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A Statistical Optimization Approach to Body Mass Index Based on the Anthropometric Measurements

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ABSTRACT

Anthropometric indicators are commonly applied in health and nutritional assessments because they are simple, economical, and non-invasive. Among these indicators, Body Mass Index (BMI) is extensively used to evaluate obesity and nutritional status; however, it provides limited information regarding body fat distribution and composition. As a result, exclusive dependence on BMI may lead to misclassification in certain individuals. To address this limitation, recent research has emphasized the optimization of BMI prediction through the incorporation of multiple anthropometric measurements. This study examines the combined role of body weight, waist circumference, hip circumference, and neck circumference in enhancing BMI estimation. Advanced statistical optimization techniques, particularly Response Surface Methodology (RSM), provide a robust framework for analysing the simultaneous effects of these variables while capturing nonlinear relationships and interaction effects. The optimized models have potential applications in refining obesity classification, improving risk assessment, and supporting public health and clinical decision-making. This approach highlights the value of multivariate anthropometric optimization in overcoming the inherent limitations of traditional BMI-based evaluations...

Keywords BMI, Optimization, neck circumference, hip circumference, waist circumference

1. INTRODUCTION:

Body Mass Index (BMI) is widely employed as a practical anthropometric index for assessing nutritional status and categorizing individuals as underweight, normal weight, overweight, or obese in both clinical practice and population-based studies. BMI is computed as the ratio of body mass in kilograms to the square of height in meters (kg/m^2) and is endorsed by the World Health Organization as a standard indicator for large-scale obesity surveillance. Despite its extensive application, BMI does not directly quantify body fat content or regional fat distribution and may inaccurately classify individuals with elevated muscle mass or atypical fat deposition patterns (1,2). Consequently, increasing attention has been directed toward improving BMI prediction and interpretation through the inclusion of additional anthropometric variables such as body weight, waist circumference (WC), hip circumference (HC), and neck circumference (NC). These measures capture distinct aspects of central, peripheral, and upper-body adiposity and, when integrated within statistical or optimization frameworks, can enhance BMI estimation and obesity classification. This literature review consolidates existing research on the contribution and optimization of these anthropometric parameters for BMI prediction. Body weight represents a core anthropometric variable and constitutes a direct input in BMI calculation. Although body weight alone cannot differentiate between adipose and lean tissue, it remains strongly associated with BMI across diverse populations. Numerous investigations have reported robust correlations between body weight and BMI, underscoring its central role as a primary predictor in anthropometric optimization models (3). Waist circumference is widely recognized as a surrogate marker of abdominal obesity and visceral fat accumulation. A substantial body of evidence indicates that WC exhibits a strong positive association with BMI and, in many cases, provides superior prediction of cardiometabolic risk compared to BMI alone (4,5). This is largely attributed to the fact that abdominal fat deposition is more closely linked to insulin resistance, cardiovascular disease, and metabolic syndrome than overall adiposity (6). Hip circumference reflects gluteofemoral fat storage and underlying muscle mass, which have been associated with favourable metabolic profiles. HC shows strong correlations with BMI and contributes to improved BMI estimation when incorporated into multivariate regression models alongside WC and body weight (7). Several studies have demonstrated that HC independently enhances obesity prediction and strengthens the performance of anthropometric models [8].Neck circumference has recently gained prominence as a practical and reliable indicator of upper-body subcutaneous fat. Unlike WC, NC is minimally influenced by respiratory movement or postprandial abdominal distension and can be easily measured in routine clinical settings. Empirical studies report significant positive relationships between NC and BMI, WC, and total body fat percentage (8,9). Moreover, NC has been associated with cardiometabolic risk factors independently of BMI, indicating its potential added value in optimized anthropometric prediction models (10). Both cross-sectional and longitudinal studies consistently confirm a strong linear relationship between body weight and BMI. Regression-based analyses frequently identify weight as the dominant contributor to BMI variability, although normalization by height remains essential for standardization across individuals and populations (3,11). Similarly, WC and HC demonstrate strong positive correlations with BMI across different age groups and ethnic backgrounds. Reported correlation coefficients typically range from 0.75 to 0.85 for WC and from 0.80 to 0.88 for HC, reinforcing their suitability as surrogate predictors of BMI when direct height or weight measurements are unavailable (7,12). Evidence also indicates that NC increases progressively across BMI categories, with overweight and obese individuals exhibiting significantly larger NC values than those of normal weight (8,13). Multivariate analyses have shown that NC independently predicts BMI even after adjusting for WC and HC, highlighting its unique contribution to anthropometric modelling (8,9).

Response Surface Methodology (RSM), first introduced by Box and Wilson (14), comprises a set of statistical and mathematical techniques designed to model and optimize responses influenced by multiple independent variables. RSM facilitates the identification of optimal predictor combinations by explicitly accounting for interaction and nonlinear effects. Given the complex and multivariate nature of anthropometric influences on BMI, RSM offers a promising approach for optimizing predictive relationships between anthropometric inputs and BMI as the response variable. Conventional anthropometric studies have predominantly employed linear and multiple regression techniques to estimate BMI or classify obesity status based on anthropometric measures (3). While these methods provide clear interpretability, they are often limited in their ability to capture nonlinear trends and interaction effects among variables such as WC, HC, and NC. More advanced techniques, including polynomial regression and machine learning algorithms, have been investigated to enhance predictive accuracy (15). However, such methods may be prone to overfitting or reduced interpretability. In contrast, RSM provides an effective compromise by incorporating quadratic and interaction terms within a structured experimental design framework. RSM (16–18) has been widely applied in biological research to optimize systems governed by multiple interacting factors, including enzyme kinetics, pharmaceutical formulation, and biochemical process optimization (19–21). In food and nutrition sciences, RSM has proven effective in optimizing nutrient composition and product quality, demonstrating its ability to model biological variability and complex response behaviour (22–25).

Although direct applications of RSM to anthropometric BMI prediction remain limited, several studies have successfully employed RSM to optimize health-related outcomes influenced by multiple physiological parameters. These investigations underscore the methodological suitability of RSM for adaptation to anthropometric modeling and support its potential application in optimizing BMI prediction using multiple body measurements.

The present study successfully applied Response Surface Methodology (RSM) to investigate and model the combined influence of key anthropometric parameters—body weight, waist circumference, hip circumference, and neck circumference—on Body Mass Index (BMI). The coded experimental design comprising 29 runs,

2. Material and Method

The present investigation was conducted on college going girl students' **participants different aged,** studying in Mata Sundri Girls College, **Mansa District, Punjab**. Participants were **randomly selected**. Data were obtained from individuals attending various instrument used in Anthropometry parameters study. In total, **five variables** were recorded, comprising **four input parameters and One output parameter.** The study employed **four primary anthropometric variables—body weight, neck circumference, Waist and Hip circumference as input parameters** to predict a range of anthropometric dimensions. The measurement units of all input variables are presented in **Table 1.**

Table-1

Weight (Kg)	A =(35-38)	B= (39-42)	C=(43-46)
Waist Circumference (in Cm)	J= (24-26)	K=(27-29)	L= (30-32)
Hip Cicumference (in Cm)	R=(27-28)	S=(29-30)	T=(31-32)
Neck Circumference (in Cm)	11	12	13

3. Result and Discussion

Table 2 shows the coded experimental design matrix alongside the measured Body Mass Index (BMI) values, created to examine the combined effects of key anthropometric factors: weight, waist circumference, hip circumference, and neck circumference. The design includes 29 experimental runs, each representing a distinct combination of the input variables. The independent variables are expressed in coded form to standardize the data and support statistical analysis, following standard Response Surface Methodology (RSM) procedures. Several **center-point runs** (Runs 3, 6, 11, 22, and 25), where all inputs are set to zero, were included to assess experimental error and enhance the reliability of the model.

The dependent variable, BMI (kg/m²), shows values ranging from 13.81 to 20.04, reflecting variations resulting from different combinations of anthropometric measurements. Higher BMI values are generally observed when weight and waist circumference are at their upper coded levels, indicating their major influence on BMI. Hip and neck measurements also affect BMI, mainly through their interactions with other variables rather than as individual factors. Conversely, lower BMI values occur when weight and waist circumference are at lower coded levels, showing a clear negative relationship under these conditions.

Table-2 Data Collected

Run	Weight	Waist	Hip	Neck	BMI
1	1	1	0	0	18.15
2	-1	0	-1	0	16.7
3	0	0	0	0	17.22
4	1	-1	0	0	17.57
5	-1	0	0	1	17.51
6	0	0	0	0	20.04
7	0	1	0	1	17.22
8	1	0	0	-1	18.51
9	-1	-1	0	0	16.36
10	-1	1	0	0	16.92
11	0	0	0	0	17.22
12	1	0	0	1	19.38
13	0	1	1	[illegible]	[illegible]
14	0	1	-1	[illegible]	[illegible]
15	-1	0	1	[illegible]	[illegible]
16	0	0	1	[illegible]	[illegible]
17	0	1	0	[illegible]	[illegible]
18	0	0	-1	[illegible]	[illegible]
19	0	0	-1	[illegible]	[illegible]
20	1	0	-1	[illegible]	[illegible]
21	0	-1	1	[illegible]	[illegible]
22	0	0	0	[illegible]	[illegible]
23	0	0	1	[illegible]	[illegible]
24	0	-1	0	1	14.84
25	0	0	0	0	17.22
26	0	-1	0	-1	16.13
27	0	-1	-1	0	18.08
28	1	0	1	0	18.15
29	-1	0	0	-1	14.11

Table-3 ANOVA Result

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	19.08	4	4.77	2.93	0.0417	significant
A-Weight	14.61	1	14.61	8.98	0.0063	
B-Waist	0.0010	1	0.0010	0.0006	0.9803	
C-Hip Circum.	0.1519	1	0.1519	0.0933	0.7626	
D-Neck	4.32	1	4.32	2.66	0.1163	

Table-3 Depict the Anova results. The Model F-value of 2.93 implies the model is significant. There is only a 4.17% chance that an F-value this large could occur due to noise. P-values less than 0.0500 indicate model terms are significant. In this case A is a significant model term. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

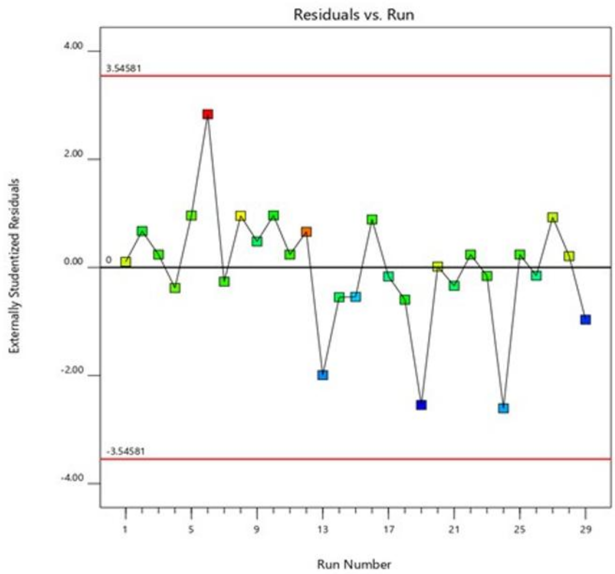

Figure-1 Residual plot

The figure-1 illustrates a **residual versus run plot** for the regression model developed to predict BMI from anthropometric parameters, including **weight, waist, hip, and neck measurements.** Residuals represent the **difference between the observed BMI values and those predicted by the model**. In this plot, the residuals have been **externally studentized**, meaning they are scaled by an estimate of their standard deviation that does not include the current observation, which helps to clearly identify potential outliers or extreme values. The horizontal red lines at approximately **±3.54581** denote the **critical limits**, beyond which residuals may indicate influential points that could disproportionately affect the model. Most residuals fall within these boundaries, suggesting that the **model predictions are robust** and that no significant outliers are present.

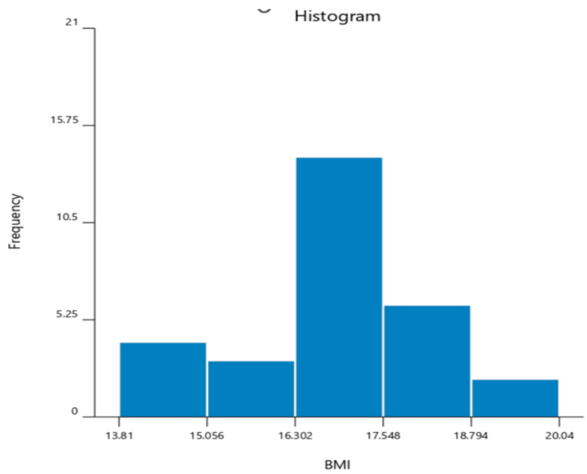

Figure-2

The figure-2 displays a **histogram of Body Mass Index (BMI) values** derived from the experimental runs. BMI values are plotted along the horizontal axis, while the vertical axis shows the number of observations within each class interval. This graphical representation allows evaluation of the **distribution pattern, data dispersion, and overall balance** of the BMI results. The BMI values span from approximately **13.81 to 20.04**, demonstrating a moderate level of variation among the experimental conditions. Most observations are concentrated within the **intermediate BMI range**, particularly between **16.3 and 17.5**, indicating that most of the experimental parameter combinations yield BMI values close to this range. The number of observations decreases progressively toward both the lower and upper ends of the distribution, suggesting limited occurrences of extreme BMI values. Overall, the distribution appears **approximately symmetric**, with no pronounced skewness, which indicates consistency and reliability in the experimental dataset.

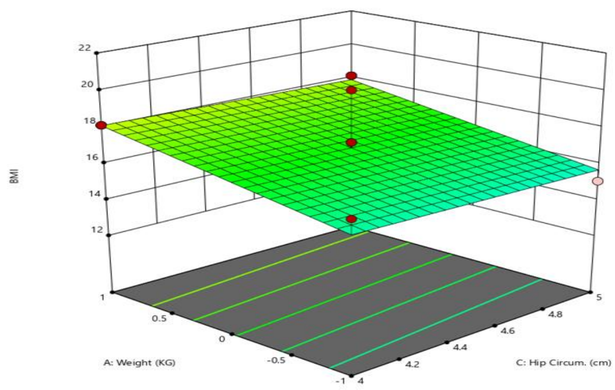

Figure-3.1 Graph between weight & Hip

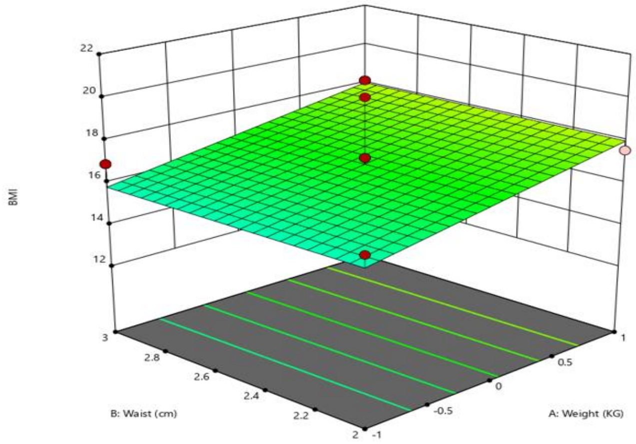

Figure-3.2 Graph between weight & Waist

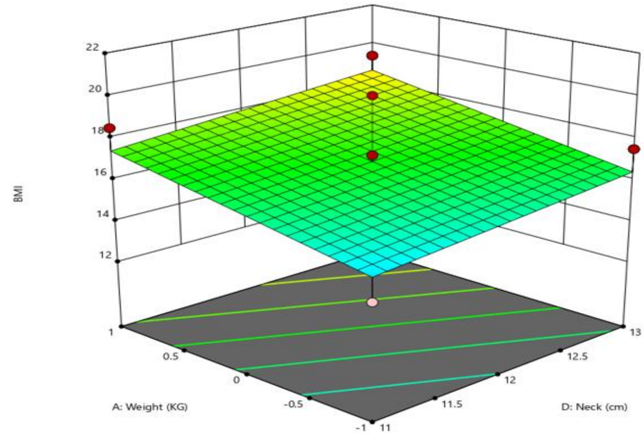

Figure-3.3 Graph between weight & Neck

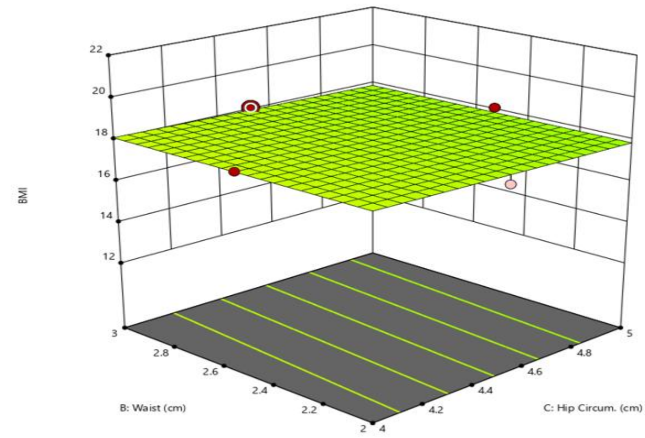

Figure-3.4 Graph between Waist & Hip

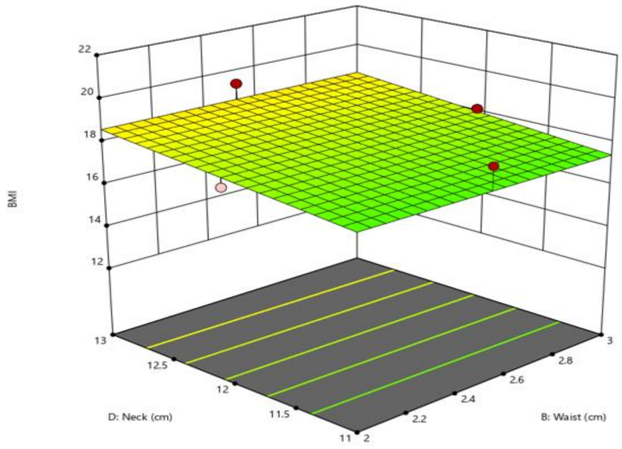

Figure-3.5 Graph between waist & Neck

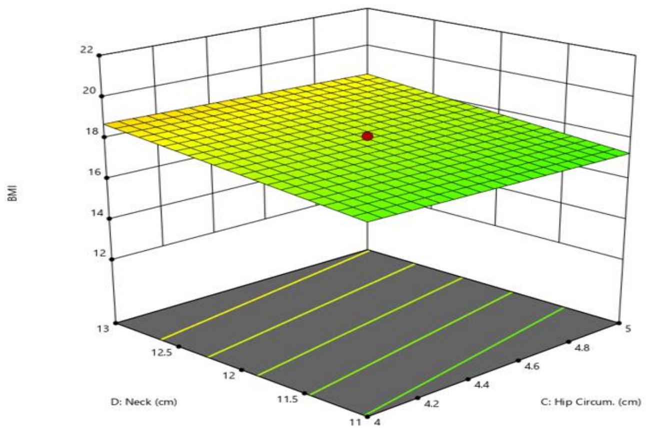

Figure-3.6 Graph between Hip & Neck

The 3-D graph from 3.1to 3.6 describe two parametric effects with one output in Response surface methodology (26–29). Figure 3.1 illustrates a smooth and systematic change in BMI across the studied parameter space, indicating a consistent relationship between the selected inputs and the response. BMI increases distinctly with rising body weight, highlighting weight as the most influential parameter in BMI determination. Hip circumference also affects BMI; however, the comparatively gentler slope along this axis suggests a weaker contribution than that of weight. The slight curvature of the surface reflects interaction effects between weight and hip circumference. The uniform and continuous nature of the surface confirms the robustness of the developed model and its capability to provide reliable predictions. Figure 3.2 depicts a steady rise in BMI with increasing body weight, reinforcing the dominant role of weight in influencing BMI. Waist circumference also contributes noticeably, with larger waist values leading to higher BMI levels. Nevertheless, the steeper gradient observed along the weight axis compared to the waist axis indicates that weight exerts a stronger individual effect on BMI than waist circumference. Figure 3.3 presents a clear upward trend in BMI as body weight increases, once again confirming weight as the primary driver of BMI variation. In contrast, neck circumference shows a relatively moderate effect, as evidenced by the gentler slope in its direction. This suggests that variations in neck circumference alone result in smaller changes in BMI when compared with changes in body weight. Figure 3.4 shows relatively mild slopes along both the waist and hip directions, indicating that changes in these parameters produce moderate variations in BMI when compared with weight-driven effects observed in other interaction plots. An increase in waist circumference leads to a gradual elevation in BMI, reflecting the role of central fat accumulation. Hip circumference also exhibits a positive influence, although its impact appears less pronounced. Figure 3.5 demonstrates an overall increase in BMI with rising neck and waist circumferences. Among the two, waist circumference has a more substantial influence, as indicated by the steeper gradient along the waist axis, confirming its stronger association with BMI. Neck circumference also contributes to BMI variation, though its effect remains comparatively modest. Figure 3.6 illustrates a gradual change in BMI across the range of neck and hip circumferences. BMI increases moderately with increasing hip circumference, as reflected by the gentle slope along this axis. Neck circumference also influences BMI; however, its individual contribution is relatively limited when compared with waist-related effects observed in other response surface plots. The table-4 depict optimize result as per data avialable row represents **anthropometric measurements** of an individual (or a category of individuals) and the **corresponding Body Mass Index (BMI).** Here is a clear explanation of each parameter and how the BMI value is interpreted.Establish relationships between body measurements and BMI. Identify underweight populations. Develop predictive or optimization models for BMI based on anthropometric parameters. The **low BMI (16.325)** suggests that the individual has **insufficient body mass** relative to height. The **waist and hip measurements** are relatively small, supporting the classification of a lean body type. A **neck circumference of 11 inches** is also indicative of low upper-body fat.

Table-4 Optimization Results

Number	Weight	Waist	Hip Circum.	Neck	BMI
1	39-42	30-32	29-30	11	16.325

4. Conclusion

The observed BMI values varied between 13.81 and 20.04 kg/m², demonstrating a clear spread in the response due to different combinations of anthropometric inputs. The ANOVA results verified that the proposed regression model is statistically acceptable, as reflected by a Model F-value of 2.93 and a low probability of 4.17% that such a value could result from random variation. Among the considered factors, body weight was identified as the most influential variable affecting BMI, followed by waist circumference. In contrast, hip and neck circumferences primarily affected BMI through their interactions with other parameters rather than as strong independent contributors. Evaluation of residual plots and BMI distribution histograms confirmed the stability and reliability of the dataset, with no abnormal or influential observations detected.

The response surface and interaction analyses showed smooth and well-defined patterns, indicating a dependable relationship between the selected inputs and BMI. In all interaction cases, BMI increased progressively with higher body weight, reaffirming its dominant influence. Waist circumference demonstrated a stronger association with BMI compared to hip and neck measurements, emphasizing the role of abdominal fat accumulation. Optimization analysis further highlighted the practical value of the developed model by identifying anthropometric conditions linked to low BMI. The optimized BMI of 16.325 corresponds to an underweight classification, supported by relatively small waist, hip, and neck dimensions, which are characteristic of a lean body structure. Overall, the study clearly quantifies the relationships between body measurements and BMI, confirms the suitability of RSM for BMI prediction and optimization, and offers a reliable approach for detecting underweight populations using easily measurable anthropometric parameters.

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