (0.17, 0.99)	0.43* (0.21, 0.92)
Overweight	1.92* (1.01, 2.84)	1.21** (1.01, 3.11)
Obese Class 1	2.11*** (1.23, 2.90)	1.98* (1.30, 3.91)
Obese Class 2	3.27* (2.01, 4.23)	3.23*** (2.59, 4.12)
Obese Class 3	3.99* (2.54, 4.97)	3.82*** (3.11, 5.23)

Note: \* p<0.01, \*\* p<0.05, \*\*\* p<0.10; figures within parentheses reflect lower and upper confidence interval (CI)

ventions aimed at weight gain, which might not be necessary if their weight is actually within a healthy range for their age. Similarly, those labeled as overweight might face unnecessary weight loss programs, which could negatively affect their health.

Table 2 presents results from logistic regression analysis where WHO BMI threshold is the main predictor variable. For older adults aged 60 to 74 years old, those who were underweight were 0.86 (95% CI: 0.17, 0.99) times as likely to have CM conditions than their counterparts in the normal BMI category. Those in the overweight category were 1.92 times (95% CI: 1.01, 2.84) as likely to have CM conditions. This association was true for all three classes of obesity as well.

For older adults aged 75 and above, those who were underweight were 0.43 times (95% CI: 0.21, 0.92) as likely to have CM conditions than their counterparts in the normal BMI category. Overweight older adults were 1.21 times as likely (95% CI: 1.01, 3.11) to have CM conditions than their counterparts. Older adults belonging to obese class 1, 2 and 3 were 1.98 (95% CI: 1.30, 3.91), 3.23 (95% CI: 2.59, 4.12) and 3.82 (95% CI: 3.11, 5.23) times as likely respectively to have CM conditions than their counterparts in the normal BMI category.

The significant risk associated with being overweight in the 60 to 74 age group reinforces the well-known health risks of excess weight, such as hypertension, diabetes, and cardiovascular diseases. However, the reduced risk in the older age group suggests that BMI might not be as strong a predictor of chronic conditions in the very elderly, possibly due to a “survivor effect” where those who reach 75 and beyond might have better overall health regardless of their BMI.

Table 3 presents results from logistic regression analysis where New BMI cut-offs were the main predictor variable. For older adults aged 60 to 74 years old, those belonging to the low risk 2 and low risk 3 category were 1.28 times (95% CI: 1.11, 2.93) and 1.56 times (95% CI: 1.21, 3.19) as likely respectively to have CM conditions than their counterparts in the low risk 1 category. Those who belonged to the increased risk (+) category were 3.34 times (95% CI: 2.87, 4.01) as likely to have CM conditions and those belonging to the substantially increased risk category were 4.12 times (95% CI: 3.59, 5.51) as likely to have CM conditions.

The magnitude of odds ratios of older adults aged 75 and above was along similar lines like their counterparts aged 60 to 74.

**Table 3: Logistic Regression with New BMI Cut-Offs as Predictor Variables**

Category (Ref. Low Risk 1)	60-74 years old	75+ years old
Increased Risk (-)	1.01 (0.43, 2.11)	1.82* (1.11, 2.11)
Low Risk 2	1.28** (1.11, 2.93)	1.11*** (1.02, 3.25)
Low Risk 3	1.56*** (1.21, 3.19)	1.23*** (1.05, 2.99)
Increased Risk (+)	3.34** (2.87, 4.01)	2.96** (1.70, 4.55)
Substantially Increased Risk	4.12*** (3.59, 5.51)	3.96** (1.84, 4.78)

Note: \* p<0.01, \*\* p<0.05, \*\*\* p<0.10

**Table 4: Sensitivity, Specificity, and AUCs of BMI Cut-Offs in Training Dataset**

		WHO-BMI Cut-offs			BMI-CM-Risk Cut-Offs		
		Sensitivity	Specificity	AUC	Sensitivity	Specificity	AUC
<b>Men</b>	60-74 years	66	33.5	0.58	<b>66.2</b>	<b>33.8</b>	<b>0.69</b>
	75+ years	62.3	37.7	0.62	<b>65.1</b>	<b>44.9</b>	<b>0.68</b>
<b>Women</b>	60-74 years	65.4	30.8	0.66	63.1	<b>38.2</b>	<b>0.69</b>
	75+ years	63.3	32.5	0.64	60.6	<b>39.7</b>	<b>0.71</b>

Note: Values marked in bold indicate improvements in sensitivity, specificity, or AUCs from WHO-BMI cut-offs.

The association of new BMI cut-offs to CM conditions is stronger as compared to that between WHO BMI cut-offs and CM conditions. These new cut-offs also provide a more nuanced classification that capture health risks more effectively. For example, the progressive increase in the odds of CM conditions across the low risk and higher risk categories suggests that the New BMI cut-offs may better reflect the continuum of health risks associated with BMI, offering superior predictive power.

**2. Confirmatory analysis**

Table 4 shows the results of sensitivity, specificity and AUCs of both BMI cut-offs in the training dataset. This analysis was stratified by age and sex to see whether the proposed cut-offs demonstrated an improvement over BMI cut-offs for different sub-sections of the population as well. In males aged 60-74 years old, the sensitivity and specificity of WHO-BMI cut-offs were 66.0 and 33.5 respectively. The corresponding values for New BMI cut-offs were 66.2 and 33.8 respectively, an improvement of 0.2 and 0.3 in the sensitivity and specificity respectively. In males aged 75 years and above,

New BMI cut-offs recorded an improvement of 2.8 in sensitivity over WHO BMI cut-offs and the AUC was also 0.06 points higher for the former. Among women aged 60-74 years old and 75 years and above, the specificity of New BMI cut-offs was 7.4 and 7.2 points higher respectively than WHO BMI cut-offs.

Table 5 shows the agreement between BMI cut-offs and waist circumference in comprehensive dataset. For this purpose, New BMI cut-offs were re-categorized into three groups: low risk, increased risk and substantially increased risk. The kappa values among males aged 60-74 years old and 75 years and above were 0.72 and 0.66 respectively. In both the categories, the kappa value for New BMI cut-offs was higher than that of WHO-BMI cut-offs. For males aged 60-74 years old, the increase was of 0.04 points and the corresponding increase was 0.11 points for males aged 75 years and above. For females aged 60-74 years old, the kappa value for WHO-BMI groups was higher than that of New BMI cut-offs. However, for females aged 75 years and above, the kappa value of New BMI cut-offs was 0.04 points higher than that of WHO-BMI cut-offs.

**Table 5: Agreement Statistics Between BMI Cut-Offs and Waist Circumference in Comprehensive Dataset**

	Waist Circumference Agreement with	Linear Weighted Kappa	95% Confidence Interval	
<b>Men: 60-74 years</b>	WHO-BMI Cut-Offs	0.68	0.60	0.72
	60-74 Years Old BMI-CM-Risk Cut-Offs	<b>0.72*</b>	0.66	0.79
<b>Men: 75+ years</b>	WHO-BMI Cut-Offs	0.55	0.48	0.60
	75+ Years Old BMI-CM-Risk Cut-Offs	<b>0.66*</b>	0.59	0.71
<b>Women: 60-74 years</b>	WHO-BMI Cut-Offs	0.62	0.57	0.71
	60-74 Years Old BMI-CM-Risk Cut-Offs	0.59	0.55	0.69
<b>Women: 75+ years</b>	WHO-BMI Cut-Offs	0.71	0.63	0.80
	75+ Years Old BMI-CM-Risk Cut-Offs	<b>0.75*</b>	0.70	0.82

\*Improvement from WHO-BMI cut-offs

## Discussion of Key Findings

**Findings based on New BMI cut-offs suggested a decrease in the threshold for underweight, but an increase in the threshold for overweight among older adults aged 60-74. Among older adults aged 75 years and above, the New BMI cut-offs suggested a decrease in the threshold for all three categories, namely, underweight, overweight and obesity.** The Increased Risk (-) category corresponds to the WHO category of underweight. This is an important category because there are many studies that discuss the association of overweight and obesity with CVDs. However, studies linking underweight with CVDs, although rare, have also been coming up (Zhu et al., 2015, Flegal et al., 2009). Additionally, a U-shaped relationship between BMI and mortality also establishes the importance of this category (Held et al., 2022, Hu et al., 2020; Park et al., 2017).

**The BMI-CM age-stratified risk groups offer improvements in classification as far as CM conditions are concerned.** The age-specific nature of these cut-offs will also provide tailored cut-off points along the aging continuum. This is very important as there are considerable changes in body composition with increase in age (Borkan, 1983) and, hence, using the same cut-off for the entire age group may be incorrect.

These results call for a granular approach to assessing health risks in older adults. For older adults in the age group 60-74, the emphasis might remain on avoiding overweight and obesity to reduce the risk of chronic conditions. However, for the oldest adults, clinicians might need to focus more on overall health status, including factors like muscle mass, mobility, and nutrition, rather than BMI alone. This analysis reveals that BMI's role as a predictor of chronic medical conditions varies significantly with age, especially in older adults. While higher BMI is generally associated with greater health risks, the degree of this risk changes with age, suggesting that both clinical practice and public health strategies should consider age-specific factors when addressing weight and health in older adults.

## Scope for Further Research

While the proposed age-specific cut-offs demonstrate improvements in classifying older adults in LASI data, further research is needed to ascertain their functionalities in other populations and ethnicities and in the context of other health outcomes. Additionally, subject to the availability of longitudinal data, BMI-mortality relationship could be explored using these cut-offs. Longitudinal data could also be used for understanding how changes in BMI and the transition between these revised groupings would impact health outcomes. Further studies could also consider how self-reported BMI data functions with respect to these groupings. Lastly, while further exploration of these BMI cut-offs is important, it is also crucial to bolster the development of alternate improved indicators of nutrition, which maintain the accessibility of BMI but also include the accuracy of its alternatives.

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