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Estimation of egg albumen height in Nick Brown hens: A comparison of Ridge and LASSO regression methods

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Abstract

This study aims to estimate albumen height in eggs obtained from Nick Brown hens using external egg quality traits. Egg weight, egg width, egg length, shape index, Haugh unit, shell weight, and shell thickness are included in the model as independent variables. Multiple linear regression analysis is first applied, and the model is statistically significant (R^2 = 0.94, r = 0.97). However, strong relationships among variables and high VIF values indicate that model coefficients may be unstable and that multicollinearity may affect the results. Ridge and least absolute shrinkage and selection operator (LASSO) regression methods are therefore applied to obtain more reliable and stable estimates. These approaches are evaluated to improve model stability and enhance prediction performance in the presence of highly correlated variables. The findings indicate that LASSO regression demonstrates better performance than Ridge regression, with higher explanatory power (R^2 = 0.95) and lower information criteria (AIC, AICc, and BIC). In conclusion, penalized regression methods provide more reliable estimates than multiple linear regression in data structures with multicollinearity, and LASSO regression is more effective in terms of model performance and model parsimony.

Keywords: Multicollinearity, LASSO regression, Nick Brown hens, Ridge regression, Egg quality traits

INTRODUCTION

Egg quality is considered an important indicator of economic value and biological performance in studies aimed at increasing efficiency in animal production. Egg albumen height is accepted as one of the main parameters in determining egg freshness and internal quality traits (Akçay and Sarıözkan, 2015). Reliable estimation of this trait has critical importance for both selection programs and the optimization of production systems. The literature reports that multiple linear regression analyses are widely used to model relationships among egg quality traits; however, high correlations among variables may negatively affect model reliability (Ölmez and Yağanoğlu, 2023; Yavuz, 2025). Strong relationships are frequently observed among external egg quality traits (such as egg weight, width, length, and shape index), and this situation leads to the emergence of multicollinearity (Kurşun and Gök, 2025). This problem increases the variance of coefficient estimates in multiple linear regression, thereby reducing interpretability and prediction accuracy (Akçay and Sarıözkan, 2015). Therefore, penalized and shrinkage-based regression methods such as Ridge, least absolute shrinkage and selection operator (LASSO), Liu, and Elastic Net, as well as principal component regression (PCR), have been increasingly used in recent years (Herawati et al., 2024). Various studies demonstrate that these methods improve model stability and reduce prediction error, particularly in highly correlated data structures (Altenbany, 2021).

Research on the estimation of egg quality traits in poultry indicates that external quality parameters provide a strong basis for explaining internal quality indicators; however, careful method selection is required in the modeling process due to high dependency among variables (Gök and Kurşun, 2025b; Tolun, 2025). In this context, not only the coefficient of determination but also model stability and information criteria should be considered.

In this study, egg albumen height in Nick Brown hens is estimated using external egg quality traits, and multiple linear regression is compared with Ridge and LASSO regression methods. The aim of the study is to identify the method that provides the most appropriate prediction performance under multicollinearity and to develop a more reliable modeling approach for egg quality estimation.

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MATERIALS AND METHODS

The dataset used in this study consists of 95 table eggs collected from a 40-week-old Nick Brown hen flock. Egg dimensions (length and width) were measured using a digital caliper with ±0.01 mm precision, while egg weight was measured using an electronic balance with ±0.01 g accuracy. After breaking the eggs on a glass breaking table, albumen height, width, and length were recorded using a Vernier caliper (INSIZE, ±0.01 mm). Shell weight was measured after cleaning the internal contents of the eggs using a precision balance, and shell thickness was calculated as the average of measurements taken from blunt, equatorial, and sharp ends.

Based on the collected data, shape index and Haugh unit were calculated using the following formulas (Kurşun and Gök, 2025):

Shape Index = Egg Width (mm)/Egg Length(mm)x100 (1)

Haugh unit= 100 log (Albumen Height +7.57-1.7 x Egg Weight^0.37) (2)

The dependent variable was egg albumen height, while the independent variables included egg weight (g), egg width (mm), egg length (mm), shape index (%), Haugh unit (dimensionless), shell weight (g), and shell thickness (mm). Multiple linear regression analysis was applied to examine the relationships among variables. Multiple linear regression is a parametric method used to explain and predict a dependent variable based on multiple independent variables. The model is mathematically expressed as.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon \quad (3)$$

In this equation, Y represents the dependent variable, β_0 represents the intercept, β_1–β_n represent regression coefficients, X_1–X_n represent independent variables, and ε represents the error term (Gök and Kurşun, 2025a; Gök et al., 2026).

However, in multiple linear regression analyses, high correlations among independent variables may lead to multicollinearity (Kurşun and Gök, 2025). This situation reduces the reliability of coefficient estimates and weakens interpretability. Therefore, the level of association among independent variables was evaluated using correlation coefficients, variance inflation factor (VIF), and tolerance value (TV).

A correlation coefficient value of 0.75 or higher indicates a strong linear relationship between variables (Tolun, 2025). VIF measures the degree of linear dependency of one independent variable on the others, and values above 10 indicate severe multicollinearity. VIF is calculated as.

$$VIF = 1 / (1 - R^2) \quad (4)$$

TV is defined as $1 - R^2$, and values below 0.1 indicate a high risk of multicollinearity (Gök and Kurşun, 2025b).

Before applying Ridge and LASSO regression analyses, all independent variables were standardized to ensure comparability of coefficients and to avoid scale-related bias.

When multicollinearity is detected, penalized regression methods are used to mitigate its effects. In this study, Ridge and LASSO regression methods were applied to obtain more reliable estimates.

Ridge regression is a penalized regression method used to reduce multicollinearity and improve prediction accuracy in datasets with highly correlated independent variables (Hoerl and Kennard, 1970). The method constrains the sum of squared coefficients using a penalty parameter λ.

$$\hat{\beta}^{\text{ridge}} = \beta^{\text{argmin}\langle ||y - X\beta||_2^2 + \lambda ||\beta||_2^2 \rangle} \quad (5)$$

Here, $||y - X\beta||_2^2$, represents the residual sum of squares, $\lambda||\beta||_2^2$, represents the L2 penalty term, and λ is the penalty parameter.

When λ = 0, the model reduces to ordinary multiple linear regression when λ equals zero. As λ increases, the regression coefficients are progressively shrunk, leading to reduced variance and more stable estimates, particularly in the presence of highly correlated predictors. The optimal λ value was determined using 10-fold cross-validation (k = 10), and the value that minimized the cross-validation error was selected as the final tuning parameter for the Ridge regression model. Coefficient behavior across different λ values is commonly assessed using trace plots, which help evaluate model stability and guide the selection of an appropriate λ. These plots typically include the range of λ values used for coefficient trajectories to better illustrate the shrinkage pattern of the parameters. Ridge regression is widely applied in areas such as biology, animal science, and engineering, where multicollinearity is frequently encountered (Hoerl and Kennard, 1970).

LASSO regression is a penalized regression method used to reduce multicollinearity and improve prediction accuracy (Tibshirani, 1996). It applies an L1 penalty on the absolute values of coefficients, shrinking some coefficients exactly to zero, thereby enabling variable selection.

$$\hat{\beta} = \beta^{\text{argmin}} \left\{ \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right\}^2 + \lambda \sum_{j=1}^{p} |\beta_j| \quad (6)$$

Here, $\left\{\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right\}^2$, represents the estimation error, $\lambda\sum_{j=1}^{p}|\beta_j|$, the penalty is applied to the sum of the absolute values of the coefficients (L1 norm), where λ represents the penalty coefficient.

When λ = 0, the model reduces to multiple linear regression when λ equals zero. As λ increases, irrelevant variables are gradually shrunk toward zero, resulting in a simpler and more parsimonious model. Similar to Ridge regression, the optimal λ value in LASSO regression was determined using k-fold cross-validation, with the λ minimizing prediction error selected as the final tuning parameter. The variation of coefficients across different λ values is typically examined using coefficient path plots, which illustrate how variable effects shrink and how variable selection emerges as the penalty increases. These coefficient paths were evaluated over a predefined λ sequence to observe selection behavior under different levels of regularization. LASSO regression is widely used in biological and production data settings characterized by high dimensionality and multicollinearity (Tibshirani, 1996).

For model comparison, commonly used criteria in the literature were applied. The coefficient of determination (R^2) indicates the proportion of variance in the dependent variable explained by the independent variables.

Akaike information criterion (AIC), corrected Akaike information criterion (AICc), and Bayesian information criterion (BIC) evaluate model fit while penalizing complexity; lower values indicate better model performance (Tolun et al., 2023; Tolun et al., 2024). Model comparison criteria are presented in Table 1 (Çetenak et al., 2024; Gök, 2025; Şahin and Gök, 2025; Gök and Şahin, 2026).

Table 1. Model comparison criteria.

Criterion	Equality
Coefficient of Determination	$R^2 = 1 - \sum(y_i - \hat{y}_i)^2 / \sum(y_i - \bar{y}_i)^2$
Akaike Information Criterion	$AIC = nx\ln\left(\frac{MSE}{n}\right) + 2k$
Corrected Akaike Information Criterion	$AICc = nx\ln\left(\frac{MSE}{n}\right) + \left(\frac{n(n+p)}{n-p-2}\right)$
Bayesian Information Criterion	$BIC = nx\ln\left(\frac{MSE}{n}\right) + k\ln(n)$

MSE: Mean Squared Error; y_i: observed value for the i-th observation; $\hat{y}_i$: predicted value for the i-th observation obtained from the model; $\bar{y}_i$: mean of all observations; n: total number of observations; k: number of parameters; p: number of independent variables.

RESULTS AND DISCUSSION

The multiple linear regression model equation used to estimate egg albumen height in the study is defined as follows.

$$\widehat{\text{Albumen Height}} = \hat{\beta}_0 + \hat{\beta}_1\text{Egg Weight} + \hat{\beta}_2\text{Egg Width} + \hat{\beta}_3\text{Egg Length} + \hat{\beta}_4\text{Shape Index} + \hat{\beta}_5\text{Haugh Unit} + \hat{\beta}_6\text{Shell Weight} + \hat{\beta}_7\text{Shell Thickness} + \quad (7)$$

The overall results of the multiple linear regression analysis for this model are presented in Table 2. The coefficient estimates, standard errors, t-statistics, and p-values are given in Table 3, while the correlation coefficient (r) and R^2 are reported in Table 4.

Table 2. Results of the multiple linear regression analysis.

	Sum of Squares	df	Mean Square	F	p
Regression	109.75	7	15.67	224.82	<.0001
Residual	6.06	87	0.07		
Total	115.81	94			

Table 3. Multiple linear regression analysis coefficients, standard errors, t-statistics and p values.

Variables	Regression Coefficient (β)	Std. Error of the Estimate	t	p
Constant	-5.79	-	-	-
Egg Weight	0.02	0.01	2.41	0.01
Egg Width	-0.14	0.22	-0.61	0.54
Egg Length	0.087	0.17	0.48	0.62
Shape Index	0.081	0.14	0.57	0.56
Haugh Unit	0.10	0.003	35.81	<.0001
Shell Weight	0.05	0.04	1.26	0.20
Shell Thickness	-0.004	0.002	-2.79	0.006

Table 4. r and R^2 obtained from the multiple linear regression analysis.

r	R^2	Std. Error of the Estimate
0.97	0.94	0.26

The multiple linear regression model was found to be statistically significant overall (F = 224.82, < 0.0001). The R^2, 0.94 indicates that the independent variables explain 94% of the total variation in egg albumen height.

When the regression coefficients are examined in detail, egg weight, Haugh unit, and shell thickness are found to have statistically significant effects on albumen height ($p < 0.05$). In contrast, egg width, egg length, shape index, and shell weight do not reach statistical significance despite being included in the model ($p > 0.05$).

The r 0.97 indicates a strong linear relationship between albumen height and the independent variables.

On the other hand, the lack of significant contribution from some variables and the possible presence of strong relationships among predictors raise concerns regarding multicollinearity. To evaluate this issue in detail, relationships among independent variables are analyzed using VIF values and the TV, and the results are presented in Table 5.

Table 5. Degree of association among independent variables.

Correlation Matrix									
Veriables	EW	EWi	EL	SI	HU	SW	ST	VIF	TV
EW	1							3.82	0.26
EWi	0.73**	1						104.15	0.009
EL	0.32**	-0.06	1					202.79	0.005
SI	0.17	0.62**	-0.81**	1				325.02	0.003
HU	0.03	0.22**	-0.27**	-0.34**	1			1.16	0.85
SW	0.43**	0.26**	0.18	0.04	0.03	1		2.10	0.47
ST	0.15	0.01	0.04	-0.03	-0.07	0.62**	1	1.75	0.56

EW: Egg Weight, Ewi:Egg Width, EL: Egg Length, SI: Shape Index, HU:Haugh Unit, SW: Shell Weigth, ST: Shell Thickness. *p < 0.05, **p < 0.01, ***p < 0.001.

The examination of correlation coefficients reveals a considerable degree of multicollinearity among the independent variables. In particular, the strong positive relationship between egg weight and egg width (r = 0.73) and the high negative relationship between egg length and shape index (r = -0.81) indicate substantial dependency among variables. This structure is considered a potential factor contributing to the statistical insignificance of some regression coefficients.

The multicollinearity problem is further supported by VIF values and TV. Very high VIF values observed for shape index (VIF = 325.02), egg width (VIF = 202.79), and egg length (VIF = 104.15) indicate severe collinearity among these variables, reducing the reliability of coefficient estimates.

In contrast, Haugh unit (VIF = 1.16), shell thickness (VIF = 1.75), and shell weight (VIF = 2.10) exhibit low VIF values and more appropriate TV results, indicating that these variables contribute more independently and reliably to the model.

The findings demonstrate that multicollinearity has a pronounced effect on the regression results and complicates the direct interpretation of coefficients. Therefore, Ridge and LASSO regression methods are applied to improve the reliability of model estimates.

All analyses are performed using SAS 9.4 statistical software. The estimation results for Ridge and LASSO regression approaches are presented in Table 6 and Table 7, respectively. In addition, the variation of Ridge regression coefficients with the penalty parameter (lambda) is illustrated in the trace plot in Figure 1, while coefficient path plots for LASSO regression are provided in Figure 2.

Table 6. Estimation results obtained using the Ridge regression method.

Variables	Regression Coefficient (β)	Std. Error of the Estimate	VIF	TV
Constant	8.18	-	-	-
Egg Weight	0.12	0.12	3.4	0.29
Egg Width	-0.17	-0.17	8.4	0.11
Egg Length	0.18	0.18	8.8	0.11
Shape Index	0.28	0.28	9.2	0.10
Haugh Unit	1.05	1.05	1.1	0.90
Shell Weight	0.04	0.04	2.0	0.50
Shell Thickness	-0.10	-0.10	1.7	0.58

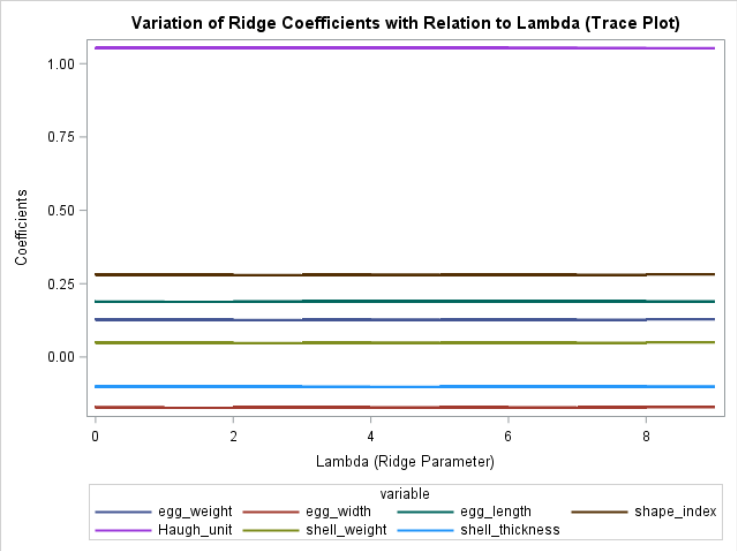


Figure 1. Trace plot of the Ridge regression coefficients.

Table 7. Estimation results obtained using the LASSO regression method.

Variables	Regression Coefficient (β)
Constant	-0.06
Egg Weight	0.02
Egg Width	0
Egg Length	-0.01
Shape Index	0
Haugh Unit	0.10
Shell Weight	0.04
Shell Thickness	-0.004

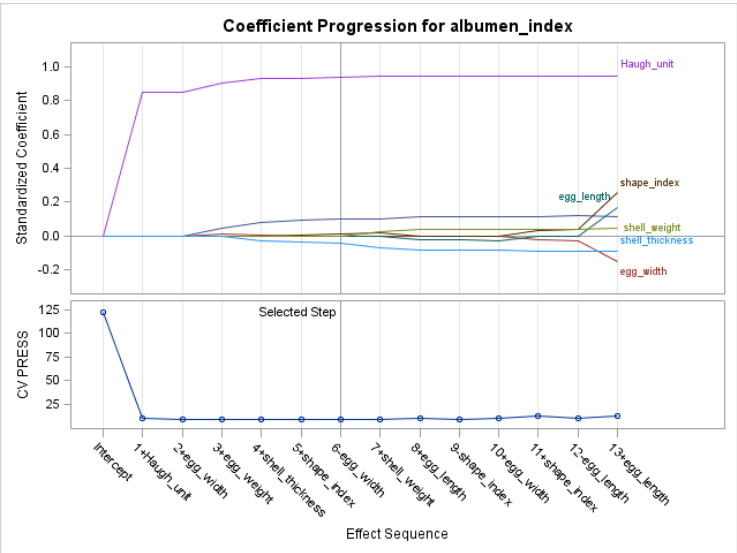


Figure 2. Coefficient path plot for the LASSO regression method.

According to the Ridge regression results, all independent variables are retained in the model, and although their coefficients are shrunk, none are eliminated. This is consistent with the fundamental property of Ridge regression, which performs coefficient shrinkage while preserving all predictors in the model.

The magnitude of variable effects on the dependent variable differs across predictors. Some variables show stronger contributions, whereas others have relatively weaker influence. Nevertheless, retaining all variables suggests that jointly considering external egg quality traits enhances the explanatory capacity of the model.

The VIF values suggest a moderate degree of multicollinearity among the predictors; however, all values remain within acceptable thresholds, supporting the suitability of the model. The Ridge coefficient path plot (Figure 1) further demonstrates

that as λ increases along the specified sequence, the coefficients progressively shrink and stabilize, indicating improved model robustness under regularization.

In contrast, the LASSO regression yields a more parsimonious model structure. In this case, some coefficients are reduced exactly to zero, resulting in the exclusion of certain variables, while the remaining predictors retain explanatory power for the dependent variable.

The importance of variables varies across predictors, and the LASSO approach enhances model interpretability by eliminating weaker predictors. The coefficient path plot (Figure 2) shows that as λ increases, coefficients are gradually shrunk and some are driven exactly to zero, producing a simpler model structure. This behavior confirms the variable selection and shrinkage properties of LASSO regression.

Based on the estimated coefficients, the models are expressed as follows.

Ridge regression model:

$$\widehat{\text{Albumen Height}} = 8.18 + 0.12\text{Egg Weight} - 0.17\text{Egg Width} + 0.18\text{Egg Length} + 0.28\text{Shape Index} + 1.05\text{Haugh Unit} + 0.04\text{Shell Weight} - 0.10\text{Shell Thickness} + \quad (8)$$

LASSO regression model:

$$\widehat{\text{Albumen Height}} = -0.06 + 0.02\text{Egg Weight} + 0\text{Egg Width} - 0.01\text{Egg Length} + 0\text{Shape Index} + 0.10\text{Haugh Unit} + 0.04\text{Shell Weight} - 0.004\text{Shell Thickness} + \quad (9)$$

When Ridge and LASSO regression results are evaluated together, penalized regression approaches are effective in reducing multicollinearity. Ridge regression retains all variables and provides a more comprehensive model structure, whereas LASSO regression enables the development of simpler and more interpretable models through variable selection.

To compare model performance, R^2 as well as information criteria (AIC, AICc, and BIC) are used. The comparison results are presented in Table 8.

Table 8. Estimated results of the model comparison criteria.

Regression	R^2	AIC	AICc	BIC
Ridge	0.94	18.25	31.02	18.92
LASSO	0.95	-151.86	-150.58	-245.84

Model performance comparison indicates that both Ridge and LASSO regression models exhibit high explanatory power. Although the Ridge regression model provides strong explanatory capability with a high coefficient of determination, it yields higher values for information criteria (AIC, AICc, and BIC) compared to the LASSO model.

The LASSO regression model demonstrates a higher coefficient of determination ($R^2 = 0.95$) together with lower AIC, AICc, and BIC values. This indicates a more balanced performance in terms of both model fit and explanatory power.

When all evaluation criteria are considered together, the LASSO regression model appears to be more advantageous than Ridge regression, providing both higher explanatory power and better model fit through lower information criterion values.

A review of the literature shows that methods such as Ridge, LASSO, Liu, Elastic Net, and PCR are widely used to address multicollinearity problems. Studies by Gök and Kurşun (2025a, 2025b), Kurşun and Gök (2025), Şahin (2025), and Yavuz (2025) report that these approaches improve prediction accuracy and reduce the effects of multicollinearity in egg quality data. Tolun (2025) and Yener et al. (2025) demonstrate that LASSO and Liu methods are effective in model simplification and predictive performance. Çiftsüren and Akkol (2018) and Ölmez and Yağanoğlu (2023) state that Ridge and LASSO methods reduce standard errors, leading to more reliable estimates. Topal et al. (2013) show that Ridge and PCR reduce variance caused by multicollinearity. Akçay and Sarıözkan (2015) emphasize the stability of Ridge regression in highly correlated data structures. Altenbany (2021) and Herawati et al. (2024) report that Elastic Net provides balanced performance across different datasets. Ergişi et al. (2024) conclude that Ridge, LASSO, and PCR outperform multiple linear regression in terms of generalization ability.

In this study, Ridge and LASSO regression methods were compared with multiple linear regression for estimating egg albumen height in Nick Brown hens. Although the multiple linear regression model exhibited high explanatory power ($R^2 = 0.94$), strong correlations among independent variables and high VIF values indicated a clear multicollinearity problem. These findings are consistent with those reported by Şahin (2025), Yavuz (2025), and Kurşun and Gök (2025).

The Ridge regression model retained all variables while shrinking coefficients, resulting in a more stable structure. In contrast, the LASSO regression model eliminated some variables by shrinking their coefficients to zero, thereby producing a more parsimonious model. Similarly, Gök and Kurşun (2025b) and Çiftsüren and Akkol (2018) emphasize the advantage of LASSO in variable selection. Model comparison results show that LASSO regression achieves higher R^2 (0.95) and lower AIC, AICc, and BIC values compared to Ridge regression. These findings are consistent with those reported by Tolun (2025), Yener et al. (2025), and Altenbany (2021).

Overall, the results demonstrate that penalized regression methods provide more reliable and stable estimates than multiple linear regression in the presence of multicollinearity. In particular, the superior performance of LASSO regression in terms of both model simplification and information criteria demonstrates that it is a more appropriate method for estimating egg albumen height in Nick Brown hens.

CONCLUSION

The results of the analysis indicate that the multiple linear regression model developed for estimating egg albumen height in Nick Brown hens has a high explanatory power ($R^2 = 0.94$); however, a clear multicollinearity problem exists among the independent variables. High VIF values observed for some variables significantly reduce the reliability of the multiple linear regression coefficients.

Ridge regression improves model stability by shrinking coefficient magnitudes while retaining all variables in the model structure. In contrast, LASSO regression reduces model complexity by shrinking some coefficients to zero and thus performs variable selection. Model comparison criteria show that LASSO regression achieves better model performance than Ridge regression, with higher explanatory power ($R^2 = 0.95$) and lower AIC, AICc, and BIC values.

These findings indicate that in datasets with multicollinearity, model performance should not be evaluated solely based on the coefficient of determination, and that information criteria and model simplicity should be considered together.

In this context, LASSO regression provides a more effective approach in terms of variable selection and model fit under multicollinearity, while Ridge regression can be considered an alternative method in cases where preserving all variables is preferred.

Ethical Statements and Declarations

Conflict of Interest

The author declares that she has no known competing financial or non-financial interests that could have influenced the work reported in this manuscript.

Author Contribution

The study conception and design were jointly performed by KK and MB. Material preparation, data collection, and analysis were carried out equally by KK and MB. The first draft of the manuscript was written by KK and MB collaboratively. Both authors read and approved the final manuscript.

Generative AI Statement

Generative AI tools were used only for language editing and English translation purposes. The author takes full responsibility for the content of the manuscript.

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