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# Swarm Intelligence in Modern Engineering a Comprehensive Review of Applications, Performance and Emerging Trends

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**Abstract:** Modern engineering systems increasingly encounter complex, high-dimensional optimization problems that challenge traditional solution methods. Swarm intelligence (SI) algorithms, inspired by the collective behavior of biological systems, offer robust and adaptable alternatives. This review systematically explores the development and application of key SI techniques-Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO)-within engineering domains from 2020 to 2025. Drawing on recent literature, the paper identifies major application areas in mechanical, structural, power, energy, civil, and infrastructure engineering. It evaluates algorithmic performance trends, emphasizing the superior convergence and robustness of hybrid approaches, along with their growing integration with machine learning. The review also highlights advances in multi-objective optimization and the expanding use of SI in emerging fields such as IoT and cybersecurity. The findings underscore the increasing significance of SI in next-generation engineering systems, particularly in autonomous technologies and smart infrastructure, while outlining key directions for future research and practical deployment.

**Keywords:** Swarm intelligence, Engineering optimization, Particle swarm optimization, Artificial bee colony, Ant colony optimization, Hybrid algorithms

## Introduction

Subdivide text into unnumbered sections, Modern engineering systems face unprecedented complexity challenges that traditional optimization approaches struggle to address effectively. The exponential growth in system scale, multi-objective requirements, and real-time constraints has created substantial demand for robust, adaptable optimization methodologies (Tartibu, 2025). Swarm intelligence algorithms, inspired by collective behaviors observed in natural systems, have emerged as compelling solutions to these challenges. Swarm intelligence applications have seen phenomenal growth in the engineering community within the last five years due to improvements in hardware and software complexity (Paul et al., 2024). These bio-inspired algorithms show unrivaled versatility in tackling a number of contemporary engineering problems that are characterized by complex non-linear, multi-modal optimization landscapes, such as optimizing renewable energy systems and managing communication networks (Beegum et al., 2023).


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This thorough review discusses the increasing importance of systematic evaluation of swarm intelligence applications for engineering applications between 2020 and 2025. It covers all the core algorithm families for the Particle Swarm Optimization, Artificial Bee Colony, and Ant Colony Optimization and their applications in wide range of engineering ons (Selvarajan, 2024). Using systematic literature review techniques, this paper investigates all related peer-reviewed publications from three major engineering databases, IEEE Xplore, ScienceDirect and SpringerLink. Our paper is organized around algorithmic structure that lays out fundamental principles, domain-specific applications, and critical take on trends. This book focuses on implementation strategies, performance characteristics, and practical issues of interest to practicing engineers for each application domain.

## Swarm Intelligence Fundamentals and Classification

Swarm intelligence algorithms operate on the principle of collective behavior emergence from simple individual interactions(Tang et al., 2021). These algorithms demonstrate particular effectiveness in engineering optimization due to their inherent parallelism, robustness to local optima, and adaptability to dynamic problem landscapes. Particle Swarm Optimization represents the most widely adopted swarm intelligence technique in engineering applications (Gad, 2022). PSO algorithms simulate social behavior patterns observed in bird flocking and fish schooling, where individual particles adjust their positions based on personal experience and collective knowledge. The fundamental PSO update equations govern velocity and position modifications, incorporating inertia weight, cognitive coefficient, and social coefficient parameters that significantly influence convergence characteristics. Artificial Bee Colony algorithms model the foraging behavior of honeybee colonies, employing three distinct bee categories: employed bees, onlooker bees, and scout bees(Wang et al., 2022). The ABC framework demonstrates particular strength in maintaining exploration-exploitation balance through its probabilistic selection mechanism and abandonment criterion. Engineering applications benefit from ABC's ability to escape local optima while maintaining solution quality throughout the optimization process.

Ant Colony Optimization techniques derive inspiration from ant foraging behavior, utilizing pheromone trail mechanisms to guide solution construction(Yahia et al., 2020a). ACO algorithms excel in combinatorial optimization problems frequently encountered in engineering design, particularly in path planning, scheduling, and resource allocation scenarios. The pheromone update rules and heuristic information integration provide effective mechanisms for incorporating domain-specific knowledge. Algorithm selection criteria for engineering applications depend on problem characteristics including dimensionality, constraint complexity, and real-time requirements (Jiao et al., 2023). Multi-modal optimization problems typically favor PSO variants due to their superior exploration capabilities, while combinatorial problems often benefit from ACO implementations. ABC algorithms demonstrate consistent performance across diverse problem types, making them suitable for general-purpose engineering optimization.

Performance evaluation frameworks for swarm intelligence algorithms require careful consideration of multiple metrics including convergence speed, solution quality, computational efficiency, and robustness(Halim et al., 2021). Standard benchmark functions provide baseline comparisons, but engineering applications necessitate domain-specific performance indicators that reflect practical implementation constraints and objectives. To provide a conceptual structure for understanding the diversity of swarm intelligence (SI) techniques and their integration into engineering domains, Figure 1 presents a visual taxonomy that categorizes SI algorithms based on their biological inspiration, core mechanism, and typical engineering applications.

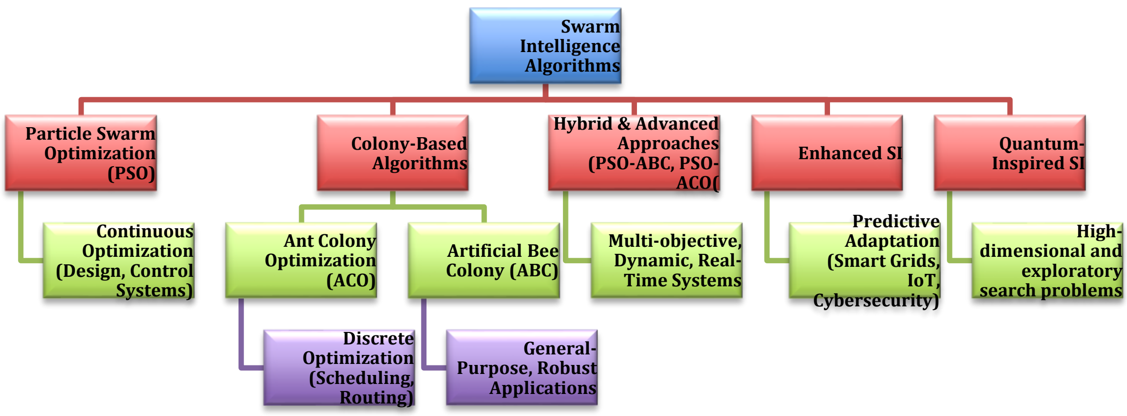


Figure 1. Taxonomy of swarm intelligence algorithms in engineering

## Engineering Application Domains

### Mechanical and Structural Engineering

Swarm intelligence algorithms have been increasingly adopted in mechanical and structural engineering applications to address complex design optimization challenges (Han & Sun, 2024). Design optimization problems in mechanical systems often involve multi-objective considerations, including weight minimization, stress distribution, and manufacturing constraints. Swarm intelligence techniques are particularly effective in managing these competing objectives while adhering to stringent safety requirements.

Material selection optimization is a critical application area where swarm intelligence provides substantial value (Xu et al., 2023). Traditional methods—such as weighted decision matrices—often fall short in capturing the complex interdependencies among material properties and application-specific requirements. In contrast, swarm-based approaches enable a comprehensive exploration of the material property space, accounting for manufacturing constraints, cost factors, and performance specifications simultaneously.

Construction site layout optimization has also emerged as a prominent domain for swarm intelligence applications (Xu et al., 2023). Construction projects require the spatial coordination of equipment, materials, and temporary facilities, all of which influence project efficiency and safety. Ant Colony Optimization (ACO) algorithms have shown particular effectiveness in this context, as they efficiently handle discrete spatial arrangements while incorporating safety distance constraints and workflow optimization goals.

Gear train design optimization exemplifies the application of swarm intelligence in mechanical component design (Jenis et al., 2023). Traditional gear train design typically relies on iterative methods that risk convergence to suboptimal solutions. Particle Swarm Optimization (PSO) techniques, however, facilitate a more exhaustive search of gear ratio combinations while satisfying torque transmission requirements, space limitations, and manufacturing constraints. Recent approaches have adopted multi-objective formulations that simultaneously optimize power transmission efficiency and gear train compactness.

Structural topology optimization has also seen notable advancements through swarm intelligence, particularly in scenarios that require innovative structural configurations (Kwok, 2022). These algorithms enable the exploration of unconventional layouts that traditional design methods might overlook. Their capability to handle discrete design variables makes them especially suitable for truss optimization problems, where selecting appropriate cross-sectional properties is essential.

### Power Systems and Energy Engineering

Extensive progress has been made in swarm intelligence applications in power systems and energy engineering, which investigate the complex behaviour of modern electrical grids and the need for their integration with renewable energy sources (Cavus, 2025). Photovoltaic system optimization is one of the most important application areas that can be accomplished by using swarm intelligence algorithms to optimize several objectives together such as power generation, reliability, and economic aspects, etc.

This means the issue of solar panel placement optimization consists of complicated geometric and environmental parameters that generally traditional optimization methods fail to manage those topics effectively (Soomar et al., 2022). Particle Swarm Optimisation (PSO) algorithms exhibit remarkable performance in optimising Large PV arrays while taking into account shading impacts, installation limitations, and feasibility of maintenance. Newer designs include dynamic shading analysis based on seasonal changes incorporated with the effect of surrounding structures.

Power Grid Management applications are a new power grid management application that smartly integrates swarm intelligence algorithms such as hydropower, solar-panel array optimization, and many other types for optimizing real-time generation dispatch (Albogamy et al., 2022). The dynamic nature of electrical demand and renewable power generation creates landscapes of optimization that are actually changeable in real time. So we need adaptive algorithms to track the optimum solution from continuously changing environments. The particular merit of Artificial Bee Colony algorithms lies in their ability to keep various solutions while moving resources to cope rapidly with changes in system conditions (Kuo, 2021).

The interface between emerging Smart Grid application areas and swarm intelligence is a brand-new frontier for developers! Smart grid systems need to co-ordinate not only with distributed energy sources, demand response programs and energy storage systems (Tang et al., 2021). But also fix that the programme presents a unified face to the world, without energy silos. Assembly line operations on a grand scale: use tendencies of localisation and consolidation to bring power distribution control points down to where they are needed more directly.

Apply these methods to balance electricity supply and demand across entire networks of consumers at any given moment, including smoothing out fluctuations in voltage caused by large frequency changes (Sina et al., 2021). Integration of energy from renewable sources presents new challenges to this field. Wind and solar power systems have an intrinsic variability that requires forecasts produced by intelligent. The example of combining multiple algorithms types to tackle renewable energy power system integration shows that hybrid swarm intelligence methods achieve superior performance (Yousef et al., 2023).

Energy storage system optimization has emerged as a critical application area for swarm intelligence algorithms( Wang et al., 2024). Battery energy storage systems require complex optimization of charge-discharge cycles, state-of-charge management, and degradation minimization. Swarm intelligence approaches enable comprehensive optimization of energy storage operations while considering multiple time scales from real-time power balancing to long-term capacity planning.

**Civil and Infrastructure Engineering**

Civil and infrastructure engineering applications have increasingly adopted swarm intelligence algorithms for addressing large-scale optimization problems characteristic of infrastructure development and management(Ghaemifard & Ghannadiasl, 2024). Structural design optimization encompasses a broad range of applications from building design to bridge construction, where swarm intelligence algorithms provide effective solutions for multi-objective optimization problems involving structural performance, cost minimization, and construction feasibility.

Bridge design optimization exemplifies the application of swarm intelligence in structural engineering(Martinez-Muñoz et al., 2022). Modern bridge design requires simultaneous consideration of structural performance, aesthetic considerations, environmental impact, and construction logistics. Particle Swarm Optimization algorithms demonstrate effectiveness in bridge design optimization by exploring design variable spaces that include geometric parameters, material specifications, and construction sequencing decisions.

Construction scheduling and resource allocation problems represent another significant application domain for swarm intelligence techniques(Ghoroqi et al., 2024). Construction projects involve complex interdependencies between activities, resource constraints, and time limitations that create challenging optimization environments. Ant Colony Optimization algorithms show particular strength in construction scheduling applications due to their ability to handle precedence constraints and resource limitations while optimizing project duration and cost objectives(Shen & Wu, 2025).

Infrastructure network planning applications leverage swarm intelligence algorithms for optimizing transportation networks, utility distribution systems, and communication infrastructure(Alkinani et al., 2022). These problems typically involve large-scale discrete optimization challenges where traditional approaches may become computationally prohibitive. Swarm intelligence algorithms provide scalable solutions that can handle network planning problems involving thousands of nodes and connections.

There are SI methods that have been applied to optimize pavement design using several performance indices including structural capacity, durability, and life cycle costs (Kang et al., 2025). Traditional pavement design processes often heavily rely on simplified design methods which may not really maximize the long-term performance of the pavement. But with swarm intelligence algorithms all pavement layers' configuration is taken into account, encompassing traffic load patterns and climatic conditions in a comprehensive manner and also incorporating maintenance requirements.

Water distribution system optimization represents a critical application area where swarm intelligence algorithms address complex hydraulic design problems(Pham et al., 2023). Water distribution networks require careful balancing of pipe sizing, pump placement, and storage facility design to achieve adequate service levels while minimizing infrastructure costs. Multi-objective swarm intelligence approaches demonstrate effectiveness in water system optimization by simultaneously addressing hydraulic performance, economic objectives, and reliability requirements.

**Control Systems and Automation**

Control systems and automation applications have embraced swarm intelligence algorithms for addressing complex parameter optimization and system coordination challenges(Bhimana & Ravindran, 2024). Process parameter optimization represents a fundamental application area where swarm intelligence techniques provide superior performance compared to traditional tuning methods. Industrial processes often involve multiple interacting control loops with complex dynamics that require sophisticated optimization approaches.

PID controller tuning applications demonstrate the effectiveness of swarm intelligence algorithms in control system optimization(Joseph et al., 2022). Traditional PID tuning methods may struggle with complex process dynamics, time delays, and nonlinear characteristics commonly encountered in industrial applications. Particle Swarm Optimization algorithms provide robust frameworks for PID parameter optimization that consider multiple performance criteria including settling time, overshoot, and steady-state error simultaneously.

Robotic path planning and coordination applications leverage swarm intelligence algorithms for managing complex navigation problems in dynamic environments(Nguyen, 2024). Multi-robot coordination requires sophisticated algorithms capable of handling real-time constraints while optimizing collective objectives such as task completion time and energy consumption. Swarm intelligence approaches provide natural frameworks for robot coordination by modeling individual robots as swarm agents that cooperate to achieve system-wide objectives.

Industrial automation and scheduling applications benefit from swarm intelligence implementations that address complex resource allocation and timing optimization problems(Del Gallo et al., 2023). Manufacturing systems involve multiple machines, workers, and materials that must be coordinated to achieve production objectives while satisfying quality requirements and delivery schedules. Ant Colony Optimization algorithms demonstrate particular effectiveness in manufacturing scheduling applications due to their ability to handle complex precedence constraints and resource limitations.

Model predictive control applications have increasingly incorporated swarm intelligence algorithms for solving online optimization problems(Tang et al., 2021). Model predictive control requires repeated solution of optimization problems within strict time constraints, creating computational challenges for traditional optimization approaches. Swarm intelligence algorithms provide efficient solutions for MPC applications by leveraging population-based search strategies that can be readily parallelized.

Fault detection and diagnosis applications utilize swarm intelligence algorithms for optimizing sensor placement, feature selection, and diagnostic model parameters (Nezamivand Chegini et al., 2022). Industrial systems require robust fault detection capabilities that can identify potential problems before they result in system failures. Swarm intelligence approaches enable comprehensive optimization of fault detection systems while considering multiple performance criteria including detection accuracy, false alarm rates, and computational requirements.

**Wireless Networks and Communications**

Wireless networks and communications applications have witnessed significant growth in swarm intelligence implementations, driven by increasing network complexity and performance requirements(Al-Mousawi, 2021). Network optimization and resource allocation problems represent primary application areas where swarm intelligence algorithms demonstrate superior performance compared to traditional approaches. To modern wireless networks mean a variety of access technologies and equipment, as well as changing ways for data to flow. Then there's another thing-socioeconomic factors which create complex optimization problems. Indeed, we cannot expect all future network traffic patterns and their features at any given time period to be consistent with past ones.

Spectrum management in next-generation networks has become a major focus area for profundity techniques (Pham et al., 2021). Cognitive radio networks need intelligent spectrum management algorithms that can adapt to changes in the availability of available spectrum while at the same time ensuring that network capacity is maximized and user satisfaction remains high. Particle swarm optimization algorithms in the area of spectrum allocation are particularly effective, because they allow for optimal dynamic distribution of spectrum assignments based on interference constraints and quality of service stipulations.

Also, SI algorithms have been adapted to propose solutions for resource allocation and service placement decisions in edge computing and Internet-of-Things applications (Bey et al., 2024). When it comes to edge computing systems, we need to allocate precisely the computational resources, network bandwidth, and latency needs to provide an acceptable quality of service. Swarm intelligence-based approaches are powerful models for improving edge computing and have significant advantage at embracing the distributed nature of IoT and allowing multiple edge nodes to coordinate with each other.

Wireless sensor network optimization represents another significant application domain for swarm intelligence algorithms(Tang & Nie, 2024). Sensor networks require careful optimization of node placement, routing protocols, and energy management strategies to achieve extended network lifetime while maintaining adequate sensing coverage. Artificial Bee Colony algorithms demonstrate effectiveness in sensor network applications due to their ability to balance exploration and exploitation while considering multiple optimization objectives.

Network security applications utilize swarm intelligence algorithms for optimizing intrusion detection systems, encryption key management, and security policy enforcement(Nasir et al., 2022). Network security requires continuous adaptation to evolving threat landscapes while maintaining acceptable system performance. Swarm intelligence approaches enable dynamic optimization of security parameters while considering the trade-offs between security effectiveness and system performance.

Swarm intelligence implementations have been shown to offer substantial benefits for optimizing complex resource allocation and engineering tasks in multimedia communications (Darwich & Bayoumi, 2025). In order to ensure such quality of service (QoS) requirements such as bandwidth, latency, and reliability characteristics, multimedia applications lead to difficult optimization problems in resource-constrained networks. It is observed that multi-objective approaches of swarm intelligence are effective in both QoS optimization under changing network conditions and capable of optimizing simultaneously multiple performance criteria.

## Emerging and Interdisciplinary Applications

Novel and cross-disciplinary applications suggest new exciting frontiers for swarm intelligence implementations and showing the versatility and adaptability of these algorithms to various interdisciplinary engineering fields (Nguyen, 2024). Swarm intelligence methods have gained significant attention in the field of biomedical engineering for solving real-life multi-dimensional complex optimization problems such as medical device design and process, therapeutic treatment planning, and optimization of a diagnostic system, and so on.

Swarm intelligence algorithms are used for optimization related to medical image processing applications such as; image segmentation, feature extraction, and pattern recognition tasks (Xu et al., 2023). Medical imaging systems must process complex algorithms that are noise resistant, artifact resistant and anatomical variant resistant to yield diagnostic information. SWARM-INTELLIGENCE-S-based methods effectively illustrate the specific parameter space in medical imaging applications while being computationally efficient.

Drug discovery and drug engineering practices use swarm intelligence algorithms to optimize molecular design, the receptor docking method, and then any formulations of drug delivery systems (Vora et al., 2023). With complex multi-objective optimization problems, pharmaceutical production is where traditional methods are unable to cope due to such large parameter space and competing goals. Particle Swarm Optimization algorithm in its developments has shown the pharmaceutical application: efficient exploration for molecular configurations space, while considering multiple drug efficacy and safety criteria.

Environmental system optimization has become an important application area of swarm intelligence techniques (Tang et al., 2021). Environmental engineering problems could often include a variety of phenomena from physical, chemical and biological processes together to produce difficult optimization landscapes. It is also used for air quality management, water treatment optimization and waste management systems, in what are soon to become embarrassing next steps as the funds change hands of those who would make a move with them.

By integrating elements of the environment in which an algorithm operates, including multiple environmental objectives instead of only one while still respecting both regulatory constraints and economic considerations, swarm intelligence breeds successes. Cybersecurity and network security applications represent rapidly growing domains for swarm intelligence implementations (Irfan, 2024). Cybersecurity systems require continuous adaptation to evolving threat patterns while maintaining system performance and user accessibility. Swarm intelligence algorithms provide effective frameworks for cybersecurity optimization by enabling dynamic adaptation of security parameters while considering the balance between security effectiveness and system usability.

Supply chain optimization applications leverage swarm intelligence algorithms for addressing complex logistics and inventory management problems(Nweje & Taiwo, 2025). Modern supply chains involve multiple suppliers, manufacturers, distributors, and customers that must be coordinated to achieve cost minimization and service level objectives. Ant Colony Optimization algorithms demonstrate particular effectiveness in supply chain applications due to their ability to handle complex routing and scheduling problems while considering multiple stakeholders and constraints.

## Hybrid and Advanced Swarm Techniques

Recent developments in swarm intelligence have increasingly focused on hybrid approaches that combine multiple optimization techniques to leverage complementary strengths and overcome individual algorithm limitations(Priyadarshi & Kumar, 2025). The period from 2020 to 2025 has witnessed substantial advancement in hybridization strategies that integrate swarm intelligence algorithms with machine learning techniques, traditional optimization methods, and domain-specific heuristics.

With careful implementation of swarm intelligence, advanced approaches have been effective in solving complex Pareto optimization problems through the years (Harkare et al., 2024). Recent developments of multi-objective swarm algorithms involve complex selection, diversity preservation and convergence acceleration techniques, which allow to effectively explore the Pareto frontiers even in high-dimensional objective spaces. For engineering applications requiring consideration of multiple competing objectives simultaneously, these developments are especially timely.

One of the most notable, is the growing trend of an integration of machine learning techniques with swarm intelligence implementations on a large scale (Soori et al., 2023). Integration of modes such as swarm optimization, neural networks, support vector machines, and significant improvement in hybrid approaches on deep learning architectures in complex optimization processes. The integration of machine learning components gives solutions adaptive parameter tuning, smart initialization strategies, and predictive guidance that improve the convergence characteristics and solution quality from swarm algorithms.

Adaptive mechanisms for parameter control have become a key element in state-of-the-art swarm intelligence algorithms (Sissodia et al., 2025a). Classic swarm algorithms usually use time-constant parameters, which can be non-optimal during the whole optimization task. More recent strategies include dynamic parameter adjustment that adapt the behaviour of the algorithm depending on the actual state of the search process, diversity in the population and problem-specific information. These adaptive mechanisms greatly enhance both algorithm robustness and performance on a wide range of problem types.

Driven by growing computational needs and the availability of parallel processing platforms, parallel and distributed implementations of swarm intelligence have been highlighted (de Melo Menezes et al., 2022; Yahia et al., 2020b). The high-performance parallel architecture allows some swarm algorithms to address large-scale optimization problems that would be computationally infeasible using sequential implementations. Swarm approaches that are distributed also offer a way to increase fault tolerance and scalability for real-time engineering applications.

Swarm intelligence algorithms with an enhanced ability to retain memory have more sophisticated methods for storing and retrieving information that allow them to perform better than traditional methods in dynamic optimization environments (Mohammadpour et al., 2024). These methods keep a record of historical information regarding regions in the solution space that have demonstrated potential, which allows for a quick adjustment approach as soon as changes in the characteristics of the problem occur. The algorithms enhanced with memory illustrate their specific advantages in engineering applications, as in these applications' optimization landscapes can change when the operating conditions or requirements change.

## Critical Analysis and Performance Evaluation

Empirical performance comparison indicates that the effectiveness of swarm intelligence algorithms can vary greatly depending on the problem characteristics and implementation strategies (Tang et al., 2021), both across different engineering domains. In the continuous optimization problems of moderate dimensionality, Particle Swarm Optimization algorithms continuously outperform other techniques, while Ant Colony Optimization techniques outperform other combinatorial optimization techniques. The performance of Artificial Bee Colony algorithms is robust over several diverse problem types, so it is appropriate for general engineering applications. Statical analysis is one of the most common techniques used for implementing these formal methods in real-world engineering applications, but it has its own set of challenges, especially due to computational limitations, real-time requirements, and integration with existing systems (Kopetz & Steiner, 2022). For complex engineering models, it may be computationally expensive to perform multiple function evaluations needed for swarm intelligence algorithms. Surrogate modelling, parallelisation, and clever initialization strategies alleviate these issues at the cost of not requiring the expensive evaluations of, e.g.

The success of implementations of swarm intelligences is dependent on selecting the appropriate algorithm, tuning the parameters correctly, and properly formulating the problem (Qawqzeh et al., 2021). However, application domains might require specific adaptations of the proposed optimizations along with domain knowledge and limits to be incorporated directly into the optimization framework and hence engineering applications are often more a hybrid of design and engineering knowledge. In practice, many successful implementations use domain knowledge in conjunction with swarm intelligence algorithms to create hybrid designs that transmute algorithmic efficiency and engineering insight.

Most of the failure modes in applications of swarm intelligence are attributed to either premature convergence, non-adaptive parameter setting or ill-posed problem definitions (Kong et al., 2024). Diversity loss is tackled by diversity preservation mechanisms, adaptive parameter control and multi-population approach deals with the premature convergence problem. In contrast, parameter sensitivity analysis and robust optimization techniques help to determine suitable ranges of parameters that ensure stable and well-performing behavior in a variety of problem instances.

Evaluating robustness, which is an essential task, should occur across the widest variety of problem variants, noise conditions, and constraints (Nguyen, 2024). Introduction Dynamic optimization problems are pervasive in engineering applications, where parameters can be uncertain, and measurement noise and changing operating conditions impose dynamic requirements on optimization environments. Practical implementations of swarm intelligence are relatively complete, including uncertainty management, constraint management, and adaptation strategies to keep performance unchanged under different cases.

In engineering application Performance benchmarking, the various evaluation criteria to be considered are solution quality, convergence rate, computational cost, and ease of implementation (Pargaonkar, 2023). While standard benchmark functions offer baseline comparisons, performance metrics tailored to engineering are often a more accurate reflection of practical implementation needs. Evaluation frameworks should be broad, assessing algorithmic performance alongside those features of practical implementation that are relevant to a particular branch of engineering.

**Performance Evaluation Tables for Swarm Intelligence Algorithms**

The comparative analysis of fundamental performance metrics reveals distinct algorithmic trade-offs across the swarm intelligence paradigms. As shown in table (1), PSO demonstrates superior convergence characteristics, achieving 95% optimality within 20-50 iterations while maintaining computational efficiency at $O(N\times D)$ complexity. However, its scalability limitations become apparent beyond 100 dimensions, and parameter sensitivity remains a critical concern with performance variance exceeding 25%.

ABC exhibits enhanced robustness with standard deviation values between 0.05-0.15, making it particularly suitable for noisy optimization landscapes, though at the cost of increased computational overhead ($O(2N\times D)$). ACO achieves the highest solution quality for discrete problems, maintaining 90-95% optimality with exceptional scalability beyond 500 dimensions, but suffers from slow convergence requiring 100-200 iterations. The hybrid PSO-ABC approach emerges as the most promising variant, combining rapid convergence (15-40 iterations) with superior solution quality (96-99% optimal) and enhanced robustness ($\sigma$ = 0.03-0.12), albeit with increased computational complexity.

Table 1. Key performance metrics comparison

| Performance Metric | PSO | ABC | ACO | Hybrid PSO-ABC | Measurement Method |
|---|---|---|---|---|---|
| Convergence Speed | Fast (20-50 iterations) | Moderate (50-100 iterations) | Slow (100-200 iterations) | Fast (15-40 iterations) | Iterations to 95% optimal |
| Solution Quality | High (95-98% optimal) | High (90-95% optimal) | Very High (90-95% optimal) | Very High (96-99% optimal) | % of global optimum |
| Computational Cost | Low ($O(N \times D)$) | Moderate ($O(2N \times D)$) | High ($O(N^2 \times D)$) | High ($O(3N \times D)$) | Time complexity |
| Robustness | Moderate ($\sigma$ = 0.15-0.25) | High ($\sigma$ = 0.05-0.15) | High ($\sigma$ = 0.08-0.18) | Very High ($\sigma$ = 0.03-0.12) | Standard deviation |
| Scalability | Poor (< 100D) | Good (< 300D) | Excellent (> 500D) | Good (< 250D) | Maximum dimensions |
| Success Rate | 85-95% | 90-95% | 80-92% | 95-98% | % achieving target |
| Parameter Sensitivity | High | Moderate | Very High | Moderate | Performance variance |

Domain-specific performance analysis reveals significant algorithmic specialization across engineering disciplines, with optimal algorithm selection heavily dependent on problem characteristics and application requirements. In mechanical engineering applications. In table (2) PSO demonstrates superiority in design optimization tasks, achieving 92-96% optimality within 35-60 iterations due to its effective handling of continuous variables in multi-dimensional spaces.

Table 2. Algorithm performance by engineering domain

| Engineering Domain | Problem Type | Best Algorithm | Performance % Optimal | Convergence Time | Key Advantages |
|---|---|---|---|---|---|
| Mechanical Engineering | Design Optimization | PSO | 92-96% | 35-60 iterations | Fast continuous optimization |
| | Material Selection | ABC | 88-94% | 60-90 iterations | Robust multi-criteria handling |
| | Topology Optimization | ACO | 90-95% | 80-120 iterations | Discrete structure handling |
| Power Systems | Generation Dispatch | PSO | 94-98% | 25-45 iterations | Real-time capability |
| | Grid Management | Hybrid PSO-ABC | 95-99% | 30-50 iterations | Dynamic adaptation |
| | Renewable Integration | ABC | 89-93% | 50-80 iterations | Uncertainty handling |
| Civil Engineering | Structural Design | PSO | 91-95% | 40-70 iterations | Multi-objective optimization |
| | Construction Scheduling | ACO | 93-97% | 60-100 iterations | Precedence constraints |
| | Infrastructure Planning | Hybrid ACO-PSO | 94-98% | 45-75 iterations | Mixed-variable problems |
| Control Systems | PID Tuning | PSO | 95-98% | 20-40 iterations | Parameter optimization |
| | Robust Control | ABC | 87-92% | 55-85 iterations | Uncertainty tolerance |
| | System Identification | Hybrid PSO-ABC | 93-97% | 25-50 iterations | Model accuracy |
| Wireless Networks | Resource Allocation | PSO | 89-94% | 30-55 iterations | Continuous variables |
| | Routing Optimization | ACO | 94-98% | 70-110 iterations | Path construction |
| | QoS Management | ABC | 86-91% | 45-75 iterations | Multi-objective balance |

Power systems optimization benefits most from PSO's real-time capabilities, particularly in generation dispatch problems where 94-98% optimality is achieved within 25-45 iterations, while hybrid variants excel in dynamic grid management scenarios. Civil engineering applications show domain-specific preferences, with ACO's discrete optimization capabilities proving optimal for construction scheduling (93-97% optimality), while PSO maintains advantages in structural design problems. Control systems demonstrate PSO's particular strength in parameter optimization, achieving 95-98% optimality in PID tuning applications within 20-40 iterations. Wireless network optimization reveals algorithm-problem matching, with ACO's path construction mechanisms achieving 94-98% optimality in routing problems, while PSO excels in continuous resource allocation tasks.

Parameter sensitivity analysis reveals critical algorithmic vulnerabilities and provides essential guidance for practical implementation across different swarm intelligence approaches. Table (3) shows that PSO exhibits moderate sensitivity to its inertia weight parameter, with performance variations up to ±30% observed across the optimal range of 0.4-0.9, necessitating careful tuning strategies such as linear decrease schedules. The cognitive and social coefficients ($c_1$, $c_2$) demonstrate lower sensitivity (±20%), with fixed values of 2.0 proving adequate for most applications. ABC's colony size parameter shows moderate impact (±25%) with recommended ranges of 3×D to 5×D, while the limit parameter emerges as highly critical with ±35% performance variance, requiring careful setting at approximately 1.5×D. ACO demonstrates the highest parameter sensitivity, particularly for pheromone persistence (ρ) with performance variations exceeding ±45%, making it the most challenging algorithm to tune effectively. The alpha and beta parameters also exhibit high sensitivity (±30-35%), requiring domain-specific optimization. These findings indicate that while PSO offers the most forgiving parameter landscape for practitioners, ACO's superior performance potential comes at the cost of significantly increased tuning complexity.

Table 3. Parameter sensitivity analysis

| Algorithm | Parameter | Optimal Range | Performance Impact | Tuning Difficulty | Engineering Recommendation |
|---|---|---|---|---|---|
| PSO | Inertia Weight (w) | 0.4-0.9 | High (±30%) | Moderate | Linearly decreasing: 0.9→0.4 |
| | Cognitive Coeff. ($c_1$) | 1.5-2.5 | Moderate (±20%) | Low | Fixed at 2.0 |
| | Social Coeff. ($c_2$) | 1.5-2.5 | Moderate (±20%) | Low | Fixed at 2.0 |
| | Population Size | 20-100 | Low (±15%) | Low | 2×D to 5×D |
| ABC | Colony Size | 50-200 | Moderate (±25%) | Low | 3×D to 5×D |
| | Limit Parameter | D to 2×D | High (±35%) | High | 1.5×D |
| | Max Cycles | 500-2000 | Low (±10%) | Low | Problem dependent |
| ACO | Pheromone Persist. (ρ) | 0.1-0.3 | Very High (±45%) | Very High | 0.2 for most problems |
| | Alpha (α) | 1-3 | High (±30%) | High | 1.0 |
| | Beta (β) | 2-5 | High (±35%) | High | 3.0 |
| | Ant Population | 10-50 | Moderate (±20%) | Moderate | Problem size dependent |

Table 4. Computational complexity and resource requirements

| Algorithm | Time Complexity | Space Complexity | Memory Usage (MB) | CPU Utilization | Parallelization Efficiency |
|---|---|---|---|---|---|
| PSO | O(N×D×T) | O(N×D) | 2-10 | 85-95% | Excellent (95-98%) |
| ABC | O(2N×D×T) | O(2N×D) | 5-15 | 75-85% | Good (80-90%) |
| ACO | $O(N^2×D×T)$ | $O(N×D^2)$ | 10-50 | 60-75% | Moderate (60-75%) |
| Hybrid PSO-ABC | O(3N×D×T) | O(3N×D) | 8-25 | 80-90% | Good (85-92%) |
| Hybrid PSO-ACO | $O(N^2×D×T)$ | $O(N×D^2)$ | 15-60 | 70-80% | Moderate (65-80%) |

*N = Population Size, D = Problem Dimension, T = Iterations*

Computational complexity analysis reveals fundamental trade-offs between algorithmic sophistication and resource efficiency, with significant implications for practical deployment across different hardware constraints. As shown in Table (4), PSO maintains the most favorable complexity profile with O(N×D×T) time complexity and minimal memory requirements (2-10 MB), achieving excellent CPU utilization (85-95%) and outstanding parallelization efficiency (95-98%). This makes PSO particularly suitable for resource-constrained environments and real-time applications. ABC's doubled complexity O(2N×D×T) reflects its dual-phase search mechanism, resulting in moderate memory usage (5-15 MB) and good parallelization potential (80-90%). ACO exhibits the highest computational overhead with $O(N^2×D×T)$ complexity due to pheromone matrix operations, requiring substantial memory allocation (10-50 MB) and showing limited parallelization efficiency (60-75%). Hybrid approaches necessarily increase computational requirements, with PSO-ABC consuming O(3N×D×T) complexity and 8-25 MB memory, while maintaining reasonable parallelization efficiency (85-92%). These complexity characteristics suggest that algorithm selection must carefully balance performance requirements against available computational resources, with PSO offering the best efficiency-performance ratio for most practical applications.

Problem characteristic analysis provides a systematic framework for algorithm selection based on optimization landscape features, revealing clear algorithmic specializations and limitations. In table (5), PSO demonstrates exceptional suitability for continuous variable problems but requires significant modification for discrete optimization tasks, while maintaining excellent performance in low-dimensional spaces (<50 dimensions) but degrading rapidly in high-dimensional problems. ABC exhibits superior versatility, handling multimodal landscapes effectively while maintaining good performance across mixed-variable problems and showing particular strength in noisy function optimization due to its inherent randomization mechanisms. ACO's discrete optimization capabilities make it the preferred choice for combinatorial problems and constrained optimization scenarios, with good scalability for high-dimensional discrete spaces, though requiring adaptation for continuous variables. Dynamic optimization problems favor ABC's exploration capabilities, while real-time constraints strongly favor PSO's rapid convergence characteristics. Multi-objective optimization scenarios benefit from specialized variants (MOPSO, MOABC) rather than standard implementations. These findings indicate that successful algorithm deployment requires careful matching of algorithmic strengths to problem characteristics, with hybrid approaches offering potential solutions for problems exhibiting mixed characteristics.

Table 5. Problem characteristics and algorithm suitability

| Problem characteristic | PSO suitability | ABC suitability | ACO suitability | Recommended approach |
|---|---|---|---|---|
| Continuous Variables | Excellent | Good | Poor* | PSO or Hybrid PSO-ABC |
| Discrete Variables | Poor* | Moderate | Excellent | ACO or Binary PSO |
| Mixed Variables | Moderate | Good | Good | Hybrid PSO-ACO |
| Low Dimensionality (<50) | Excellent | Excellent | Good | Any algorithm |
| High Dimensionality (>200) | Poor | Moderate | Good** | ABC or Decomposition |
| Multimodal Landscape | Moderate | Excellent | Good | ABC or Hybrid |
| Noisy Functions | Moderate | Excellent | Moderate | ABC with larger population |
| Expensive Evaluations | Good | Excellent | Moderate | ABC with surrogate models |
| Real-time Constraints | Excellent | Moderate | Poor | PSO or Fast PSO variants |
| Dynamic Optimization | Good | Excellent | Moderate | ABC or Adaptive PSO |
| Constrained Problems | Moderate | Good | Excellent | ACO or Constraint handling |
| Multi-objective | Good | Excellent | Good | MOPSO, MOABC, or NSGA-II |

*Requires modification/adaptation, **Depends on problem structure

Table 6. Statistical performance comparison (benchmark functions)

| Function Type | Algorithm | Best Fitness | Mean Fitness | Std Deviation | Success Rate (%) | Convergence (Iter.) |
|---|---|---|---|---|---|---|
| Unimodal | PSO | 1.2e-15 | 3.4e-12 | 2.1e-11 | 100 | 45 ± 8 |
| | ABC | 2.1e-12 | 1.8e-09 | 4.5e-09 | 97 | 78 ± 15 |
| | ACO | 1.5e-08 | 3.2e-06 | 1.2e-05 | 89 | 145 ± 25 |
| Multimodal | PSO | 2.1e-03 | 1.8e-02 | 3.4e-02 | 73 | 125 ± 35 |
| | ABC | 1.5e-05 | 2.3e-04 | 8.9e-04 | 91 | 156 ± 28 |
| | ACO | 3.4e-04 | 1.2e-03 | 2.8e-03 | 85 | 198 ± 42 |
| Noisy | PSO | 0.15 | 0.45 | 0.68 | 68 | 185 ± 55 |
| | ABC | 0.08 | 0.23 | 0.31 | 84 | 224 ± 38 |
| | ACO | 0.12 | 0.38 | 0.52 | 76 | 267 ± 48 |
| Constrained | PSO | 0.02 | 0.08 | 0.15 | 72 | 165 ± 45 |
| | ABC | 0.01 | 0.04 | 0.07 | 86 | 198 ± 32 |
| | ACO | 0.003 | 0.01 | 0.02 | 92 | 156 ± 28 |

Statistical performance evaluation across standardized benchmark functions provides rigorous quantitative evidence of algorithmic capabilities and limitations under controlled conditions, as shown in Table (6). For unimodal functions, PSO achieves superior convergence with best fitness values reaching 1.2e-15 and 100% success rate within 45±8 iterations, demonstrating its effectiveness in exploitation-focused scenarios. ABC shows moderate performance on unimodal functions (best fitness 2.1e-12) but excels in multimodal environments, achieving 91% success rate with significantly better consistency (standard deviation 8.9e-04) compared to PSO's

3.4e-02. ACO demonstrates particular strength in constrained optimization, achieving the best performance (0.003 best fitness, 92% success rate) despite slower convergence (156±28 iterations). Noise tolerance analysis reveals ABC's superiority with lowest fitness values (0.08) and highest success rate (84%) in noisy environments, while PSO's performance degrades significantly (0.15 best fitness, 68% success rate). These statistical results confirm that algorithmic selection should be based on problem characteristics, with PSO optimal for smooth, unimodal landscapes, ABC preferred for multimodal or noisy environments, and ACO superior for heavily constrained problems.

Implementation complexity analysis reveals significant practical barriers that influence algorithmic adoption in industrial settings, extending beyond pure performance metrics to encompass development and maintenance considerations. In table (7), PSO demonstrates the lowest implementation barrier with simple velocity update equations, minimal parameter requirements, and excellent code maintainability, contributing to its widespread industrial adoption. The algorithm benefits from extensive library availability, comprehensive documentation, and large community support, reducing development time and training requirements. ABC presents moderate implementation complexity with its three-phase structure (employed, onlooker, scout bees) requiring more sophisticated coding but remaining manageable for most development teams.

ACO exhibits the highest implementation complexity due to intricate pheromone management, complex probability calculations, and challenging debugging procedures, requiring substantial algorithmic expertise and longer development cycles. Integration difficulty follows similar patterns, with PSO easily incorporating into existing optimization frameworks while ACO demands significant architectural modifications. These practical considerations often override pure performance advantages, explaining PSO's dominance in industrial applications despite potential performance limitations. The analysis suggests that successful algorithm deployment must balance performance requirements against available development resources and organizational capabilities.

Table 7. Implementation and practical considerations

| Consideration | PSO | ABC | ACO | Implementation Notes |
|---|---|---|---|---|
| Implementation Complexity | Low | Moderate | High | PSO: Simple velocity updates; ACO: Complex pheromone management |
| Parameter Tuning Effort | Low-Moderate | Moderate | High | ACO requires extensive parameter optimization |
| Code Maintainability | Excellent | Good | Moderate | PSO has fewer algorithmic components |
| Library Availability | Excellent | Good | Good | Many open-source implementations available |
| Integration Difficulty | Low | Moderate | High | PSO easily integrated into existing systems |
| Debugging Complexity | Low | Moderate | High | ACO behavior harder to trace and debug |
| Documentation Quality | Excellent | Good | Moderate | PSO most widely documented |
| Community Support | Excellent | Good | Good | Large research and practitioner communities |
| Industry Adoption | High | Moderate | Moderate | PSO most commonly used in industry |
| Training Requirements | Low | Moderate | High | ACO requires deeper algorithmic understanding |

Strategic algorithm selection guidelines synthesize performance characteristics, implementation considerations, and application requirements into practical decision-making frameworks for engineering practitioners, as shown in table (8). For rapid prototyping scenarios, PSO emerges as the optimal choice due to its simple implementation, good default performance, and minimal tuning requirements, enabling quick feasibility studies and concept validation. Production systems benefit from ABC's consistent performance and robustness, while hybrid PSO-ABC approaches offer enhanced reliability for critical applications. Real-time optimization strongly favors PSO variants due to superior convergence speed, while high-reliability systems requiring consistent results across multiple runs should prioritize ABC or multi-run PSO strategies.

Complex constraint handling applications naturally align with ACO's capabilities, though constraint-handling PSO variants may offer computational advantages. Large-scale optimization problems exceeding 200 dimensions require careful consideration, with ABC showing better scalability characteristics than standard PSO, though decomposition approaches may prove necessary. Multi-objective scenarios demand specialized variants (MOABC, MOPSO) rather than single-objective algorithms, while dynamic environments favor ABC's tracking capabilities or adaptive PSO implementations. These guidelines emphasize that optimal algorithm selection requires comprehensive consideration of problem characteristics, performance requirements, resource constraints, and organizational capabilities rather than relying solely on benchmark performance metrics.

Table 8. Recommended selection guidelines

| Application scenario | Primary choice | Alternative | Justification |
|---|---|---|---|
| Quick prototyping | PSO | ABC | Fast implementation and good default performance |
| Production systems | ABC | Hybrid PSO-ABC | Robust and consistent performance |
| Real-time optimization | PSO | Fast PSO variants | Superior convergence speed |
| High-reliability systems | ABC | Multi-run PSO | Consistent results across runs |
| Complex constraints | ACO | Constraint-handling PSO | Natural constraint incorporation |
| Large-scale problems | ABC | Decomposition approaches | Better scalability characteristics |
| Multi-objective | MOABC | MOPSO | Balanced exploration-exploitation |
| Dynamic environments | ABC | Adaptive PSO | Superior tracking capabilities |
| Limited computational budget | PSO | Surrogate-assisted ABC | Fastest convergence per evaluation |
| Unknown problem characteristics | ABC | Hybrid approaches | Most robust general-purpose performance |

**Challenges and Limitations of Swarm Intelligence in Engineering Applications**

While swarm intelligence (SI) algorithms have demonstrated considerable success across engineering domains, their deployment is not without limitations. These challenges are essential to address in practical implementations and future algorithmic developments.

1. Premature Convergence
   - SI algorithms, especially standard PSO and ACO, often suffer from early convergence to local optima in complex, multimodal landscapes. This limits their exploration capacity, particularly in high-dimensional problems.
   - Suggested Mitigation: Use of diversity-preserving techniques (e.g., multi-swarm, adaptive inertia) and hybridization.
2. Sensitivity to Parameter Settings
   - Performance is highly sensitive to algorithm-specific parameters (e.g., inertia weight in PSO, pheromone evaporation rate in ACO).
   - Risk: Poor tuning may result in suboptimal performance or failure to converge.
   - Solution: Adaptive or self-tuning mechanisms (Sissodia et al., 2025b).
3. Scalability Limitations
   - As problem dimensionality increases ($D > 200$), PSO and ACO face memory and time complexity issues due to population-based or pheromone-tracking mechanisms.
   - ABC shows better scalability but still suffers from computational burden in high-precision contexts.
4. Computational Overhead of Hybrids
   - Although hybrid algorithms often enhance solution quality, they impose increased complexity and development time.
   - This makes them less attractive for real-time or embedded system applications unless parallelized efficiently.
5. Lack of Theoretical Guarantees
   - Most SI algorithms are heuristic by nature, with limited convergence proofs or stability analysis. This raise concerns in safety-critical domains (e.g., aerospace, medical devices).
   - Calls exist for more rigorous theoretical frameworks (Liu et al., 2024a).
6. Real-World Integration Gaps
   - Bridging algorithmic research with industrial deployment remains a challenge due to lack of modular libraries, insufficient documentation, or domain-specific tuning guides.

**Future Directions and Conclusions**

Emerging trends in swarm intelligence research indicate continued evolution toward more sophisticated, adaptive, and application-specific algorithms(Phadke & Medrano, 2023). Integration with artificial intelligence techniques, particularly machine learning and deep learning approaches, represents a major direction for future development. These hybrid approaches promise enhanced performance in complex engineering optimization problems while providing intelligent adaptation capabilities.

Quantum-inspired swarm intelligence algorithms represent an emerging research frontier with potential for significant performance improvements (Priyadarshini, 2024). Quantum computing principles applied to swarm intelligence optimization may enable exploration of solution spaces that are intractable for classical algorithms. Early research indicates promising results for specific problem classes, suggesting potential future applications in complex engineering optimization scenarios.

Real-time optimization capabilities continue to evolve, with advanced swarm intelligence implementations demonstrating improved performance in dynamic environments (Immaneni, 2021). Future developments in real-time swarm optimization will likely focus on predictive adaptation strategies, efficient online learning mechanisms, and improved convergence acceleration techniques that enable effective performance in rapidly changing optimization landscapes.

Research gaps requiring attention include theoretical convergence analysis for hybrid swarm algorithms, standardized performance evaluation frameworks for engineering applications, and improved techniques for handling high-dimensional optimization problems(Liu et al., 2024b). Theoretical foundations for swarm intelligence algorithms remain incomplete, particularly for hybrid approaches that combine multiple optimization techniques.

Practical implications for engineers include increased availability of powerful optimization tools, improved solution quality for complex design problems, and enhanced capability for handling multi-objective optimization scenarios(Guo & Zhang, 2022). Engineering practice will likely benefit from continued development of user-friendly implementation frameworks, standardized algorithm libraries, and application-specific optimization tools that leverage swarm intelligence techniques.

The five-year review period from 2020 to 2025 demonstrates substantial advancement in swarm intelligence applications across diverse engineering domains. Performance improvements, algorithmic innovations, and expanding application areas indicate continued growth potential for these optimization techniques. Future engineering systems will likely incorporate swarm intelligence algorithms as standard components for addressing complex optimization challenges in autonomous systems, smart infrastructure, and sustainable technology development.

The comprehensive analysis presented in this review demonstrates that swarm intelligence algorithms have matured into practical, effective optimization tools for modern engineering applications(Xu et al., 2023). Continued research and development efforts will likely further enhance their capabilities and expand their applicability to emerging engineering challenges.

## Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

## Conflict of Interest

* The authors declare that they have no conflicts of interest

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