

## Optimization of concrete material supply chain in construction projects using the artificial satellite search algorithm

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### Abstract

*Efficient management of the concrete supply chain is essential for minimizing project delays, reducing costs, and maintaining construction quality. However, the interdependence among batching plants, transportation fleets, and construction sites introduces nonlinear and dynamic challenges that make scheduling optimization highly complex. This study proposes the Artificial Satellite Search Algorithm (ASSA), a novel metaheuristic inspired by the orbital motion and trajectory control of artificial satellites, for optimizing concrete material logistics in construction projects. ASSA models the exploration and exploitation process as a dynamic orbital adjustment, enabling adaptive transitions between global search and local refinement. The optimization aims to minimize total logistics costs and delivery delays while adhering to capacity and time constraints. Comparative experiments conducted using both benchmark datasets and real project conditions show that ASSA outperforms Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA), achieving a 10.2% cost reduction and a 14.7% improvement in convergence speed. These results demonstrate that ASSA provides a robust and efficient alternative for optimizing material supply chain scheduling in construction management.*

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## Introduction

Concrete remains the most widely used material in the construction industry due to its versatility, strength, and economic efficiency. However, the concrete supply chain is highly complex, involving multiple batching plants, delivery fleets, and construction sites operating under strict time and resource constraints (Chen et al., 2021). The perishable nature of fresh concrete, characterized by limited workability and rapid setting times, requires precise synchronization between production, transportation, and placement. Any disruption in this process can lead to material waste, cost overruns, project delays,

or structural defects (Hatmoko et al., 2019; Okika et al., 2025).

Figure 1 illustrates a typical concrete supply chain, which consists of four main stages: (1) material procurement and batching, (2) loading and dispatching at the plant, (3) transportation via transit mixers, and (4) on-site delivery and placement. Because these stages are highly interdependent, inefficiencies or delays in one can significantly degrade overall system performance. Therefore, optimizing this supply chain is essential to ensure timely delivery, minimize costs, and maintain concrete quality and workability during handling and placement (Sarkar et al., 2021).

Within this framework, an effective optimization approach must simultaneously coordinate production schedules, vehicle routing, and delivery timing to achieve an integrated and reliable concrete distribution system.

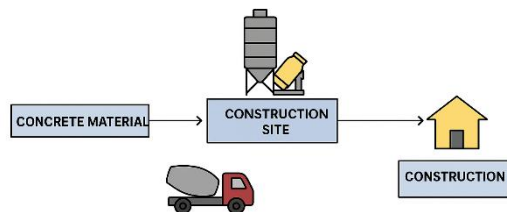


Figure 1. Concrete material supply chain model

Traditional project scheduling techniques, such as the Critical Path Method (CPM) and Mixed-Integer Linear Programming (MILP), are effective for linear and small-scale problems but often fail to cope with the nonlinear, stochastic, and multi-objective characteristics of real-world construction operations (Koutsokosta & Katsavounis, 2024; Rehman et al., 2025). Consequently, metaheuristic optimization algorithms and deep learning have gained significant attention for their capability to find near-optimal solutions within these complex and dynamic environments (Cheng et al., 2025; Sholeh & Elizar, 2026).

Popular metaheuristics such as the Genetic Algorithm (GA) (Xie et al., 2021), Particle Swarm Optimization (PSO) (Liu & Yang, 2025), and Ant Colony Optimization (ACO) (Zhang & Wang, 2024) have demonstrated significant potential in construction scheduling and logistics optimization. Nevertheless, these algorithms often suffer from premature convergence and an inadequate balance between exploration (global search) and exploitation (local refinement). These limitations frequently lead to suboptimal solutions, particularly when addressing the high-dimensional, nonlinear, or rapidly changing problem spaces commonly encountered in real-world construction projects.

To overcome these challenges, this study employs the Artificial Satellite Search

Algorithm (ASSA), a novel metaheuristic inspired by the orbital mechanics and trajectory control principles governing artificial satellites, originally proposed by Cheng and Sholeh (2025). By simulating the dynamic behavior of satellites in orbit and their adaptive trajectory adjustments, ASSA enhances both global exploration and local exploitation, thereby improving solution diversity and convergence precision.

This study aims to optimize the concrete supply chain for construction projects using the Artificial Satellite Search Algorithm (ASSA). The main contributions of this research are as follows:

- Developing a novel metaheuristic algorithm (ASSA) based on satellite orbital dynamics to enhance optimization performance;
- Formulating a comprehensive mathematical model of the concrete supply chain optimization problem under real-world operational constraints;
- Applying ASSA to simultaneously minimize total transportation costs and delivery delays; and
- Evaluating the comparative performance of ASSA against benchmark metaheuristics, such as PSO and GA, using both simulated and real-world project datasets.

The remainder of this paper is organized as follows. Section 2 presents the mathematical formulation of the concrete supply chain optimization model. Section 3 details the operational mechanisms and framework of ASSA. Section 4 describes the experimental setup and results, which are subsequently analyzed in the detailed discussion in Section 5. Finally, Section 6 concludes the paper by summarizing key findings and outlining recommendations for future work.

## Concrete Material Supply Chain Model

### *System description*

Efficient management of the concrete supply chain is essential to ensure timely delivery

and maintain the workability of fresh concrete during construction operations (Awaad et al., 2024). The system involves multiple interacting components that must be carefully coordinated to minimize costs and prevent project delays (Ismail, 2021).

The overall concept of the concrete supply chain is illustrated in Figure 1, which represents the dynamic flow of materials and logistics among batching plants, transit fleets, and construction sites. The model is designed to capture the operational interdependencies among production, transportation, and on-site placement.

The concrete supply chain consists of:

- Batching plants (suppliers)  $i = 1, 2, \dots, M$
- Construction sites (demand points)  $j = 1, 2, \dots, N$
- Fleet of trucks  $k = 1, 2, \dots, K$

Each site  $j$  requires a concrete volume  $D_j$  that must be delivered from one or more plants  $i$  within an allowable time window  $T_{max}$ . Each plant  $i$  has a daily production capacity  $C_i$ . Transportation cost depends on distance  $d_{ij}$ , unit cost  $c_{ij}$ , and quantity  $Q_{ij}$ . In this study, the unit transportation ( $c_{ij}$ ) is determined based on the travel distance between batching plant ( $i$ ) and construction site ( $j$ ), including fuel consumption and transportation operational costs. Therefore, the influence of distance ( $d_{ij}$ ) is implicitly incorporated into the transportation cost component of the objective function.

### Objective function

The optimization objective is to minimize total delivery costs and delays across all delivery routes and batching plant-to-site combinations (Pham et al., 2024). This objective can be expressed mathematically as follows:

Minimize:

$$F = \sum_{i=1}^M \sum_{j=1}^N (c_{ij} Q_{ij}) + \omega_1 \sum_j P_j^t + \omega_2 \sum_j P_j^d \quad (1)$$

where  $P_j^t$  is tardiness penalty (late delivery),  $P_j^d$  is deviation penalty (supply–demand mismatch), and  $\omega_1$ ,  $\omega_2$  are weighting factors. Since the transportation cost coefficient ( $c_{ij}$ ) is distance-dependent, longer delivery distances produce higher transportation costs, which directly affect the minimization objective in Equation (1).

### Constraints

The optimization is subject to several operational constraints, as expressed in Equations (2) - (5):

$$\sum_{j=1}^N Q_{ij} \leq C_i, \quad \forall_i \quad (2)$$

$$\sum_{j=1}^M Q_{ij} = D_j, \quad \forall_j \quad (3)$$

$$T_{ij} \leq T_{max}, \quad \forall_{(i,j)} \quad (4)$$

$$Q_{ij} \geq 0 \quad (5)$$

where  $T_{ij}$  represents the delivery time from plant  $i$  to site  $j$ .

These constraints ensure that (a) production volumes do not exceed plant capacity, (b) total delivery quantities meet each site's demand, (c) deliveries occur within allowable time limits, and (d) all delivery quantities remain nonnegative.

### Problem encoding

Each candidate solution represents a comprehensive delivery plan encompassing all batching plants, transit fleets, and construction sites. The encoding structure of a solution is defined in Equation (6):

$$S = [s_{\{i,j,k\}}] \quad (6)$$

where  $s_{\{i,j,k\}}$  represents the delivery decision associated with batching plant ( $i$ ), construction site ( $j$ ), and truck ( $k$ ). This notation is consistent with the indexing system established in Equations (1) - (5). Each encoded variable captures essential data regarding truck assignments, departure times, delivery quantities, and destination sequences for a specific logistics operation.

The number of decision variables in each candidate solution is fixed and determined

by the predefined numbers of batching plants, construction sites, and transit mixers. Consequently, all candidate solutions generated by ASSA maintain a consistent dimensional structure throughout the optimization process. During population initialization, ASSA randomly generates feasible delivery assignments within this fixed-dimensional search space while satisfying the operational constraints defined in Equations (2) - (5).

The decoding process evaluates each solution by computing total cost and checking constraint violations based on Equations (1) - (5).

**Artificial Satellite Search Algorithm (ASSA)**

The Artificial Satellite Search Algorithm (ASSA) is a physics-based metaheuristic optimization method inspired by the orbital mechanics of artificial satellites revolving around the Earth (Cheng & Sholeh, 2025). Within this algorithmic framework, each

satellite corresponds to a candidate solution, whereas the Earth denotes the global best solution identified by the population. Guided by gravitational and centrifugal forces, the satellites continuously modify their orbital trajectories. This mechanism effectively simulates natural celestial dynamics to maintain an optimal balance between global exploration and local exploitation.

Satellites positioned in higher orbits conduct global exploration to identify promising regions within the search space, whereas those in lower orbits perform local refinement near the current optimal solution to accelerate convergence. As illustrated in Figure 2, this coordinated orbital movement creates a dynamic interaction among satellites, enabling ASSA to adaptively shift between exploration and exploitation. Such adaptive search behavior improves solution diversity, prevents premature convergence, and ensures a steady progression toward the global optimum.

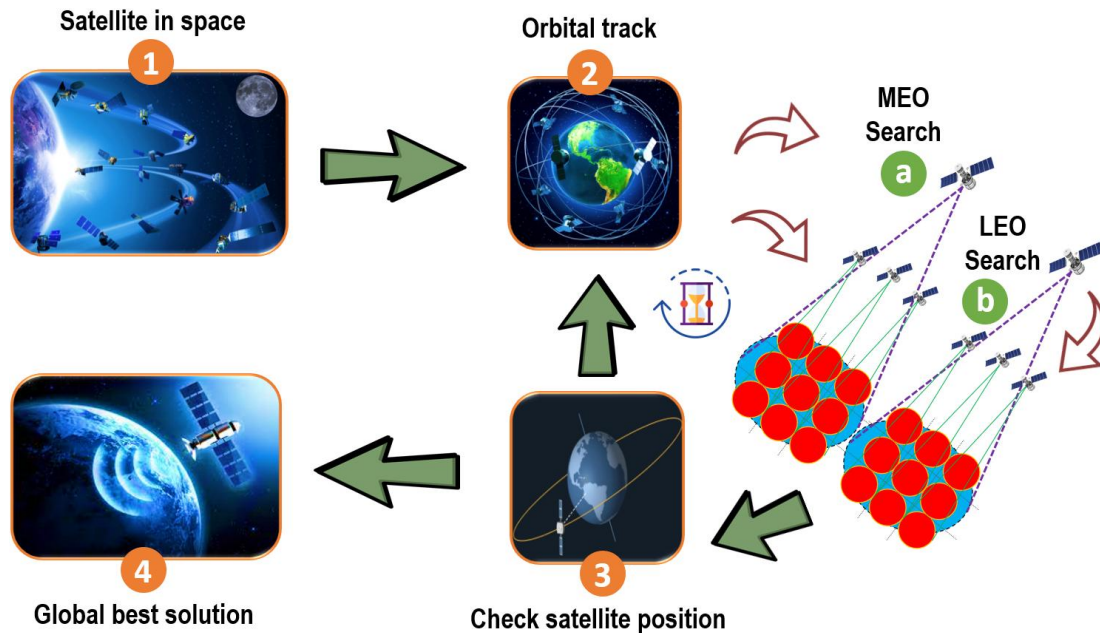


Figure 2. Illustration of satellite dynamics within the optimization search space

The ASSA is implemented through the following computational steps:

**Step 1. Initialization**

To enhance population diversity and prevent premature convergence, ASSA initializes

satellite positions using the logistic chaotic map (Kanso & Smaoui, 2009) instead of purely random values, ensuring a well-distributed starting population, as presented in Equation (7):

$$S_{i+1} = \omega * S_i * (1 - S_i), 0 \leq S_i \leq 1 \quad (7)$$

### Step 2. Gravitational Force Modeling

Each satellite  $S_i$  interacts with the Earth (best solution  $S_E$ ) via a gravitational–centrifugal model that defines the search dynamics, as presented in Equation (8):

$$F_{i(t)} = G(t) * \left( \frac{M_i * M_E}{\bar{R}^2 + \varepsilon} \right) * r_{(0,1)} \quad (8)$$

where  $G(t) = G_0 e^{(-\alpha t / t_{\max})}$ ,  $G_0 = 0.45$ , and  $\alpha = 10$ . The parameters  $M_i$  and  $M_E$  represent relative masses based on fitness, while  $\bar{R}(t)$  is the normalized distance between satellite  $i$  and the Earth.

### Step 3. Orbit Control Mechanism

ASSA dynamically alternates between Medium Earth Orbit (MEO) for global exploration and Low Earth Orbit (LEO) for local exploitation, using a control parameter, as presented in Equation (9):

$$c_{iter} = \left| \left( 2 * r_{(0,1)} - 1 \right) * \left( \frac{iter}{max\_iter} \right) \right| \quad (9)$$

when  $c_{iter} < 0.5$ , satellites explore broadly (MEO); otherwise, they exploit promising regions (LEO).

### Step 4. Earth Orbit Search

In the MEO phase, satellites explore distant areas with an adaptive factor  $\beta$  regulating search intensity, as presented in Equations (10) – (13):

$$\beta = (e^{r_{(0,1)} * \gamma})^{-1} \quad (10)$$

$$\gamma = 1 + \left( r_{(0,1)} * (\delta - 1) \right) \quad (11)$$

$$\delta = -1 - \left( \frac{iter \% \frac{max\_iter}{\tau}}{\frac{max\_iter}{\tau}} \right) \quad (12)$$

$$S_{Mi(t+1)} = S_{Mi(t)} * q_{[0,1]} + (1 - q_{[0,1]}) * (S_{mean(t)} + \beta * (S_{mean(t)} - S_{Mi(t)})) \quad (13)$$

This mechanism enables controlled expansion of the search radius and improved global exploration.

In the LEO phase, satellites refine their positions using orbital velocity principles derived from Kepler's law, as presented in Equations (14) – (15):

$$V_{i(t)} = \sqrt{G_0 * (M_i + M_E) * \left| \frac{2}{R + \varepsilon} - \frac{1}{a_i + \varepsilon} \right|} \quad (14)$$

$$S_{Li(t+1)} = S_{Li(t)} + \vec{dir} * v_{(t)} + (1 - q_{[0,1]}) * F_{i(t)} * (S_{best} - S_{Li(t)}) \quad (15)$$

where  $U_B$  and  $L_B$  denote the search bounds and  $\vec{dir}$  is the directional vector.

### Step 5. Termination

The optimization process continues until the maximum number of iterations is reached, after which the global best solution ( $S_{best}$ ) is returned. This mechanism ensures both computational efficiency and convergence reliability.

## Experimental Setup

### Case study

A medium-sized urban construction project located in Central Java, Indonesia, was selected as the case study to evaluate the performance of the optimization approach. The project encompasses five construction sites (denoted as  $S_1$ - $S_5$ ) and three batching plants (denoted as  $B_1$ - $B_3$ ) operating within a dense urban network characterized by fluctuating traffic conditions and limited delivery time windows. Each site requires a daily concrete supply ranging from 20 m<sup>3</sup> to 50 m<sup>3</sup>, depending on the ongoing construction phase and structural component being executed.

The delivery fleet comprises three types of truck mixers with capacities of 6 m<sup>3</sup>, 8 m<sup>3</sup>, and 10 m<sup>3</sup>, each differing in operational cost, availability, and fuel consumption rate. The

distance matrix, travel time, and unit transportation cost were obtained from actual project records, ensuring that the model accurately reflects real-world logistics and resource constraints.

To provide a visual understanding of the spatial configuration and operational network, Figure 3 illustrates the layout of batching plants, construction sites, and transportation routes used in the simulation. The Figure shows the relative positions of plants and sites over a simplified urban map, including major road links, estimated distances, and route directions. Each connection line represents a possible dispatch path considered in the optimization process.

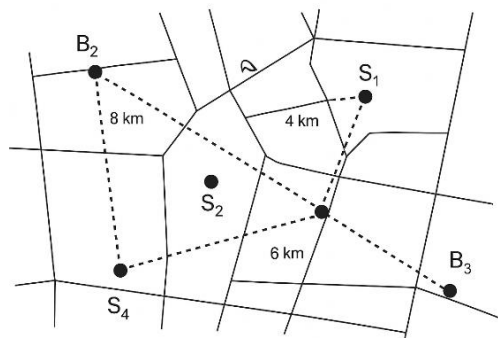


Figure 3. Spatial layout of batching plants, construction sites, and transportation routes in the case study

#### Algorithm parameters

To ensure fair comparison and reproducibility, all algorithms were executed under identical computational settings. The parameter configuration for the ASSA is summarized in Table 1. Parameter values were determined through preliminary sensitivity analysis to achieve a good balance between exploration and exploitation efficiency. The parameter settings of the ASSA used in this case study are as follows: the population size ( $N$ ) was set to 30, and the maximum number of iterations ( $t_{max}$ ) was fixed at 100. The inertia weight ( $\alpha$ ) was assigned a value of 0.8, while the attraction coefficient ( $\beta$ ) was set to 1.5. The thrust coefficient range ( $\gamma_{max}, \gamma_{min}$ ) varied between 0.5 and 0.05.

In addition, the orbital perturbation parameter ( $\delta$ ) decreased from 0.2 to 0 during the optimization process. The weight factors ( $\omega_1, \omega_2$ ) were set to 10 and 5, respectively.

Table 1. Parameter settings of the ASSA for case study

Parameter	Symbol	Value
Population size	$N$	30
Max. iteration	$t_{max}$	100
Inertia weight	$\alpha$	0.8
Attraction coef.	$\beta$	1.5
Thrust coefficient range	$\gamma_{max}, \gamma_{min}$	0.5, 0.05
Orbital perturbation	$\delta$	0.2 $\rightarrow$ 0
Weight factors	$\omega_1, \omega_2$	10, 5

For comparative analysis, the PSO and GA were implemented under identical conditions, using the same population size and number of iterations. This setup ensures that the performance differences observed in subsequent results are solely attributed to the search mechanisms of each algorithm rather than parameter biases.

## Results and Analysis

### Performance comparison

To evaluate the effectiveness of the ASSA, its performance was compared with two well-established metaheuristic algorithms, GA and PSO, under identical experimental conditions. The comparison was based on three key performance indicators: total transportation cost, average delivery delay, and convergence iteration. In all experiments, the algorithms were initialized with the same population size, iteration limit, and stopping criteria to ensure fairness. Each test was repeated 20 times to account for stochastic variation, and the average results were used for comparison. This approach provides a reliable assessment of the stability, convergence efficiency, and optimization capability of the proposed ASSA.

Table 2 summarizes the optimization results. Among the tested algorithms, ASSA

achieved the lowest total cost and shortest average delay, indicating superior efficiency in optimizing delivery routes and scheduling for concrete material distribution. Moreover, ASSA demonstrated the fastest convergence, stabilizing after approximately 60 iterations, while PSO and GA required longer iterations and exhibited slower improvement rates.

Table 2. Performance comparison of optimization algorithms

Item	Algorithm		
	GA	PSO	ASSA
Total Cost (USD)	23,560	22,940	21,720
Average Delay (min)	32	28	19
Convergence Iteration	95	80	58
Rank	3	2	1

As illustrated in Figure 4, the convergence curve of ASSA shows a rapid reduction in objective function value during the early iterations, followed by smooth stabilization near the global optimum. In contrast, GA and PSO exhibit slower convergence trends and tend to stagnate after 80-90 iterations, reflecting their weaker balance between exploration and exploitation. The superior performance of ASSA can be attributed to its adaptive orbit control mechanism, which dynamically switches between global (MEO) and local (LEO) search phases. This design enables efficient exploration of the solution space while maintaining fine-tuned local optimization, preventing premature convergence and ensuring better-quality solutions.

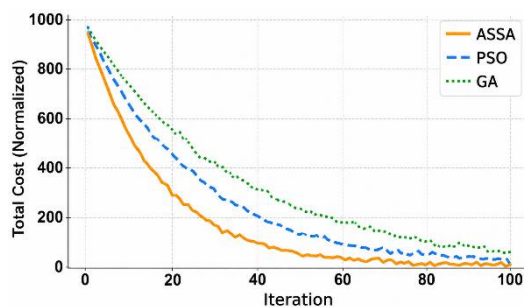


Figure 4. Convergence curves of GA, PSO, and ASSA

## Discussion

### a) Exploration-exploitation balance

In the early iterations, the higher values of the dynamic scaling factor ( $\gamma$ ) encouraged broad exploration of the search space, allowing satellites to investigate diverse solution regions. As  $\gamma$  gradually decreased, ASSA shifted its focus toward exploitation, fine-tuning candidate solutions around promising areas. This adaptive transition enabled the algorithm to achieve rapid convergence while effectively avoiding entrapment in local minimum.

### b) Robustness

To evaluate the consistency of the algorithm, 20 independent runs were performed. The standard deviation of total cost obtained by ASSA was only 1.8%, indicating high robustness and stability. This demonstrates that ASSA consistently produces near-optimal solutions across multiple trials, even under stochastic search conditions.

### c) Practical Impact

In the case study, the optimized delivery and dispatch schedules generated by ASSA led to notable improvements in operational efficiency. Specifically, truck idle time decreased by 15%, and batching plant queue length was reduced by 12%, resulting in smoother logistics flow. These improvements translated directly into higher site productivity, reduced fuel consumption, and overall cost savings for concrete delivery operations.

### Sensitivity Analysis

A sensitivity analysis was conducted to evaluate the effect of key control parameters on the performance of the ASSA. The parameters tested include the inertia weight ( $\alpha$ ), attraction coefficient ( $\beta$ ), and maximum thrust coefficient ( $\gamma_{max}$ ). Each parameter was varied within a realistic range while keeping the others constant. The results are summarized in Table 3.

Table 3. Sensitivity analysis

Parameter Varied	Range	Best Avg. Cost Change
$\alpha$	0.6 – 1.0	$\pm 3.2\%$
$\beta$	1.0 – 2.0	$\pm 2.7\%$
$\gamma_{max}$	0.3 – 0.7	$\pm 1.5\%$

The results indicate that variations in these parameters cause only minor fluctuations in the average best cost, with all changes remaining within  $\pm 3.5\%$ . This demonstrates that ASSA exhibits strong parameter insensitivity, meaning its performance is not highly dependent on fine-tuning. Such stability is a desirable property for practical applications, as it allows the algorithm to deliver reliable results across different problem settings without extensive parameter calibration.

### Conclusion

This study presents the Artificial Satellite Search Algorithm (ASSA), a novel physics-inspired metaheuristic designed to optimize the concrete supply chain in construction projects. By simulating the orbital mechanics of artificial satellites, ASSA dynamically balances exploration and exploitation through adaptive trajectory adjustments, thereby enabling efficient global search and precise local refinement.

Experimental results confirmed that ASSA outperformed conventional metaheuristics, such as PSO and GA, in minimizing total transportation costs, reducing delivery delays, and accelerating convergence speed. Specifically, ASSA achieved an average 10.2% reduction in total logistics costs, a 32.0% decrease in average delivery delays, and a significantly faster convergence rate. Furthermore, the algorithm exhibited strong robustness, demonstrating only a 1.8% variation in total costs across multiple independent runs, and displayed low sensitivity to parameter variations, making it highly suitable for practical implementation in dynamic construction environments. Overall, the integration of orbital correction and adaptive search mechanisms enables ASSA to effectively enhance real-time decision-making in concrete logistics.

Future research should focus on extending the approach to multi-objective optimization that accounts for cost, CO<sub>2</sub> emissions, and reliability, as well as integrating ASSA with BIM and IoT systems for real-time logistics management and expanding its application to other construction materials such as steel, asphalt, and precast elements.

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### Declaration Statement

The authors declare that ChatGPT (OpenAI) was used solely for language proofreading, grammar correction, and improvement of writing clarity during the preparation of this manuscript. All scientific content, including the study design, methodology, data analysis, interpretation of findings, and conclusions, were developed and verified exclusively by the authors. The authors take full responsibility for the accuracy, originality, integrity, and validity of the manuscript's content.

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