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Review

Quantum Information Systems: Foundations, Intelligent Algorithms, and Cross-Industry Applications

Fengyi Wang * and Yang Lu

School of Computer and Artificial Intelligence, Beijing Technology and Business University, Beijing 102488, China
* Correspondence: wangfengyi2001@gmail.com

How To Cite: Wang, F.; Lu, Y. Quantum Information Systems: Foundations, Intelligent Algorithms, and Cross-Industry Applications. *Journal of Emerging Technologies with Industrial Applications* **2026**, *1*(1), 3.

Received: 15 August 2025
Revised: 30 October 2025
Accepted: 13 November 2025
Published: 7 January 2026

Abstract: Quantum Information Systems (QIS) have emerged as a transformative paradigm, integrating the principles of quantum mechanics with advanced computational and communication technologies to address complex problems beyond the capabilities of classical systems. This review provides a comprehensive synthesis of current developments, beginning with the foundational principles that define QIS, including its theoretical underpinnings, quantum state representations, and computational frameworks. It then examines advances in quantum computing for QIS, with a focus on hardware architectures, the design and optimization of core algorithms, and the computational advantages over classical approaches. The discussion extends to quantum machine learning for QIS, exploring hybrid quantum–classical learning models, quantum data encoding techniques, and optimization strategies. Finally, it surveys diverse application domains, such as finance, industrial information integration, energy systems, healthcare, and intelligent transportation. In addition, the paper highlights pressing technological, data-centric, algorithmic, and ecosystem-level challenges, and discusses future trajectories shaped by innovations such as quantum blockchain, quantum artificial intelligence, and decentralized QIS. Through a structured and integrative analysis, this work aims to provide a roadmap for researchers and practitioners navigating the rapidly evolving QIS landscape.

Keywords: quantum information systems; quantum computing; quantum machine learning; quantum algorithms

1. Introduction

In recent years, Quantum Information Systems (QIS), which integrate quantum computing, quantum communication, and quantum sensing into a unified framework, have emerged as a pivotal force in transforming the paradigm of information science. By exploiting quantum phenomena such as superposition, entanglement, and interference, QIS can outperform classical systems in specific tasks, offering unprecedented capabilities in high-performance computing, secure communication, intelligent optimization, and large-scale data processing. The inherently interdisciplinary nature of QIS has generated profound impacts not only in physics and computer science but also in a wide range of industries, including finance, industrial information integration, energy systems, intelligent transportation, and healthcare.

From a research perspective, the development of QIS is driven by advances in hardware, algorithms, and data processing. On the hardware side, the rapid iteration of quantum computer prototypes and quantum networks has enabled early-stage validation of quantum algorithms such as Shor's, Grover's, quantum support vector machines (QSVM), and quantum principal component analysis. In parallel, progress in quantum data encoding and hybrid quantum–classical learning frameworks has laid the foundation for quantum machine learning and quantum optimization. However, existing research still faces critical challenges, including limited hardware scalability, high overheads in quantum error correction, inefficiencies in classical-to-quantum data encoding, and the absence of unified international standards and interdisciplinary talent development programs.

Despite these barriers, the future trajectory of QIS is becoming increasingly clear. Emerging directions such as quantum blockchain, quantum artificial intelligence, and decentralized quantum networks are rapidly progressing from conceptual models to prototype implementations, promising to reshape the architecture of information systems and to lead the next generation of secure, intelligent, and globally interconnected computing ecosystems. Against this backdrop, a systematic review of QIS is essential—not only for enabling the academic community to understand its research landscape and frontier trends but also for providing strategic guidance to industry stakeholders.

The contributions of this study are threefold: (1) it proposes a multi-layered analytical framework for QIS, systematically covering its theoretical foundations, core algorithms, data processing methods, and industrial applications; (2) it integrates the latest advancements from quantum computing, quantum finance, and quantum machine learning to reveal their cross-disciplinary synergies within QIS; and (3) it synthesizes current technological, data-related, algorithmic, and ecosystem challenges, offering insights into future development trends and research directions.

As depicted in Figure 1, the rest of this paper is organized as follows: Section 2 provides relevant information about the literature, reviews the existing literature and outlines the progress of QIS research; Section 3 discusses the basic principles, core algorithms and learning paradigms of QIS; Section 4 studies its applications in finance, industrial information integration, energy, transportation and healthcare; Section 5 analyzes the main challenges and future trends; Section 6 concludes the paper with final comments and perspectives.

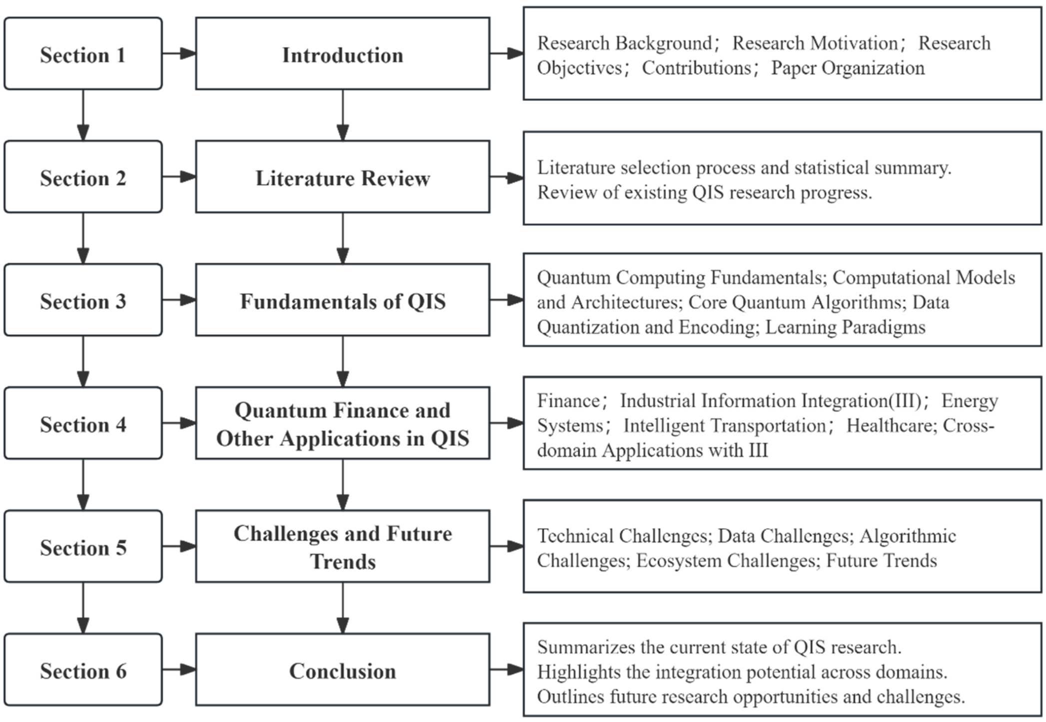

Figure 1. Structure of the paper.

2. Literature Review

2.1. Literature Search and Selection Criteria

To comprehensively understand the current state of QIS research, we conducted a systematic literature search in leading academic databases, including Web of Science (WoS), IEEE Xplore, and Google Scholar. Multiple keywords and Boolean operators were employed to maximize coverage, including: “quantum information system” OR “quantum computing” OR “quantum communication” OR “quantum machine learning” OR “industrial information integration” OR “industrial applications” OR “cross-domain integration”. The initial search retrieved 244,354 records.

To ensure credibility and academic rigor, only peer-reviewed journal articles and review articles were retained, resulting in 193,631 records. After excluding open-access journals, the number of articles decreased to 94,467. Restricting the publication period to 2015–2025 further reduced the dataset to 51,869 articles. Finally, we filtered for Hot Papers and Highly Cited Papers, producing a final dataset of 678 articles for in-depth analysis.

2.2. Descriptive Analysis

As summarized in Table 1, the 678 selected articles come from 557 different high-quality journals. The average total citation count per article is 305 (Table 1). This demonstrates that QIS is an interdisciplinary field, with collaboration being a key indicator of its research output.

Table 1. Main information of featured articles.

Description	Result
Timespan	2015–2025
Source	557
Documents	678
Average citations per document	305

A temporal analysis of publications between 2015 and 2025 reveals a significant growth trajectory in QIS research, particularly after 2022, coinciding with significant advances in quantum hardware and cloud-based quantum computing platforms (Figure 2).

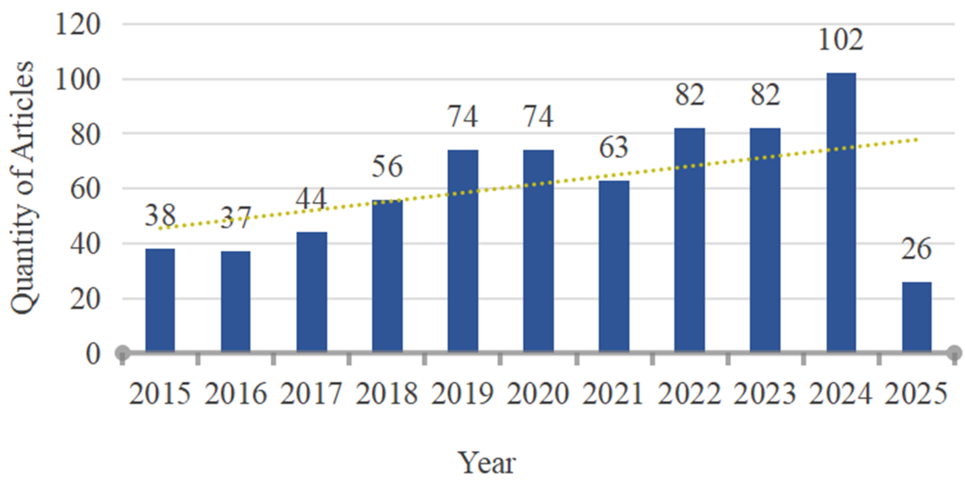

Figure 2. Publication trend (2015–2025).

Table 2 shows that Nature leads with 90 publications, followed by Nature Physics (61) and Nature Photonics (47), indicating that QIS research is highly represented in top multidisciplinary and physics-focused journals. While other outlets such as Advanced Materials and Chemical Engineering Journal also contribute notable volumes, the overall distribution reflects the interdisciplinary nature of QIS, spanning physics, materials science, chemistry, and engineering.

Table 2. The top 12 Source of Selected Articles.

Source Title	Number
Nature	90
Nature physics	61
Nature photonics	47
Advanced materials	36
Chemical engineering journal	17
Nature nanotechnology	16
Chemical reviews	11

Table 2. *Cont.*

Source Title	Number
Advanced functional materials	9
Acs applied materials & interfaces	8
Acs nano	8
Laser & photonics reviews	8
Nano energy	8
Nature reviews materials	8

2.3. Temporal and Geographic Trends

Following the methodology applied in the three prior reviews, the selected literature was categorized into four major thematic clusters: Fundamentals of QIS; Quantum Computing for QIS; Quantum Machine Learning for QIS and Application Domains of QIS.

Fundamentals of QIS examines the underlying principles of quantum mechanics, the methods of information representation, and the models of quantum computation. Quantum Computing for QIS focuses on hardware platforms, the foundations of quantum algorithms, and the advantages offered by quantum computation. Quantum Machine Learning for QIS investigates hybrid quantum–classical algorithms, the paradigms of quantum learning, and various optimization techniques. The application domains of QIS encompass finance, industrial information integration, energy systems, healthcare, and intelligent transportation.

As shown in Table 3, each paper was mapped to one or more clusters, providing a multi-dimensional perspective on the field. The classification structure draws directly from the systematic approach of the Quantum Computing, Quantum Finance, and Quantum Machine Learning reviews, ensuring both coverage breadth and thematic consistency.

Table 3. Thematic Clusters of QIS.

Thematic Cluster	Scope & Description	Research Focus
Fundamentals of QIS	Covers the fundamental principles of quantum mechanics, quantum state representation methods, and computational models underlying QIS.	Core concepts: qubits, superposition, and entanglement; Quantum logic gates and quantum circuit model [1]; Quantum measurement theory and its role in information retrieval [2]; Comparative applicability of computational frameworks: gate model, adiabatic quantum computing, and topological quantum computing [3].
Quantum Computing for QIS	Encompasses hardware platforms, core quantum algorithms, and computational advantages over classical systems.	Mainstream hardware architectures: superconducting qubits, trapped ions, photonic quantum computing [4]; Scalability and fault-tolerance challenges in quantum hardware; Classical quantum algorithms: Shor's algorithm, Grover's algorithm, Quantum Fourier Transform (QFT); Machine learning–related algorithms: Quantum Support Vector Machine (QSVM), Quantum Principal Component Analysis (QPCA) [5]; Potential applications in combinatorial optimization, numerical simulation, and secure communication [6].
Quantum Machine Learning for QIS	Explores hybrid quantum–classical algorithms, learning paradigms, and optimization techniques in QIS.	Quantum supervised learning, quantum unsupervised learning, and quantum reinforcement learning; Quantum encoding strategies: amplitude encoding, angle encoding, basis encoding [7]; Variational Quantum Algorithms, Quantum Neural Networks, quantum clustering [8]; Applications of hybrid quantum–classical training frameworks in high-dimensional and nonlinear tasks [9]; Performance and limitations of QML in pattern recognition, predictive analytics, and complex system modeling
Application Domains of QIS	Covers cross-industry applications of QIS in finance, industrial information integration, energy systems, healthcare, and intelligent transportation.	Finance: portfolio optimization, high-frequency trading, risk management, quantum-secure payments [10]; Industrial Information Integration: IIoT data processing, supply chain optimization, intelligent manufacturing [11]; Energy Systems: power grid optimization, renewable energy forecasting [12]; Healthcare: drug molecule modeling, medical data privacy protection [13]; Intelligent Transportation: scheduling optimization, vehicle-to-everything (V2X) security [14].

While previous reviews have examined quantum computing in industrial settings, quantum algorithms for financial applications, and quantum-enhanced machine learning, several key shortcomings remain. Most studies focus on a single technology pillar, without integrating the full quantum information system (QIS) architecture. Some studies simultaneously explore multiple application areas within a unified QIS framework. Few studies systematically explore the integration of quantum hardware, algorithms, and domain-specific solutions with operational systems.

We further screened these papers, primarily focusing on abstracts. For example, the research had to focus on one of quantum computing, quantum communication, quantum storage, or quantum algorithms, and incorporate practical applications. The papers also had to address industrial integration, cross-industry applications, or the application of quantum technology to specific fields. Papers were required to provide substantial theoretical contributions, novel frameworks, or experimental validation. Ultimately, we obtained 64 papers for literature analysis.

This review addresses these shortcomings by integrating the technological, algorithmic, and application-oriented dimensions of QIS into a unified analytical framework, providing a comprehensive and structured understanding of the field.

3. Fundamentals of Quantum Information Systems

Quantum Information Systems (QIS) represent an emerging class of computational and communication architectures that utilize quantum mechanical principles to process and transmit information. Unlike classical systems, where information is encoded in binary digits (bits) assuming discrete states of 0 or 1, QIS encodes information in quantum bits (qubits) capable of existing in superposition and exhibiting entanglement. This unique capability allows QIS to execute certain computational tasks exponentially faster, transmit information with unconditional security, and integrate diverse functional modules—computation, storage, and communication—into a unified system.

From an industrial perspective, QIS serve as the foundational infrastructure for quantum-enhanced applications in finance, machine learning, optimization, and secure data integration. The study of QIS fundamentals thus demands an understanding of the physical principles, mathematical structures, and architectural models that underpin their operation.

3.1. The foundations of Quantum Computing

The fundamental operations of QIS are rooted in the fundamental principles of quantum mechanics, which together define a computational paradigm that differs from that of classical systems (Table 4).

Table 4. The foundations of quantum computing.

Concept	Core Principle	Applications & Challenges
Superposition	A qubit exists in a linear combination of basis states, allowing parallel information encoding.	Powers quantum search and optimization; coherence is easily lost.
Entanglement	Correlated quantum states exhibit non-local dependencies beyond classical systems.	Foundation of quantum teleportation and networking; highly noise-sensitive.
Interference	Constructive and destructive phase interactions amplify desired computational outcomes.	Central to Grover's search and quantum optimization; requires precise phase control.
Measurement	Quantum observation probabilistically collapses a state into a definite classical outcome.	Provides computational results; introduces stochastic uncertainty.
Tunneling	Exploits quantum probability to overcome local energy barriers in optimization processes.	Key to quantum annealing; hardware-dependent performance.
No-cloning Theorem	The impossibility of perfectly copying an unknown quantum state ensures intrinsic data security.	Protects quantum communication; restricts direct state replication.

3.1.1. Superposition

A quantum bit (qubit) can exist in a coherent linear combination of the computational basis states 0 and 1. This property allows a quantum register of n qubits to represent 2^n states simultaneously, enabling exponential parallelism in information encoding and processing. Superposition underpins the enhanced state-space exploration capability of QIS, which is particularly advantageous in search, optimization, and simulation tasks [15–17].

3.1.2. Entanglement

Quantum entanglement represents a non-classical correlation between qubits, such that the state of one qubit instantaneously determines the state of another, regardless of spatial separation. This phenomenon allows for coordinated quantum operations across distributed nodes, forming the theoretical basis of quantum networking, quantum teleportation, and certain multi-qubit algorithms. In QIS, entanglement is a critical enabler for error correction codes and secure multi-party computation [18–20].

3.1.3. Quantum Interference

By manipulating probability amplitudes, quantum interference can be engineered to amplify the likelihood of correct computational paths while suppressing incorrect ones. This selective amplification forms the mathematical foundation of quantum algorithms such as Grover's search and the Quantum Approximate Optimization Algorithm (QAOA). Effective interference control enables QIS to achieve computational speedups in both unstructured search and combinatorial optimization problems [21,22].

3.1.4. Measurement Postulate

In quantum mechanics, measurement projects a qubit's superposed state onto one of the computational basis states, with the outcome probability determined by the squared magnitude of its amplitude. This inherent probabilistic nature introduces stochasticity into QIS outputs, necessitating repeated measurements to achieve statistically reliable results. While measurement collapses quantum coherence, it also serves as the final extraction mechanism for computational outputs in QIS [23].

3.1.5. Quantum Tunneling

Quantum tunneling describes the ability of a particle to pass through an energy barrier that would be insurmountable in classical physics. In quantum computing, tunneling enables quantum annealing systems (such as those used in optimization tasks) to escape local minima and converge toward global optima more efficiently. This mechanism underpins the computational power of adiabatic quantum computing and certain heuristic solvers [24].

3.1.6. No-Cloning Theorem

This principle asserts that it is impossible to create an identical copy of an arbitrary unknown quantum state. It underpins the security of quantum communication—particularly in quantum key distribution—by making undetected eavesdropping physically impossible. In distributed quantum computing and quantum machine learning, the no-cloning constraint necessitates alternative methods such as quantum teleportation or entanglement swapping for transferring quantum information [25].

Collectively, these principles form the operational backbone of QIS. By integrating superposition, entanglement, interference, and probabilistic measurement, quantum computing architectures can explore vast computational spaces, solve classically intractable problems, and establish new paradigms for secure and efficient information processing.

3.2. Core Quantum Algorithm

Core quantum algorithms form the computational backbone of QIS, enabling exponential or quadratic speedups for specific classes of problems. These algorithms leverage the principles of superposition, entanglement, and interference to tackle computational tasks that are intractable for classical systems.

3.2.1. Shor's Algorithm

Shor's algorithm provides exponential acceleration for integer factorization, reducing the complexity from sub-exponential classical algorithms to polynomial time in the number of digits. The algorithm consists of two main components: a modular exponentiation stage and the Quantum Fourier Transform (QFT) to extract the periodicity of modular functions. Its ability to efficiently factor large integers undermines the security of RSA, Diffie–Hellman, and other number-theoretic cryptosystems, prompting the rapid advancement of post-quantum cryptography. Experimental implementations have been demonstrated on photonic, superconducting, and trapped-ion platforms, though scaling to cryptographically relevant sizes remains a major hardware challenge [26].

3.2.2. Grover's Algorithm

Grover's algorithm achieves a quadratic speedup for searching unstructured datasets, reducing query complexity from $O(N)$ to $O(\sqrt{N})$. It operates by iteratively applying an oracle function to mark solutions and a diffusion operator to amplify their amplitudes via constructive interference. While originally designed for database search, Grover's framework extends to combinatorial optimization, constraint satisfaction problems, and cryptanalysis of symmetric-key cryptography. Its simplicity makes it a benchmark for near-term quantum devices, although its performance is sensitive to oracle construction and noise levels [27,28].

3.2.3. Quantum Fourier Transform (QFT)

QFT is the quantum analogue of the classical discrete Fourier transform, with a complexity of $O((\log N)^2)$. It transforms computational basis states into the frequency domain, enabling period-finding—a central step in Shor's algorithm—and other applications such as phase estimation, hidden subgroup problems, and quantum signal processing. QFT circuits require only logarithmic depth but involve controlled rotation gates, making fault-tolerant implementation dependent on efficient decomposition into native gate sets [29].

3.2.4. Quantum Support Vector Machine (QSVM)

QSVM extends the classical support vector machine framework into the quantum domain by exploiting quantum feature maps and kernel evaluations. Classical input vectors are encoded into quantum states, and inner products in high-dimensional Hilbert spaces are computed via quantum circuits. This yields polynomial or exponential speedups in kernel computation for certain datasets, with applications in finance (credit risk assessment, fraud detection), bioinformatics (gene classification), and materials science. The primary challenges involve efficient data encoding and mitigating noise in quantum feature space evaluations [30,31].

3.2.5. Quantum Principal Component Analysis (QPCA)

QPCA utilizes quantum phase estimation to extract eigenvalues and eigenvectors of a density matrix that represents the covariance structure of large datasets. By operating directly on quantum-encoded data, it can achieve an exponential speedup compared to classical PCA for certain structured inputs. QPCA has potential applications in dimensionality reduction for high-frequency trading, anomaly detection in cybersecurity, and medical imaging analysis. However, it requires quantum access to data, which is a non-trivial constraint in most real-world scenarios [32].

3.2.6. Quantum k-Means Clustering

Quantum k-means combines amplitude encoding with quantum distance estimation to accelerate cluster assignment by leveraging amplitude encoding and quantum distance estimation; the algorithm achieves $O(\log N)$ complexity in distance computation compared to classical $O(N)$ methods. By exploiting superposition, distances between a data point and all cluster centroids can be computed in parallel, potentially reducing computational complexity from $O(Nk)$ to polylogarithmic in N and k. This makes it attractive for large-scale pattern recognition problems, such as predictive maintenance in industrial IoT, real-time social network analysis, and satellite image classification. Practical deployment remains limited by the cost of state preparation and the need for error mitigation [33].

3.2.7. Quantum Neural Network (QNN)

QNNs integrate parameterized quantum circuits (PQC) with classical optimization loops, enabling hybrid quantum–classical deep learning architectures. Quantum layers can naturally represent complex, high-dimensional correlations that are difficult for classical networks to capture, making QNNs promising for quantum chemistry simulations, drug discovery, and generative modeling in materials design. Current research focuses on overcoming barren plateau issues in optimization, improving expressivity via entanglement-aware architectures, and adapting QNNs to noisy intermediate-scale quantum (NISQ) devices (Table 5) [34,35].

Table 5. Core quantum algorithm.

Concept	Core Principle	Applications & Challenges
Shor's Algorithm	Leverages quantum parallelism and QFT for efficient integer factorization.	Applied in cryptanalysis; limited by circuit depth and error rates.
Grover's Algorithm	Employs amplitude amplification to accelerate unstructured searches.	Enhances search and optimization; requires well-defined oracles.
Quantum Fourier Transform (QFT)	Maps computational states into the frequency domain for phase estimation and interference.	Integral to Shor's algorithm and signal analysis; constrained by gate complexity.
Quantum SVM (QSVM)	Implements quantum kernels to represent complex data relationships in high-dimensional spaces.	Benefits financial modeling and bioinformatics; sensitive to data encoding errors.
Quantum PCA (QPCA)	Extracts eigenvectors and eigenvalues via quantum phase estimation techniques.	Facilitates anomaly detection and dimensionality reduction; requires quantum-accessible datasets.
Quantum k-means	Executes clustering through superposition-based distance evaluation.	Useful in pattern recognition and IoT analytics; limited by state preparation costs.
Quantum Neural Networks (QNNs)	Integrate quantum circuits with adaptive parameters for hybrid learning.	Applicable to AI, chemistry, and materials modeling; faces training instability.

3.3. Learning Paradigms

Quantum learning paradigms extend the foundational principles of classical machine learning by exploiting distinct quantum mechanical properties such as superposition, entanglement, and quantum interference, thereby enabling novel approaches to data representation, feature extraction, and model optimization within QIS.

3.3.1. Supervised Learning

In supervised learning, quantum models such as Quantum Support Vector Machines (QSVMs) and Quantum Neural Networks (QNNs) are trained on labeled datasets, leveraging quantum kernel methods and parameterized quantum circuits to map classical data into exponentially large Hilbert spaces and capture complex non-linear decision boundaries. This integration of quantum parallelism with classical optimization offers the potential for significant acceleration in training and improved classification accuracy, particularly in domains such as financial fraud detection, medical image diagnosis, and sentiment analysis of large-scale textual data [36].

3.3.2. Unsupervised Learning

In contrast, quantum unsupervised learning addresses tasks where labeled data are unavailable, aiming to uncover hidden patterns, clusters, and latent structures. Approaches such as quantum k-means clustering and Quantum Principal Component Analysis (QPCA) employ amplitude encoding, quantum distance estimation, and quantum phase estimation to process massive datasets in parallel and reveal correlations that may remain inaccessible to classical methods. These techniques have been applied to anomaly detection in cybersecurity, market segmentation in finance, and sensor data analysis in industrial IoT environments. Nevertheless, the implementation of large-scale quantum unsupervised learning faces challenges related to circuit depth, interpretability of results, and the mitigation of hardware noise in Noisy Intermediate-Scale Quantum (NISQ) devices [37].

3.3.3. Quantum Reinforcement Learning (QRL)

Quantum reinforcement learning (QRL) represents a further evolution of learning paradigms, embedding quantum computation directly into the agent–environment interaction loop. By utilizing amplitude amplification and quantum value iteration, QRL enables more efficient exploration of vast state–action spaces and accelerates policy evaluation, offering potential benefits in autonomous navigation, real-time supply chain optimization, and robotic path planning under uncertainty. However, realizing the full potential of QRL requires overcoming the technical barriers of integrating quantum processors with classical control systems, scaling algorithms to continuous state–action domains, and ensuring the stability of hybrid quantum–classical frameworks [38].

3.3.4. Hybrid Paradigms

Emerging hybrid paradigms are beginning to blur the boundaries between quantum and classical learning (Table 6). For example, variational quantum autoencoders compress data into a quantum latent space before performing classical post-processing, and hybrid deep learning architectures integrate quantum-enhanced feature extraction modules with conventional neural networks. Such hybrid approaches are particularly promising for near-term quantum devices, as they balance the computational advantages of quantum processing with the robustness and scalability of classical machine learning pipelines. Collectively, these paradigms illustrate the breadth of quantum-enhanced learning strategies and highlight their transformative potential in shaping the future capabilities of QIS [39].

Table 6. Quantum learning paradigms.

Concept	Core Principle	Applications & Challenges
Supervised Learning	Quantum models learn mappings from labeled data through kernel-based inference.	Applied in classification and diagnostics; limited by data transfer and model stability.
Unsupervised Learning	Quantum clustering and decomposition methods uncover latent data structures.	Supports anomaly detection and finance analytics; interpretability remains limited.
Reinforcement Learning	Quantum-enhanced policies accelerate exploration and convergence.	Applied in robotics and autonomous systems; integration with classical control remains complex.
Hybrid Paradigms	Combines quantum feature extraction with classical optimization pipelines.	Enables near-term quantum AI; synchronization and scaling remain open challenges.

4. Quantum Finance and Other Applications in QIS

Beyond foundational research, QIS technologies are increasingly being deployed in diverse application domains, ranging from finance to energy, transportation, and healthcare. The following subsections outline these domain-specific applications (Figure 3).

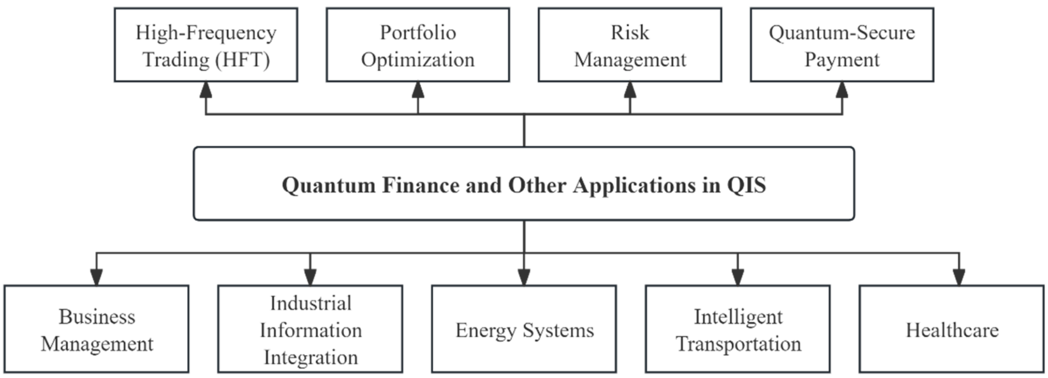

Figure 3. Quantum Finance and Other Applications in QIS.

4.1. High-Frequency Trading (HFT)

High-Frequency Trading operates at the microsecond timescale, where marginal latency reductions can yield significant profit differentials. Quantum computing offers the potential to transform HFT by enabling massive parallel processing of rapidly evolving market data streams. Techniques such as Quantum Amplitude Estimation (QAE) and quantum Monte Carlo simulation allow simultaneous evaluation of thousands of market-making strategies, each encoded into quantum states and analyzed in parallel [40]. A quantum-enhanced matching engine could assess multiple order book states concurrently, reducing decision latency from milliseconds to nanoseconds. Variational Quantum Algorithms (VQAs) further enable adaptive execution strategies that can dynamically reconfigure parameters in response to stochastic price movements [41]. Nonetheless, deploying quantum processors within low-latency trading systems remains challenging due to classical–quantum input/output bottlenecks and the requirement for quantum-compatible data feeds [42].

4.2. Portfolio Optimization

Portfolio optimization problems, often formulated as constrained quadratic optimization, require balancing expected return, portfolio risk, and compliance constraints. Quantum approaches such as quantum annealing and the Quantum Approximate Optimization Algorithm (QAOA) excel at exploring exponentially large solution spaces. For instance, the Markowitz mean–variance optimization framework can be transformed into a Quadratic Unconstrained Binary Optimization (QUBO) problem, enabling near-instantaneous identification of Pareto-optimal portfolios on quantum annealers. Hybrid quantum–classical workflows have emerged as a promising strategy: classical algorithms preprocess large covariance matrices, perform factor reduction, and filter feasible assets, while quantum solvers handle the final combinatorial search. This reduces qubit requirements and mitigates hardware noise effects, positioning hybrid methods as an interim solution until large-scale fault-tolerant quantum computers become available [43].

4.3. Risk Management

Risk management relies on accurate modeling of tail events, extreme volatility, and contagion effects across asset classes. Quantum Monte Carlo methods offer quadratic convergence advantages in estimating Value at Risk (VaR) and Conditional Value at Risk (CVaR), significantly reducing the number of simulation paths required. Quantum Machine Learning (QML) techniques further enhance factor models by capturing nonlinear dependencies between macroeconomic variables and asset returns. For example, quantum kernel methods can detect hidden correlation structures in large, heterogeneous portfolios, enabling more robust stress testing. Hybrid QML–classical architectures allow real-time recalibration of risk models, which is essential in fast-changing markets characterized by regime shifts and structural breaks [44].

4.4. Quantum-Secure Payment

Shor's algorithm poses a severe threat to RSA, ECC, and other public-key cryptosystems, prompting the financial sector to explore quantum-resistant payment infrastructures. Quantum Key Distribution (QKD) provides information-theoretic security by leveraging quantum principles to detect any eavesdropping attempt. Pilot QKD-secured payment channels have been demonstrated between major financial hubs, integrating seamlessly with interbank messaging systems such as SWIFT. Near-term strategies include combining QKD with post-quantum cryptography (PQC) to ensure both immediate deployability and long-term resilience against quantum attacks [45].

4.5. Business Management

Quantum information systems (QIS) can be applied in business environments, helping managers drive innovation and competitive advantage, and propelling enterprises towards intelligent and sustainable development. The core of QIS lies in leveraging the parallelism of quantum computing and the high security of quantum communication. Therefore, enterprises can process massive amounts of nonlinear data, optimize complex decision-making models, and improve the accuracy and real-time performance of predictions in extremely short times. For business managers, quantum information can redefine management thinking. It helps enterprises achieve multi-dimensional simulation and performance optimization in product development, achieve dynamic optimal solutions for resource allocation in supply chain management, and realize highly personalized recommendations and demand responses in customer service.

4.6. Industrial Information Integration

Industrial Information Integration leverages QIS to address complex industrial optimization problems, from real-time data fusion in IIoT environments to large-scale production scheduling. Quantum algorithms can process heterogeneous sensor data streams in parallel, improving predictive maintenance by correlating subtle patterns across multi-source datasets. In supply chain management, QAOA and quantum annealing enable optimization of multi-echelon inventory systems under stochastic demand. Furthermore, secure industrial communication can be enhanced through quantum cryptography, preventing industrial espionage in cross-border data exchanges [46,47].

4.7. Energy Systems

Energy systems optimization benefits from QIS through improved grid stability, renewable energy forecasting, and efficient resource dispatch. Quantum algorithms, such as QUBO formulations solved by quantum annealers, can optimize load balancing in smart grids considering fluctuating renewable generation. Quantum-enhanced weather modeling improves the accuracy of wind and solar output forecasts, while QKD ensures secure communication in energy trading markets. Integration with decentralized energy markets may also be facilitated by quantum blockchain architectures, ensuring both transaction transparency and tamper-resistance [48].

4.8. Intelligent Transportation

Intelligent transportation systems stand to benefit significantly from the computational capabilities of QIS, particularly in the optimization of traffic flows, routing, and autonomous vehicle coordination [49]. Quantum algorithms such as QAOA and quantum annealing can address large-scale vehicle routing problems (VRP) with time-dependent constraints, achieving near-optimal solutions more rapidly than classical solvers. For urban traffic management, quantum-enhanced simulation frameworks can model millions of vehicle interactions in parallel, enabling real-time congestion mitigation strategies. In autonomous driving, hybrid quantum–classical reinforcement learning models have been proposed to accelerate decision-making in highly dynamic environments, leveraging quantum parallelism to explore vast state–action spaces efficiently. Furthermore, quantum-secured vehicular communication protocols, based on QKD, offer robust protection against cyberattacks targeting connected transportation infrastructure [50].

4.9. Healthcare

The healthcare sector presents vast opportunities for QIS, spanning from drug discovery to patient-specific treatment optimization. Quantum algorithms are particularly promising in computational chemistry, where variational quantum Eigensolver (VQE) and quantum phase estimation (QPE) can model molecular interactions at quantum precision, accelerating the identification of candidate compounds for diseases such as cancer and Alzheimer’s. In medical imaging, quantum principal component analysis (QPCA) enables rapid dimensionality reduction and feature extraction from high-resolution scans, improving diagnostic accuracy. Quantum machine learning models have been applied to genomic data analysis, identifying complex genetic markers linked to disease susceptibility with greater efficiency than classical methods [51]. Furthermore, secure handling of sensitive health records can be achieved through QKD-based hospital network infrastructure, ensuring compliance with data protection regulations such as HIPAA and GDPR. Early pilot projects have demonstrated hybrid quantum–classical pipelines for real-time sepsis prediction in intensive care units, highlighting the near-term potential of QIS in critical care.

5. Challenges and Future Trends

With the development of quantum information systems, related research has raised many technical and theoretical challenges. At the same time, future development trends are gradually emerging, providing important pathways for further research (Figure 4).

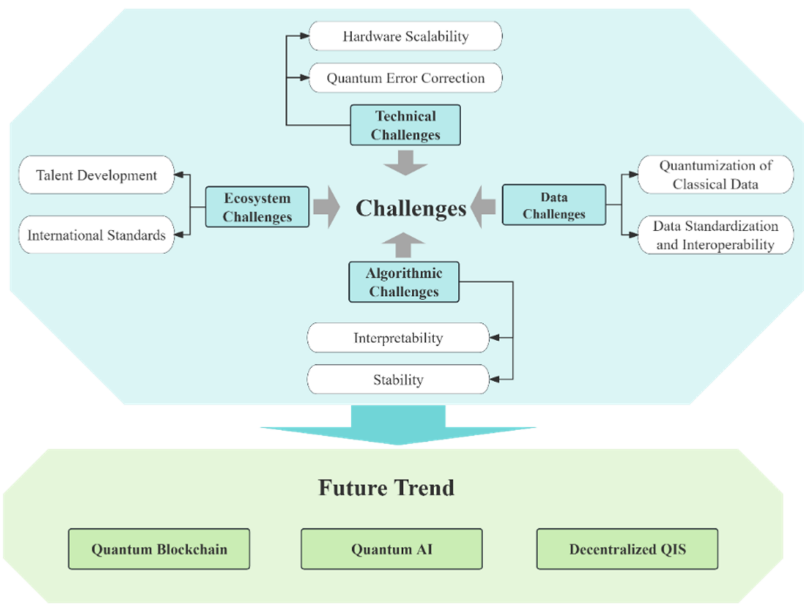

Figure 4. Challenges and Future Trends of QIS.

5.1. Technical Challenges

5.1.1. Hardware Scalability

Hardware scalability remains one of the most critical bottlenecks in the practical deployment of QIS. Current mainstream platforms—including superconducting qubits, trapped ions, topological qubits, and photonic quantum computing—face limitations in qubit count, fidelity of gate operations, and connectivity topology. Scaling from today's devices with hundreds of physical qubits to fault-tolerant systems with millions of logical qubits will require improvements in qubit fabrication consistency, cross-chip interconnection, and integration of cryogenic control electronics. For instance, superconducting qubits encounter exponential growth in wiring complexity and thermal management challenges as system size increases, while trapped-ion systems are constrained by gate speed and optical stability. Emerging solutions include modular quantum computing architectures, photonic interconnects, and advanced 3D packaging with silicon photonics integration [52].

5.1.2. Quantum Error Correction (QEC)

Due to extreme susceptibility to decoherence, fault-tolerant quantum computation fundamentally relies on robust QEC schemes. The surface code, a leading candidate, offers a relatively high fault-tolerance threshold but requires thousands of physical qubits to encode a single logical qubit, imposing significant hardware demands [53]. Research is moving toward low-overhead QEC codes, noise-adapted compilation strategies, and topological quantum computing approaches that leverage the inherent error resilience of anyonic systems. Integrating QEC with hardware-aware compilers and co-designed architectures will be critical for scalable, long-term quantum system operation [54].

5.2. Data Challenges

5.2.1. Quantumization of Classical Data

In most real-world applications, raw data is generated in classical form and must be encoded into quantum states via amplitude encoding, phase encoding, or hybrid methods. For high-dimensional and streaming data scenarios—such as industrial IoT or financial time series—encoding efficiency becomes a bottleneck. Moreover, trade-offs between fidelity, scalability, and hardware compatibility mean that no single encoding method fits all scenarios. Efficient, hardware-native encoding strategies are therefore an urgent research priority [55].

5.2.2. Data Standardization and Interoperability

Cross-domain QIS applications demand unified data representation and interface standards. Currently, quantum hardware and software platforms differ widely in instruction sets, data formats, and metadata conventions, limiting the portability of algorithms and models. Industry-wide efforts, such as the Quantum Data Exchange Protocol (QDEP), aim to define common APIs, data schemas, and security standards to enable seamless interoperability. This will be vital for integrating QIS into heterogeneous computing environments that blend classical and quantum resources [56].

5.3. Algorithmic Challenges

5.3.1. Interpretability

Although algorithms such as quantum machine learning and quantum approximate optimization algorithm have shown strong performance in optimization and pattern recognition tasks, their decision-making processes remain opaque. In sensitive domains like finance and healthcare, algorithm transparency is critical for compliance, auditability, and trust. Advances in quantum state visualization, feature importance analysis, and hybrid interpretable models will be necessary to meet regulatory and ethical requirements [57].

5.3.2. Stability

Quantum algorithms often suffer from instability due to hardware noise, input perturbations, and parameter initialization sensitivity. Parameterized quantum circuits (PQC), for instance, are prone to barren plateau phenomena, where gradients vanish and learning stalls. Improving stability requires optimized circuit topologies, advanced variational optimization techniques, and noise-aware training methods. Hybrid quantum–classical workflows that dynamically adapt circuit depth to hardware conditions are emerging as a promising solution [58].

5.4. Ecosystem Challenges

5.4.1. Talent Development

QIS is an inherently interdisciplinary field combining quantum physics, computer science, mathematics, engineering, and domain-specific expertise. There is a global shortage of professionals with this breadth of skills. Building a sustainable talent pipeline requires structured quantum education programs, cross-disciplinary graduate training, and accessible cloud-based experimentation platforms that allow hands-on practice with real quantum devices [59].

5.4.2. International Standards

The international competition in quantum technologies is increasingly shifting toward the battle for standards. Areas such as quantum communication protocols, post-quantum cryptography testing, and quantum random number generator certification require globally agreed frameworks. Without such standards, interoperability will be compromised, leading to market fragmentation. Strengthening international collaboration through organizations like ISO and ITU will be crucial for harmonizing QIS development worldwide.

5.5. Future Trends

5.5.1. Quantum Blockchain

Integrating quantum communication with distributed ledger technology could create quantum-secure blockchain networks [60]. Such systems would leverage Quantum Key Distribution (QKD) for unbreakable transaction signatures and employ quantum acceleration in consensus algorithms to enhance throughput. Applications include secure cross-border payments, tamper-proof supply chain tracking, and decentralized identity management [61].

5.5.2. Quantum AI

The convergence of quantum computing and artificial intelligence is expected to push Quantum Machine Learning (QML) from experimental validation toward industrial deployment [62]. Quantum AI could accelerate drug discovery, financial modeling, and autonomous systems by offering faster model training, higher-dimensional feature extraction, and enhanced optimization capabilities compared to classical methods [63].

5.5.3. Decentralized QIS

With the emergence of a quantum internet, decentralized QIS will integrate distributed quantum computing, storage, and communication across global networks. This will enable secure, cross-border collaborative computation, allowing users to access quantum resources on demand. Potential use cases span scientific research, multinational finance, and industrial automation, supported by quantum-encrypted communication channels [64].

6. Conclusions

Quantum Information Systems (QIS) represent a transformative paradigm that merges quantum computing, quantum communication, and quantum sensing into a unified framework capable of addressing computational and security challenges beyond the reach of classical systems. This review has synthesized insights from quantum computing foundations, algorithmic advancements, and domain-specific applications—spanning finance, industrial information integration, energy, transportation, and healthcare—while also exploring the multi-layered challenges and emerging trends that will shape QIS in the coming decades. By integrating perspectives from quantum hardware scalability, error correction, data encoding, and algorithm design, the discussion has highlighted both the technological potential and the practical constraints inherent to QIS development.

The analysis underscores that QIS is inherently interdisciplinary, requiring collaboration across quantum physics, computer science, engineering, and domain expertise. Industry applications such as quantum-secure financial transactions, optimization in supply chains and energy grids, and accelerated drug discovery demonstrate the transformative potential of QIS to revolutionize high-value sectors. However, realizing these benefits will depend on overcoming significant challenges, including hardware scalability, robust quantum error correction, standardization of quantum data protocols, and the cultivation of a skilled workforce capable of bridging the quantum–classical divide.

Looking forward, the convergence of QIS with emerging paradigms such as quantum blockchain, quantum artificial intelligence, and decentralized quantum networks will likely redefine both computational infrastructure and global information ecosystems. Achieving this vision will require not only sustained investment in research and development but also the establishment of international standards, open innovation platforms, and cross-border collaborations. As the field evolves, QIS has the potential to become a cornerstone of the next era of secure, intelligent, and globally interconnected information systems—driving scientific discovery, economic growth, and societal resilience.

Author Contributions

F.W.: data curation, writing—original draft preparation; Y.L.: writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

This article does not involve data that needs to be disclosed.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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