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Perspective on the Body Mass Index (BMI) and Variability of Human Weight and Height

Mark P. Silverman[1,2]

[1]G A Jarvis Prof. of Physics, Emer., Trinity College, Hartford, CT, USA
[2]Tall Pines Research, Simsbury, CT, USA
Email: mark.silverman@trincoll.edu

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Abstract

The body mass index (BMI) is a medical risk factor that has been in use since 1972 to identify degrees of weightiness, in particular obesity and severe underweight. Over the past few years there has been much strident criticism of the BMI in traditional news media, health-related internet sites, and some medical journals over whether the index adequately identifies obesity of individuals in diverse demographics. As the research scientist (nuclear and medical physicist) who recently derived the exact statistical distribution functions of human weight, height, and BMI, I have found that much of this criticism is based on misunderstanding and misuse of the statistical nature of the BMI. In this Perspective, I attempt to make clear (1) what the BMI is, (2) why it was defined as it was, (3) how human height, weight, and BMI vary in a population, (4) the effective way to employ the BMI in clinical settings, and (5) what criteria to bear in mind if the BMI is to be replaced by some other medical index.

Keywords

Body Mass Index, Cut-Offs, Obesity, Overweight, Variability of Weight, Variability of Height, Correlation of Weight and Height, Lognormal Distribution

1. Introduction

Obesity is reported to be a chronic condition of epidemic proportions, associated with higher risks of hypertension, diabetes, heart disease, stroke, certain cancers, dementia, and other pathologies [1]-[4]. It is characteristic of populations in both developed and developing countries, of adults and children, and of both genders. The prevalence of obesity in the US is considered to be especially alarming. The US Centers for Disease Control and Prevention (CDC) report in Ref. 1 that the overall obesity rate for all age groups and both genders in the US is in excess of 40% of the population. The fraction of the US population classified as either overweight and/or obese is reported to be approximately 75% [5]. Relative to normal weight, obesity of all grades was found to pose a significantly higher risk of death [6].

In the foregoing cited studies—and many others that have investigated the relationship of obesity to health—the principal biomedical index used to identify and classify degrees of weightiness has been and remains at present the body mass index (BMI). Much has been written recently about the BMI; it is a highly controversial issue. Some critics call for replacing it [7]. Some say it is psychologically harmful to individuals [8]. At least one suggested it might be a scam [9]. These cited articles are just a sample of a cacophony of critical opinions in the news media, the internet, and some medical journals regarding the index first introduced by Ancel Keys as the BMI in 1972 [10].

While some criticism is justified, much of what I have seen ranged from misunderstandings to outright absurdity. I am the research scientist (nuclear and medical physicist) who recently determined the exact statistical distribution functions of human height, weight, and body mass index [11] [12], and tested these relations for men and women separately in a large diverse anthropometric survey of U.S. Army personnel [13]. To my knowledge, such a comprehensive analysis of this kind has not been done before, and it gives me a singular perspective on the nature and utility of the BMI.

In this article I would like to make clear what the BMI is, why it was defined as it was, how it varies in a population, the appropriate way to use it in clinical settings, and what one needs to consider if seeking to replace it.

2. Variability of Human Height, Weight, and BMI

Defined as the ratio of a person's weight (in kilograms) to the square of height (in meters), the BMI can vary widely within a random group of people. Technically, the BMI is not a number, but a composite random variable [14]. To be usefully applied, the details of how height, weight, and BMI vary in a population need to be understood. And *that* is precisely what I worked out in deriving these statistical distribution functions.

A statistical distribution function yields the probability of a given group having a particular value (or range of values) of the associated variable. Of what good is knowing this mathematical expression? The short answer is that it tells you *everything statistical* that can be known about the variable of interest. It generates every statistical moment (of which there is an infinite number) that a researcher or clinician might need. The lowest and most familiar moments are the *mean*, which signifies average, the *variance*, which signifies the spread about the mean, and the *skewness,* which signifies deviations from symmetry about the mean. Skewness plays a significant role in the application of the BMI.

Besides statistical moments, the exact distribution function provides a systematic way to assign boundaries (referred to as cutoff points) for BMI ranges (expressed by statistical quantiles) that classify degrees of weightiness. Currently in use by the World Health Organization (WHO) are five intervals (quintiles) for adults representing the conditions of severe underweight, underweight, normal weight, overweight, and obesity [15]. The longstanding inflexibility of the WHO ranges underlying this classification has drawn the ire of many critics who claim that the BMI cannot usefully indicate the health risks of diverse groups. In fact, with the use of the now known statistical distribution functions it can, and I will explain how.

The fundamental expression I derived follows from the mathematical definition of the BMI and therefore pertains to any and all populations. However, this general expression contains five measurable parameters that uniquely determine how height and weight vary in any designated population. These parameters are effectively the mean and variance of height, the mean and variance of weight, and the Pearson correlation [16] between weight and height. The parameters can be obtained from a statistical survey of the group of interest, such as was done of U.S. Army personnel. The WHO protocol of "one size fits all" cutoffs is *not* a statistically appropriate way to use the BMI.

Graphically, the distributions of height, weight, and BMI differ from a symmetric bell-shaped figure—or "normal curve"—that has approximated human physical attributes from the end of the 19th Century to the present. Rather, a plot of any one of the three variables on the horizontal axis and the probability of occurrence of that variable on the vertical axis yields a curve that rises steeply from baseline to a maximum, then descends more slowly towards baseline in a long, curved tail, such as shown in **Figure 1** for the BMI. This asymmetry displays the statistical property of skewness. In the previously cited papers [11] [12], I have shown rigorously that the BMI follows what is called a lognormal distribution [17], and that height and weight *together* comprise a bivariate lognormal distribution [18]. These distributions are given explicitly in the **Appendix**. To set BMI cutoff points appropriately requires that account be taken of weight and height together because weight is statistically correlated with height.

To picture the property of correlation, imagine plotting the weight of a person on the vertical axis and the person's height on the horizontal axis. Now do that for thousands of individuals in a particular group. The mass of points (called a scatter diagram) takes the form of a cigar-shaped cloud rising from lower left (short height) to upper right (tall height) at some angle to the horizontal axis. That angle (or an equivalent mathematical expression) yields the Pearson correlation coefficient comprising the fifth BMI distribution parameter. If weight were statistically independent of height, the scatter diagram would have taken the form of a circular cloud of points.

In view of the preceding, I can now answer the question: "Why is the BMI defined the way it is?" This is really equivalent to asking: "What is BMI all about, anyway?" Answers to the latter in both popular and medical media have often been muddled. A recent example [19] illustrates my point. After examining herself in a mirror, one critic described the BMI as having been designed specifically for cylindrical geometry, whereas what she believed was needed was a medical index designed for spherical geometry. However, the BMI is *not* concerned with geometry at all, but only with weight as a proxy for fat.

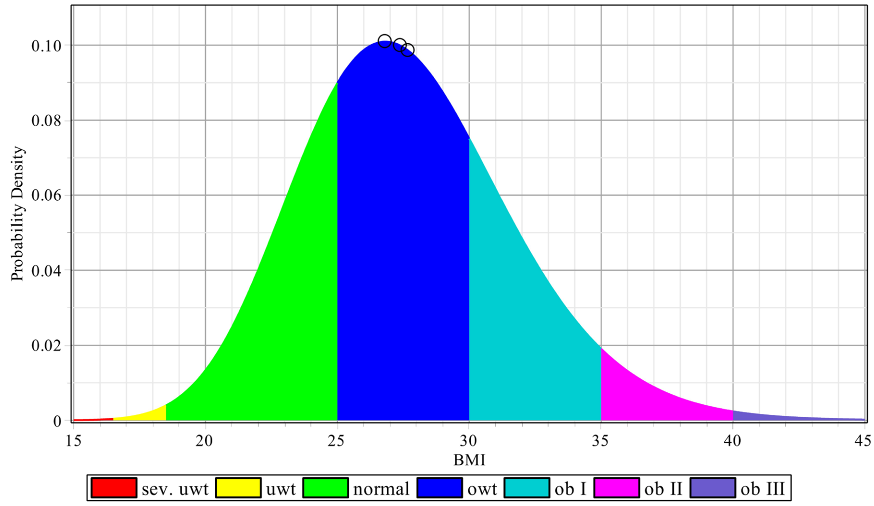

Figure 1. Exact BMI distribution of the ANSUR male cohort with color-coded partitions according to WHO categories. Abbreviations and colors in the legend correspond respectively to: (1) severe underweight (red), (2) underweight (yellow), (3) normal weight (green), (4) overweight (blue), (5) obesity class I (cyan), (6) obesity class II (fuchsia), (7) obesity class III (slate blue). Circular symbols of black, blue, and red respectively mark BMI values corresponding to the mode, median, and mean of the distribution.

Dividing weight by the square of height leads to a quantity statistically *independent* of height. In fact, the exact BMI distribution I derived *predicts* that BMI is uncorrelated with height for a diverse adult population. This relation is by no means obvious. Indeed, one might have thought on the basis of dimensional analysis [20] alone that human weight would be proportional to the 3rd power of length. Statistically, that is not the case. A scatter diagram of thousands of individual BMI values in the U.S. Army survey versus corresponding heights forms a circular cloud, confirming that the BMI and height are not correlated. Readers who have studied statistics may recall that two uncorrelated variables are not necessarily independent. That is not the case here. Advanced statistical tests in [11] [12] rigorously showed the independence of BMI and height empirically and theoretically. This independence, together with the convenience of measurement of weight and height, is one of the primary reasons why the BMI has been used for so many years as a medical risk factor linked to weight. Despite criticism, BMI still underlies the definition of obesity in recent comprehensive clinical trials [21], as well as serves as the triggering criterion in the newly proposed medical category of pre-clinical obesity [22].

A criticism I have seen recycled multiple times in the press and internet takes the form of an example of different body types (e.g. muscled, average, obese), which have been configured to have the same numerical BMI score [23]. While meant to dramatize the diagnostic impotence of the BMI, the example is largely irrelevant in clinical practice. When someone shaped like Arnold Schwarzenegger shows up for an annual physical, no competent physician is going to mistake his health profile for that of someone shaped like Chris Christie! The BMI is just one of a number of indications that clinicians use together with personal observations and common sense to gauge risks to the health of their patients because of an apparently high weight. Among these indications, for example, are central obesity, hypertension, and levels of triglyceride, high density lipoprotein (HDL), and plasma glucose [15].

Nevertheless, the claim is frequently made that BMI values do not correlate with individual adiposity (fat content) [24]. As of this writing, several of the most recent clinical trials tend to refute it. In a study [25] of 2,225 adults 20 to 59 years of age researchers found that approximately 98% of participants evaluated as obese on the basis of BMI values were confirmed as such by direct measurement of adiposity by dual-energy X-ray absorptiometry (DEXA). Results were said to be consistent across age, sex, race, and ethnicity. Adjustments were made, however, in the BMI cut-off points for different demographics. Another study [3] using the standard BMI intervals to identify specific classes of obesity in a cohort of more than 270,000 participants, found that obesity, and therefore the BMI identifications, strongly correlated with 16 serious health outcomes. One might infer, therefore, that the BMI values in this study were correctly associated with fat and not muscle.

3. The Problem of the Standard BMI Cut-Off Points

Much of the historical and ongoing criticism of the BMI centers on the matter of arbitrary and inconsistent cut-off points [26]. For example, in 1993 the WHO convened an expert group for the purpose of establishing uniform categories of the BMI. Initially, four categories were established, later to be expanded to five major categories (as listed previously) of which the last category (obesity) was subdivided into three classes. Concurrently with the WHO, the U.S. National Institutes of Health (NIH) established its own set of four categories, which in 1998 were adjusted to agree with the WHO quartiles. As expressed in one critique, this adjustment instantaneously transformed millions of Americans from normal weight to overweight [27].

It is precisely in the matter of establishing reliable, systematic category boundary points that knowledge of the exact BMI distribution function for specific groups is indispensable. The primary utility of the BMI is to establish a normal weight range from which to determine degrees of deviation that correlate with various health risks. Division of a continuous quantity like BMI values into discrete categories always entails a degree of arbitrariness. However, once a set of categories is created, the recently derived statistical distribution function provides a means to calculate rigorously the proportion of a particular group that falls between any two specified values of the variable.

A plot of the distribution function against its variable is *not* a histogram, which is the chart one can construct from a finite sample. Rather, it is the graphical embodiment of the "population statistics" obtained (in principle) by sampling a theoretically infinite population of the designated group. The calculated proportions show the true distribution of probability among the different categories. Examination of these probabilities provides insight into the consistency of any set of arbitrarily chosen cut-off values that define the categories and can indicate when these cut-off points need revising. Moreover, tracking how the relative probabilities of the categories change over time can reveal important population trends and associated medical issues.

As an illustrative example, consider the BMI distribution of the male cohort (sample size 4,082) of the Anthropometric Survey of U.S. Army Personnel (ANSUR) referred to in the Introduction [13] and analyzed in detail in Ref. [12]. The analysis yielded, among many other statistics, the five parameters required to calculate the unique exact BMI distribution function for this group. As described previously, a large sampling of the U.S. Army would be expected to comprise a diverse population in regard to race and ethnicity, as well as to include predominantly healthy individuals, since there are physical requirements that must be met to be in the military. **Figure 1** shows a plot of the ANSUR male BMI distribution, partitioned and color-coded to reflect the expanded WHO classification categories and cut-offs as summarized below [15]:

CATEGORY	BMI (kg/m^2)	PROPORTION (%)
Severely underweight (sev uwt)	0 - < 16.5	0.025
Underweight (uwt)	16.5 - < 18.5	0.33
Normal weight (normal)	18.5 - < 25.0	26.2
Overweight (owt)	25.0 - < 30.0	46.8
Obesity Class I (ob I)	30.0 - < 35.0	22.0
Obesity Class II (ob II)	35.0 - < 40.0	4.17
Obesity Class III (ob III)	≥40.0	0.47

(The BMI parameters of the ANSUR female cohort differ slightly, but do not lead to a qualitatively different distribution.)

Perhaps the most strikingly incongruous feature of this partitioning is the green sector marking the proportion of the male cohort classified as normal weight. Ordinarily, the statistical term "normal" is expected to apply to the sector of a distribution centered on some average measure (e.g. mode, median, or mean) and extending beyond and below this average by 1 or 2 standard deviations. With the WHO cut-off points, however, the normal sector in **Figure 1** is far to the left of the mode (location of maximum), median (boundary of 50th percentile), and mean, designated respectively by black, blue, and red circular symbols near the peak of the blue sector. The blue sector, which covers 46.8% of the distribution, represents the category of overweight, and the three subclasses of obesity together make up 26.7%, which is about the same proportion as the normal weight category, 26.2%. Only a tiny fraction of the ANSUR male distribution falls in the two categories of underweight.

The discordance of terms regarding normality is partly a matter of semantics and partly a matter of medical risk prediction. Statistically, the word "normal" is a relic of the (incorrect) belief that human physical attributes vary in accordance with the symmetric bell-shaped Gaussian (or normal) distribution, whereby the characteristics of the majority comprise the region centered on the symmetry axis where the mean, mode, and median all coincide. Medically, in regard to weight, the word "normal", as used by the WHO and NIH, signifies the proportion of individuals whose weight (adjusted for height) poses no obvious risk of metabolic and other disease. Why, then, might the two senses of normality not both apply to the ANSUR BMI distribution?

Several explanations may account for the partitioning displayed in **Figure 1**. One explanation is that the ANSUR male cohort, assumed to be diverse and healthy, is not representative of the population from which the WHO derived their cut-off points. Statistically, the preponderantly high BMI values of individuals in the ANSUR group may signify muscularity, rather than adiposity. This is certainly plausible for members of the military if they are in good health. Alternatively, if the statistically normal condition of the cohort is in fact to be overweight due to adiposity (with the attendant risks of metabolic disease and other pathologies), then that may reflect a lowering of physical standards in recruitment as a consequence of an increasingly overweight general population from which recruits come. This is also plausible according to numerous studies of increasing overweight and obesity among both children and adults in the U.S.

The exact BMI distribution function, having been derived recently, was not available to those who compiled the ANSUR data. However, retrospectively, given the discordance between expectations for the designated group (*i.e.* military men) and the associated WHO weight classifications in **Figure 1**, an appropriate follow-up might have been to conduct adiposity measurements, such as in Ref. [25], to establish whether the BMI of ANSUR male participants correlated primarily with fat or muscle. If the outcome were to be the former, then steps could be taken to tighten recruitment criteria and to implement programs to help improve the health of military personnel specifically and the public generally. If, however, the outcome were to be the latter—in which case the overweight range defined by BMI is really the statistically derived normal weight range of the group with no apparent adverse physiological consequences—then the following steps ought to be taken: (1) revise the BMI cut-offs for this particular group to reflect more accurately their health risks, and (2) archive the exact ANSUR BMI distribution function parameters for future use with other groups comparable to the ANSUR population.

Ultimately, the objective should be to compile such sets of parameters and associated sets of revised cut-off points for a broad spectrum of demographics so that this information can be made accessible to researchers and clinicians. It is to be emphasized that the task of transforming such statistical data into actionable guidelines is *not* meant to be the work of clinicians. This is a complex task, requiring adequate knowledge of statistics, medicine, and epidemiology, that should be undertaken by international health organizations such as the WHO or national health agencies such as the NIH in the US.

A program to compile the necessary data would first have to determine what criteria—such as race, ethnicity, specific cultural community, geography, physiology, pre-existing medical conditions, etc.—will define the demographics to study. Clearly, this must be done selectively, because for each defined group of interest anthropometric surveys would need to be organized and implemented in order to acquire reliable statistics that uniquely define the BMI distribution for that group. Once the statistics, in particular the lognormal distribution parameters, for the group is known, a distribution function like that in **Figure 1** can be generated, and quantile boundaries can be established that accurately represent different grades of risk. And at the end of the process, the resulting information must be made available for clinicians to consult and understand. Ideally, the information would be localized online so that a primary care physician could view it on a digital device when examining a patient. In this way researchers and clinicians, especially those involved in primary care, can better discern what is truly a normal weight range for a given group and the extent to which departures from normality actually pose risks of disease.

4. Conclusions: Lessons to Take away

The principal message of this Perspective is the following: BMI is a statistical risk factor for disease associated with weight, independent of height (for adults), and characteristic of groups rather than of individuals. Nevertheless, when the exact lognormal BMI distribution function with its five group-specific parameters is applied to the appropriate group of interest, the resulting statistics, including cut-off points if determined appropriately, can be used by clinicians to counsel individual patients within that group about the health implications of their BMI scores. Obese patients at greatest risk will generally have scores that fall under that skewed tail (as shown in **Figure 1**), so it is important that the exact distribution function be used in setting up cutoff points and in tracking changes in time of the distribution of BMI values.

Although not the focus of attention here, it is worth noting that various alternatives to the BMI have been proposed over the years—such as the Benn Index [28], Rohrer's Index [29], non-power law indices [30], and empirical parametric models [31]—all purporting to determine more satisfactorily than BMI a single optimal expression relating weight, size, and risk. A comprehensive historical review and comparison of body weight indices is given in reference [32]. These alternatives usually involved fitting a hypothesized model to data. However, the only expression that embodies complete statistical information for a chosen set of random variables is the probability distribution function or one of its equivalent transformations (such as the cumulative distribution function, moment-generating function, or characteristic function [33]). A complete statistical theory, in contrast to a formula acquired by curve-fitting, is valid over the entire allowed ranges of its variables, provides a rigorous means of estimating probabilities, moments, confidence limits, correlations, and quantiles, and applies to populations other than just the one (or few) used to create the model. Researchers who look to replace the BMI should keep the foregoing points in mind.

A second takeaway with potentially broad biological implications is that human height and weight jointly vary in a bivariate lognormal distribution to such perfection that just five population parameters currently suffice to predict within statistical uncertainties an extensive hierarchy of higher moments and correlations [11]. How this comes about is currently not known. Whereas the BMI is a defined quantity for which the exact mathematical form of the distribution function is calculable, the joint distribution function of human height and weight must be inferred and tested empirically. In principle no finite number of statistical tests can mathematically prove the exactness of a conjectured distribution.

Nevertheless, there are deep physical principles, such as the Principle of Maximum Entropy [34] [35], by which to infer the most probable distribution, given an initial set of observations. As the sample size increases, the maximum entropy distribution can become astronomically more probable than any other distribution. Under appropriate conditions, which are fulfilled by the initial information from which the joint distribution function of height and weight was derived, the bivariant lognormal distribution *is* the maximum entropy probability distribution.

As a matter of practical application, a distribution function may be regarded as effectively exact when it correctly predicts all testable statistical moments and correlations within the uncertainties limited by sample size. The current predictive success of the joint lognormal distribution of human height and weight suggests that this is not a statistical coincidence. If further research into the genetic and/or environmental determinants of height and weight can account for what appears to be an exact distribution, then medical science will likely have learned something fundamental about the biology of human development.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix A.

Statistical Distribution Functions of BMI, Weight and Height

In the expressions to follow, a random variable will be denoted by an upper-case letter (e.g. Z), and the realization of that variable, such as the outcome of a measurement or input to a calculation, will be denoted by the corresponding lower-case letter (e.g. z). The symbols employed are as follows:

Random Variables

Weight	W
Height	H
BMI	$Z = W / H^2$

Parameters

m_1 = mean value of ln(W)

m_2 = mean value of ln(H)

s_1 = standard deviation of ln(W)

s_2 = standard deviation of ln(H)

r = Pearson correlation of ln(W) and ln(H)

Note: The mean, variance, and correlation of W and H are given in Refs [11] [12].

I. Probability Density Function of BMI:

$$p_Z(z) = \frac{\exp\left(-\left(\ln(z) - m_1 + 2m_2\right)^2 / 2\left(s_1^2 + 4s_2^2 - 4rs_1s\right)\right)}{z\sqrt{2\pi\left(s_1^2 + 4s_2^2 - 4rs_1s_2\right)}}$$

II. Bivariate Probability Density Function of Height and Weight:

where

$$p_{(H,W)}(h, w) = \frac{1}{2\pi s_1 s_2 \sqrt{1-r^2}} \frac{\exp\left(-q_{h,w}/2\right)}{hw}$$

$$q_{h,w} = \frac{1}{\left(1-r^2\right)}\left[\left(\frac{\ln(w) - m_1}{s_1}\right)^2 - 2r\left(\frac{\ln(w) - m_1}{s_1}\right)\left(\frac{\ln(h) - m_2}{s_2}\right) + \left(\frac{\ln(h) - m_2}{s_2}\right)^2\right]$$

III. Parameters of the male ANSUR cohort:

Weight	$m_1 = 4.4351$	$s_1 = 0.1654$
Height	$m_2 = 0.5624$	$s_2 = 0.0390$
Correlation	$r = 0.4716$	

Appendix B. Author's Information

Author: Dr. Silverman is a nuclear and medical physicist, the G. A. Jarvis Professor of Physics Emeritus at Trinity College and a senior scientist at Tall Pines Research. This article was conceived and written by him alone with no reliance on artificial intelligence.