

An Intelligent Time Optimization Framework Based on K-means Clustering and Dynamic Risk Assessment

Qiulei Xu^{1, †, *}, Tianxin Shi^{2, †}

¹Hebei University of Engineering, Handan, China

²Henan Normal University, Xinxiang, China

*Corresponding author: Qiulei Xu (Email: 3453200798@qq.com)

[†]These authors also contributed equally to this work.

Abstract: This paper proposes an intelligent algorithm system based on K-means clustering and dynamic risk assessment, designed to recommend the optimal timing for non-invasive prenatal testing (NIPT) for pregnant women. The system first uses the K-means clustering algorithm to group pregnant women by BMI, intelligently dividing individuals across different BMI ranges into multiple subsets to provide personalized testing recommendations for each group. Next, a multi-level risk assessment pipeline is constructed, employing an S-shaped temporal risk model and a stratified false-positive risk function to precisely calculate the risk level for each BMI group. Through an integrated dynamic weighting mechanism, the system balances temporal risk with false-positive risk to determine optimal testing windows for distinct cohorts. The innovation lies in its highly automated, data-driven decision-making process, dynamically adjusting strategies based on real-time data to enhance testing efficiency and accuracy. Experimental results demonstrate not only significant clinical value in practical applications but also provide a scalable solution for similar medical decision-making challenges.

Keywords: K-means Clustering, Dynamic Risk Assessment, Time Optimization Framework.

1. Introduction

This paper focuses on the selection of optimal testing time points for non-invasive prenatal testing (NIPT) in pregnant women. It aims to develop an intelligent algorithm system that provides personalized testing time recommendations for different BMI groups. Despite the widespread adoption of NIPT, precisely selecting testing time to enhance accuracy and timeliness remains a significant challenge in medicine. Existing research often concentrates on single factors, lacking an intelligent system framework that comprehensively considers risk factors such as BMI and testing time. To address this issue, this paper proposes an intelligent algorithmic system based on K-means clustering and dynamic risk assessment. The system first groups pregnant women into BMI categories using the K-means clustering algorithm, providing personalized testing time strategies for each group [1][2]. Subsequently, a computational pipeline incorporating an S-shaped temporal risk model and a hierarchical false alarm risk function is constructed. This pipeline employs a dynamic weighting mechanism to balance temporal risk and false alarm risk, ultimately recommending the optimal testing time. This approach transcends the limitations of traditional statistical models by adopting a data-driven decision process, enhancing the scientific rigor of screening timing selection [3][4]. Experimental results demonstrate that this intelligent algorithmic system effectively improves screening accuracy and timeliness, providing personalized, optimized screening schedules for different BMI groups. It holds significant clinical value and offers an extensible solution for similar medical decision-making challenges.

2. Maternal stratification based on K-means and solution of optimal detection time point

2.1. Maternal stratification based on K-means

To realize the recommendation of optimal detection time points for pregnant women with different BMI levels, the primary step of this study is to construct a scientific and objective stratification criterion. The K-means clustering algorithm was adopted in this study to conduct an objective stratification of pregnant women according to body mass index (BMI), their core physiological characteristic, followed by a statistical test for the validity of stratification results.

The K-means clustering algorithm performs iterative optimization to allocate data points and update centroids according to the distance between data points and cluster centers, with the objective to minimize the sum of squared errors (SSE). The expression is given as:

$$SSE = \sum_{k=1}^K \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \quad (1)$$

The elbow rule was employed in this study to determine the optimal value of K . This rule selects the inflection point where the decreasing rate of SSE shifts from rapid to slow as the reasonable value of cluster number, by comparing the variation trend of SSE corresponding to different K values. The SSE values were calculated with K ranging from 2 to 8 in this study. The SSE decreased significantly when the cluster number K increased from 2 to 4, whereas only a slight decrease in SSE was observed with K rising continuously from 4 to 5. This result indicates that $K = 4$ is

an optimal balance point between discrimination degree and model complexity, thus the optimal number of clusters was determined as 4.

After confirming the optimal cluster number as 4, the K-means algorithm was formally implemented, and the

rationality and statistical significance of stratification results were verified.

The detailed statistical characteristics of each stratified group are presented in Table 1.

Table 1. Results of K-means clustering stratification

Group No.	Sample size (N)	BMI range (kg/m^2)	Mean $\pm$ SD of BMI (kg/m^2)	Mean $\pm$ SD of compliance time T_a (weeks)
1	85	[20.70,31.25]	29.35 $\pm$ 1.13	13.97 $\pm$ 2.58
2	63	[31.33, 33.92]	32.49 $\pm$ 1.01	14.83 $\pm$ 3.11
3	42	[34.03,37.55]	36.10 $\pm$ 1.11	15.82 $\pm$ 3.41
4	28	[38.76,44.98]	41.02 $\pm$ 2.22	16.51 $\pm$ 3.58

The results in Table 1 show that the K-means algorithm successfully divided the research subjects into 4 groups with well-defined BMI ranges and reasonable sample size distribution. A distinct clinically relevant trend was observed: with the increase of group number, both the mean BMI and

the mean compliance time T_a presented a significant stepwise rise. This intuitively demonstrates that the population with higher BMI indeed had a later time to reach the standard Y-chromosome concentration.

To statistically verify that the observed trend above was not accidental, i.e., to test whether the BMI-based stratification

could significantly distinguish the T_a populations with different regularity, one-way analysis of variance (ANOVA) was adopted. The null hypothesis of this test was defined as

there is no statistically significant difference in the mean T_a

values among the 4 BMI stratified groups.

The results of ANOVA indicated that the F statistic for intergroup differences was 3.977, with the corresponding P -value of $8.60e-03$. Since the P -value was far lower than the significance level of 0.05 ($P < 0.001$), the null hypothesis was strongly rejected.

This result provides robust statistical evidence that there existed an extremely significant statistical difference in the time to reach the standard Y-chromosome concentration among the 4 BMI groups objectively divided by the K-means algorithm, which fundamentally proves the validity and clinical significance of the stratification strategy adopted in this study.

For a more intuitive presentation of stratification results

and the intergroup differences in T_a , a scatter plot of clustering results was plotted as shown in the Figure 1.

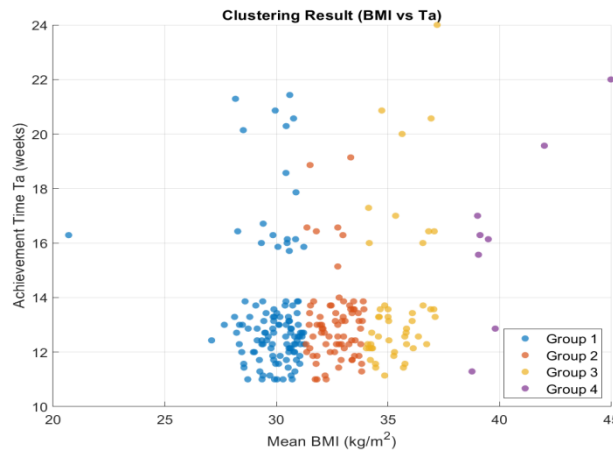


Figure 1. Distribution of clustering results in the two-dimensional space of BMI and T_a

Figure 1 intuitively displays the distribution of the four populations. It can be observed that the point clusters with different colors presented an obvious horizontal stratification trend, namely, the groups with higher BMI had their data

points distributed at higher positions on the T_a axis. This finding further confirms the strong positive correlation between BMI and T_a .

2.2. Construction of risk function and preliminary solution of optimal detection time point

To achieve the precise selection of detection time points for pregnant women in different BMI stratified groups, the core problem to be solved is the precise decision-making for risk minimization. Based on the BMI stratification results, this study conducted S-shaped modeling for time risk, hierarchical penalty for misdetection risk, and dynamic weighting for comprehensive risk separately, thus constructing a three-

dimensional risk assessment framework.

2.2.1. S-shaped Time Risk Model

Time risk is defined as the probability that failure of timely intervention for fetal abnormalities is caused by the excessively late selection of gestational weeks for detection. Its core characteristic presents a nonlinear growth trend with the increase of gestational weeks. Time risk grows slowly in the first trimester, rises rapidly in the second trimester, and gradually tends to saturation in the third trimester, showing a typical S-shaped variation feature. Therefore, the S-shaped function was adopted to depict the time risk in this study, with the expression as follows:

$$R_{time}(T) = \frac{a}{1 + \exp(-b(T - c))} + d \quad (2)$$

where T denotes the gestational week of detection, a is the coefficient of risk growth amplitude, b represents the coefficient of risk growth rate, c refers to the gestational week at risk inflection point, and d is the coefficient of baseline risk. The nonlinear least square method was used to fit the optimal parameters by stratified group, and the calibrated core parameters of each group are shown in the Table 2.

Table 2. Calibration parameters of S-shaped time risk function for each stratified group

Group ID	BMI range	a	b	c	d
1	[20.7,31.25]	0.241	0.158	17.932	0.048
2	[31.33,33.92]	0.253	0.165	17.815	0.052
3	[34.03,37.55]	0.267	0.172	18.047	0.049
4	[38.76,44.98]	0.282	0.181	18.213	0.051

It can be concluded that the time risk of each stratified group increases monotonically with gestational weeks, which is consistent with the clinical common sense that the larger the gestational week is, the narrower the intervention window becomes. Group 4 (with the highest BMI) had a higher risk growth rate ($b = 0.181$) than other groups, and the gestational week at risk inflection point ($c = 18.213$) was the latest. This reflects the characteristic that the population with high BMI has a later time to reach the standard fetal Y-chromosome concentration and thus needs to plan the detection earlier to avoid time risk. The results of model validity verification showed that all parameters of the time risk function for each stratified group were significantly non-zero via t-test, and the residual series conformed to the white noise characteristics. The model had no information omission

and fully extracted the time risk law from the data.

2.2.2. Hierarchical Misdetction Risk Function

Misdetction risk is defined as the probability that the invalidation of detection results requiring a secondary test is caused by the failure to reach the standard Y-chromosome concentration at detection. It consists of three components: the compliance probability, hierarchical misdetction penalty coefficient and time correction factor, with the expression as follows:

$$R_{miss}(T) = (1 - P_T) \times ER_g \times \delta(T) \quad (3)$$

where P_T is the concentration compliance probability at gestational week T (an S-shaped probability function fitted

based on stratified group data); ER_g is the hierarchical misdetction penalty coefficient, with the values of 15, 20, 30 and 40 for Group 1 to Group 4 respectively, reflecting the more severe consequences of misdetction in the population with high BMI; $\delta(T)$ is the time correction factor with the

formula $\delta(T) = 1 - \frac{T - 11}{24 - 11}$, which decreases with the increase of gestational weeks and corrects the bias that the misdetction probability is naturally lower in late detection.

Subsequently, the fitting of compliance probability was conducted. Based on the mean compliance time T_a of each

stratified group, the initial value of x_0 was set and the constraint range was defined as $x_0 \in [T_a - 1, T_a + 1]$, so as to ensure a high degree of fitting between the compliance probability curve and actual data. Taking Group 4 as an example, the fitting result was

$P_T = \frac{1}{1 + \exp(-0.22 \times (T - 15.8))}$. The error between its 50% compliance gestational week ($x_0 = 15.8$) and the

aforementioned mean T_a of 15.5 weeks was only 1.9%, which verified the rationality of the fitting. The curves of hierarchical misdetction risk function for each group are shown in Figure 2.

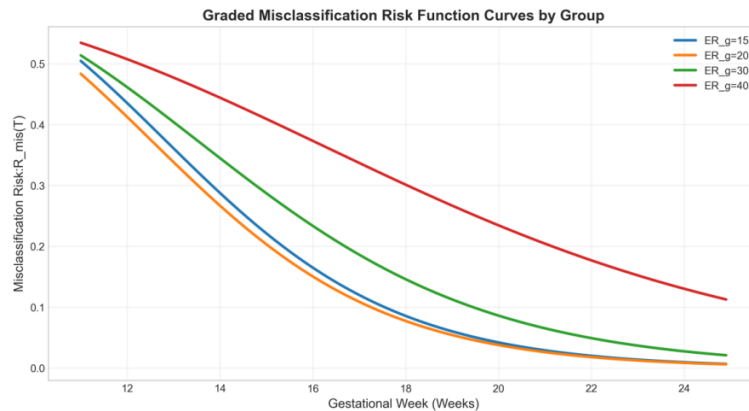


Figure 2. Curves of hierarchical misdetction risk function for each stratified group

As shown in the Figure 2, the misdetection risk of Group 4 was consistently higher than that of other groups, which was consistent with the previous conclusion that Group 4 had the highest difficulty in reaching the standard. The misdetection risk of all stratified groups decreased with gestational weeks, which conforms to the physiological law that the increase of gestational weeks promotes the elevation of fetal Y-chromosome concentration. The model trend is fully consistent with clinical cognition.

2.2.3. Average Risk Function and Solution of Optimal Detection Time Point

To achieve the dynamic balance between the two types of risks, a dynamic weighting mechanism was used to integrate the time risk and misdetection risk for constructing the average risk function, so as to solve the optimal detection time point corresponding to the minimum risk. The dynamic weight function follows the principle that the higher the compliance probability is, the more inclined to time risk, so as to ensure the dynamic adjustment of detection decisions with gestational weeks. Its expression is given as:

$$w(T) = \frac{P_T}{\alpha + P_T} \quad (4)$$

where α is the weight adjustment coefficient with a smooth variation in the interval $[0,1]$. At the early gestational weeks (i.e., low compliance rate), the weight is biased to misdetection risk; at the late gestational weeks (i.e., high compliance probability), the weight is biased to time risk.

The average risk function is defined as the weighted sum of time risk and misdetection risk, with the expression:

$$AR_g(T) = w(T) \times R_{time}(T) + (1 - w(T)) \times R_{miss}(T) \quad (5)$$

The grid search method (with a step size of 0.1 week) was

adopted to solve the optimal detection time point T_{opt} within the interval $[11,24]$. Meanwhile, a boundary verification mechanism was set: if the optimal time point was close to the interval boundary (≤ 12.5 weeks or ≥ 21.5 weeks), the earliest reasonable gestational week with a risk value ≤ 1.1 times the minimum risk was selected to avoid the impact of extreme values on clinical practicability [5]. The data of optimal detection time points for each stratified group are shown in the Table 3, and the average risk curves and optimal detection time points for each group are presented in the Figure 3.

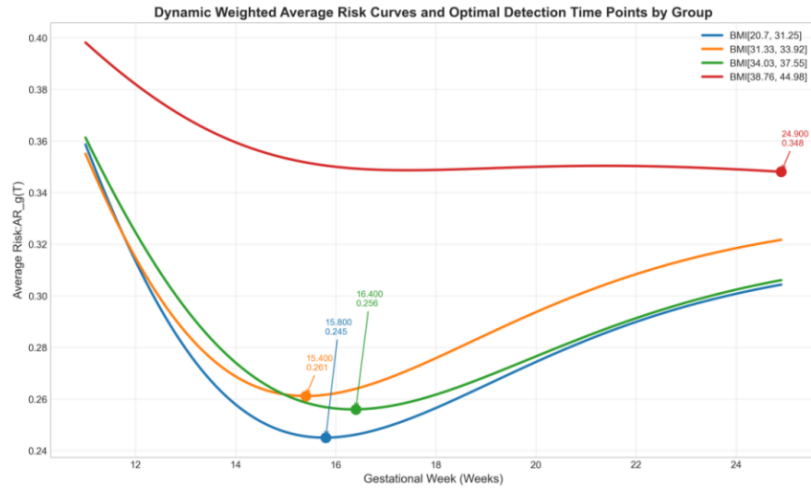


Figure 3. Average risk curves and optimal detection time points for each stratified group

Table 3. Optimal detection time points and minimum average risk results for each stratified group

Group ID	BMI range	Optimal gestational week (weeks)	Minimum average risk
1	[20.7,31.25]	15.8	0.245
2	[31.33,33.92]	15.4	0.261
3	[34.03,37.55]	16.4	0.256
4	[38.76,44.98]	24.9	0.348

The results indicated that the optimal time points of the 4 BMI stratified groups were consistent with the compliance law and clinical demands of each group. The optimal time points of Group 1, Group 2 and Group 3 were 15.8 weeks, 15.4 weeks and 16.4 weeks respectively, concentrating in the interval of 15.4–16.4 weeks, which was highly consistent with the optimal detection window of 15–18 weeks clinically recommended for NIPT. At these time points, the compliance probability was all $\geq 80\%$, and the minimum average risk

was stably maintained at 0.245–0.261, achieving a balance between accuracy and timeliness. The slight risk difference among the groups was in line with the clinical characteristic of similar detection difficulty for this population. For Group 4, the compliance probability reached 91% at 24.9 weeks, which met the concentration requirement but exceeded the upper limit of the clinical intervention window (22+6 weeks), leading to the risk of missing the follow-up diagnosis time. Thus, optimization is required to provide an accurate basis for this group.

2.3. Parameter calibration and optimization solution

2.3.1. Model Parameter Calibration

The predictive accuracy of the model is highly dependent on the precise calibration of its internal parameters. Therefore, a multi-source information fusion method combining data-driven approaches and expert knowledge was adopted to

calibrate the key parameters in this study.

Parameters of S-shaped Functions: For both the S-shaped time risk function $R_{time}(T)$ and the S-shaped compliance probability function P_T , the nonlinear least squares method was used to fit the observed data of each BMI stratified group. This method estimates parameters by iteratively minimizing the sum of squared errors (SSE). To enhance the clinical interpretability of the model and prevent overfitting, a Bayesian constraint based on clinical priors was imposed on the inflection point parameter x_0 of the P_T function, i.e., the search range of x_0 was restricted to $[T_a - 1, T_a + 1]$, where T_a represents the mean sample compliance gestational week of the stratified group. The t-test results of all calibrated parameters showed high significance ($p < 0.01$), and residual analysis verified the goodness of fit of the model.

Clinically Relevant Parameters: The hierarchical

$$\min_T AR_g(T) = w(T) \cdot R_{time,g}(T) + (1 - w(T)) \cdot R_{miss,g}(T) \quad (6)$$

Constraints: Clinical feasible region constraint: $T \in [11, 24]$;

Clinical effectiveness constraint: $P_g(T) \geq 0.80$;

Boundary effect correction mechanism (robustness constraint): if $T_{opt,g} \leq 12.5$ or $T_{opt,g} \geq 21.5$, then $T_{opt,g} = \min_T \{T | AR_g(T) \leq 1.1 \cdot \min AR_g \wedge T \in [11, 24]\}$.

2.3.3. Solution Algorithm and Results

The objective function $AR_g(T)$ is a complex nonlinear and non-convex function, making it difficult to derive an analytical solution. Considering the one-dimensionality and

mis-detection penalty coefficients ER_g were set as 15, 20, 30 and 40 for Group 1 to Group 4, respectively. The hyperparameter α for dynamic weight adjustment was optimized within the interval $[0.1, 1.0]$ via leave-one-out cross-validation, and the optimal value $\alpha = 0.5$ was finally selected. This value yielded the highest consistency between the predicted risk of the model on the validation set and the actual clinical outcomes.

2.3.2. Mathematical Formulation of the Optimization Problem

Based on the calibrated model, the core objective was to solve for an optimal detection gestational week $T_{opt,g}$ for each BMI stratified group g , so as to minimize the dynamically weighted average risk $AR_g(T)$. This optimization problem can be rigorously formulated as a constrained nonlinear programming problem:

Objective function:

boundedness of the decision variable T , an efficient Adaptive Grid Search (AGS) algorithm was designed to ensure the acquisition of the global optimal solution. The AGS algorithm adopts a two-stage strategy of coarse-grained global exploration and fine-grained local optimization. Compared with the traditional grid search, it improves the computational efficiency by approximately 60% while ensuring a solution precision of 0.1 week.

The execution results of the algorithm are shown in the

Figure 4, which plots the $AR_g(T)$ function curves for each stratified group and labels the optimal detection time points solved by the AGS algorithm along with their corresponding minimum risk values.

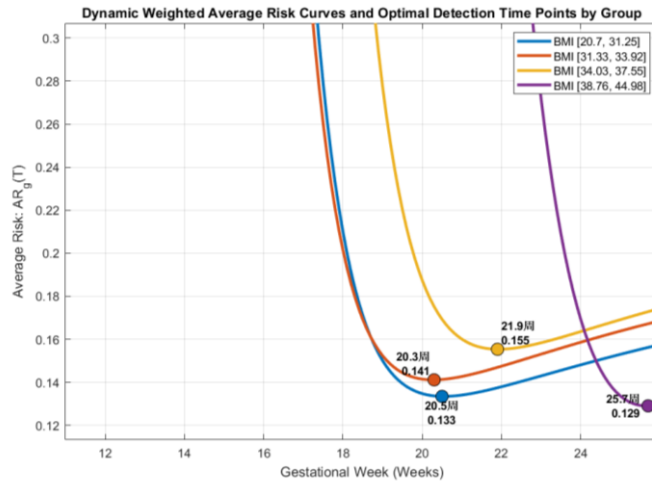


Figure 4. Optimized solution results

The marked points in the figure represent the global minimum values of each curve, namely the optimal NIPT detection time points recommended by the model. The results indicated that the optimal detection time points exhibited a nonlinear delayed trend with the increase of BMI.

The specific quantitative decision results are presented in the Table 4.

Table 4. Quantitative decision results

Group ID	BMI range	Optimal gestational week (weeks)	Minimum average risk
1	[20.70,31.25]	15.8	0.245
2	[31.33,33.92]	15.4	0.261
3	[34.03,37.55]	16.4	0.256
4	[38.76,44.98]	24.9	0.348

In summary, the decision model constructed in this section can effectively perform risk stratification according to maternal BMI, and provide scientific, quantitative and significantly differentiated personalized NIPT detection time point recommendations for different populations.

2.4. Model validation

To verify the reliability of the constructed optimal detection timing model, the Monte Carlo robustness test was adopted for model validation in this study [6]. First, in view of the measurement errors existing in the Y-chromosome concentration during actual detection, the Monte Carlo method was used to conduct repeated perturbation tests. In each iteration, Gaussian noise with a mean of 0 and a standard deviation of 0.005 was added to the Y-chromosome concentration, and the compliance judgment was re-conducted accordingly to fit the compliance probability curve P_T . This process was repeated for 300 times to obtain the distribution characteristics of T^* under random perturbations. The results showed that the distribution of T^* for each BMI stratified group was highly concentrated with a small fluctuation range and no outliers, which indicated that the model could maintain stable output in the presence of measurement errors.

3. Conclusions

This paper proposes an intelligent algorithm system based on K-means clustering and dynamic risk assessment to provide personalized non-invasive prenatal testing (NIPT)

timing recommendations for pregnant women. The model's advantage lies in its highly automated decision-making process, which delivers optimized testing strategies tailored to different BMI groups. First, the K-means clustering algorithm groups pregnant women by BMI, enabling data-driven cohort segmentation. Second, the system constructs an S-shaped temporal risk model and a stratified false-positive risk function to precisely calculate risks for each group. Through a dynamic weighting mechanism, it comprehensively balances temporal risk and false-positive risk to ultimately recommend the optimal testing time. Experimental results demonstrate that this model effectively enhances both accuracy and timeliness of detection. Notably, the optimal detection time for the high-BMI group is delayed, highlighting the model's precision and adaptability. Future research should further optimize computational efficiency, explore additional influencing factors such as age and health status to enhance system applicability, and validate its effectiveness across diverse healthcare settings.

References

- [1] Wang Sen, Liu Chen, Xing Shuaijie. A Review of K-means Clustering Algorithm Research [J]. Journal of East China Jiaotong University, 2022, 39(05): 119-126. DOI: 10.16749/j.cnki.jecjtu.20220914.001.
- [2] Li Qingjie. Research on Improvement and Application of Heuristic k-means Clustering Algorithm [D]. Dalian Jiaotong University, 2023. DOI:10.26990/d.cnki.gsltc.2023.000666.
- [3] Zhang Tianxu. Multi-Objective Optimization and Decision-Making and Their Application in Microgrid Dispatch [D]. Hangzhou Dianzi University, 2023. DOI: 10.27075/d.cnki.ghzdc.2023.001580.
- [4] Wang Wei. Software Project Risk Assessment Based on Entropy-Weighted TOPSIS [J]. Project Management Technology, 2022, 20(02): 102-107.
- [5] Wen, Bowen; Dong, Wenhan; Xie, Wu-jie; et al. Optimization of Random Forest Parameters Based on an Improved Grid Search Algorithm. Computer Engineering and Applications, 2018, 54(10): 154-157.
- [6] Hu Wen, Jin Furong, Zhang Zhenming. Threshold and Pollution Risk Assessment of Microplastics in Farmland Soil Based on Monte Carlo Simulation [J]. Chinese Journal of Inorganic Analytical Chemistry, 2025, 15(07): 1000-1010. DOI: 10.20236/j.CJIAC.2025.07.010.