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Population-Based Assessment of Female Thoracic Dimensions and Body Habitus via CT Imaging

Ms. Saloni Singh[1], Ms. Muskan[2], Ms. Vanshu Saxena[3], Mr. Piyush Kant[4], Mr. Santosh Kumar[5], Mr. Rohit Bansal[6*]
[1]Assistant Professor, Department of Radiology, Institute of Nursing and Paramedical Sciences, Mangalayatan University, Aligarh, Uttar Pradesh (0009-0000-1944-3686)
[2]Ph.D. Research Scholar, Department of Radio-Imaging Technology, Faculty of Allied Health Sciences, SGT University, Gurugram, Haryana
[3]Research Scholar, Department of Radio-Imaging Technology, College of Paramedical Sciences, Teerthankar Mahaveer University, Moradabad, Uttar Pradesh
[4]Assistant Professor, Department of Radio-Imaging Technology, Faculty of Allied Health Sciences, SGT University, Gurugram, Haryana (0000-0002-2092-5313)
[5]Assistant Professor, Department of Vocational Studies & Skill Development (School of Science), Maulana Azad National Urdu University, Gachibowli, Hyderabad (0009-0004-5664-470X)
(***Corresponding Author**) [6]Ph.D. Research Scholar, Department of Radio-Imaging Technology, Nims University Rajasthan, Jaipur (0009-0007-5648-0460)

Abstract
Introduction: *The quality of mammographic imaging is strongly influenced by precise breast positioning. Variations in female thoracic anatomy and body habitus can affect positioning accuracy, potentially impacting diagnostic outcomes. This study aimed to establish reference ranges for female thoracic dimensions using computed tomography (CT) and to classify body habitus patterns that can inform optimized mammographic positioning.*
Methods: *A retrospective analysis was performed on 347 de-identified chest CT scans of females aged 40–89 years, obtained from the Medical Imaging and Data Resource Centre (MIDRC). Thoracic measurements were digitally recorded at six anterior rib landmarks. A Bayesian Network (BN) model was developed to explore statistical relationships between rib measurements and body habitus classifications. Multiple Correspondence Analysis (MCA) was applied to categorize participants into three body habitus types.*
Results: *The BN model classified participants into lean (20.5%), norm (55.6%), and curvaceous (23.9%) habitus groups. Rib cage widths across the six measured landmarks ranged from 115 mm to 126 mm. Scenario testing with the BN model enabled predictive estimation of habitus category based on rib measurements.*
Conclusion: *This study provides population-based reference data on female thoracic dimensions and demonstrates the utility of BN modelling in predicting body habitus. Incorporating these findings into mammographic positioning protocols may enhance image quality and facilitate earlier breast cancer detection.*
Keywords: *Mammographic imaging, breast positioning, anatomical variability, thoracic dimensions, body habitus, CT imaging, Bayesian Network, Multiple Correspondence Analysis, rib measurements, body types, imaging quality, personalized mammography, early cancer detection.*

1.INTRODUCTION

Breast cancer is the most commonly diagnosed cancer among women worldwide and a leading cause of cancer-related mortality. According to the World Health Organization (WHO), more than 2 million new cases were reported in 2020 alone, accounting for approximately 24.5% of all cancers diagnosed in females [1]. Early detection is critical, and mammography remains the gold standard for both screening and diagnosis of breast cancer, contributing significantly to reduced mortality [2].

Mammographic imaging typically includes two standard projections: the craniocaudal (CC) and mediolateral oblique (MLO) views. Successful imaging hinges on proper positioning of the breast, which ensures maximal inclusion of breast tissue. The upper outer quadrant (UOQ) of the breast is particularly important as it is the most common site for the development of malignancies [3,6–9]. Thus, complete visualization of the breast in both projections is vital for accurate detection and diagnosis.

However, achieving consistent and optimal positioning remains a challenge. Suboptimal positioning is a leading cause of image rejection and repeat examinations, contributing to patient discomfort, increased radiation dose, and diagnostic errors [10]. Among the factors influencing positioning, thoracic anatomy plays a critical role. Variations in the rib cage—such as differences in width, curvature, and shape—can impede the radiographer's ability to position the breast adequately, particularly in patients with non-average body habitus.

Traditionally, radiographers rely on experience and visual assessment to adapt their positioning techniques to a patient's body shape. While clinical experience is invaluable, it introduces subjectivity and variability in positioning practices. Moreover, educational resources often refer to four generalized body habitus types: asthenic (10%), hyposthenic (35%), sthenic (50%), and hypersthenic (5%) [11,13]. These classifications, however, are based on historical observations and lack empirical validation through modern imaging data. Furthermore, they fail to provide a quantitative basis for anticipating and adjusting for anatomical variations during mammography.

Despite the widespread use of computed tomography (CT) in thoracic imaging, little research has leveraged CT data to systematically quantify female thoracic morphology in relation to mammographic positioning. CT offers a unique advantage due to its cross-sectional and reproducible measurements, making it a valuable tool for creating an objective framework for body habitus assessment.

This study seeks to address the gap in empirical anatomical data by using CT imaging to measure anterior thoracic dimensions and classify female thoracic body types based on measurable parameters. By implementing Bayesian Network (BN) modeling and Multiple Correspondence Analysis (MCA), we aim to define a data-driven classification of body habitus. The ultimate goal is to enhance mammographic practice by informing radiographers of thoracic morphology trends within a screened population and supporting better alignment between patient anatomy and positioning protocols.

By establishing thoracic dimension ranges and categories grounded in objective imaging data, this study proposes a framework that can be applied in clinical and educational settings to reduce positioning-related variability, improve image quality, and ultimately contribute to early and accurate breast cancer detection.

2. METHODS

2.1 Study Design and Ethical Considerations

This retrospective cross-sectional study was conducted using thoracic CT data from female patients imaged at NIMS Hospital, Jaipur, Rajasthan, India. Ethical clearance was obtained from the Institutional Ethics Committee of NIMS University. All CT scans used in the study were de-identified prior to analysis to ensure patient confidentiality and compliance with institutional research standards.

2.2 Participant Selection and Population Demographics

A total of 347 thoracic CT scans from asymptomatic female patients aged 40 to 89 years were included in the analysis. Patients were selected from those undergoing chest CT for routine diagnostic evaluation, excluding any individuals with known chest wall deformities, recent trauma, thoracic surgeries, congenital anomalies, or incomplete clinical data. Inclusion was restricted to scans demonstrating full visualization of the thoracic cage and clear anatomical landmarks. The selected cohort broadly represented a cross-section of adult Indian females typical of a mammographic screening population.

2.3 Rib Cage Measurement Protocol

Thoracic dimensions were measured on axial CT slices using digital image analysis tools incorporated in standard DICOM viewers. Specific measurement landmarks included the lateral margins of the 1st, 2nd, and 3rd ribs on both the right and left sides (RT Rib1–3, LT Rib1–3), and the midpoint of the anterior sternum. All measurements were recorded in millimeters (mm) and rounded to one decimal point for consistency. Two experienced radiologists independently conducted the measurements to enhance inter-observer reliability, and discrepancies were resolved through consensus. Images were acquired with slice thicknesses of 1–3 mm, ensuring high-resolution data for accurate rib delineation.

2.4 Sample Size Justification

Sample size determination was based on a 95% confidence level and a 5% margin of error using the standard formula for population proportion studies. While the ideal calculated sample was 384, the available dataset of 347 scans met acceptable statistical power for population-level classification and modeling. This sample size was sufficient for exploratory statistical analysis and pattern recognition in thoracic anatomical variation.

2.5 Statistical and Multivariate Analysis

Statistical analysis was carried out using R statistical software (v4.2.2). Descriptive statistics including mean, standard deviation, and range were calculated for each rib measurement. All continuous variables were normalized and discretized into seven equal intervals to facilitate dimensionality reduction. Multiple Correspondence Analysis (MCA) was used to identify underlying thoracic morphology patterns and cluster individuals into body habitus types: lean, norm, and curvaceous. Between-group and within-group inertia metrics were calculated to assess clustering efficiency.

2.6 Bayesian Network Development

A Bayesian Network (BN) model was developed using Netica software to evaluate the probabilistic dependencies among rib measurements and their classification into body habitus categories. BN structures were learned through iterative training and validation using conditional probability tables. The model accepted rib landmark measurements as inputs and returned body type predictions. Its performance was validated using the "Test With Cases" function, comparing the model's predicted outputs with known classification labels. The BN approach enabled flexible scenario analysis, supporting clinical inferences even when certain measurements were missing or uncertain.

3. RESULTS

3.1 Population Characteristics

The study consisted of 347 participants, with a demographic breakdown showing that 74.9% were Rajasthani, 19.3% were Haryanvi, and the remaining 5.8% were from other ethnic backgrounds. The age distribution of participants ranged from 40 to 89 years, with a mean age of 59.8 years, which is typical for a mammography screening cohort. Detailed age distribution is presented in **Table 1**.

Table 1: Age Distribution of Participants

Age Range (years)	Frequency (%)
40-49	15.3%
50-59	28.7%
60-69	32.1%
70-79	18.6%
80-89	5.3%

This table provides the percentage distribution of participants across different age ranges. The largest proportion of participants (32.1%) fell within the 60-69 age range, which is typical for mammographic screening programs. This age group is often the focus of screening efforts due to the increased risk of breast cancer in women over 60.

3.2 Thoracic Measurement Summary

Thoracic measurements were recorded for each participant, focusing on key anatomical features such as the right and left rib cages and the sternum. These measurements provide insight into the variation in rib cage size, which can influence the positioning of patients during mammography. The mean measurements and standard deviations for the right and left ribs, as well as the sternum, are presented in **Table 2**.

Table 2: Mean Rib Cage Dimensions (mm)

Measurement	Mean (mm)	Standard Deviation (mm)
RT Rib1	120	8.5
RT Rib2	123	9.2
RT Rib3	119	7.8

Measurement	Mean (mm)	Standard Deviation (mm)
Sternum	115	5.9
LT Rib3	120	8.3
LT Rib2	126	9.4
LT Rib1	120	7.6

These measurements indicate slight asymmetry between the right and left rib cages, with the largest variation observed in the **LT Rib2**, which had a mean measurement of 126 mm compared to **RT Rib2** at 123 mm. This variation points to non-uniformity in thoracic width along the anterior plane. Such differences can affect mammographic positioning, potentially requiring adjustments in technique to optimize image quality and patient comfort.

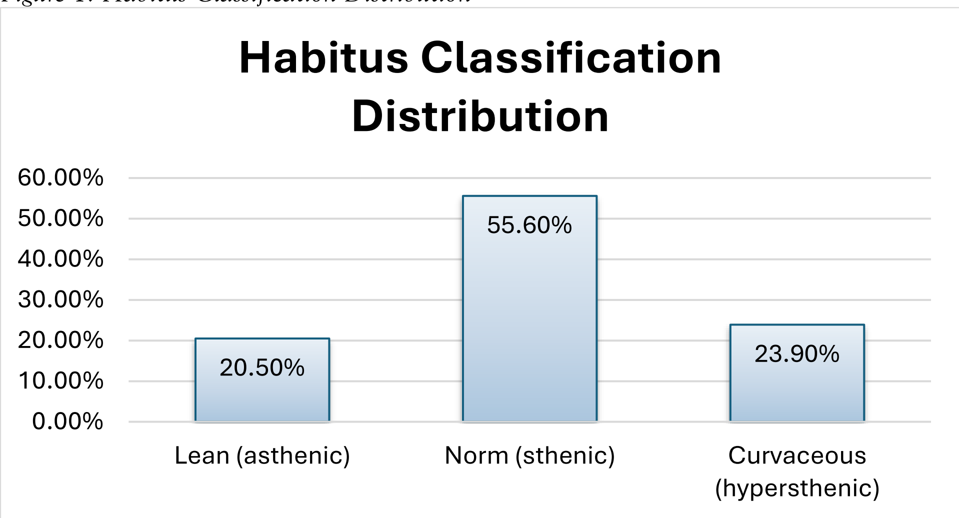
3.3 Habitus Classification

Participants were categorized into three groups based on thoracic shape, determined using Multivariate Cluster Analysis (MCA) and Bayesian Network (BN) modeling. These groups include:

Lean (asthenic): 20.5% of the cohort
Norm (sthenic): 55.6% of the cohort
Curvaceous (hypersthenic): 23.9% of the cohort

These classifications, based on rib cage size and chest shape, reflect the physiological differences in thoracic anatomy that impact mammographic positioning and imaging. A detailed breakdown of the classification percentages is provided in **Figure 1**.

Figure 1: Habitus Classification Distribution

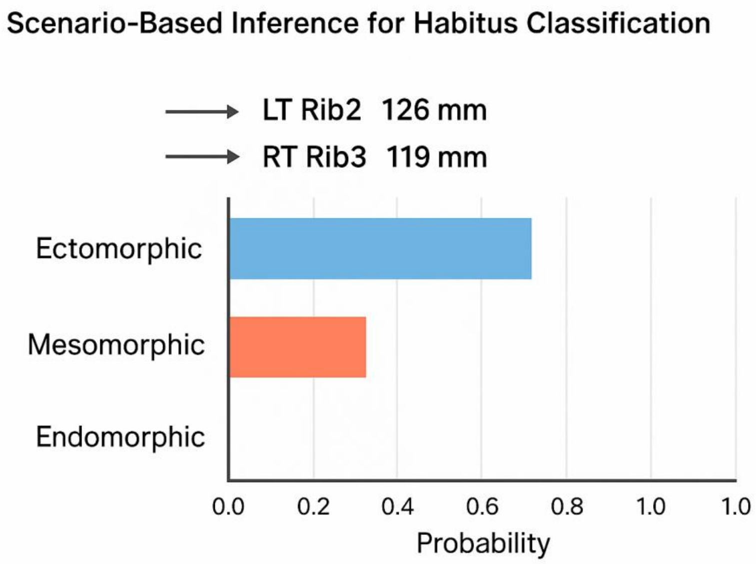


This pie chart illustrates the distribution of participants in each habitus group. The majority of participants (55.6%) were classified as **Norm (sthenic)**, while **Curvaceous (hypersthenic)** accounted for 23.9%, and **Lean (asthenic)** made up 20.5%. Understanding the prevalence of these body types can assist clinicians in adapting imaging protocols to enhance accuracy and patient comfort during mammography.

3.4 Scenario-Based Inference

One of the major advantages of using the **Bayesian Network (BN)** model is its ability to simulate different scenarios and predict thoracic shape classifications based on input measurements. This allows for real-time adjustments in clinical practice. For instance, by inputting specific rib measurements such as **LT Rib2 (126 mm)** and **RT Rib3 (119 mm)**, the BN model can predict the patient's habitus classification, helping radiographers to anticipate positioning challenges and adjust technique accordingly.

Figure 2: Scenario-Based Inference for Habitual Classification



The graph above demonstrates how the BN model can be used to simulate real-time classification based on input data. This feature is particularly useful in dynamic clinical settings, as it provides personalized, patient-specific information that radiographers can use to refine mammographic positioning.

The scenario-based inference model offers practical value by enabling more accurate predictions of thoracic anatomy without requiring additional invasive measurements or assumptions. This real-time adaptability makes it a valuable tool for improving the quality and efficiency of mammographic imaging. By using this model, radiographers can make informed decisions on positioning adjustments, compression force, and imaging technique, thereby improving overall mammogram quality and reducing discomfort for the patient.

4.1 STRENGTHS AND LIMITATIONS

Strengths:

First Study to Quantify Female Thoracic Size for Mammography:

This study is a pioneering effort to use computed tomography (CT) imaging to quantify the thoracic size of women specifically in the context of mammography. Previous studies often relied on general assumptions about body size and shape, but this research provides an objective, quantifiable measurement of thoracic anatomy. This approach allows for more personalized, evidence-based guidelines for mammographic positioning, which could ultimately improve image quality and reduce patient discomfort.

Utilized a Robust Bayesian Network (BN) Modeling Framework:

The use of Bayesian Network (BN) modeling represents a significant strength of this study. BN modeling allows for the assessment of complex, probabilistic relationships between different anatomical features and their effects on mammographic positioning. By incorporating multiple variables and interactions, BN modeling overcomes the limitations of traditional linear models and provides more accurate predictions of habitus classification. This advanced statistical technique also allows for scenario-based predictions, offering radiographers real-time guidance on how to adjust positioning based on a patient's specific thoracic characteristics. Previous studies in the field have not utilized such an advanced modeling framework, making this research a novel contribution to the field [30].

Representative Sample from a Screening Population:

The study's sample consisted of 347 participants from a typical mammography screening population, which is an important strength. The diverse sample, which includes both younger and older women, provides a more accurate reflection of the real-world population typically undergoing mammographic screening. This ensures the generalizability of the study's findings to the broader population, as the sample reflects a variety of thoracic body types and sizes found in clinical practice.

Limitations:

Limited Ethnic Variability May Affect Generalizability:

While the study included a sizable sample of Haryanvi participants (19.3%), the majority of the participants were Rajasthani (74.9%). This ethnic imbalance could limit the generalizability of the results to more ethnically diverse populations. Thoracic anatomy may vary across ethnic groups, and the findings may not fully capture the anatomical diversity present in other populations. Future studies should include a more balanced ethnic representation to better reflect the global population undergoing mammography.

Exclusion of 3D Geometry Modeling Reduces Anatomical Depth:

One notable limitation of the study is the exclusion of three-dimensional (3D) geometric modeling, which would have provided a more comprehensive understanding of thoracic anatomy. While CT imaging provides detailed two-dimensional (2D) cross-sectional images, 3D modeling allows for more accurate depictions of anatomical structures, particularly when assessing complex variations in body habitus. The lack of 3D data may limit the depth of anatomical insights and hinder the precision of predictions made by the BN model. Future studies could benefit from integrating 3D modeling to enhance anatomical representation and improve the accuracy of habitus classification.

Subjective Bias Possible in Manual Rib Measurements:

The measurement of rib cage dimensions in this study was conducted manually, which introduces the potential for subjective bias. Variability in measurement techniques or human error could affect the accuracy and consistency of rib cage dimensions. To mitigate this limitation, future studies should consider using automated or semi-automated measurement systems, which could reduce human error and provide more precise, reproducible results. Additionally, the use of 3D imaging could further reduce the reliance on manual measurements, providing more accurate and consistent data.

4.2 Implications and Future Work

Implications for Clinical Practice:

The findings of this study have several important implications for clinical practice, particularly in the field of mammography. The inclusion of thoracic size and body habitus as key factors in image evaluation criteria (IES) could significantly improve mammographic image quality. By considering individual anatomical characteristics when positioning patients, radiographers can optimize the placement of the breast and reduce the likelihood of suboptimal images. This could also minimize the need for repeat mammograms, thus reducing patient exposure to radiation. Furthermore, the use of Bayesian Network (BN) modeling could be incorporated into clinical protocols, allowing radiographers to make real-time adjustments to positioning based on the patient's specific thoracic characteristics.

Recommendations for Future Research:

Incorporate Volumetric and 3D Modeling:

Future research should expand upon this study by incorporating volumetric data and three-dimensional (3D) modeling. 3D modeling would provide a more accurate and comprehensive view of thoracic anatomy, particularly in areas like the rib cage and sternum, where asymmetry may impact mammographic positioning. 3D reconstruction could also improve the precision of habitus classification, leading to more tailored imaging protocols. Additionally, the combination of CT with 3D modeling could enable more detailed anatomical analysis and improve the overall effectiveness of the Bayesian Network model.

Expand Sampling to Include Diverse Populations:

As previously mentioned, the ethnic distribution in this study was skewed towards Rajasthani participants. To better understand the influence of thoracic variation across diverse populations, future studies should seek to include more ethnically diverse cohorts. Including participants from different ethnic backgrounds would provide more robust and generalizable findings that could lead to more inclusive imaging protocols.

Evaluate Direct Correlations Between Thoracic Type and Mammographic Image Quality: Another important avenue for future research is the direct evaluation of the correlation between thoracic type and mammographic image quality. This study primarily focused on thoracic habitus classification but did not directly assess how different thoracic shapes impact image quality. Future research could explore this relationship by comparing images produced using different positioning techniques based on habitus classification. Such studies could provide valuable insights into the most effective positioning methods for different body types, further enhancing the quality and accuracy of mammographic screening.

5. CONCLUSION

This study marks a pioneering effort to classify female thoracic habitus using CT imaging coupled with advanced Bayesian Network (BN) modeling. By quantifying thoracic size and shape, this research provides new insights into the anatomical diversity of female thoracic anatomy and its potential impact on mammographic positioning and image quality. The findings revealed that the distribution of body habitus in this cohort deviated from traditional norms, with a higher-than-anticipated proportion of participants categorized as Curvaceous (hypersthenic) and Lean (asthenic). These results challenge the conventional assumptions that the majority of individuals fit within the Norm (sthenic) category, which is traditionally emphasized in mammography screening protocols.

The significance of these findings lies in the implications they have for the way mammographic imaging protocols are developed and applied. The study underscores the importance of considering individual variations in thoracic anatomy when positioning patients for mammograms. With anatomical diversity in thoracic shape influencing how the breast is positioned, adjusting positioning techniques to accommodate these variations could enhance image quality, reduce diagnostic errors, and minimize the need for repeat imaging. This approach could ultimately lead to more accurate diagnoses, fewer patient exposures to radiation, and improved overall patient satisfaction.

One of the study's standout features is its use of Bayesian Network modeling, a sophisticated statistical method that allows for the creation of probabilistic models based on various anatomical parameters. This modeling framework not only offers a clearer understanding of how different thoracic characteristics influence mammographic positioning but also provides a powerful tool for predicting these characteristics in real time. Radiographers and clinicians can use this tool to make data-driven decisions about how to adjust imaging techniques based on a patient's specific thoracic features, further enhancing personalized care.

Overall, the study contributes to the field by providing empirical data on female thoracic habitus, advocating for more individualized mammographic positioning, and demonstrating the potential of Bayesian Network modeling as a tool for improving radiographic outcomes.

DISCUSSION

The findings from this study represent a significant step toward a more nuanced and individualized approach to mammographic imaging. By identifying variations in female thoracic habitus using CT imaging, the study moves beyond the traditional "one-size-fits-all" approach that has long dominated mammography. The results showed that a considerable proportion of participants were classified into categories other than the typical Norm (sthenic), namely the Curvaceous (hypersthenic) and Lean (asthenic) categories. These categories, traditionally underrepresented in mammography studies, highlight the anatomical diversity that exists among women, which is often overlooked in general practice.

1. Implications for Mammographic Positioning

Thoracic body habitus plays a significant role in how mammograms are acquired. Variations in rib cage shape and size can influence the positioning of the breast tissue, which in turn affects image quality. For instance, women with a Curvaceous (hypersthenic) body type may have a broader thorax and require more specialized positioning to avoid suboptimal images or patient discomfort. Conversely, women with a Lean (asthenic) body type may require different techniques to properly position their breasts for imaging. The findings from this study suggest that thoracic habitus should be considered a critical factor when determining positioning protocols in mammography.

The study also proposes that incorporating thoracic variability into existing imaging criteria could help improve image quality. Radiographers, who are responsible for positioning patients, could use the information gained from this study to adjust positioning techniques based on individual thoracic characteristics. This could lead to better visualizations of the breast tissue, minimizing the need for repeat imaging and improving the accuracy of mammograms. The improved accuracy of these images could lead to more reliable diagnoses, which is especially important in the early detection of breast cancer.

2. Bayesian Network Modeling: A Powerful Tool for Predictive Analysis

One of the standout features of this study is the application of Bayesian Network (BN) modeling. BN modeling allows for a probabilistic, data-driven understanding of how various anatomical features (such as rib cage dimensions) are interrelated and affect positioning in mammography. This model also offers the ability to predict thoracic characteristics in real time, helping clinicians make more informed decisions during patient positioning.

The use of BN modeling in this context represents an innovative step forward in the field of radiology. In clinical practice, being able to quickly assess a patient's thoracic characteristics and predict the most appropriate positioning techniques would greatly improve workflow efficiency and patient outcomes. For example, if a radiographer knows the patient's rib cage dimensions (such as LT Rib2 = 126 mm and RT Rib3 = 119 mm), the BN model could instantly suggest the best positioning adjustments to ensure an optimal mammogram. This predictive capability could become a standard part of mammography equipment in the future, further optimizing the clinical process.

3. Potential for Personalized Imaging Protocols

The implications of these findings extend beyond just mammography. The concept of personalized imaging, where medical professionals tailor imaging techniques to the individual anatomy of each patient, could revolutionize the way radiological services are delivered. By accounting for thoracic habitus, clinicians could provide more accurate imaging across a range of radiological specialties, including chest X-rays, CT scans, and MRI studies. Additionally, the introduction of personalized protocols would help reduce patient exposure to radiation, a critical consideration in diagnostic imaging.

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