Quantum-Inspired Optimisation for Large-Scale Artificial Intelligence: A Critical Comparative Review of Algorithms, Scalability, and Practical Applicability

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Abstract: ***The increasing complexity of artificial intelligence (AI) has created a need for effective optimisation of highdimensional, nonlinear, and computationally expensive problems. Quantum-inspired optimisation provides an alternative approach by employing quantum-inspired representations and search mechanisms within classical computing systems. This review examines major approaches, including Quantum-Inspired Evolutionary Algorithms (QIEA), Quantum-Inspired Genetic Algorithms (QIGA), Quantum-Inspired Particle Swarm Optimisation (QIPSO), quantum annealing-related approaches, and hybrid methods. Their applications in machine learning, feature selection, hyperparameter optimisation, reinforcement learning, healthcare, finance, cybersecurity, robotics, and smart manufacturing are reviewed. Particular emphasis is placed on solution quality, convergence behaviour, computational cost, scalability, robustness, and reproducibility. The review identifies inconsistent benchmarking, parameter sensitivity, computational overhead, and limited reproducibility as major challenges. The findings indicate that quantum-inspired optimisation should not be considered universally superior to classical optimisation, as its effectiveness depends on problem structure and evaluation conditions. Future research should focus on scalable, hybrid, explainable, and reproducible optimisation frameworks for realistic large-scale AI applications.***

Keywords: Artificial Intelligence, Quantum-Inspired Algorithms, Quantum Computing, Optimisation, Machine Learning, Quantum Annealing, Evolutionary Algorithms, Large-Scale Optimisation

1. Introduction

Artificial intelligence (AI) has expanded rapidly across fields such as healthcare, finance, transportation, manufacturing, cybersecurity, and scientific computing. With the growing use of massive datasets, complicated model architectures and high-dimensional decision spaces in artificial intelligence systems, optimization has become a vital component of AI system development. Optimisation is applied at many steps of the AI workflow, including model training, feature selection, hyperparameter tuning, neural architecture design, reinforcement learning, scheduling and resource allocation. In particular, hyperparameter and model-configuration optimisation can require huge, computationally expensive search spaces, thereby making efficient search techniques vital for practical AI development [1].

Conventional optimisation techniques such as gradientbased methods, evolutionary algorithms, particle swarm optimisation, and simulated annealing are still relevant when handling machine learning and computational optimisation challenges. However, the selection of an optimisation method is significantly influenced by the characteristics of the problem, such as its dimensionality, the structure of the objective function, the constraints, the computational budget and the search versus exploitation trade-off. Population-based methods such as particle swarm optimisation provide mechanisms to explore complex search spaces through interactions between potential solutions. In contrast, evolutionary techniques enhance populations of candidate solutions through selection and variation mechanisms The computational complexity of modern AI applications is increasing, thereby stimulating interest in alternative optimisation algorithms capable of exploring huge nonlinear search spaces. Quantum annealing and the Quantum Approximate Optimisation Algorithm (QAOA) are examples of optimisation paradigms enabled by quantum computing. However, effective quantum processing is still hampered by hardware availability, noise, limited coherence, and other implementation issues in contemporary quantum systems [2], [3], [4]. A related, but different, computational route is provided by quantum-inspired optimisation. Quantum-inspired algorithms do not require an actual quantum computer but apply some of the principles of quantum mechanics to classical computational frameworks. These notions may include probabilistic solution representations, superposition-inspired encoding, quantum-inspired rotation mechanisms and interferenceinspired search behaviour. One significant class of such methods is Quantum-Inspired Evolutionary Algorithms (QIEAs), which have been studied for combinatorial and other complex optimisation problems on classical computing platforms [6], [7]. The importance of quantum-inspired optimisation does not lie in the use of quantum terminology, but rather in whether its representations and search processes yield effective computational behaviour for particular optimisation problems. Hence, quantum-inspired techniques have been explored for applications such as feature selection, machine-learning optimisation, combinatorial optimisation, and other large-scale search issues. But their performance can be affected by algorithm design, representation and parameter choices, issue complexity, and processing resources. Therefore, to claim superiority over conventional optimisation methods, it is necessary to conduct controlled comparisons with suitable baselines, consistent assessment criteria, and comparable computing budgets. There is growing interest in this study, yet the extant literature is varied. Studies often differ in their datasets, benchmark functions, objective formulations, parameter settings, stopping criteria, evaluation measures, and computing environments. Because of these discrepancies, a direct comparison of quantum-inspired optimisation with conventional optimisation is impossible. Other key areas for further exploration include scalability, computational overhead, reproducibility, explainability, and integration with modern artificial intelligence frameworks. In this review, we discuss quantum-inspired optimisation algorithms from both algorithmic and application-oriented viewpoints with special focus on Quantum-Inspired Evolutionary Algorithms (QIEA), Quantum-Inspired Genetic Algorithms (QIGA), Quantum-Inspired Particle Swarm Optimisation (QIPSO), quantum-annealing-based optimisation, and hybrid quantum-inspired methods. This review investigates their underlying representations and search algorithms, explores their uses in artificial intelligence and related fields, and critically assesses their computational properties, shortcomings, and practical usability. The main contributions of this review are:

- It presents a systematic review of relevant quantuminspired optimisation techniques and their computational principles. It deals with the use of quantum-inspired optimisation in machine learning, feature selection, hyperparameter optimisation, reinforcement learning, healthcare, financial modelling, cybersecurity, robotics, and smart manufacturing.
- It critically evaluates quantum-inspired approaches for solution quality, convergence behaviour, exploration capability, computational cost, scalability, resilience and reproducibility, rather than assuming universal supremacy.
- It highlights important methodological and practical limitations in the current literature and suggests research options for developing more scalable, reproducible, and application-oriented quantum-inspired optimisation frameworks for large-scale AI.

2. Literature Review

Research on optimization for artificial intelligence has developed alongside the increasing complexity of machine learning models, datasets, and decision spaces. Classical optimization methods, including gradient-based optimization, evolutionary computation, swarm intelligence, and simulated annealing, have been extensively investigated for model training, feature selection, parameter optimization, and combinatorial decision problems. Their effectiveness, however, depends on the characteristics of the objective function, search space, constraints, and computational resources available for the optimization process. These considerations have encouraged continued investigation of alternative population-based and metaheuristic search strategies. Quantum computing has introduced a separate family of optimization approaches motivated by quantum-mechanical computation. Quantum annealing and gate-based methods such as the Quantum Approximate Optimization Algorithm (QAOA) have been investigated for combinatorial optimization and related problems. However, these approaches rely on quantum-computing resources and are therefore subject to the limitations of current quantum hardware, including noise, limited coherence, finite qubit resources, and implementation overhead. Such constraints have contributed to continuing interest in computational approaches that can exploit quantuminspired concepts without requiring a physical quantum computer [5], [6]. Quantum-inspired optimization developed from the use of selected quantum concepts within classical computational algorithms. Rather than representing information using physical qubits, quantum-inspired evolutionary methods employ mathematical or probabilistic representations that can encode multiple candidate states and guide population-based search. Han and Kim introduced an influential quantum-inspired evolutionary framework based on a probabilistic Q-bit representation and quantum-inspired update operations, while Zhang subsequently provided a broad survey of quantum-inspired evolutionary algorithms implemented on classical computers and discussed their theoretical foundations, applications, advantages, and limitations[5], [6]. Subsequent research has expanded quantum-inspired optimization beyond early evolutionary formulations. Quantuminspired approaches have been investigated in evolutionary computation, swarm intelligence, combinatorial optimization, feature selection, parameter optimization, and machine-learning applications. Recent work has also examined quantum-inspired optimization for QUBO and related formulations, demonstrating continued interest in classical optimization methods that incorporate quantum-inspired representations or search mechanisms [6], [7], [8]. Feature selection represents an important application area because selecting an informative subset from a highdimensional feature space can be formulated as a combinatorial optimization problem. Quantum-inspired evolutionary approaches have been investigated for searching feature subsets while balancing predictive performance and the number or complexity of selected features. A recent survey of quantum-inspired evolutionary algorithms for feature subset selection examined 56 studies and identified recurring use of probabilistic representations, quantum-inspired rotation operators, and different objective-function formulations. The survey also highlighted open problems concerning algorithm design, objective functions, and the evaluation of quantum-inspired feature-selection methods[9].

Quantum-inspired methods have also been considered in broader machine-learning contexts. Recent reviews distinguish quantum-inspired machine learning from quantum machine learning by emphasizing that quantum-inspired approaches can use quantum-mechanical concepts within classical computational frameworks. The literature spans several directions, including optimization, probabilistic representations, tensorbased methods, and other computational techniques motivated by quantum theory. This distinction is important because the computational requirements and claims associated with quantum-inspired methods should not be conflated with those of algorithms that require actual quantum hardware[10], [11]. Another important direction is the development of hybrid optimization strategies. Hybrid approaches combine quantuminspired search mechanisms with established evolutionary, swarm-based, local-search, or machine-learning procedures. The motivation is generally to exploit complementary search behaviours, such as broad exploration combined with local refinement. However, hybridization also increases algorithmic complexity and may introduce additional parameters, computational costs, and implementation choices. Consequently, an observed performance improvement cannot automatically be attributed to the quantum-inspired component without appropriate ablation studies and controlled comparisons. Despite the growing body of research, comparison across studies remains difficult. Existing investigations frequently employ different benchmark functions, datasets, objective functions, parameter settings, stopping criteria, computational environments, and performance measures. Consequently, reported improvements in convergence, solution quality, or computational efficiency cannot always be interpreted as evidence of general superiority. Fair evaluation requires clearly defined baselines, comparable computational budgets, consistent evaluation metrics, and sufficient reporting of experimental configurations. The literature also indicates that scalability and reproducibility remain important challenges. As optimization problems increase in dimensionality, the cost of evaluating candidate solutions and maintaining populations can become substantial. Similarly, algorithm performance may depend on representation choices, population size, update rules, initialization, stopping conditions, and other hyperparameters. These factors make it difficult to separate the contribution of the quantum-inspired mechanism from the effects of general metaheuristic design. Recent work on quantum-inspired optimization therefore continues to emphasize improved formulations, scalable solvers, hybrid strategies, and more rigorous computational comparisons[8], [7]. Overall, the literature demonstrates substantial interest in quantum-inspired optimization as a family of classical computational strategies motivated by concepts from quantum mechanics. However, the existing evidence does not support treating quantum-inspired optimization as a universally superior replacement for conventional optimization. Its potential value appears to be problem-dependent and should be evaluated according to solution quality, convergence behaviour, computational cost, scalability, robustness, and reproducibility. These observations provide the basis for the structured review and comparative analysis presented in the following sections.

3. Review Methodology

This study presents a structured qualitative literature review of quantum-inspired optimization algorithms and their applications in artificial intelligence. The review was designed to identify major algorithmic approaches, examine their underlying search mechanisms, characterize their application domains, and critically assess reported advantages, limitations, computational considerations, and research gaps. The review specifically emphasizes quantum-inspired methods that implement selected quantum-motivated concepts on classical computing platforms, while distinguishing them from optimization methods that require physical quantum hardware.

4. Review Objectives

The review was guided by four principal objectives: (i) to identify major quantum-inspired optimization approaches relevant to artificial intelligence; (ii) to examine the computational representations and search mechanisms employed by these approaches; (iii) to synthesize their applications across different AI-related optimization problems; and (iv) to identify methodological, computational, and practical limitations that influence their applicability to large-scale AI systems.

5. Literature Search Strategy

The literature search focused on scholarly publications addressing quantum-inspired optimization, quantum-inspired evolutionary computation, quantum-inspired machine learning, and related artificial intelligence optimization problems. Search concepts were constructed using combinations of terms including “quantum-inspired optimization,” “quantuminspired algorithms,” “quantum-inspired evolutionary algorithms,” “quantum-inspired genetic algorithms,” “quantuminspired particle swarm optimization,” “quantum-inspired machine learning,” “quantum-inspired artificial intelligence,” “feature selection,” “hyperparameter optimization,” and “largescale optimization.” Additional searches were performed using algorithm-specific and application-specific terminology identified during the initial examination of the literature.

6. Eligibility Criteria

Studies were considered relevant when they addressed a quantum-inspired optimization method or a closely related computational approach and provided information on its algorithmic mechanism, the optimization problem, applications, performance characteristics, limitations, or future research directions. Priority was given to peer-reviewed journal articles, established conference publications, scholarly surveys, and foundational publications that provided sufficient technical information available for analysis. [12]. Studies were excluded when their primary focus was unrelated to optimization, when they required physical quantum computation without providing relevant insight into the quantum-inspired methods considered in this review, or when insufficient technical information was available to determine the relationship between the proposed approach and the optimization problem.

7. Information Extraction and Analysis

For each relevant study, information was examined using common analytical categories, including the optimization approach, representation or search mechanism, problem formulation, application domain, evaluation criteria, computational characteristics, and reported limitations. Particular attention was given to the distinction between the optimization mechanism itself and the application in which it was evaluated. This distinction was used to avoid interpreting performance reported for a specific dataset or problem formulation as evidence of general algorithmic superiority.

8. Comparative Synthesis

Because the reviewed studies differ substantially in datasets, objective functions, benchmark problems, parameter configurations, stopping criteria, computational environments, and evaluation metrics, the literature was synthesized qualitatively rather than through statistical meta-analysis. The comparative analysis therefore considered solution quality, convergence behavior, exploration and exploitation characteristics, computational cost, scalability, robustness, and reproducibility. Conventional optimization approaches were treated as important baselines for comparison rather than assumed to provide universal performance improvements.

9. Scope and Limitations

The purpose of this review is to provide a structured technical synthesis of the available literature rather than a quantitative meta-analysis of effect sizes. The heterogeneity of existing studies limits direct numerical comparison between algorithms. In addition, differences in experimental design, implementation details, computational resources, and benchmark selection can substantially influence reported performance. These limitations were therefore considered when interpreting findings and identifying research directions for quantuminspired optimization in large-scale artificial intelligence.

10. Fundamentals of Quantum-Inspired Algorithms

Quantum-inspired optimization algorithms are classical computational methods that incorporate selected concepts motivated by quantum mechanics into optimization procedures. Unlike quantum algorithms that require quantum hardware, quantum-inspired methods are implemented on conventional computing platforms. Their objective is not to reproduce physical quantum computation exactly, but to use mathematical representations and search mechanisms inspired by concepts such as superposition, probability amplitudes, quantum measurement, rotation, and interference to guide the exploration of complex solution spaces[5], [6].

11. Quantum-Inspired Representation

A central concept in many quantum-inspired evolutionary algorithms is the probabilistic representation of candidate solutions. A binary decision can be represented using a pair of probability amplitudes, conventionally expressed as

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \tag{1}$$

where α and β represent probability amplitudes associated with the two possible states. The amplitudes satisfy the normalization condition.

$$|\alpha|2 + |\beta|2 = 1. \tag{2}$$

This representation should be interpreted as a mathematical encoding used by a classical optimization algorithm rather than as a physical qubit implemented on quantum hardware. During optimization, probability amplitudes can be modified according to update rules designed to increase the likelihood of promising candidate configurations while maintaining sufficient diversity for continued exploration[5], [6].

12. Quantum-Inspired Search Mechanisms

Quantum-inspired optimization methods employ different mechanisms to update candidate solutions. In evolutionary formulations, quantum-inspired rotation operators can modify probability amplitudes according to the relationship between the current candidate and the best-known solution. This mechanism can influence the transition between exploring alternative configurations and exploiting promising regions of the search space. Other quantum-inspired methods incorporate probabilistic sampling, interference-inspired transformations, or population-based update mechanisms[5], [6]. The effectiveness of these mechanisms depends on the representation, update strategy, initialization procedure, population size, stopping criteria, and characteristics of the objective function. Consequently, quantum-inspired terminology alone does not establish an optimization advantage. Performance must be evaluated experimentally against appropriate conventional baselines using comparable computational budgets and evaluation criteria.

13. Quantum-Inspired Versus Quantum Optimization

Quantum-inspired optimization should be distinguished from optimization algorithms that require physical quantum processors. Quantum optimization approaches such as quantum annealing and QAOA operate within quantum-computing paradigms and are constrained by the capabilities of available quantum hardware[2], [3], [4]. Quantum-inspired algorithms, in contrast, use classical computational resources while adopting selected mathematical concepts motivated by quantum mechanics[5], [6]. This distinction is important when interpreting reported performance. Improvements obtained by a quantum-inspired algorithm should be attributed to its computational representation and search mechanism rather than interpreted as evidence of quantum computational speedup. In practical AI applications, the relevant question is therefore whether the quantum-inspired formulation provides a measurable advantage in solution quality, convergence, computational cost, scalability, robustness, or other application-specific objectives when compared with appropriate classical methods.

14. Major Categories of Quantum-Inspired Algorithms

14.1 Quantum-Inspired Evolutionary Algorithm (QIEA)

Quantum-Inspired Evolutionary Algorithms (QIEAs) constitute an important class of quantum-inspired optimization methods designed to operate on classical computing systems. A characteristic feature of QIEAs is the use of probabilistic representations that allow a candidate solution to encode information about multiple possible states before a classical observation or sampling operation generates an explicit solution. This representation provides a mechanism for maintaining population diversity while guiding the search toward promising regions of the solution space[5], [6]. A typical QIEA consists of several stages, including initialization of the probabilistic population, observation or sampling of candidate solutions, evaluation using an objective or fitness function, and updating of the probabilistic representation. In the formulation introduced by Han and Kim, quantum-inspired individuals are represented using Q-bits and updated using quantum-inspired rotation gates. The update mechanism modifies the probability amplitudes according to the relationship between the observed solution and the best solution identified during the search.[5] The probabilistic representation can provide a useful balance between exploration and exploitation. During early stages of optimization, a broader probability distribution can maintain diversity among candidate solutions, whereas subsequent updates can increase the probability of selecting configurations associated with favorable objective values. The effectiveness of this process depends on the update rule, rotation strategy, initialization, population size, stopping condition, and structure of the optimization problem[6]. QIEAs have been investigated for combinatorial optimization, feature selection, scheduling, parameter optimization, and other problems involving large or complex search spaces. Their appeal lies in the ability to implement quantum-inspired representations and update mechanisms without requiring physical quantum hardware. However, the quantum-inspired representation does not by itself guarantee superior optimization performance. Computational cost, parameter sensitivity, representation choices, premature concentration of probability distributions, and scalability must be considered when evaluating QIEA-based approaches against conventional evolutionary and other metaheuristic methods[5], [6]. QIEAs have been investigated for problems including feature selection, scheduling, combinatorial optimization, image processing, and machine learning. Their main attraction is the ability to maintain a compact probabilistic representation while supporting broad exploration of the search space. However, their effectiveness depends on factors such as the solution representation, update strategy, population configuration, and problem characteristics. In large-scale applications, the computational cost of repeated solution generation and probability updates must also be considered when evaluating practical scalability and efficiency[5], [6].

14.2 Quantum-Inspired Genetic Algorithm (QIGA)

Quantum-Inspired Genetic Algorithms (QIGAs) extend genetic-algorithm search using probabilistic representations motivated by quantum-inspired computation. Instead of representing each individual solely as a conventional binary chromosome, a QIGA can maintain probability information associated with alternative states and generate candidate chromosomes through observation or sampling. This representation can preserve information about multiple candidate configurations during the search and can be particularly useful for discrete and combinatorial optimization problems[5], [13]. A typical QIGA combines population initialization, observation of candidate chromosomes, fitness evaluation, and probability-update operations. The probabilistic representation is modified based on the quality of observed solutions, so that configurations associated with favorable fitness values become more likely to appear in subsequent iterations. Higherorder quantum-inspired genetic formulations have also been investigated to extend the representation and search behavior beyond simple independent binary variables[13]. The main potential advantage of QIGA is its ability to maintain probabilistic information while performing populationbased search. This can support exploration of alternative configurations and reduce the need to commit prematurely to a single solution representation. However, performance depends on the probability-update mechanism, population size, initialization, stopping criteria, and problem representation. Increasing the complexity of the probabilistic representation can also increase computational and implementation requirements. QIGA approaches have been applied primarily to discrete and combinatorial optimization problems, including feature selection and other configuration problems. Their suitability for artificial intelligence applications should therefore be evaluated according to the structure of the underlying search problem rather than assumed solely from the quantum-inspired representation. Meaningful evaluation requires comparison with appropriate genetic algorithms and other established optimization methods using consistent objective functions, computational budgets, and performance metrics[6], [13].

14.3 Quantum-Inspired Particle Swarm Optimization (QIPSO)

Quantum-Inspired Particle Swarm Optimization (QIPSO) combines the population-based search behavior of particle swarm optimization with probabilistic or quantum-inspired mechanisms to represent and update candidate solutions. Conventional particle swarm optimization models candidate solutions as particles whose positions are influenced by individual and population-level search information. Quantum-inspired formulations modify this search process through alternative position representations or update mechanisms intended to influence the exploration of the search space[14], [15]. In a QIPSO framework, candidate solutions are iteratively evaluated against an objective function, while the search mechanism updates the population using information from promising solutions. Quantum-inspired representations can introduce additional stochasticity or probabilistic behavior into the search process, potentially allowing candidate solutions to explore regions that a deterministic update rule may not reach efficiently. The precise mechanism, however, varies considerably between QIPSO formulations and should therefore be described according to the specific algorithm being evaluated. The potential advantage of QIPSO lies in its ability to combine population-based exploration with alternative search representations. However, the effectiveness of such methods depends on the formulation of the position-update mechanism, initialization, parameter settings, population diversity, stopping criteria, and characteristics of the objective function. Excessive concentration around promising regions may reduce diversity and limit exploration, while overly stochastic updates may increase computational effort without producing proportional improvements in solution quality. QIPSO approaches can be considered for continuous, nonlinear, multimodal, and application-specific optimization problems, including parameter optimization and other artificial intelligence tasks. Their practical value should be established through controlled comparisons with conventional PSO and other appropriate optimization baselines. Evaluation should consider objective function quality, convergence behavior, computational cost, scalability, robustness, and sensitivity to algorithm parameters, rather than relying solely on the final objective value.

14.4 Quantum Annealing

Quantum annealing (QA) is a quantum optimization approach in which an optimization problem is represented as an energy landscape, and the computational process seeks lowenergy configurations corresponding to favorable solutions. The approach is particularly associated with combinatorial optimization problems that can be formulated using suitable Ising or quadratic unconstrained binary optimization representations. Unlike QIEA and QIGA, which are generally implemented as classical quantum-inspired algorithms, physical quantum annealing relies on quantum hardware and thus falls into a different computational category.[16], [4] The practical relevance of quantum annealing is influenced by the formulation of the optimization problem, the quality of the mapping to the underlying energy model, hardware connectivity, embedding requirements, noise, and available computational resources. Problems that cannot be represented efficiently in the required formulation may incur additional costs for transformation or embedding. Consequently, a favorable result on a quantum-annealing platform should not automatically be interpreted as evidence of general superiority over classical optimization methods.

Current quantum hardware also introduces practical limitations associated with noise, finite coherence, device connectivity, calibration, and limited computational resources. These constraints are important when considering the use of quantum annealing for large-scale artificial intelligence optimization. Comparisons with strong classical baselines are therefore necessary to determine whether using quantum hardware provides a meaningful advantage for a particular problem formulation[3], [4]. Quantum annealing is relevant to AI-related optimization tasks such as scheduling, routing, resource allocation, portfolio optimization, and other discrete decision problems when they can be formulated appropriately. However, its role in this review is considered separately from classical quantuminspired algorithms because the computational requirements, implementation assumptions, and sources of performance advantage are fundamentally different.

14.5 Hybrid Quantum-Inspired Algorithms

Hybrid quantum-inspired algorithms combine quantuminspired search mechanisms with established classical optimization or artificial intelligence techniques. The motivation for hybridization is to exploit complementary search behaviors, such as broad, population-based exploration alongside local refinement, adaptive parameter adjustment, or problemspecific heuristics. Such combinations can be particularly relevant when a single optimization mechanism does not adequately address both global exploration and local exploitation. Hybrid formulations may combine quantum-inspired evolutionary mechanisms with genetic algorithms, particle swarm optimization, differential evolution, local search, or machinelearning procedures. The resulting framework can be designed to improve search diversity, accelerate refinement, or incorporate domain-specific information into the optimization process. However, the performance of a hybrid algorithm depends on how the component methods interact and on whether the additional computational complexity produces a measurable benefit[6], [8], [7]. An important methodological issue is attribution of performance. When a hybrid method outperforms a baseline, the improvement cannot automatically be attributed to the quantum-inspired component. Additional components, parameter tuning, population size, initialization, local-search procedures, or computational budgets may also contribute to the observed result. Controlled experiments should therefore include appropriate ablation studies and comparisons with the corresponding non-quantum-inspired hybrid formulation. Hybrid quantum-inspired methods are potentially relevant to complex AI optimization problems involving large search spaces, multiple constraints, or competing objectives. Their practical evaluation should consider solution quality, convergence behavior, computational cost, scalability, parameter sensitivity, robustness, and reproducibility. The objective should be to determine whether the quantum-inspired component makes a measurable contribution beyond what is obtainable from well-designed classical hybrid optimization strategies.

14.6 Applications of Quantum-Inspired Algorithms in Artificial Intelligence

Quantum-inspired optimization has been investigated across a range of artificial intelligence and computational decision problems in which large, nonlinear, discrete, or multimodal search spaces make optimization challenging. The applications considered in this review include machine learning and deep learning, feature selection, hyperparameter optimisation, reinforcement learning, healthcare prediction and classification [17], financial modelling, cybersecurity, and robotics and smart manufacturing. Across these domains, the role of quantuminspired optimization is primarily to provide alternative search representations or population-based mechanisms for exploring candidate solutions on classical computing platforms. Its practical value remains dependent on problem formulation, computational resources, algorithm configuration, and the quality of the baseline methods used for comparison.

14.7 Machine Learning and Deep Learning

Machine learning and deep learning involve optimization at several levels, including model parameter estimation, loss minimization, architecture selection, and hyperparameter configuration. As model dimensionality and configuration spaces increase, optimization can become computationally expensive, particularly when objective functions are nonlinear, multimodal, discontinuous, or expensive to evaluate. Hyperparameter optimization is itself a challenging search problem because candidate configurations may require repeated model training and validation[1]. Quantum-inspired optimization can be incorporated into selected machine-learning optimization tasks to search for parameter configurations, model structures, or other discrete and continuous decision variables. Probabilistic and populationbased representations can provide alternative mechanisms for exploring candidate configurations without relying exclusively on gradient information. Quantum-inspired evolutionary methods are particularly relevant when the optimization problem contains discrete decisions or a complex search landscape[5], [6]. However, quantum-inspired optimization should not be considered a universal replacement for gradient-based deeplearning training. Modern neural networks can contain very large numbers of parameters, making direct population-based optimization computationally demanding. The practical value of a quantum-inspired method therefore depends on the formulation of the optimization problem, search-space dimensionality, computational budget, and baseline method. Evaluation should consider predictive performance, convergence behaviour, computational cost, and generalization rather than accuracy alone.

14.8 Feature Selection

Feature selection can be formulated as a combinatorial optimization problem in which the objective is to identify an informative subset of variables while reducing redundant or irrelevant features. For a dataset containing n candidate features, the number of possible binary feature subsets is 2n, making exhaustive evaluation increasingly impractical as dimensionality increases. This characteristic makes feature selection an important application area for population-based and probabilistic optimization methods. Quantum-inspired evolutionary approaches can represent candidate feature subsets using binary or probabilistic representations and evaluate them according to an objective function that combines predictive performance with feature-subset complexity. The resulting optimization process can search for a balance between retaining informative variables and reducing dimensionality. Recent literature has specifically examined quantum-inspired evolutionary algorithms for feature-subset selection and has identified the diversity of representations, objective functions, and update mechanisms used across existing studies[9], [5], [6]. The effectiveness of quantum-inspired feature selection depends on the representation, objective function, optimization parameters, and predictive model used for evaluation. Performance should therefore be assessed using multiple criteria, including predictive performance, number of selected features, computational cost, subset stability, and independent validation performance. An optimization method that produces only a marginal predictive improvement while substantially increasing computational requirements may not provide a practical advantage.

14.9 Hyperparameter Optimization

Hyperparameter optimization involves identifying suitable configurations for machine-learning models, including learning rates, regularization parameters, batch sizes, network architectures, and other training settings. When multiple hyperparameters interact, the resulting search space can become large and computationally expensive. Each candidate configuration may require model training and validation, making the number and cost of objective-function evaluations important considerations[1]. Quantum-inspired optimization can be used as an alternative search mechanism for exploring such configuration spaces. A population-based or probabilistic representation can maintain multiple candidate configurations and iteratively update the search toward configurations associated with favourable validation performance. The objective function can also incorporate computational or model-complexity constraints when the application requires a balance between predictive performance and resource consumption. The usefulness of quantum-inspired hyperparameter optimization depends on search-space dimensionality, objectivefunction cost, algorithm parameters, and the model being optimized. Meaningful evaluation should therefore report predictive performance together with the number of objectivefunction evaluations, training time, convergence behaviour, and computational resources. Comparisons with established methods such as random search, Bayesian optimization, and conventional evolutionary optimization are necessary before practical advantages can be established[1].

Table 1: Comparative Characteristics of Major Quantum-Inspired Optimization Approaches

Approach	Core Representation / Mechanism	Search Characteristics	Suitable Problem Types	Typical Applications	Key Limitations
QIEA	Probabilistic solution representation with quantum-inspired amplitude updates	Maintains population diversity and balances exploration with exploitation	Discrete, combinatorial, and population-based optimization	Feature selection, scheduling, machine learning optimization	Representation and update-rule sensitivity; computational overhead for large problems
QIGA	Quantum-inspired probabilistic chromosome representation with fitness-guided updates	Broad population search with adaptive probability updates	Binary, discrete, and combinatorial optimization	Feature selection, neural-network optimization, scheduling	Parameter sensitivity and additional representation-update cost
QIPSO	PSO-based population search combined with quantum-inspired or probabilistic position updates	Probabilistic exploration of candidate regions with population-based adaptation	Continuous, nonlinear, and complex optimization	AI optimization, robotics, image processing, energy management	Risk of loss of diversity; performance depends on formulation and parameter settings

Approach	Core Representation / Mechanism	Search Characteristics	Suitable Problem Types	Typical Applications	Key Limitations
Quantum Annealing	Optimization through low-energy configurations and quantum-tunnelling-based search	Searches an energy landscape for low-energy solutions	Combinatorial and constraint-based optimization formulated for annealing	Scheduling, routing, portfolio and resource optimization	Specialized hardware requirements for physical QA; scaling and implementation constraints
Hybrid Quantum-Inspired	Combines quantum-inspired mechanisms with evolutionary, swarm, local-search, or AI methods	Combines complementary exploration and exploitation mechanisms	Complex, multimodal, and application-specific optimization	Neural architecture search, hyperparameter optimization, reinforcement learning, scheduling	Increased algorithmic complexity, parameter count, and computational overhead

14.10 Reinforcement Learning

Reinforcement learning (RL) formulates sequential decision-making as an optimization problem in which an agent seeks to maximize cumulative reward through interaction with an environment. The optimization process must balance exploration of alternative actions with exploitation of actions that have previously produced favourable outcomes. Large or continuous state–action spaces can make policy search computationally demanding. Quantum-inspired optimization can be considered as a complementary search mechanism for selected RL problems, including policy optimization, parameter configuration, and action-selection strategies. Probabilistic representations can maintain information about alternative candidate solutions, while population-based methods can evaluate and refine candidate policies or parameter configurations. Such mechanisms may be particularly relevant to optimization problems where the policy space is discrete, combinatorial, or difficult to optimize using conventional gradient-based methods[18]. The effectiveness of a quantum-inspired approach in RL depends on the policy representation, state–action space, reward formulation, environment complexity, and computational cost of evaluating candidate policies. Evaluation should therefore consider cumulative reward, convergence behaviour, sample efficiency, computational cost, and robustness across environments. Claims of improvement should be supported by comparisons with appropriate RL baselines rather than by performance on a single environment.

14.11 Healthcare

Healthcare applications involve high-dimensional and heterogeneous data and can include optimisation tasks such as prediction, classification, feature selection, and model configuration. In these settings, optimisation can be used to identify informative variables or model configurations while balancing predictive performance and computational requirements. Quantum-inspired optimization can be formulated for selected healthcare-related optimization problems, including healthcare prediction and classification tasks [17].. Similar representations may also be formulated for clinical or biomedical featureselection problems, although their practical value depends on the characteristics and quality of the underlying data. Healthcare applications require stronger validation considerations than optimization performance alone. Clinical datasets may contain class imbalance, missing observations, limited sample sizes, and distributional differences between populations. Therefore, evaluation should consider predictive performance, computational cost, robustness, reproducibility, interpretability, and validation using independent or clinically representative data. A method that performs well on a single benchmark dataset should not automatically be considered suitable for clinical deployment.

14.12 Financial Modelling

Financial modelling involves optimization problems characterized by multiple constraints, uncertainty, dynamic data, and competing objectives. Examples include portfolio construction, asset allocation, risk management, and other decision problems involving large numbers of possible configurations. Portfolio optimization may require simultaneous consideration of expected return, risk, diversification, transaction costs, and investment constraints. Quantum-inspired optimization can provide populationbased or probabilistic mechanisms for exploring alternative financial configurations, particularly when the formulation contains discrete or combinatorial decisions[19]. However, financial optimization is highly dependent on modelling assumptions and changes in the underlying data. A solution that performs well on historical observations may not maintain its performance under different market conditions. Evaluation should therefore consider objective value, constraint satisfaction, computational cost, robustness to changing data, and out-of-sample performance. For predictive or trading-related applications, appropriate validation is particularly important because strong historical performance can result from overfitting rather than genuine generalization. Comparisons with established portfolio-optimization and conventional computational methods are therefore necessary before practical advantages can be established.

14.13 Cybersecurity

Cybersecurity systems generate optimization problems involving network, endpoint, behavioural, and other securityrelated data. Optimization can support tasks such as feature selection, intrusion-detection model configuration, anomaly detection, malware classification, and resource allocation. These problems may involve high-dimensional and dynamically changing search spaces. Quantum-inspired optimization can be applied by searching for informative feature subsets, model configurations, or decision parameters that optimize a predefined objective function. For example, a feature-selection formulation may seek to maximize predictive performance while minimizing the number of selected variables. Probabilistic and populationbased mechanisms provide alternative strategies for exploring discrete or nonlinear search spaces [20]. Cybersecurity environments are dynamic, and performance obtained on a fixed dataset may not transfer to changing attack patterns or network conditions. Evaluation should therefore consider detection performance, false-positive and false-negative rates, computational cost, robustness to distribution changes, and reproducibility. Practical deployment should additionally consider latency and resource requirements. Quantum-inspired approaches should consequently be evaluated against strong conventional baselines using representative and appropriately validated cybersecurity datasets.

14.14 Robotics and Smart Manufacturing

Robotics and smart manufacturing involve optimization problems such as path planning, task scheduling, routing, resource allocation, production sequencing, and maintenance planning. These problems can be combinatorial and may include multiple constraints, competing objectives, and changing operating conditions. As the number of tasks, machines, resources, or possible routes increases, exhaustive evaluation of all configurations becomes impractical. Quantum-inspired optimization can be used to search large solution spaces associated with these problems. In robotic path planning, for example, an optimization procedure can search for feasible paths while considering travel distance, energy consumption, safety constraints, and execution time. In manufacturing, similar formulations can be used for production scheduling, resource allocation, and sequencing under operational constraints[21], [22]. Practical performance depends on the optimization formulation, constraint-handling mechanism, computational resources, and characteristics of the operating environment. A solution that performs well under static benchmark conditions may not remain effective when schedules, traffic conditions, sensor information, or resource availability change. Evaluation should therefore consider solution quality, feasibility, execution time, computational cost, robustness, and scalability. Comparisons with established optimization methods are necessary to determine whether a quantum-inspired formulation provides a meaningful practical advantage in real-world robotics and manufacturing systems.

15. Comparative Analysis and Discussion

The literature reviewed in this study indicates that quantuminspired optimization represents a family of computational strategies rather than a single optimization method. QIEA, QIGA, QIPSO, quantum-annealing-based approaches, and hybrid formulations differ in their representations, search mechanisms, computational requirements, and the problem structures they are well-suited to. Consequently, the effectiveness of a quantum-inspired approach should be evaluated in relation to the characteristics of the optimization problem rather than assumed from the use of quantum-inspired concepts alone[6], [8], [7]. QIEA and QIGA approaches are particularly relevant to discrete and combinatorial optimization because probabilistic representations can maintain information about alternative solution configurations during the search. Their performance depends on the representation, the probability update mechanism, the population size, the initialization, and the stopping criteria. QIPSO approaches combine population-based swarm search with alternative probabilistic or quantum-inspired update mechanisms, making their behavior dependent on the specific position representation and update strategy employed. These differences make direct comparison between QIEA, QIGA, and QIPSO difficult unless the algorithms are evaluated under equivalent experimental conditions. Quantum annealing represents a fundamentally different computational approach because physical implementations require quantum hardware and an appropriate mapping of the optimization problem to an energy formulation. Consequently, performance obtained with quantum annealing should not be directly interpreted as equivalent to that of classical quantuminspired algorithms. Hardware characteristics, embedding requirements, connectivity, noise, and problem formulation can influence the outcome of quantum-annealing experiments[16], [4], [3]. Hybrid quantum-inspired methods introduce another level of complexity by combining quantum-inspired mechanisms with evolutionary algorithms, swarm intelligence, local search, or machine-learning procedures. Such combinations can provide complementary exploration and exploitation mechanisms, but an observed improvement cannot automatically be attributed to the quantum-inspired component. Ablation studies and comparisons with equivalent non-quantum-inspired hybrid methods are therefore important for identifying the actual contribution of the quantum-inspired mechanism. A major limitation across the literature is the lack of uniform experimental conditions. Studies frequently employ different datasets, benchmark functions, objective formulations, parameter settings, population sizes, stopping criteria, hardware configurations, and evaluation metrics. As a result, a reported improvement in convergence speed or objective value in one study cannot automatically be interpreted as evidence that the corresponding algorithm is generally superior to conventional optimization methods. For large-scale artificial intelligence applications, scalability should be evaluated alongside solution quality. An algorithm may identify a high-quality solution but still have limited practical value if the computational cost of generating and evaluating candidate solutions increases substantially with problem dimensionality. Similarly, faster convergence does not necessarily indicate a superior optimization method if the final solution quality, robustness, or generalization performance is inferior. Evaluation should therefore consider multiple dimensions, including solution quality, convergence behavior, computational cost, scalability, robustness, parameter sensitivity, and reproducibility. The literature also indicates that problem formulation plays a central role in determining the usefulness of quantum-inspired optimization. Discrete feature-selection problems, combinatorial scheduling problems, and constrained configuration problems may provide different opportunities for probabilistic or population-based representations than continuous differentiable model-training problems. Therefore, algorithm selection should be guided by the mathematical structure of the optimization problem rather than by the assumption that quantum-inspired methods are universally advantageous. Another important consideration is reproducibility. Reported optimization performance can be influenced by initialization, random seeds, parameter

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settings, computational hardware, implementation details, and stopping conditions. Without sufficient reporting of these factors, independent reproduction and meaningful comparison become difficult. Future studies should therefore provide complete algorithmic descriptions, parameter configurations, computational budgets, datasets, baseline implementations, and evaluation procedures. Overall, the available literature supports continued investigation of quantum-inspired optimization for selected artificial intelligence problems, but it does not establish universal superiority over conventional optimization. The strongest research opportunity lies in identifying problem classes in which quantum-inspired representations or search mechanisms yield a measurable benefit under controlled, reproducible experimental conditions. Such evaluation should distinguish improvements arising from the quantum-inspired component from those resulting from general algorithmic design, parameter tuning, or additional computational resources.

Table 2: Application-Oriented Comparison of Quantum-Inspired Optimization in Artificial Intelligence

Application Area	Optimization Task	Role of Quantum-Inspired Optimization	Evaluation Considerations	Major Practical Challenge
Machine Learning / Deep Learning	Model parameters, architecture selection, and training-related optimization	Searches candidate configurations or complements conventional learning procedures	Predictive performance, convergence, computational cost, and generalization	High-dimensional parameter spaces and expensive model evaluations
Feature Selection	Selection of informative feature subsets	Searches discrete feature combinations using probabilistic or population-based representations	Prediction performance, number of selected features, stability, and computational cost	Combinatorial growth of possible feature subsets
Hyperparameter Optimization	Learning rates, regularization, batch size, architecture, and other configuration parameters	Searches large configuration spaces using population-based or probabilistic mechanisms	Validation performance, objective evaluations, runtime, and convergence	High cost of evaluating candidate configurations
Reinforcement Learning	Policy parameters, action selection, and decision strategies	Supports exploration of alternative policies or parameter configurations	Cumulative reward, convergence, sample efficiency, and computational cost	Large state–action spaces and exploration–exploitation trade-off
Healthcare	Feature selection, diagnosis models, image analysis, and clinical decision-support optimization	Optimizes feature/model configurations and other high-dimensional decision problems	Predictive performance, robustness, interpretability, reproducibility, and external validation	Limited data, distribution shift, and requirements for reliable validation
Financial Modelling	Portfolio construction, asset allocation, risk and constraint optimization	Searches discrete or constrained investment configurations	Objective value, constraint satisfaction, computational cost, and out-of-sample robustness	Dynamic market conditions and sensitivity to modelling assumptions
Cybersecurity	Feature selection, intrusion detection, anomaly detection, and model configuration	Optimizes feature subsets and decision-model parameters	Detection performance, false-positive rate, robustness, latency, and computational cost	Changing attack patterns and distribution shifts
Robotics / Smart Manufacturing	Path planning, scheduling, routing, resource allocation, and sequencing	Searches large combinatorial solution spaces under operational constraints	Solution quality, feasibility, execution time, scalability, and robustness	Dynamic environments, multiple constraints, and real-time requirements

16. Future Research Directions

The literature reviewed in this study identifies several directions to improve the practical development and evaluation of quantum-inspired optimisation for large-scale artificial intelligence.

Scalable Optimization

Scalability remains a central challenge as AI optimisation problems increase in dimensionality, dataset size, and computational complexity. Future research should investigate representations and update mechanisms that maintain effective exploration without causing excessive computational overhead. Particular attention should be given to population size, candidate-solution evaluation cost, memory requirements, and convergence behaviour as problem dimensionality increases.

Hybrid and Adaptive Optimisation

Hybrid optimisation provides an opportunity to combine quantum-inspired search mechanisms with established evolutionary, swarm-based, local-search, or learning-based methods. Future studies should investigate adaptive mechanisms that dynamically adjust the contributions of different search strategies in response to the characteristics of the optimisation landscape. Controlled ablation experiments will be important for determining whether improvements arise specifically from the quantum-inspired component or from the additional classical optimisation mechanisms.

Benchmark Standardization

Meaningful comparison between optimisation algorithms requires more consistent experimental protocols. Future studies should use standardised benchmark functions, publicly available datasets, clearly defined objective functions, common evaluation metrics, and comparable computational budgets where appropriate. Reporting convergence curves, objective function evaluations, runtime, memory requirements, parameter settings, and random seed information would improve reproducibility and facilitate more reliable comparisons across studies.

Explainability and Interpretability

As quantum-inspired optimisation is increasingly applied to artificial intelligence systems, understanding why an optimisation strategy selects a particular solution is important. Future research should investigate interpretable representations, sensitivity analysis, feature-selection stability, and methods for analysing optimisation trajectories. Explainability is particularly important in applications such as healthcare, finance, and cybersecurity where decisions may have significant practical consequences.

Reproducibility and Experimental Reporting

Reproducibility remains an important methodological requirement for optimisation research. Future studies should provide sufficient information regarding algorithm implementation, initialisation, parameter settings, stopping criteria, computational hardware, datasets, baseline methods, and evaluation procedures. Public release of source code and experimental configurations would further support independent validation and comparison.

Integration with Large-Scale AI Systems

Future research should move beyond small benchmark problems and investigate quantum-inspired optimisation within realistic AI workflows. Potential directions include largescale hyperparameter optimisation, neural architecture search, distributed optimisation, edge and cloud computing, reinforcement learning, and resource allocation. The key research question should be whether quantum-inspired mechanisms provide measurable benefits under realistic computational constraints rather than whether they perform well only on selected benchmark functions.

Real-World Validation

A further priority is validation under realistic operating conditions. Optimisation methods evaluated only on static benchmark datasets may not capture changes in data distributions, constraints, resource availability, or environmental conditions encountered in practical systems. Future studies should therefore evaluate robustness under changing conditions and report both optimisation performance and application-level outcomes. Overall, future progress will depend on moving from isolated algorithmic demonstrations toward reproducible, problem-specific, and application-oriented evaluation. Establishing clear evidence for when quantum-inspired optimisation provides a measurable advantage over strong conventional baselines will be essential for determining its practical role in large-scale artificial intelligence.

17. Conclusion

Quantum-inspired optimisation has evolved into a diverse family of classical computational strategies that incorporate selected concepts from quantum mechanics into optimisation procedures. This review examined major approaches, including Quantum-Inspired Evolutionary Algorithms, Quantum-Inspired Genetic Algorithms, QuantumInspired Particle Swarm Optimisation, quantum-annealingrelated optimisation, and hybrid quantum-inspired methods, with an emphasis on their representations, search mechanisms, applications, and practical limitations. The reviewed literature indicates that quantum-inspired approaches can provide alternative mechanisms for exploring complex optimisation spaces, particularly for discrete, combinatorial, nonlinear, and multimodal problems. Applications have been investigated across machine learning, feature selection, hyperparameter optimisation, reinforcement learning, healthcare, financial modelling, cybersecurity, robotics, and smart manufacturing. However, the available evidence does not support treating quantum-inspired optimisation as a universally superior alternative to conventional optimisation methods. Reported performance depends strongly on problem formulation, algorithm design, parameter settings, computational resources, baseline selection, and evaluation methodology. A major finding of this review is that direct comparison across studies remains difficult because of differences in datasets, benchmark problems, objective functions, computational environments, evaluation metrics, and experimental protocols. Consequently, improvements reported in individual studies should be interpreted within their specific experimental contexts. Establishing broader conclusions requires standardised benchmarks, transparent computational budgets, reproducible implementations, and comparisons with strong conventional baselines. Future development should therefore focus on scalable and adaptive optimisation mechanisms, rigorous evaluation of hybrid methods, standardised benchmarking, reproducibility, explainability, and validation on realistic, large-scale artificial intelligence problems. The most important research objective is not to demonstrate that a method is quantum-inspired, but to determine whether the associated representation or search mechanism yields a measurable and reproducible advantage in a well-defined optimisation problem. Overall, quantum-inspired optimisation represents a promising research direction for selected artificial intelligence optimisation problems. Still, its practical significance will ultimately depend on rigorous empirical evidence demonstrating when, where, and under what computational conditions these methods offer advantages over established alternatives.

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