Using Machine Learning to Select Breast Implant Volume

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Background: In breast augmentation surgery, selection of the appropriate breast implant size is a crucial step that can greatly affect patient satisfaction and the outcome of the procedure. However, this decision is often based on the subjective judgment of the surgeon and the patient, which can lead to suboptimal results. The authors aimed to develop a machine-learning approach that can accurately predict the size of breast implants selected for breast augmentation surgery.

Methods: The authors collected data on patient demographic characteristics, medical history, and surgeon preferences from a sample of 1000 consecutive patients who underwent breast augmentation. This information was used to train and test a supervised machine-learning model to predict the size of breast implant needed.

Results: The study demonstrated the effectiveness of the algorithm in predicting breast implant size, achieving a Pearson correlation coefficient of 0.9335 ($P < 0.001$). The model generated accurate predictions in 86% of instances, with a mean absolute error of 27.10 mL. Its effectiveness was confirmed in the reoperation group, in which 36 of 57 patients (63%) would have received a more suitable implant size if the model's suggestion had been followed, potentially avoiding reoperation.

Conclusions: The findings show that machine learning can accurately predict the needed size of breast implants in augmentation surgery. By integrating the artificial intelligence model into a decision support system for breast augmentation surgery, essential guidance can be provided to surgeons and patients. This approach not only streamlines the implant selection process but also facilitates enhanced communication and decision-making, ultimately leading to more reliable outcomes and improved patient satisfaction. *(Plast. Reconstr. Surg.* 154: 470e, 2024.)

Breast augmentation surgery is one of the most frequently performed cosmetic procedures in the world. The selection of the appropriate breast implant size is crucial, because this significantly influences patient satisfaction and surgical outcomes. However, this decision often relies on the subjective judgment of the surgeon and patient, which can lead to suboptimal results.[1,2]

Various methods, including external silicone sizers, computer simulations, and virtual reality tools, have been used to determine the desired breast implant volume before surgery.[3–5] No single method is without limitations. Implant selection is centered on individual patient characteristics and not just a volumetric process. Surgeons work collaboratively with their patients, combining external sizers with breast measurements to select the appropriate implant.[6–8] To facilitate this process, various measurement systems have been proposed and advocated, including the AK method, High-5, TEPID, ICE, and Number Y, which have been extensively reviewed elsewhere.[9] Despite the

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trend toward measurement-based preoperative evaluation, reoperation for size change remains one of the most common reasons for returning to the operating room after breast augmentation, ranging from 2% to 20%.[1,3,6] Furthermore, a significant number of patients seen by plastic surgeons express dissatisfaction with their breast implant size despite not requiring additional surgery.[10–12]

Machine learning, a branch of artificial intelligence (AI), has been increasingly applied in medicine, but has not been applied extensively in plastic and reconstructive surgery. It allows for the analysis of large amounts of data and identification of patterns that may not be readily apparent to the human eye.[13–17] Given that breast implant selection requires analysis of large amounts of data and identification of complex patterns, it is well-suited for machine learning approaches.

In this study, we developed a machine-learning model for the accurate prediction of breast implant size in augmentation surgery. The model was trained using medical records that included demographic and anthropometric measurements. Focusing on breast implant size selection, our study evaluated whether machine learning and AI could improve a surgeon's ability to predict implant size accurately, thereby increasing the precision of preoperative evaluations and improving patient satisfaction and surgical outcomes.

PATIENTS AND METHODS

Study Design and Participants

After obtaining approval from the institutional review board, we conducted a 2-phase retrospective study on a consecutive series of women (≥18 years of age) who underwent uncomplicated bilateral breast augmentation at our institution between 2016 and 2022 (n = 1000). Patients with ptosis, desire for mastopexy, tuberous breast, or a history of previous breast surgery were excluded.

We trained our machine-learning model using data from the initial 800 cases, and subsequently performed a retrospective analysis of the remaining 200 cases to assess the accuracy of the model in predicting the implant size chosen by the surgeon and the patient.

In the second phase, after the model was built and tested, we collected additional data on reoperation cases due to size changes at our institution between 2016 and 2022 (n = 57) and examined whether patients would have received a more suitable implant size if our machine learning algorithm model's suggestion had been followed at that time. These reoperation cases were not included in the initial sample (n =1000); therefore, they were not used to train the model. All study data were stored securely, and the research was conducted in compliance with the Declaration of Helsinki. All patients provided informed consent to participate in the study.

Data Collection

We collected data from the patients' medical records, including demographic information (age, height, weight, socioeconomic status [SES], and educational level) and morphometric measurements (breast base width, sternal notch–to–nipple distance, and soft-tissue pinch thickness). In addition, we documented the ultimate selected breast implant volume (in milliliters) for each participant. Patients needing different sizes for each breast were excluded from this investigation.

In the second phase, patients' medical records were scrutinized to identify cases of reoperation within the past 5 years, wherein the primary rationale for surgery was size alteration due to patient dissatisfaction. None of these cases was included in the sample used to train the algorithm.

Demographic Data and Morphometric Measurements

Weight and height were ascertained by the nursing staff on the date of implant selection and were treated as continuous variables. Educational attainment was gauged using a solitary indicator (ie, years of completed schooling, partitioning patients into 3 cohorts: high school as the highest educational achievement, college graduation as the highest educational achievement, or postgraduate education [master's degree and above] as the highest educational achievement). Education was regarded as a categorical variable.

Breast size preferences were evaluated on the basis of responses to a singular question: "What is your desired increase in breast size?" This question was used by our team to translate subjective preferences into quantifiable measures. The patients were given 3 options to choose from. Type 1 included patients who desired their breasts to be less than 50% larger than their current size; type 2, to be larger than their current size by more than 50% but less than 100%; and type 3, more than 100% larger than their current size. A staff nurse provided assistance if patients encountered difficulties visualizing these size modifications.

SES was self-evaluated, with patients categorizing themselves into one of the 3 primary groups: low, middle, or high SES. These inputs served as categorical variables for the model training.

Breast base width was characterized as a linear measurement of the base width of the breast mound from the visible medial border to the visible lateral border in the frontal view, as delineated in other studies.[5] Sternal notch–to–nipple distance was denoted as the linear distance from the sternal notch (the perceptible indentation at the neck's base between the collarbones) to the nipple-areola complex. Soft-tissue pinch thickness of the upper pole was determined by isolating the skin and subcutaneous tissue superior to the breast parenchyma, applying firm pressure, and quantifying the thickness using a caliper.

Implant Selection

We chose the implant volume collaboratively with the patient, using a combination of methods of volume estimation: engaging in a detailed verbal discussion with the patient about the desired result, viewing photographs of previous patients, using specially designed external contoured silicone sizers in a bra, and using the Crisalix computer simulation system (Crisalix Virtual Aesthetics) in selected cases. Our comprehensive approach allowed for consideration of patients' unique anatomic characteristics and preferences, leading to a personalized implant selection process.

Surgery

All surgical procedures were performed by the same board-certified plastic surgeon (F.V.B.) working as part of an integrated multidisciplinary team. Before the operation, patients were informed about the risks and benefits of their respective procedures.

Only round textured silicone gel–filled implants were used, all of which were from 2 manufacturers (Allergan Inc. and Motiva, Inc.). The follow-up protocol included visits at 1 week; 1, 3, and 6 months; and 1 year after surgery. The patients were followed up for at least 9 months after surgery.

A regimen of surgical steps was maintained when possible. This regimen was a modification of the previously described surgical technique.[18] Decisions regarding the placement of the incision, volume, and pocket depended on the preferences of the patient and a tissue-based analysis performed by the attending surgeon.

Machine-Learning Model Development

We randomly divided the data set into 2 parts: 80% (800 cases) for training the machine-learning model and 20% (200 cases) for validation.

We used a supervised machine-learning decision-tree regression algorithm that used the decision-tree regressor class from the scikit learn library in Python version 3.9 (Python Software Foundation).[19] The code was made available in an open-source depository (https://github.com/drfibasile/PRS-Using-Machine-Learning-to-Predict-Breast-Implant-Size) and can be used by third parties to test their own data sets. All patient data were compiled from electronic charts using Microsoft Excel (Microsoft Corp.) .csv files and fed to Python code.

This machine-learning modality excels in predicting continuous target variables through the recursive partitioning of input space into regions, each delineated by specific decision rules. The construction of a tree-like structure, with internal nodes representing decision rules based on input features and leaf nodes signifying predicted output values, allows for a high degree of interpretability. The model was trained using patient data (weight, height, education, breast size preferences, and SES) and morphometric information (breast base width, sternal notch–to–nipple distance, and pinch-test results) as input features.

Model Evaluation and Validation

To evaluate the performance of our machine-learning model, we assessed its predictive accuracy using a validation data set of 200 patients who were not included in the training phase. We defined exact size prediction as a prediction that precisely matched the chosen implant size in milliliters. A prediction was deemed accurate if it fell within a 30-mL range of the actual size chosen by the patient. This definition was based on practical considerations: the breast implant brands used in this study offer size increments averaging 32 mL, thereby establishing a 30-mL difference as a meaningful threshold for predictive accuracy. Averages and standard deviations were calculated and compared. In addition, the variable importance was calculated to identify the most important features that influenced implant size.

Reoperation

In the second phase, we identified 57 secondary cases from the same period, in which a change in implant size was the sole reason for reoperation. Patients who underwent reoperation for reasons

Table 1. Distribution of Continuous Variables Analyzed

Statistic	Age (yr)	Weight (kg)	Height (cm)	Distance (cm)	Base Width (cm)	Pinch Test (cm)	Implant Size (mL)
Mean	29.4	62.7	166.3	18.1	10.9	3.0	318
SD	7.2	6.5	6.3	2.0	1.8	1.1	63
Minimum	18.0	45.0	147.0	13.0	7.0	2.0	200
First quantile	23.0	58.0	163.0	17.0	10.0	2.0	260
Median	29.0	62.0	167.0	18.0	11.0	3.0	300
Third quantile	34.0	66.0	170.0	19.8	12.0	3.0	373
Maximum	50.0	84.0	181.0	24.0	15.0	7.0	500

other than size dissatisfaction or who experienced significant body changes (eg, substantial weight fluctuations or childbearing) within this timeframe were excluded from the analysis. We gathered pertinent data from patient records for this analysis. Using our algorithm, we aimed to predict the optimal implant size for each patient based on the same set of continuous and categorical variables and anticipate the ideal implant size during the initial surgery. We then compared the predictions from our algorithm with the actual implant size choices made by the patients and their surgeons that later required reoperation.

Statistical Analysis

To evaluate the performance and statistical validity of our machine-learning decision-tree regression algorithm, we analyzed its predictive accuracy and assessed its significance using appropriate statistical tests.

We calculated the mean absolute error (MAE), which represents the average absolute difference between predicted and actual implant sizes. This measure provides a straightforward indication of the accuracy of the algorithm, with lower values reflecting a better performance. In addition to MAE, we computed the *F* statistic, which quantifies the ratio of explained variance to unexplained variance in the model. Furthermore, we obtained a *P* value to determine the statistical significance of our model. Statistical significance less than 0.01 was considered significant. Statistical analyses were performed using R 3.0.2 (R Core Team; R Foundation for Statistical Computing) and Python.

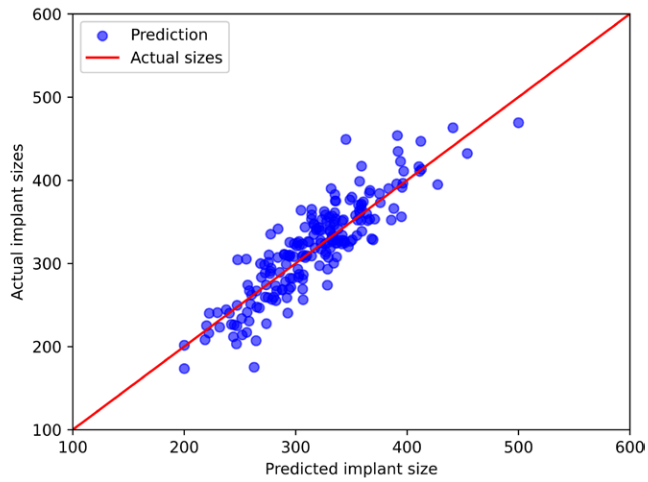

Fig. 1. Scatterplot representing the comparison between actual and predicted breast implant sizes. Each point represents a patient, with the *y* axis indicating the actual implant size and the *x* axis showing the algorithm's prediction. The *red line* indicates an exact match.

RESULTS

The analyzed database consisted of 800 patients and 9 features, in addition to the target variable, which was the implant size. A summary of the variables studied is presented in Table 1.

The algorithm's predictive accuracy was assessed using the MAE, which was 27.10. This indicates that, on average, the algorithm's predictions deviated by approximately 27.10 mL from the actual implant sizes selected. Figures 1 and 2 show charts plotting the actual versus predicted implant sizes. Figure 3 shows a histogram of the error separated by the distance from the correct volume. In 138 of the 200 cases (69%), the model predicted the exact size chosen by the patient. In 172 cases (86%), it predicted the size within a 30-mL difference (accurate prediction). In 20 cases, the difference was between 30 and 50 mL. In only 9 cases was the difference greater than 50 mL. The maximum difference was 80 mL in 1 case.

In addition to MAE, we assessed the statistical significance of our model using the *F* statistic and the corresponding *P* value. The *F* statistic, with a value of 16.68, tests the hypothesis that a model with our chosen predictors provides a better fit to the data than a model with no predictors. A large *F* statistic value suggests that there is a significant difference in fit between the 2 models. The independent variables in our study accounted for a significant amount of the variation in our outcome variable.

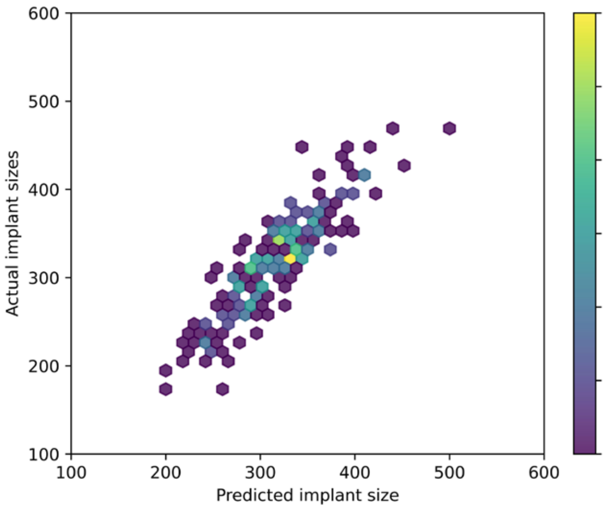

Fig. 2. Hexbin plot providing an enhanced comparison between the actual and predicted breast implant sizes. The color intensity of each hexagon corresponds to the density of data points it encompasses, proving especially advantageous in areas of the plot with a high concentration of data. This feature allows for a more nuanced visualization of instances where actual and predicted sizes closely match. Each hexagon, therefore, not only groups a set of data points but also reflects the frequency of these data points through color variation.

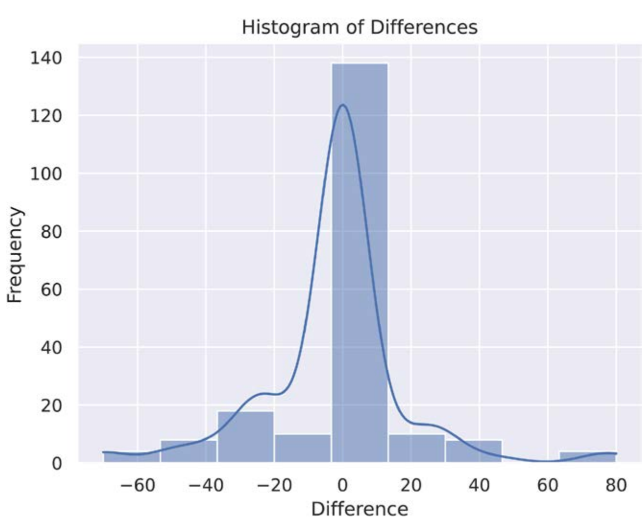

Fig. 3. Histogram of prediction errors for breast implant sizes. The *x* axis displays the error ranges in milliliters and the *y* axis represents the frequency of these errors (in total cases). The most frequent error was 0, indicating instances where the model precisely predicted the chosen implant size.

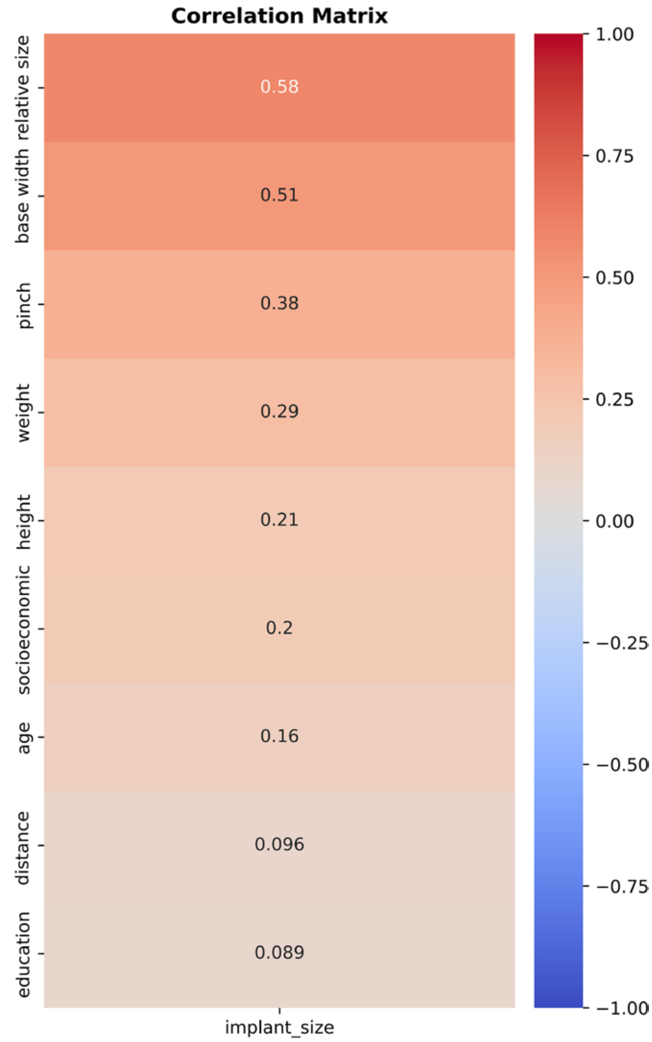

Fig. 4. Heat map of the correlation matrix representing relationships among the 9 features: relative size ($P < 0.0001$), base width ($P < 0.0001$), pinch ($P < 0.0001$), weight ($P < 0.0001$), height ($P = 0.0002$), socioeconomic status ($P = 0.0005$), age ($P = 0.036$), distance ($P = 0.041$), and education ($P = 0.046$). A correlation close to 1 or −1 indicates a strong positive or negative relationship, respectively; a correlation near 0 indicates no linear relationship. All correlations to implant size choice are statistically significant with *P* values less than 0.05.

Furthermore, the *P* value obtained from our analysis was much smaller than 0.01 (3.94×10^{-13}), and the Pearson correlation coefficient was 0.9335. These results support the statistical validity of our decision-tree regression algorithm and imply that the identified relationships between input features and breast implant sizes are not chance occurrences.

Figure 4 presents the correlation matrix, illustrating how each variable used in our study is associated with the implant size choice. Each variable exhibited either a positive or negative correlation with breast size. The algorithm integrates these variables in a complex manner to calculate the optimal implant size accurately. (**See Figure, Supplemental Digital Content 1**, which shows the full decision tree for one of the models. The tree's nodes represent the conditions based on input variables that guide the decision-making process; the branches stemming from these nodes represent the possible outcomes of these conditions. The terminal nodes, or leaves, display the final predictions of implant sizes, *http://links.lww.com/PRS/G922*.)

Reoperation

The efficacy of the model was evaluated further using another data set consisting of 57 patients who regretted their initial implant size choice and underwent additional surgery for adjustment. The model was used to predict the ideal size for the patient, and this prediction was compared with the patient's chosen size after the reoperation. In this instance, an MAE of 39 mL was observed. The model predicted exactly the patient's reoperation size choice in 39% of cases, and the prediction was considered accurate (error <30 mL) in 60% of cases. The average difference between the predicted and newly chosen size was −37 mL, indicating that, on average, the model suggested a slightly smaller size than the one chosen by the patient when having the secondary procedure ($P < 0.001$; Student t test).

The difference between the model-chosen size and the second choice was smaller than the difference between the sizes of the second and first choices (mean 87 mL), and this difference was statistically significant ($P < 0.001$; Student t test). Therefore, the model selected a size closer to the second choice than the physician's initial choice. A total of 36 of 57 patients (63%) would have received a more suitable implant size if the model's suggestion were followed, potentially avoiding reoperation.

These findings suggest that the machine-learning algorithm offers improved predictive accuracy over patient and surgeon size choices for determining optimal implant sizes, potentially minimizing size dissatisfaction and related reoperation.

DISCUSSION

AI-based decision support systems enhance health care delivery by providing physicians with real-time comprehensive information. By seamlessly integrating computational power with clinical medical expertise, these systems can improve diagnostic accuracy, optimize treatment plans, and enhance patient outcomes. As a testament to the growing significance of AI and machine learning in the field of medicine, the U.S. Food and Drug Administration has granted authorization to 581 AI models intended for medical decision-making, a significant proportion of which (nearly 400) target applications in radiology.[20–22] Large language models in particular, as highlighted in recent studies, may evolve into critical tools and represent the next logical step in AI-assisted medical decision-making.[23]

Building upon the foundations set by these models, our algorithm predicts breast implant size by handling mixed data types, modeling nonlinear relationships, capturing feature interactions, and demonstrating robustness to outliers. Decision-tree regression has been used in various medical contexts, including in predicting postoperative acute kidney injury,[24] diagnosing clinically significant prostate cancer,[25] and developing a model for osteosarcoma lung metastasis prediction.[26] These diverse applications underscore the versatility of decision-tree regression, thereby validating the choice of this technique in our study.

Our study has some limitations. The algorithm was trained on a single-institution data set, which could affect its generalizability across diverse settings. Factors such as patient demographics, cultural preferences, physician biases, surgical techniques, types of implants used, and dynamics of patient–surgeon communication can significantly influence implant size predictions. Surgeons with limited practice or fewer cases may face challenges in effectively training the model because of the paucity of data. Indeed, the saying "the tool will work best for those who need it least" could be pertinent in this context. Nonetheless, this tool can be particularly invaluable for surgeons during the training phase. By using data from their respective institutions or drawing insights from a seasoned surgeon catering to a similar patient demographic, their decision-making capabilities can be enhanced. To address these issues, the algorithm can be adapted and retrained using data sets specific to different surgeons or institutions, thereby refining its predictive accuracy and enhancing its clinical use. The determination of breast implant size historically has been guided by a combination of well-established techniques: detailed conversations with patients to understand their expectations and desired results, examining previous patients' photographs as reference points, using custom-made external silicone sizers within a bra to gauge potential outcomes, and using tools such as the Crisalix computer simulation system or virtual-reality headsets. Our algorithm can augment these methods harmoniously, acting as an auxiliary tool to refine decision-making precision.

Our study demonstrated the effectiveness of the algorithm in predicting breast implant sizes with a strong correlation (0.93) and considerable accuracy. Despite considering values with a 1-mL difference as errors, 86% of the predictions were within a 30-mL range, which is below average implant size intervals. Our study may open doors for potential applications of the ML algorithm in reconstructive breast surgery, where the type of oncologic procedure adds additional complexity to breast implant selection.

We also propose that integrating this tool into surgical practice could reduce the need for reoperations due to size dissatisfaction. We found that 36 of the 57 patients (63%) could have received a more suitable implant size if the model's suggestions were followed. Although it is challenging to quantify the exact reduction in reoperations, our findings suggest that the algorithm can help decrease their frequency. More comprehensive research is needed to explore these possibilities and evaluate the application of tailored models in various clinical scenarios, including reconstructive breast surgery.

CONCLUSIONS

We investigated the possibility of using a machine-learning model to predict the optimal size of breast implants for breast augmentation surgery. The study results demonstrated that our model offers a high level of precision that can improve preoperative planning and potentially increase patient satisfaction. The integration of objective data and computational methods has introduced a new and innovative approach to the field of plastic surgery, particularly for those contemplating breast augmentation. The incorporation of our machine-learning model as a decision support system for breast augmentation surgery may provide valuable guidance to surgeons and patients during the crucial implant selection process.

Looking ahead, we propose the integration of our model into surgical practice through training modules and user-friendly decision support interfaces, thereby promoting more personalized data-driven approaches in breast augmentation. As we continue to build on this preliminary work, we hope to contribute to the ongoing advancement of plastic surgery by promoting more data-driven and personalized approaches to breast augmentation, ultimately aiming to enhance patient outcomes and satisfaction.

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DISCLOSURE

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