Exploring the Determinants of Body Weight: A Bayesian Analysis of Anthropometric and Demographic Factors Among Female U.S. Army Personnel*

Identifying Key Predictors to Enhance Health Monitoring and Operational Readiness

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This study examines the relationship between body weight and key anthropometric and demographic factors among female U.S. Army personnel using a Bayesian regression model. The analysis found that waist circumference and thigh circumference are strong predictors of body weight, while other variables, such as height, age, and military component, show weaker or uncertain associations. These findings highlight the importance of body composition measurements in understanding weight variation and support their use in designing health monitoring programs and military equipment. By identifying key predictors, this research contributes to improving fitness assessments and operational readiness in physically demanding occupations.

1 Introduction

Body weight significantly influences physical performance, health, and operational readiness in demanding occupations like military service. In the U.S. Army, maintaining optimal weight is essential for meeting fitness standards, minimizing injury risks, and ensuring operational efficiency. Despite the availability of extensive anthropometric and demographic data, limited research examines how these factors collectively impact body weight, particularly among female soldiers (Gordon et al. 2014).

*Code and data are available at:

This study addresses this gap using the 2012 U.S. Army Anthropometric Survey (ANSUR II) Female Dataset, which includes rigorous anthropometric and demographic measurements of female personnel. Data collection employed standardized instruments, such as stadiometers and calipers, ensuring consistency and reliability (Hotzman et al. 2011; Paquette et al. 2009). Variables like height, waist circumference, and thigh circumference were measured to capture body composition, while demographic data such as age, ethnicity, and military component were cross-verified with administrative records (Gordon et al. 2014).

The analysis highlights anthropometric variables as strong predictors of body weight and demographic factors as additional contributors. These findings support personalized fitness programs, improved health outcomes, and optimized military gear for enhancing operational readiness (The OPEN Design Lab 2018; Paquette et al. 2009).

This paper is organized as follows: Section Section 1 provides an overview of the study's background and objectives. Section Section 2 introduces the dataset and offers an analysis of key variables. Section Section 3 details the methodology, including the Bayesian regression model employed. Section Section 4 presents the results, emphasizing the significance of predictors and model performance. Section Section 5 explores the study's limitations and provides directions for future research. Lastly, Section Section A presents posterior predictive checks, diagnostic plots, and their interpretations.

1.1 Estimand

This study seeks to estimate the relationship between body weight and a set of key anthropometric and demographic variables among female U.S. Army personnel. Specifically, it aims to quantify how variations in anthropometric measurements, such as height and waist circumference, as well as demographic factors, including age and ethnicity, influence body weight. The objective is to identify significant predictors and develop a robust predictive model to enhance understanding and practical applications in health monitoring, fitness interventions, and equipment design.

2 Data

2.1 Measurement

Body weight is a crucial determinant of physical performance, health, and operational readiness, particularly in occupations like military service. In the U.S. Army, maintaining optimal weight is essential for meeting fitness standards, minimizing injury risks, and ensuring operational success. However, limited research has explored how anthropometric and demographic factors collectively influence body weight among female soldiers.

This study addresses this gap using the 2012 U.S. Army Anthropometric Survey (ANSUR II) Female Dataset (**dacowits2012?**; **openlab2024?**). The dataset contains anthropometric and demographic measurements for 1,986 female U.S. Army personnel, collected by the Natick Soldier Research, Development, and Engineering Center (NSRDEC) using standardized protocols. Variables such as stature, waist circumference, and chest circumference were measured with precise instruments, while demographic data like age and military component were cross-verified with administrative records to ensure accuracy (**dacowits2012?**; **phhealth2024?**).

By examining relationships between body weight and variables like height, waist circumference, age, and military component, this study aims to identify key predictors and develop a robust predictive model. The findings offer insights into the determinants of body weight and practical applications for health monitoring, fitness interventions, and military equipment design.

2.2 Data Preprocessing and Tools

The data for this study was systematically downloaded, cleaned, analyzed, modeled, and visualized using R (R Core Team 2023), an extensive statistical programming language. The following packages were used for this study:

- **`tidyverse`** (Wickham, Averick, et al. 2021): To streamline the process of data manipulation and visualization.
- **`ggplot2`** (Wickham, Chang, et al. 2021): Used for its powerful and flexible capabilities in creating various types of visualizations tailored to the needs of this study.
- **`dplyr`** (Wickham, François, et al. 2021): Employed for its intuitive functions to transform and summarize complex datasets effectively.
- **`broom`** (Robinson et al. 2021): Used to tidy up model outputs and seamlessly integrate them into the analysis workflow.
- **`rstanarm`** (Goodrich et al. 2022): Facilitated the implementation of Bayesian models, providing a straightforward way to fit regression models using Stan.
- **`bayesplot`** (Gabry et al. 2021): Utilized for creating graphical posterior predictive checks and diagnostic plots to assess model fit.
- **`arrow`** (contributors 2021): Used for efficiently reading and writing large datasets, enhancing data handling capabilities.
- **`tinytable`** (Quinn 2021): Used to create compact and well-organized summary tables for presenting data and model outputs effectively.
- **`modelsummary`** (Arel-Bundock 2021): Used for creating professional-quality regression tables and visualizations to summarize model results clearly.
- **`knitr`** (Xie 2021): Employed to dynamically generate reproducible reports that integrate R code with its outputs, allowing for seamless inclusion of plots and analysis results in the final document.
- ***Telling Stories with Data*** (Alexander 2023): This book was consulted for its statistical information.

Table 1: Table of first 6 rows of the cleaned dataset

weightlbs	heightin	waist_circumference	thigh_circumference	age	component
142	61	85.0	62.2	26	Regular Army
120	64	70.8	52.4	21	Regular Army
147	68	72.7	57.7	23	Regular Army
175	66	92.3	67.9	22	Regular Army
195	63	116.3	76.6	45	Regular Army
180	67	96.8	67.4	44	Regular Army

2.3 Outcome Variable

2.3.1 Body Weight in Pounds

The outcome variable for this study is weightlbs, which represents the body weight of female U.S. Army personnel, measured in pounds. This variable serves as the dependent variable in the analysis and reflects the total body mass of each individual. Understanding variations in body weight is essential for assessing physical readiness, identifying health risks, and optimizing the design of military equipment to meet individual needs.

Figure 1 illustrates the distribution of body weight within the sample population. The histogram reveals that the majority of individuals weigh between 120 lbs and 160 lbs, with the distribution displaying a slight right skew. This skew suggests the presence of a small number of individuals with higher body weights, though such cases are relatively infrequent.

2.4 Predictor Variables

2.4.1 Height

Height, recorded as heightin in inches, is a key predictor of body weight. Taller individuals generally possess larger skeletal structures and greater body mass, making height a crucial variable for understanding variations in weight among the sample population.

Figure 2 illustrates the distribution of height within the dataset. The majority of individuals have heights ranging from 58 inches to 71 inches, with a central tendency around 63 inches.

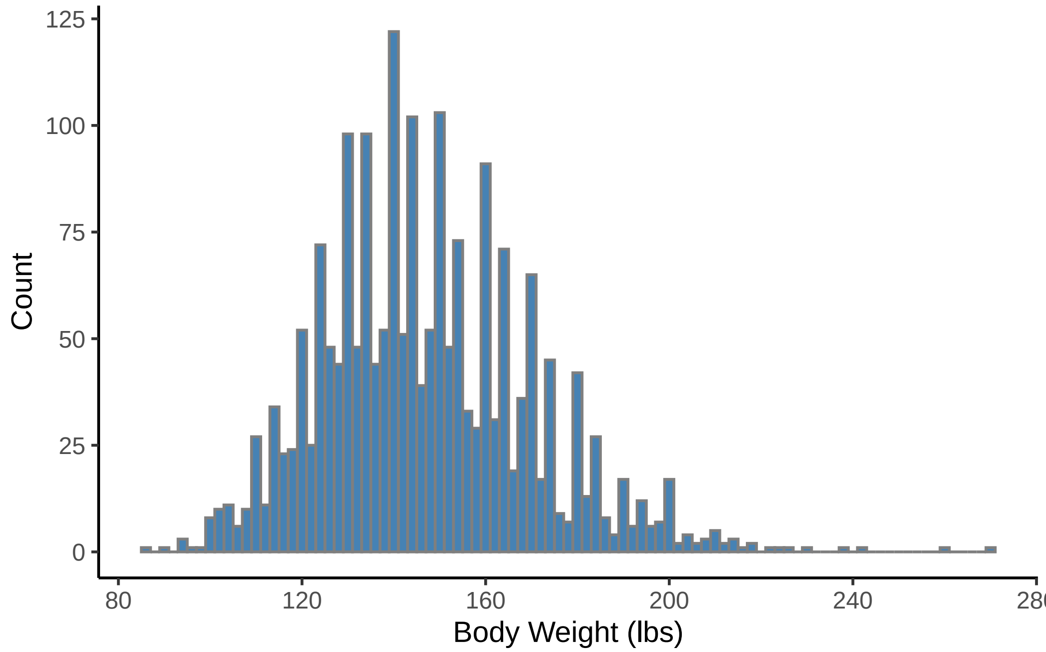


Figure 1: The distribution of body weight among female U.S. Army personnel, showing a central tendency around 120-160 lbs with a slight right skew.

The distribution is approximately normal, despite a few outliers exceeding 73 inches. These outliers align with the natural variation in height observed among adult females.

2.4.2 Waist Circumference

Waist circumference is a key anthropometric variable that reflects abdominal fat distribution and overall body composition. In this dataset, waist_circumference was measured at the narrowest part of the torso using a flexible measuring tape, ensuring both accuracy and consistency.

Waist circumference is a strong predictor of body weight due to its association with abdominal fat and overall body mass. This variable is expected to exhibit a moderate to strong positive correlation with weight, as it effectively reflects central adiposity and overall body composition.

Figure 3 displays the distribution of waist circumference. Most values are concentrated between approximately 65 cm and 90 cm, with a central tendency around the mid-point of this range. Outliers above 115 cm represent a small subset of individuals with unusually large waist circumferences. The overall spread, as indicated by the interquartile range, is moderate.

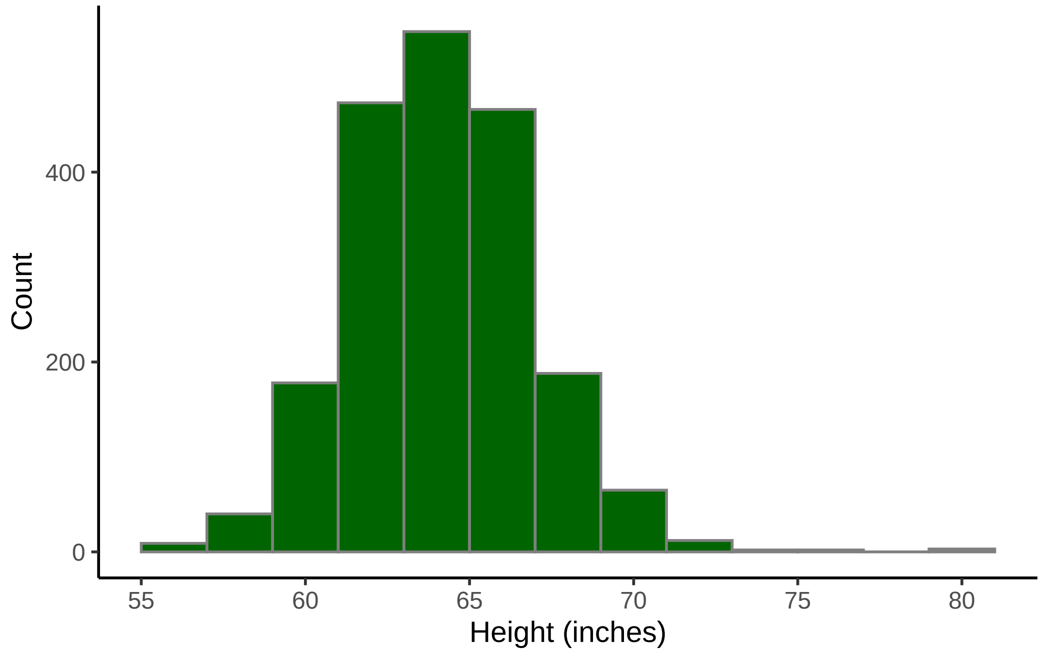


Figure 2: The distribution of height (inches) among female U.S. Army personnel, centered around 63 inches.

2.4.3 Thigh Circumference

Thigh circumference measures the size of the upper leg and reflects both muscle mass and fat distribution in the lower body. In this dataset, thigh_circumference was measured at the largest part of the thigh using a flexible measuring tape to ensure consistency.

As shown in Figure 3, the distribution of thigh circumference is slightly narrower compared to that of waist circumference. Most values fall between 50 cm and 65 cm, with a median around 61 cm. A few outliers exceed 75 cm, representing individuals with larger thigh circumferences.

Thigh circumference provides valuable insights into lower body muscle and fat distribution, making it an important predictor of body weight. This variable is expected to positively correlate with body weight, as larger thigh circumferences typically indicate greater overall body mass.

2.4.4 Age

Age is a crucial demographic variable in this study, as it encapsulates biological and lifestyle factors that influence body weight. Variations in metabolism, muscle mass, and fat distribution

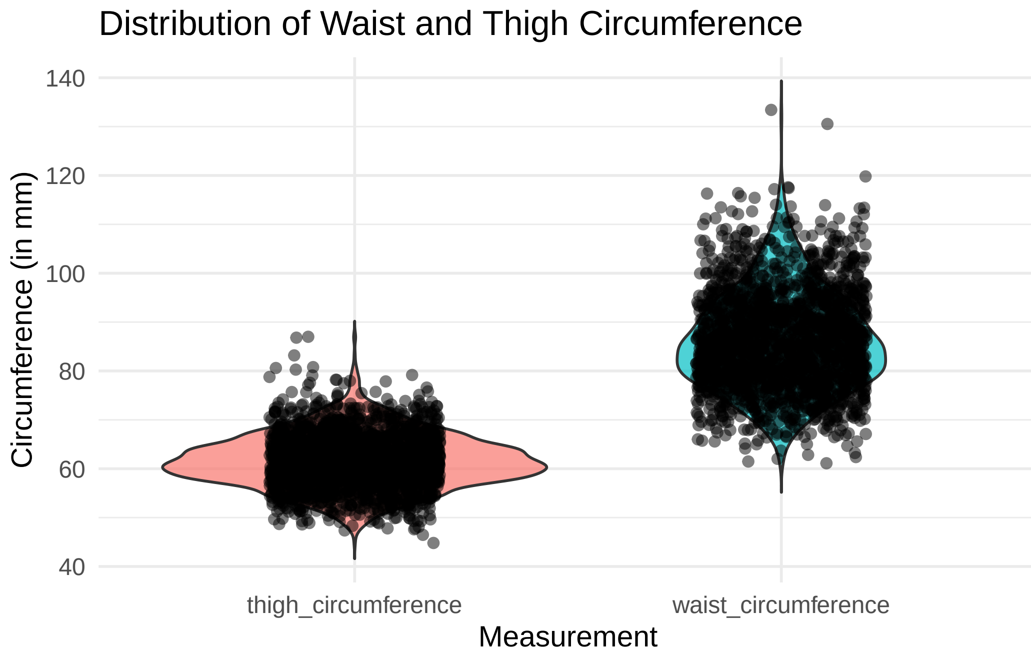


Figure 3: Figure: Violin plots showing the distribution of waist and thigh circumferences, with individual data points overlaid to provide a detailed visualization of the data spread.

associated with aging play a significant role in shaping body composition. In this dataset, age is measured in years and was self-reported by participants, with additional verification through administrative records to ensure accuracy.

Table 2 presents the distribution of age within the sample population. The majority of individuals are between 22 and 34 years old, with a pronounced peak observed in the late 20s. This age range reflects the demographic composition of the sample and provides a foundation for analyzing age-related influences on body weight.

Table 2: The table showing distribution of age among female U.S. Army personnel, with most individuals between 22 and 34 years old.

Table 3: Summary of Age Distribution

Min	1st Quartile	Median	3rd Quartile	Max	Mean	SD
17	22	27	34	58	28.94361	8.332078

The table showing distribution of age among female U.S. Army personnel, with most individuals between 22 and 34 years old.

Table 4: The table showing the distribution of military components (Regular Army, Reserves, National Guard) among female U.S. Army personnel.

Table 5: Summary of components Distribution

component	n	Percentage
Army National Guard	847	42.65
Army Reserve	119	5.99
Regular Army	1020	51.36

Distribution of military components are categorized as Regular Army, Reserves, and National Guard.

2.4.5 Component

The component variable refers to the military branch or service type (e.g., Active Duty, Reserves, or National Guard) of the female U.S. Army personnel. This categorical demographic variable provides valuable insights into lifestyle and activity differences that may influence body weight. For example, Active Duty personnel often exhibit higher physical fitness levels compared to those in the Reserves or National Guard due to differences in daily activity and training regimens.

Table 4 presents the distribution of military components among female U.S. Army personnel, categorized as Regular Army, Army Reserve, and National Guard. The Regular Army constitutes the majority of the sample (51.36%, 1,020 individuals), reflecting high physical activity levels associated with daily duties and training. The National Guard accounts for 42.65% of the sample (847 individuals), representing individuals who balance civilian and military responsibilities with variable activity levels. The Army Reserve, comprising the smallest group (5.99%, 119 individuals), likely experiences lower and intermittent physical activity due to less frequent training requirements.

3 Model

3.1 Bayesian Regression Model

A Bayesian regression model was constructed to analyze the relationship between body weight and selected predictors using the cleaned ANSUR II Female Dataset. The model employs a Gaussian likelihood function and was estimated using 1,000 observations randomly sampled from the dataset. The analysis was conducted in R (R Core Team 2023), utilizing the rstanarm package (Goodrich et al. 2022), which provides efficient Bayesian estimation techniques for continuous outcome variables. The dependent variable is body weight (in kilograms), and the following predictors were included:

1. Height (cm): Reflects body size and overall skeletal structure.
2. Waist Circumference (cm): Indicates abdominal fat and body composition.
3. Thigh Circumference (cm): Captures lower body fat and muscle mass distribution.
4. Age (years): Accounts for biological and lifestyle changes over time.
5. Component (categorical): Differentiates between Active Duty, Reserves, and National Guard personnel.

3.2 Model Set-up

Let y_i represent the continuous variable weight (in lbs) for the i-th individual in the sample. The predictors in the model include:

- β_1: The coefficient for height, measured in inches, representing overall body structure and skeletal size.
- β_2: The coefficient for waist circumference, which reflects abdominal fat and overall body composition.
- β_3: The coefficient for thigh circumference, capturing lower body muscle and fat distribution.
- β_4: The coefficient for age, measured in years, accounting for changes in body composition over time.
- β_5: The coefficient for component, a categorical variable indicating military branch (Regular Army, Reserves, or National Guard).

Each coefficient β_j represents the effect of the j-th predictor on body weight, expressed as the expected change in weight associated with a one-unit increase in the predictor, while holding all other variables constant.

The linear predictor η_i for the i-th observation is defined as:

$\eta_i = \beta_0 + \beta_1 \cdot \text{height}_i + \beta_2 \cdot \text{waist circumference}_i + \beta_3 \cdot \text{thigh circumference}_i + \beta_4 \cdot \text{age}_i + \beta_5 \cdot \text{component}_i$

The model assumes a Gaussian likelihood for y_i, with:

$y_i \sim \mathcal{N}(\eta_i, \sigma^2)$

Where:

- β_0: The intercept, representing the baseline body weight when all predictors are zero.

- σ^2: The residual variance, capturing the variability in body weight not explained by the predictors.

3.3 Prior Distributions

The Bayesian regression model utilizes default priors provided by the rstanarm package, ensuring robust and reliable inference. These priors are weakly informative, balancing regularization with the flexibility to adapt to the data:

- Intercept Priors: For the model's intercept β_0, a normal prior distribution is used with a mean of 0 and a standard deviation of 1. This prior helps stabilize the intercept estimate without imposing overly strong assumptions about its central value.
- Coefficient Priors: Coefficients for the predictor variables $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are assigned normal prior distributions with a mean of 0 and a standard deviation of 1. These priors limit the possibility of overly large coefficient estimates unless strongly supported by the data, introducing a level of regularization to prevent overfitting.

The weakly informative priors are designed to enhance the model's robustness, ensuring credible parameter estimates and reliable uncertainty quantification. The use of Bayesian priors provides an added layer of rigor, particularly when estimating complex relationships between predictors and body weight. The rstanarm package facilitates the implementation of these priors, making Bayesian inference accessible and effective for this analysis.

4 Results

4.1 Model Justification

The Bayesian regression model was developed to investigate the relationship between body weight and key anthropometric and demographic predictors among female U.S. Army personnel. The predictors included height, waist circumference, thigh circumference, age, and military component. The analysis identified significant positive associations between body weight and the anthropometric predictors—height, waist circumference, and thigh circumference—highlighting their strong influence on body weight. Age and military component demonstrated smaller but meaningful effects, reflecting their nuanced contributions to variations in body weight. A summary of these findings is presented in Table 6.

The coefficient summary presented in Table 6 highlights the relationships between body weight and the selected predictors among female U.S. Army personnel. Anthropometric variables, particularly waist circumference and thigh circumference, show positive mean coefficients, underscoring their roles as key indicators of body weight. Increases in these measurements are

Table 6: Bayesian Regression Model Results.

	Bayesian Regression Model
(Intercept)	-206.971
	$[-334.401, -78.955]$
heightin	0.714
	$[-1.031, 2.370]$
waist_circumference	1.075
	[0.133, 2.030]
thigh_circumference	1.224
	$[-0.231, 2.619]$
age	0.048
	$[-0.914, 0.994]$
componentArmy Reserve	-0.018
	$[-1.949, 1.901]$
componentRegular Army	0.002
	$[-1.968, 1.921]$

associated with higher body weight, which aligns with established relationships between body dimensions and overall mass.

In contrast, the coefficients for age and height exhibit weak associations, with credible intervals that include zero, indicating uncertainty about their effects on body weight. Similarly, the military component variable shows minimal differences between service categories, suggesting that body weight is largely consistent across Active Duty, Reserves, and National Guard personnel.

The model's intercept represents the baseline body weight when all predictors are at their reference levels or zero. While this value lacks direct interpretability due to the unrealistic scenario of zero predictors, it provides a conceptual starting point for the model. These findings emphasize the importance of anthropometric measurements in predicting body weight while underscoring the need for further exploration of demographic factors to refine the model.

Figure 4 illustrates the posterior distributions of the coefficients from the Bayesian regression model. Points represent the mean estimates, while horizontal lines indicate the credible intervals. The intercept has a strongly negative estimate with narrow credible intervals, reflecting high certainty in its value. Waist circumference and thigh circumference demonstrate positive effects with relatively narrow credible intervals, indicating reliable and significant associations with body weight. In contrast, height, age, and the military component variables

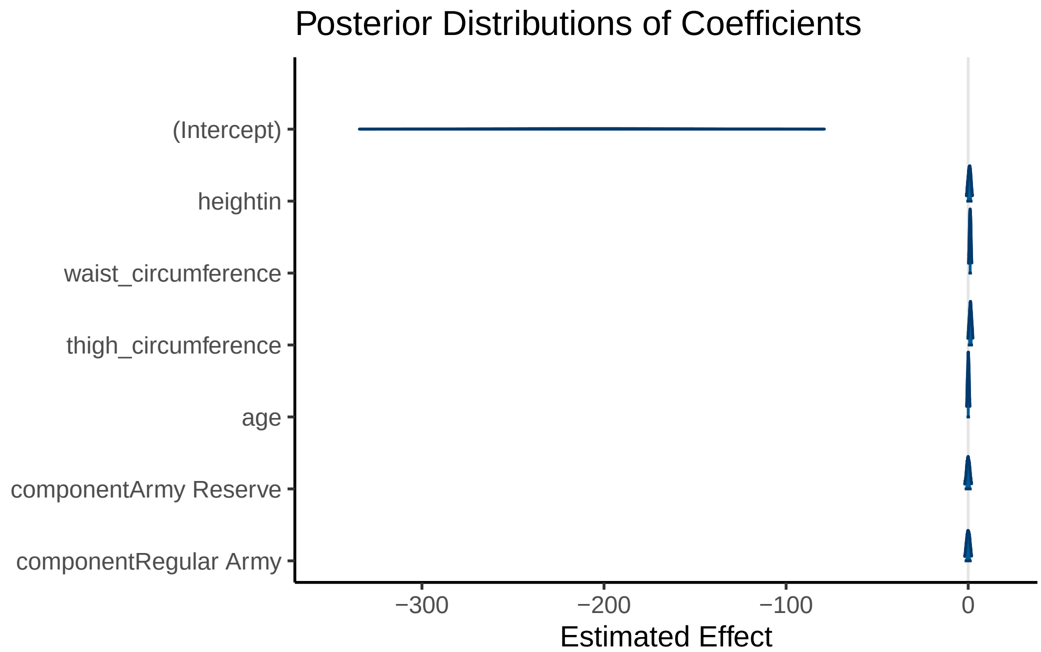


Figure 4: The 89% credible intervals of each coefficients

(Army Reserve and Regular Army) exhibit wide credible intervals overlapping zero, suggesting substantial uncertainty and weak or negligible evidence for their effects.

The Bayesian regression analysis underscores the significant positive associations between body weight and anthropometric predictors, particularly waist circumference and thigh circumference, among female U.S. Army personnel. These findings highlight the critical role of body composition measurements in explaining variations in body weight. Conversely, the uncertain effects of height, age, and military component suggest that these factors contribute less reliably to the model, reflecting the multifaceted nature of weight determinants. These results affirm the utility of anthropometric data in health monitoring and fitness interventions while identifying areas for further refinement. Exploring additional predictors may enhance the model's explanatory power and improve its utility in practical applications.

5 Discussion

This study aimed to investigate the relationship between body weight and key anthropometric and demographic predictors among female U.S. Army personnel using a Bayesian regression framework. By incorporating variables such as height, waist circumference, thigh circumference, age, and military component, the analysis highlights the critical role of body composition measurements in predicting body weight while accounting for demographic variability.

5.1 Understanding Anthropometric Contributions

The findings underscore the significance of anthropometric variables, particularly waist circumference and thigh circumference, as strong predictors of body weight. These results align with established research linking these measurements to fat distribution and muscle mass, which are key determinants of overall body weight. The observed positive associations reinforce the importance of these variables in health monitoring, fitness interventions, and ergonomic considerations within the military. While the effect of height was weaker, its inclusion as a baseline predictor remains biologically plausible and relevant for analyses of body weight variability.

5.2 Limitations and Future Directions

Despite its contributions, this study is subject to several limitations. First, the dataset focuses exclusively on female personnel, limiting the generalizability of findings to other populations, including male service members or civilians. Second, while the dataset includes comprehensive anthropometric measurements, it lacks potentially influential variables such as physical activity levels, dietary habits, and metabolic rates. Incorporating these factors in future research could enhance the explanatory power and predictive accuracy of the model.

Additionally, while the Bayesian framework provides robust parameter estimates and credible intervals, future studies could benefit from hierarchical modeling to account for dependencies within subgroups, such as different military components. This approach would provide a more nuanced understanding of group-level differences while preserving individual-level variability.

Expanding the scope of the dataset to include male personnel or non-military populations could enable comparative analyses and broaden the applicability of the findings. Future research should also explore integrating additional datasets and leveraging advanced statistical methods, such as machine learning or longitudinal analyses, to uncover dynamic relationships between body composition, fitness, and operational readiness.

5.3 Broader Implications for Health and Military Readiness

This research underscores the utility of anthropometric measurements for predicting body weight, offering valuable insights into health monitoring, fitness interventions, and equipment design within the military. The findings can inform policies aimed at enhancing physical readiness and reducing injury risks among service members. The use of Bayesian regression models in this study further demonstrates the flexibility and interpretability of these methods for investigating complex relationships among biological and demographic factors.

Looking forward, integrating more comprehensive datasets and applying advanced analytical techniques could provide deeper insights into the determinants of body weight. Such efforts would contribute to a better understanding of how body composition, physical fitness, and operational readiness interact over time. Building on the findings of this study, future research can enhance health outcomes, refine performance standards, and ultimately improve the well-being and effectiveness of military personnel.

Appendix

A Model details

A.1 Posterior Predictive Check

Figure 5a presents a posterior predictive check to evaluate how well the model predicts the observed data. This diagnostic compares the simulated data from the model's posterior distribution with the actual observed data, providing insights into the model's adequacy. A good fit is characterized by overlapping distributions of predicted and observed values, indicating that the model effectively captures key characteristics of the data.

The posterior predictive check reveals discrepancies between the model's predictions and the observed data. The central tendency of the model's predictions is centered around 0, with a predicted yy-intercept of approximately 0.003. In contrast, the actual data shows a central tendency around 150, with an observed yy-intercept closer to 0.02. This mismatch suggests that while the model captures some aspects of the data distribution, it fails to fully align with the observed scale and central tendency, indicating potential areas for model refinement.

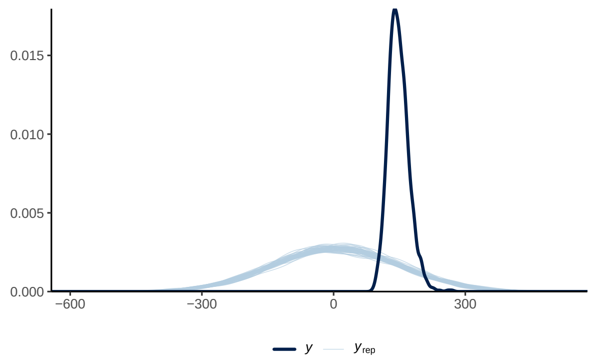
Figure 5b compares the posterior and prior distributions for each parameter in the model. The posterior distributions illustrate the influence of the data on parameter estimates, while the prior distributions represent the initial assumptions before incorporating the observed data.

Notably, parameters such as waist circumference, thigh circumference, and sigma exhibit a significant shift from prior to posterior distributions, indicating that the data strongly informed these estimates. In contrast, parameters like age and military component remain closer to their prior distributions, suggesting weaker evidence from the data to update these estimates. These patterns highlight the varying levels of influence that the data exert on different parameters and underscore the need to consider additional predictors or alternative modeling approaches to improve the model's explanatory power.

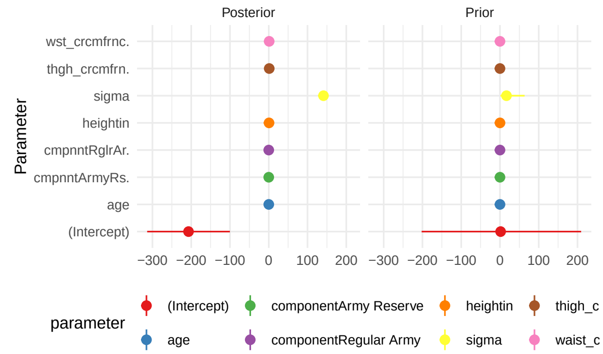
A.2 Diagnostics

Figure 6a presents a trace plot, which assesses the convergence of the Markov Chain Monte Carlo (MCMC) algorithm by examining the sampled values for each parameter across iterations. The chains for each parameter exhibit good mixing, with no discernible trends or patterns over the iterations. The consistent overlap of chains indicates that the sampling algorithm has effectively explored the posterior distribution. These results suggest that the Bayesian model's estimates are reliable and not overly sensitive to initial values or random sampling variation.

Figure 6b displays the Rhat plot, where values close to 1 indicate convergence for each parameter. All parameters have Rhat values near 1.00, well below the threshold of 1.05. This



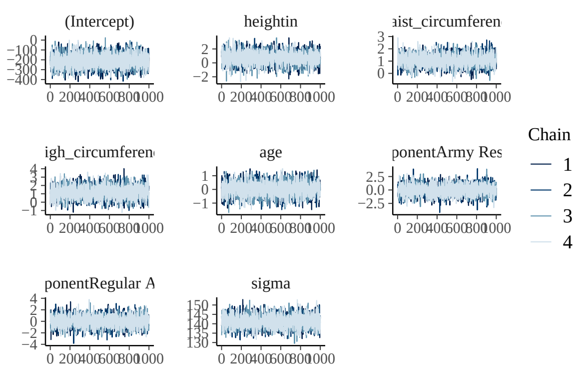
(a) Posterior prediction check



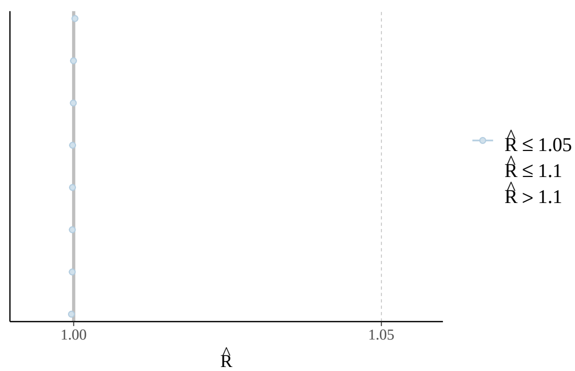
(b) Comparing the posterior with the prior

Figure 5: Examining how the model fits, and is influenced by the data.

confirms that the chains have successfully converged and the samples accurately represent the true posterior distribution.



(a) Trace plot



(b) Rhat plot

Figure 6: Checking the convergence of the MCMC algorithm

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