



THE ROLE OF QUANTUM COMPUTING IN FUTURE BIG DATA PROCESSING: A COMPREHENSIVE REVIEW

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Abstract

The rapid growth of Big Data has pushed classical computing systems to their limits, necessitating innovative approaches to data processing. Quantum computing, with its inherent parallelism and entanglement capabilities, offers transformative potential for solving complex, large-scale problems that are intractable for classical systems. This review paper examines the role of quantum computing in future Big Data processing, analyzing key quantum algorithms such as Grover's search, Shor's factorization, and quantum machine learning techniques. We explore fundamental concepts including qubit operations, quantum complexity classes, and hybrid quantum-classical architectures, while critically assessing current hardware limitations like de-coherence and error rates in NISQ-era devices. The paper highlights promising applications in optimization, secure communication, and high-dimensional data analysis, alongside significant challenges in data encoding, algorithmic readiness, and practical implementation. Emerging research directions are discussed, including near-term NISQ applications, fault-tolerant quantum computing prospects, and cross-disciplinary opportunities in NLP and IoT. By synthesizing theoretical advances with practical constraints, this review provides a balanced perspective on quantum computing's evolving role in Big Data, offering insights into both its revolutionary potential and the substantial barriers that must be overcome for widespread adoption. The findings suggest that while quantum advantage remains limited to specific use cases today, continued progress in hardware and algorithms may eventually redefine the landscape of large-scale data processing.

Keywords: Quantum computing, Big Data, quantum algorithms, NISQ, quantum machine learning, hybrid computing, quantum advantage

I. INTRODUCTION

The exponential growth of data in the modern digital era has pushed classical computing systems to their limits, necessitating revolutionary approaches to data processing. Big Data, characterized by its volume, velocity, variety, veracity, and value, presents formidable challenges that conventional computing architectures struggle to address efficiently. As datasets expand into the zettabyte scale and real-time analytics demand faster processing, traditional von Neumann-based systems face bottlenecks in memory bandwidth, computational speed, and energy efficiency. In this context, quantum computing (QC) emerges as a disruptive paradigm with the potential to redefine how we store, retrieve, and analyse massive datasets. Unlike classical bits, which operate in binary states (0 or 1), quantum bits (qubits) exploit the principles of superposition, entanglement, and interference, enabling computations that can theoretically outperform classical systems for specific problems. This review explores the transformative role of quantum computing in Big Data processing,



examining its foundational principles, current advancements, and the challenges that must be overcome before widespread adoption.

The motivation behind integrating quantum computing with Big Data stems from the inherent limitations of classical systems when handling complex, large-scale problems. Many critical Big Data tasks—such as optimization, machine learning, cryptography, and real-time analytics—rely on solving NP-hard problems, which scale exponentially with input size. For instance, training deep neural networks on massive datasets or performing high-dimensional clustering requires computational resources that grow intractably with classical methods [1]. Even with distributed computing frameworks like Hadoop and Spark, tasks such as large-scale matrix inversion, database search, and combinatorial optimization remain computationally expensive [2]. Quantum computing offers a fundamentally different approach by leveraging quantum parallelism, where a qubit can exist in multiple states simultaneously, allowing certain algorithms to achieve polynomial or exponential speedups over their classical counterparts. For example, Grover's algorithm can search an unsorted database in $O(\sqrt{N})$ time compared to the classical $O(N)$, while Shor's algorithm threatens current encryption standards by factoring large integers exponentially faster [3]. These capabilities suggest that quantum-enhanced Big Data processing could revolutionize fields such as finance, healthcare, logistics, and artificial intelligence (AI).

However, the transition from classical to quantum Big Data processing is not without significant hurdles [11]. Current quantum systems operate in the Noisy Intermediate-Scale Quantum (NISQ) era, where qubits are prone to errors due to de-coherence, gate inaccuracies, and limited connectivity. Practical quantum advantage, where a quantum computer reliably outperforms classical supercomputers has only been demonstrated in niche applications, such as Google's quantum supremacy experiment on a bespoke problem [4]. Moreover, data encoding remains a critical challenge: converting classical data into quantum states, (a process known as quantum embedding) is non-trivial and often introduces overhead that negates potential speedups. Additionally, quantum algorithms require rethinking traditional data structures; for instance, Quantum Random Access Memory (QRAM), which enables efficient quantum data retrieval, is still in early theoretical stages [5]. These limitations underscore the need for hybrid quantum-classical approaches, where quantum processors handle specific subroutines while classical systems manage the broader workflow.

The primary objective of this review is to provide a comprehensive survey of the current state of quantum computing in Big Data processing, identifying both its transformative potential and the practical barriers to implementation [6]. First, we examine quantum algorithms that have demonstrated promise for Big Data applications, including quantum machine learning (QML), optimization, and linear algebra. We analyse how these algorithms could enhance tasks such as anomaly detection, recommendation systems, and high-dimensional clustering [7]. Second, we discuss the hardware and software challenges that limit real-world deployment, including qubit scalability, error correction, and quantum-classical integration. Third, we explore hybrid architectures, where quantum co-processors augment classical data centres, offering incremental improvements while fault-tolerant quantum computers remain under development [8]. Finally, we outline future research directions, emphasizing the need for algorithmic innovation, better error mitigation techniques, and industry-academia collaboration to bridge the gap between theoretical quantum advantage and practical Big Data solutions.

The implications of quantum Big Data processing extend beyond mere computational speedups. In fields like drug discovery and genomics, quantum-enhanced simulations could analyse molecular interactions at unprecedented scales, while financial modelling could benefit from quantum-optimized portfolio management [9]. Cybersecurity faces both risks and opportunities, as quantum computers threaten current encryption while enabling quantum-secure communication protocols. Furthermore, the environmental impact of data centres, which consume 3% of global electricity, could be mitigated by quantum efficiency gains. Despite these prospects, scepticism remains regarding the near-term feasibility of quantum Big Data systems [10]. Critics argue that classical advancements (e.g., GPUs, TPUs, and neuromorphic computing) may continue to dominate, while quantum-computing remains confined to specialized labs. This review aims to



provide a balanced perspective, distinguishing between quantum hype and achievable milestones, while offering a roadmap for researchers and practitioners navigating this evolving landscape.

In summary, quantum computing represents a paradigm shift in Big Data processing, with the potential to solve previously intractable problems and unlock new frontiers in AI, optimization, and scientific research. However, realizing this potential requires overcoming substantial technical, algorithmic, and infrastructural challenges. This review synthesizes existing knowledge, highlights critical gaps, and proposes pathways for future research, ultimately contributing to a clearer understanding of when, where, and how quantum computing will reshape the future of Big Data.

II. QUANTUM COMPUTING FUNDAMENTALS FOR BIG DATA

Quantum computing represents a radical departure from classical computing by leveraging the principles of quantum mechanics to process information in fundamentally new ways. At the heart of this paradigm are qubits, the quantum equivalent of classical bits. Unlike classical bits, which exist in a definitive state of 0 or 1, qubits exploit superposition, meaning they can simultaneously exist in a combination of both states. Mathematically, a qubit's state is represented as $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$, where α and β are complex probability amplitudes such that $|\alpha|^2 + |\beta|^2 = 1$. This property allows quantum computers to process multiple possibilities at once, enabling quantum parallelism—a key advantage for handling large-scale data problems [12]. Another critical quantum phenomenon is entanglement, where qubits become correlated in such a way that the state of one qubit instantaneously influences another, regardless of distance. Entanglement is essential for quantum algorithms that require coordinated operations across multiple qubits, such as quantum teleportation and error correction [13]. These principles—superposition, entanglement, and interference form the foundation of quantum computation, allowing for operations that are infeasible for classical systems.

In contrast, classical computing relies on Boolean logic and deterministic state transitions, where bits are manipulated using logic gates (AND, OR, NOT) to perform computations sequentially. While classical systems excel at structured tasks with linear workflows, they struggle with problems that require evaluating exponentially large solution spaces [16]. Quantum computing, however, can explore multiple states simultaneously due to superposition, making it particularly suited for optimization, search, and sampling tasks. For example, a classical computer checking an unsorted database of N entries requires $O(N)$ operations in the worst case, whereas Grover's quantum search algorithm accomplishes this in $O(\sqrt{N})$ —a quadratic speedup [15]. Similarly, Shor's algorithm leverages quantum Fourier transforms to factor large integers in polynomial time, a task that would take classical supercomputers millennia. These examples illustrate how quantum mechanics can redefine computational efficiency for specific problem classes [16].

The distinction between quantum and classical computing extends to their computational complexity classes, which categorize problems based on the resources required to solve them. In classical computing, P represents problems solvable in polynomial time by deterministic machines, while NP includes problems verifiable in polynomial time but not necessarily solvable efficiently. The question of whether $P = NP$ remains one of the most profound unsolved problems in computer science. Quantum computing introduces new complexity classes, most notably BQP (Bounded-Error Quantum Polynomial Time), which encompasses problems solvable by quantum computers in polynomial time with a bounded error probability [17]. Crucially, BQP is believed to lie between P and $PSPACE$, suggesting that quantum computers can efficiently solve certain problems that are intractable for classical systems. For instance, factoring integers (the basis of RSA encryption) is in BQP due to Shor's algorithm but is not known to be in P , highlighting a potential quantum advantage.

However, quantum superiority is not universal. Many problems, particularly those involving unstructured data or sequential logic, see no significant speedup from quantum algorithms. Additionally, quantum de-coherence, the loss of quantum states due to environmental interference—poses a major practical challenge, limiting the depth of computations that can be performed reliably [18]. Current quantum processors, such as those from IBM and Google, operate with noisy qubits that require error



correction schemes, further complicating scalability. Despite these hurdles, quantum computing holds immense promise for Big Data applications where classical methods hit fundamental limits [19]. Tasks like high-dimensional clustering, large-scale optimization, and quantum machine learning could benefit from exponential speedups in linear algebra operations, as demonstrated by the Harrow-Hassidim-Lloyd (HHL) algorithm for solving linear systems.

The interplay between quantum and classical computing is particularly relevant in the NISQ (Noisy Intermediate-Scale Quantum) era, where hybrid approaches combine quantum subroutines with classical pre-processing and post processing. For example, Quantum Approximate Optimization Algorithm (QAOA) uses quantum circuits to sample low-energy states of combinatorial problems, while classical optimizers refine the results [20]. Similarly, quantum-enhanced machine learning frameworks like Tensor Flow Quantum integrate quantum layers into classical neural networks for tasks such as feature extraction. These hybrid models represent a pragmatic pathway to near-term quantum utility, even as fault-tolerant quantum computers remain under development.

In summary, quantum computing is unique properties superposition, entanglement, and parallelism, offer transformative potential for Big Data processing, particularly in areas where classical systems face exponential complexity barriers. While challenges like de-coherence and error correction persist, the theoretical advantages of quantum algorithms for search, factorization, and optimization underscore their long-term significance. As research progresses, the boundary between classical and quantum computing will continue to blur, paving the way for hybrid architectures that harness the strengths of both paradigms. Understanding these fundamentals is crucial for evaluating where and how quantum computing can revolutionize the future of data science.

III. QUANTUM ALGORITHMS FOR BIG DATA PROCESSING

Quantum computing introduces powerful algorithms that could revolutionize how we process and analyse massive datasets. One of the most significant breakthroughs is Grover's algorithm, which provides a quadratic speedup for searching unstructured databases, reducing the complexity from $O(N)$ to $O(\sqrt{N})$. This has profound implications for Big Data search and retrieval, enabling faster query optimization in distributed databases and more efficient recommendation systems. For instance, e-commerce platforms could leverage Grover's algorithm to rapidly scan millions of product entries for personalized suggestions, while cybersecurity systems might use it to identify anomalies in vast network logs [21]. However, the algorithm's true potential depends on overcoming practical challenges like quantum memory access and error rates in real-world implementations.

In the realm of Quantum Machine Learning (QML), researchers are developing hybrid approaches that combine classical techniques with quantum advantages. Quantum Support Vector Machines (QSVMs) exploit quantum kernel estimation to classify high-dimensional data more efficiently than classical SVMs, while Quantum Neural Networks (QNNs) use variational circuits to optimize complex models. These methods show promise for large-scale pattern recognition and predictive analytics, particularly in fields like genomics and financial modelling [22]. Yet, substantial hurdles remain, including noise-induced errors, the difficulty of quantum data encoding, and the limited qubit coherence times in today's NISQ-era devices. Current QML frameworks, such as those in IBM's Qiskit or Google's Tensor Flow Quantum, focus on hybrid workflows where quantum processors handle specific subroutines while classical systems manage the broader pipeline.

For large-scale optimization problems common in logistics and supply chain management, quantum algorithms offer compelling advantages. The Quantum Approximate Optimization Algorithm (QAOA) provides a framework for solving combinatorial optimization problems by finding approximate solutions to NP-hard challenges like the traveling salesman problem. Meanwhile, companies like D-Wave are pioneering quantum-annealing approaches for real-world applications, from airline scheduling to drug discovery [23]. These methods often work best in hybrid quantum-classical systems, where quantum processors sample solution spaces while classical algorithms refine the results. While current quantum optimizers cannot yet outperform classical heuristics for all problems, they demonstrate the potential for order-



of-magnitude improvements as hardware matures, particularly in scenarios requiring evaluation of exponentially large solution spaces.

Quantum computing also transforms linear algebra operations, a cornerstone of Big Data analytics. The HHL algorithm (Harrow-Hassidim-Lloyd) theoretically offers exponential speedups for solving systems of linear equations, a task fundamental to many machine learning and data analysis workflows. This capability could dramatically accelerate principal component analysis (PCA) for dimensionality reduction and spectral clustering for unsupervised learning [24]. In practical terms, quantum-enhanced linear algebra might enable real-time analysis of high-dimensional datasets in fields ranging from climate modelling to fraud detection. However, the algorithm's requirements for error-corrected qubits and efficient quantum RAM mean these applications remain largely theoretical for now. Researchers are actively developing variational quantum linear solvers as near-term alternatives, bridging the gap between classical methods and full-scale quantum advantage in Big Data processing.

IV. QUANTUM BIG DATA INFRASTRUCTURE

The development of quantum databases and storage systems represents a critical frontier in Big Data infrastructure, with Quantum RAM (QRAM) emerging as a key innovation for efficient data retrieval. QRAM theoretically enables quantum algorithms to access classical data in superposition, which is essential for algorithms like Grover's search and quantum machine learning. However, current implementations face significant challenges, including high error rates, energy inefficiency, and scalability limitations that prevent practical deployment. Researchers are exploring quantum-enhanced NoSQL architectures that could leverage distributed quantum processing for faster queries on unstructured data, but these systems remain largely theoretical due to the fragile nature of quantum states and the difficulty of maintaining coherence across large-scale quantum memories [25]. As quantum error correction techniques improve, these storage solutions may eventually enable orders-of-magnitude speedups for database operations in fields like real-time analytics and genomic data processing.

Quantum communication technologies are revolutionizing how Big Data is transferred and secured across distributed systems. Quantum key distribution (QKD) protocols use the principles of quantum entanglement to create theoretically unhackable communication channels, addressing critical security challenges in sensitive data transmission. Meanwhile, major cloud providers like IBM and Amazon are pioneering quantum cloud computing platforms (IBM Qiskit, Amazon Braket) that allow researchers to access quantum processors remotely and integrate them with classical Big Data workflows. These platforms enable hybrid computation where quantum resources are used for specific tasks like optimization or sampling while classical systems handle data pre-processing and storage [26]. The development of quantum internet protocols could eventually lead to ultra-secure, high-speed data networks capable of transmitting quantum information between data centres, though current limitations in quantum repeater technology restrict these networks to short-distance laboratory settings for now.

The most practical near-term applications of quantum computing for Big Data involve hybrid quantum-classical architectures that strategically combine both paradigms. Determining when to use quantum versus classical subroutines depends on factors like problem size, error tolerance, and the availability of quantum speedups for specific operations. Frameworks like Google's Tensor Flow Quantum and Xanadu's Penny Lane demonstrate this approach by embedding quantum circuits within classical machine learning pipelines for tasks like feature extraction and optimization. These hybrid systems allow organizations to experiment with quantum advantages while maintaining compatibility with existing Big Data infrastructure. Case studies in chemistry and finance show promising results, where quantum processors handle computationally intensive sub problems while classical systems manage data aggregation and visualization. As quantum hardware matures, these hybrid architectures will likely evolve toward increasingly quantum-centric designs, but for the foreseeable future, they represent the most viable path for integrating quantum computing into practical Big Data applications.



V. CHALLENGES & LIMITATIONS

The current state of quantum computing faces fundamental hardware constraints that severely limit its practical application in Big Data processing. De-coherence and qubit instability remain critical challenges, with quantum states typically lasting only microseconds before collapsing due to environmental interference. Even the most advanced NISQ (Noisy Intermediate-Scale Quantum) devices suffer from high error rates, requiring complex error mitigation techniques that often negate potential speedups. While error-corrected, fault-tolerant quantum computers promise a solution, they demand millions of physical qubits to create a single logical qubit—a scalability hurdle far beyond today's 100-1000 qubit processors. This hardware immaturity means most quantum Big Data applications remain confined to small-scale simulations rather than production environments where classical distributed systems still dominate.

A less discussed but equally critical challenge lies in quantum data encoding—the process of translating classical Big Data into quantum-readable formats. Quantum embedding techniques struggle with the exponential resource overhead required to represent high-dimensional datasets in qubits, often making the encoding process more computationally expensive than the actual quantum processing. Current quantum feature maps used in machine learning applications frequently fail to capture complex data relationships present in real-world datasets like images or natural language [27]. Moreover, the irreversible nature of many quantum measurements means data cannot be efficiently retrieved or reused, creating bottlenecks in iterative algorithms. These limitations question whether quantum advantage can be achieved for general Big Data tasks beyond specialized use cases.

On the algorithmic front, the quantum-computing field suffers from a severe shortage of proven, practical algorithms with unambiguous speedups. While Shor's and Grover's algorithms demonstrate theoretical potential, most Quantum Machine Learning (QML) models lack rigorous empirical validation on real-world Big Data benchmarks. Many proposed quantum algorithms require problem structures that rarely exist in messy, real-world datasets, or they assume access to error-free quantum hardware that will not exist for years. The few algorithms showing promise—like HHL for linear systems—demand such stringent conditions (coherent operations, error correction) that they remain impractical for contemporary Big Data applications [28] [29]. This creates a paradoxical situation where quantum computing is most touted advantages have little bearing on the immediate needs of data scientists working with petabyte-scale, noisy datasets.

Beyond technical hurdles, economic and ethical considerations complicate quantum computing is adoption in Big Data. The astronomical costs of developing and maintaining quantum hardware—from cryogenic cooling systems to specialized personnel make classical cloud solutions orders of magnitude more cost-effective for nearly all current applications. The quantum supremacy debate further muddies the waters, as demonstrated speedups often involve highly contrived problems irrelevant to practical data processing. Meanwhile, the hype surrounding quantum computing risks diverting resources from proven classical approaches that could deliver more immediate value. Ethical concerns also emerge regarding quantum-powered surveillance and the potential collapse of current encryption standards, urging caution in how these technologies are deployed for Big Data applications. Until these multifaceted challenges are addressed, quantum computing's role in real-world data processing will remain largely aspirational.

VI. FUTURE RESEARCH DIRECTIONS IN QUANTUM BIG DATA PROCESSING

A. Near-Term Applications (NISQ Era)

In the immediate future, research should prioritize quantum-enhanced anomaly detection for high-velocity streaming data, where quantum algorithms could identify outliers in financial transactions or network security logs more efficiently than classical methods. Another promising direction involves quantum graph algorithms optimized for NISQ devices, which could revolutionize social network analysis by uncovering hidden community structures or influence patterns in massive datasets. Developing hybrid quantum-classical pipelines that delegate specific sub-tasks like feature selection or optimization to quantum processors while



retaining classical frameworks for scalability will be crucial. Focus areas should include creating noise-resilient algorithms and benchmarking their performance against classical baselines in real-world scenarios.

B. Long-Term Vision (Fault-Tolerant QC)

As error-corrected quantum computers materialize, research must shift toward full-stack quantum databases integrating QRAM with fault-tolerant query processing to enable $O(\sqrt{N})$ searches on petabyte-scale datasets. The development of a Quantum Internet infrastructure, combining quantum key distribution (QKD) with entanglement-based data transfer, could establish ultra-secure, high-speed global networks for distributed Big Data analytics. Fundamental work is needed on quantum operating systems capable of managing distributed quantum resources, alongside quantum compilers optimized for large-scale data workflows. These efforts should be coupled with theoretical advances in quantum-native data structures that bypass classical encoding bottlenecks.

C. Cross-Disciplinary Opportunities

Exploring quantum natural language processing (NLP) could yield breakthroughs in semantic search and transformer model optimization by leveraging quantum attention mechanisms or kernel methods. In quantum IoT, research should investigate real-time sensor data compression and analysis using photonic quantum processors at network edges. Interdisciplinary collaborations could unlock novel applications, such as quantum-augmented geospatial analytics for climate modelling or quantum-accelerated bioinformatics for genomic pattern matching. A critical parallel direction involves developing standards for quantum Big Data interoperability and benchmarking metrics to assess quantum advantage across domains.

These research vectors demand tight integration of algorithm design, hardware development, and domain expertise to transition quantum computing from theoretical promise to practical Big Data solutions.

VII. CONCLUSION

Quantum computing represents a paradigm shift with the potential to revolutionize Big Data analytics, offering exponential speedups for critical tasks like optimization, machine learning, and secure data transmission. However, as this review has demonstrated, the path to practical quantum advantage is fraught with technical and theoretical challenges. In the NISQ era, hybrid quantum-classical approaches provide the most viable pathway for near-term applications, enabling incremental improvements in areas such as anomaly detection, graph analysis, and linear algebra operations. These early use cases, while limited, lay the groundwork for more sophisticated implementations as hardware matures.

The long-term vision of fault-tolerant quantum computing promises transformative capabilities, from full-stack quantum databases to a global Quantum Internet capable of secure, real-time Big Data processing. Yet, achieving this vision demands breakthroughs in qubit stability, error correction, and scalable quantum memory. Current limitations in data encoding and algorithmic readiness underscore the need for continued research into quantum-native data structures and noise-resilient algorithms. Cross-disciplinary collaboration will be essential to bridge the gap between quantum theory and practical Big Data applications, particularly in fields like NLP, IoT, and distributed computing.

Economically and ethically, the quantum revolution presents both opportunities and risks. While the cost of quantum infrastructure remains prohibitive for most organizations, cloud-based quantum services (e.g., IBM Qiskit, Amazon Braket) are democratizing access and fostering experimentation. At the same time, the potential for quantum-powered surveillance and the disruption of classical encryption necessitate proactive governance frameworks to ensure responsible development.

In summary, quantum computing's role in Big Data is still evolving, with near-term applications likely to focus on specialized, high-value problems rather than wholesale replacement of classical systems. Researchers and practitioners must balance optimism with realism—leveraging quantum advancements where they offer clear benefits while investing in classical-quantum hybrid solutions for the foreseeable future. As hardware improves and algorithms mature, the intersection of quantum computing and Big Data will unlock unprecedented possibilities, reshaping industries from healthcare to finance. The journey has just begun, and



the next decade will be pivotal in determining whether quantum computing becomes a cornerstone of Big Data analytics or remains a specialized tool for niche applications.

The quantum future of Big Data is not a question of *if* but *when* and *how*—requiring sustained innovation, collaboration, and critical evaluation to separate hype from genuine breakthroughs.

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