RSNA Press Release

AI Model Analyses Body Composition to Predict Health Risks

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OAK BROOK, Ill. – Researchers used AI to analyze whole-body MRI scans from more than 66,000 participants to create the most detailed reference map to date of how fat and muscle are distributed in the human body across age, sex and height. The study was published today in *Radiology*, a journal of the Radiological Society of North America (RSNA). Results of the study show that the quality and amount of skeletal muscle, not just visceral fat, are strong predictors of diabetes, major cardiovascular events and mortality.

Clinicians have long relied on body mass index (BMI) and body weight to estimate cardiometabolic—the connection between cardiovascular (heart/blood vessel) and metabolic (energy/nutrient processing) systems on health—and overall health risk. But BMI is a crude measure of body composition that only relies on height and weight and does not account for muscle mass or fat distribution.

“Many risk scores and treatment decisions still rely on BMI or waist circumference because they are simple to obtain,” said senior author Jakob Weiss, M.D., Ph.D., radiologist in the Department of Diagnostic and Interventional Radiology at University Medical Center Freiburg in Germany. “But BMI does not reliably reflect a person’s actual body composition.”

Dr. Weiss said the medical community also lacks reference standards for how body composition changes in asymptomatic individuals as they age, as well as differences between men and women.

“There is growing evidence that body composition measures are independent risk factors for cardiometabolic and oncological diseases and mortality,” said first author Matthias Jung, M.D., from the Department of Diagnostic and Interventional Radiology, University Medical Center Freiburg. “However, these measures are influenced by height and sex and change substantially with age.”

The retrospective study included a cohort of 66,608 individuals (mean age 57.7 years, 34,443 males, mean BMI: 26.2) who underwent whole-body MRI as participants in the UK Biobank and the German National Cohort between

April 2014 and May 2022.

The researchers calculated age-, sex-, and height-normalized body composition metrics from the MRI scans using their open-source, fully automated deep learning framework. The body composition metrics, including subcutaneous adipose tissue, visceral adipose tissue, skeletal muscle, skeletal muscle fat fraction, and intramuscular adipose tissue, were expressed as z-scores, which show how far an individual deviated from the age-, sex-, and height-adjusted norm.

The researchers then conducted statistical analyses to assess the prognostic value of z-score categories (low: $z<-1$; middle: $z=-1$ to 1; high: $z>1$) to predict the incidence of diabetes, major adverse cardiovascular events and all-cause mortality.

They found that high visceral fat was associated with a 2.26-fold increased risk of future diabetes, high intramuscular fat was associated with a 1.54-fold increased risk of future major cardiovascular events, and low skeletal muscle was associated with a 1.44-fold higher all-cause mortality beyond cardiometabolic risk factors.

"It's not only how much muscle you have, but also it's the quality of that muscle," Dr. Jung said. "Knowing the volume of intramuscular fat gives us a window into muscle quality that other methods like BMI, bioelectrical impedance analysis, or DEXA can't easily provide."

The research team also generated age-, sex-, and height-normalized reference curves for key body composition measures.

"Adjusting for confounding factors is critical for improving screening accuracy and tailoring treatment decisions," Dr. Weiss said. "This tool has the potential to identify whether an individual's body composition puts them at greater risk for metabolic disease compared to their age-matched peers."

The researchers released their open-source web-based age-, sex-, and height-adjusted body composition z-score calculator to support future research, accelerate clinical translation, enabling researchers and clinicians to normalize their own datasets for improved comparability and generalizability.

"This tool can allow clinicians to use routine imaging opportunistically," Dr. Weiss said. "A dedicated whole-body MRI is not necessarily required. If a routine CT or MRI body scan already exists, the information can be extracted for benchmarking against the reference values."

Dr. Weiss said the AI tool could also help improve risk stratification in oncology or distinguish desirable fat loss from unwanted muscle loss in patients using weight-loss drugs such as GLP-1 agonists.

"We're already imaging patients every day," Dr. Weiss noted. "On every scan of the abdomen or chest, the information is there, we just don't routinely measure or report it. AI now allows us to tap into this hidden layer of data in a quantitative, reproducible way."

Next steps for the researchers include validating the reference curves in clinical populations, especially predicting treatment toxicity, survival and recurrence in cancer patients, and developing disease-specific reference values for other patient groups.

"Body Composition in the General Population: Whole-body MRI-derived Reference Curves from Over 66,000 Individuals." Collaborating with Drs. Weiss and Jung were Marco Reisert, Ph.D., Hanna Rieder, Susanne Rospleszcz, Ph.D., Tobias Haueise, Ph.D., Tobias Pischon, Ph.D., Thoralf Niendorf, Ph.D., Hans-Ulrich Kauczor, M.D., Henry Völzke, M.D., Robin Bülow, M.D., Maximilian F. Russe, M.D., Christopher L. Schlett, M.D., M.P.H., Michael T. Lu, M.D., M.P.H., Fabian Bamberg, M.D., M.P.H., and Vineet K. Raghu, Ph.D.

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For patient-friendly information on MRI, visit *RadiologyInfo.org*.

Images (JPG, TIF):

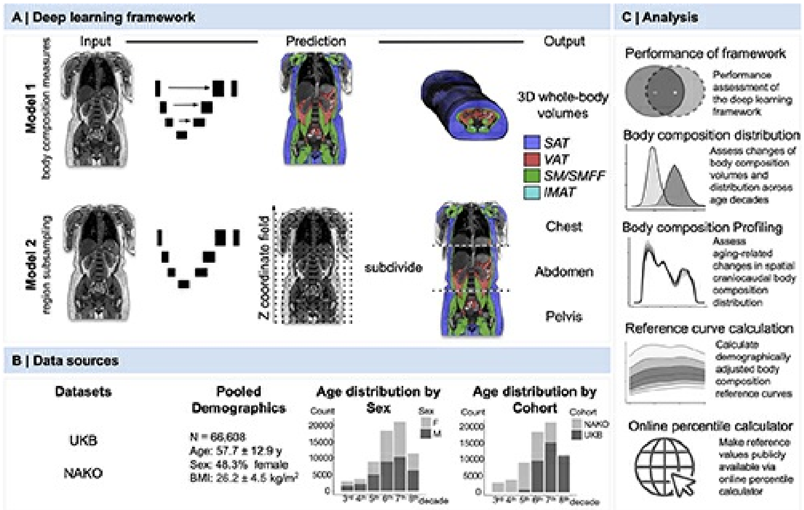

Figure 1. Overview of the study design. **(A)** The fully automated deep learning framework was developed to estimate body composition (BC) (defined as subcutaneous adipose tissue [SAT] in liters; visceral adipose tissue [VAT] in liters; skeletal muscle [SM] in liters; SM fat fraction [SMFF] as a percentage; and intramuscular adipose tissue [IMAT] in deciliters) from MRI. The fully automated framework comprised one model (model 1) to quantify different BC measures (SAT, VAT, SM, SMFF, and IMAT) as three-dimensional (3D) measures from whole-body MRI scans. The second model (model 2) was trained to identify standardized anatomic landmarks along the craniocaudal body axis (z coordinate field), which allowed for subdividing the whole-body measures into different subregions typically examined on clinical routine MRI scans (chest, abdomen, and pelvis). **(B)** BC was quantified from whole-body MRI in over 66 000 individuals from two large population-based cohort studies, the UK Biobank (UKB) (36 317 individuals) and the German National Cohort (NAKO) (30 291 individuals). Bar graphs show age distribution by sex and cohort. BMI = body mass index. **(C)** After the performance assessment of the fully automated framework, the change in BC measures, distributions, and profiles across age decades were investigated. Age-, sex-, and height-adjusted body composition reference curves were calculated and made publicly available in a web-based z-score calculator (https://circ-ml.github.io).

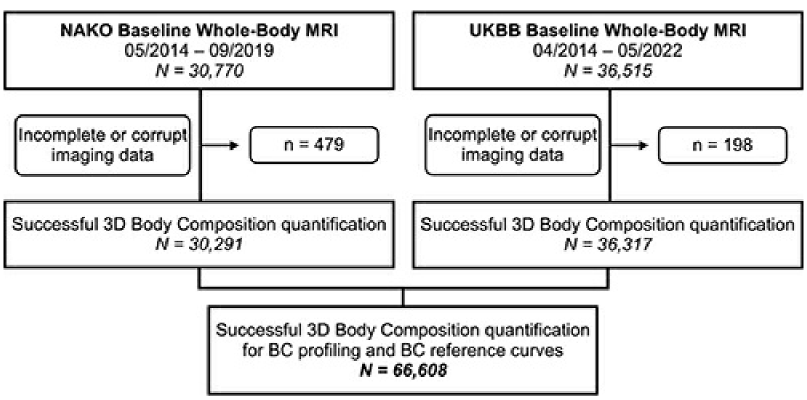

Figure 2. Flow diagram of German National Cohort (NAKO) and UK Biobank (UKBB) cohort. Body composition (BC) was defined as subcutaneous adipose tissue (in liters), visceral adipose tissue (in liters), skeletal muscle (in liters), and intramuscular adipose tissue (in deciliters). 3D = three-dimensional.

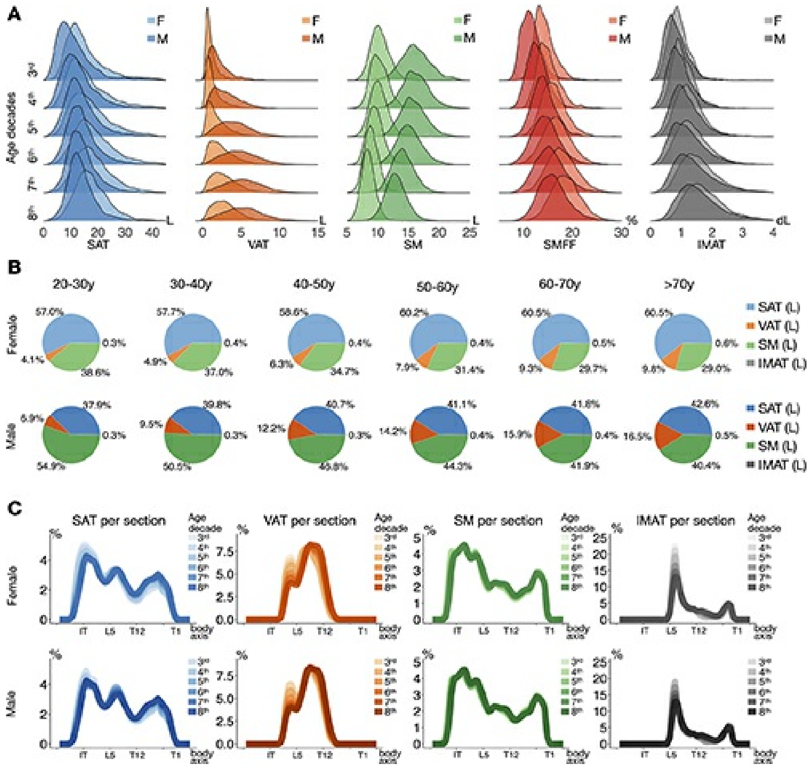

Figure 3. Body composition (BC) profiles across age decades. **(A)** Density plots show the change in BC measures subcutaneous adipose tissue (SAT) (in liters; blue), visceral adipose tissue (VAT) (in liters; orange), skeletal muscle (SM) (in liters; green), SM fat fraction (SMFF) (as a percentage; red), and intramuscular adipose tissue (IMAT) (in deciliters; gray) across age decades. Medians and IQRs are provided in Tables 3 and 4. **(B)** Pie charts show the age-related differences in the proportion of each individual BC measure (numerator) relative to the sum of all BC measures (SAT, VAT, SM, and IMAT; denominator) for females in the top row and males in the bottom row separately. Although SAT (blue) is the predominant BC compartment in females across all age decades, SM (green) is predominant in males until the age of 60 years. In both females and males, SAT (blue) remains relatively stable over time. However, there is a loss of SM (green) accompanied by a gain of VAT (orange), which is more pronounced in males than females. Additionally, there is a gain of IMAT (gray), which is more pronounced in females than males. **(C)** Profile plots demonstrate the differences in the spatial distribution of each BC measure along the craniocaudal body axis, categorized by age decades (color-coded) for females (top row) and males (bottom row). As individuals age, SAT shifts from the gluteal region to the chest, VAT moves from the pelvis to the abdomen, and SM shifts from the gluteal region to the trunk and chest in females, whereas in males, it shifts from the chest to the gluteal region. Additionally, paraspinal IMAT shifts from the lower lumbar spine to the upper thoracic spine. The x-axis displays 50 equidistant sampling points along the craniocaudal body axis, with notable anatomic landmarks at the following points: 10 for the ischial tuberosity (IT), 20 for lumbar vertebra 5 (L5), 30 for thoracic vertebra 12 (T12), and 43 for thoracic vertebra 1 (T1).

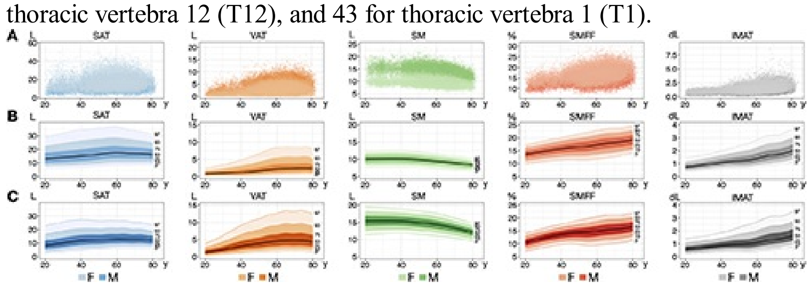

Figure 4. Scatterplots and reference curves for body composition (BC) measures. **(A)** Scatterplots of crude BC measures (defined as subcutaneous adipose tissue [SAT] in liters; visceral adipose tissue [VAT] in liters; skeletal muscle [SM] in liters; SM fat fraction [SMFF] as a percentage; and intramuscular adipose tissue [IMAT] in deciliters) as a function of age, stratified by sex. **(B, C)** Graphs show age-, sex-, and height-adjusted BC reference curves with 3rd, 10th, 25th, 50th, 75th, 90th, and 97th percentile lines for a 1.65-m-tall female **(B)** and a 1.75-m-tall male **(C)**. The variance of SAT was higher in 1.65-m-tall females, whereas the variances of VAT and SM were higher in 1.75-m-tall males compared with females across all ages. Variances for SMFF and IMAT were comparable for both sexes.

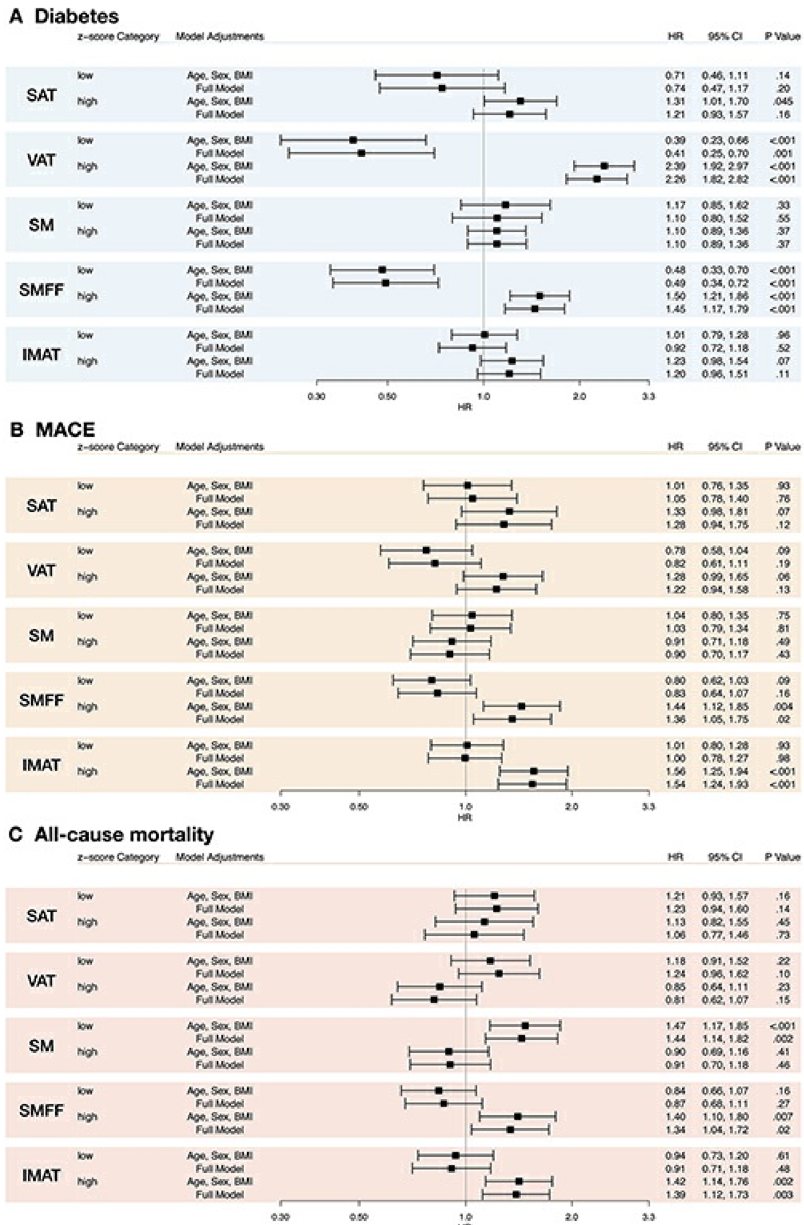

Figure 5. Hazard ratios (HRs) for the body composition (BC) z-score categories and incident diabetes, major adverse cardiovascular events (MACE), and all-cause mortality in the UK Biobank (UKB). Forest plots show HRs for high (z-score >1) and low (z-score < −1) BC z-score categories compared with the middle category (z, −1 to 1), along with 95% Cis from Cox proportional hazard regression analysis for **(A)** incident diabetes, **(B)** incident major adverse cardiovascular events, and **(C)** all-cause death in the UKB. BC was defined as subcutaneous adipose tissue (SAT) in liters; visceral adipose tissue (VAT) in liters; skeletal muscle (SM) in liters; SM fat fraction (SMFF) as a percentage; and intramuscular adipose tissue (IMAT) in deciliters. This analysis excludes individuals with prevalent diabetes or a history of myocardial infarction and/or stroke (1,872 of 36,317 individuals excluded). Models were adjusted for (a) age, sex, and body mass index (BMI) (calculated as weight in kilograms divided by height in meters squared) category (shown in the row labeled "Age, Sex, BMI" for each zscore category; n = 34 445) and (b) additional adjustments for traditional risk factors (shown in the row labeled "Full Model" for each z-score category) including race, alcohol consumption, smoking status, hypertension, antihypertensive medication, and a history of cancer (full model; n = 34 001; 444 observations deleted due to missing data) for each BC measure. After multivariable adjustment, z-score risk categories had HRs of up to 2.26 (high VAT category) for incident diabetes **(A)**, 1.54 (high IMAT) for incident major adverse cardiovascular events **(B)**, and 1.44 (low SM) for all-cause mortality **(C)** compared with the middle category.

Resources:

[Abstract link]()

Editorial link