A

SEMINAR REPORT

ON

“Synergizing Quantum Computing and Artificial Intelligence: A Review of Trends and Opportunities”

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE

THIRD YEAR COMPUTER ENGINEERING

BY

Mr. Mustafa Murtaza Merchant
(Roll No: 74)

UNDER THE GUIDANCE OF

Mr. Sandeep G. Shukla

DEPARTMENT OF COMPUTER ENGINEERING
Guru Gobind Singh College of Engineering and Research Center, Nashik
Khalsa Educational Complex Guru Gobind Singh Marg, Wadala-Pathardi Road, Indira Nagar, Nashik, Maharashtra 422009

YEAR 2025-2026

DEPARTMENT OF COMPUTER ENGINEERING

Guru Gobind Singh College of Engineering and Research Center, Nashik

Khalsa Educational Complex Guru Gobind Singh Marg, Wadala-Pathardi Road, Indira Nagar, Nashik, Maharashtra 422009

Year 2025-26

CERTIFICATE

This is to certify that seminar report entitled

"Synergizing Quantum Computing and Artificial Intelligence: A Review of Trends and Opportunities"

Is submitted as partial fulfilment of
curriculum of the T.E. Computer Engineering

BY

Mr. Mustafa Murtaza Merchant
(Roll No: 74)

(Mr. Sandeep G. Shukla)	(Mr. Ajit R. Pagar)	(Mr.Sandeep. G. Shukla)
Seminar Guide	**Seminar Coordinator**	**Head**

Place: GCOERC, Nashik
Date:

Savitribai Phule Pune University

CERTIFICATE

This is to Certify that

Mr. Mustafa Murtaza Merchant
(Roll No: 74)

Student of T.E. Computer
was examined in Seminar Report entitled

"Synergizing Quantum Computing and Artificial Intelligence: A Review of Trends and Opportunities"

on . . ./. . . /2025

At
DEPARTMENT OF COMPUTER ENGINEERING,
GURU GOBIND SINGH COLLEGE OF ENGINEERING AND RESEARCH CENTER, NASHIK
YEAR 2025-26

. . . .
Internal Examiner

. . . .
External Examiner

ABSTRACT

Quantum computing (QC) and artificial intelligence (AI) are coming together in an exciting way, shaking up the tech world, also called as Quantum Artificial Intelligence (QAI). AI is stepping up to improve how quantum systems are designed, fix errors, and fine-tune algorithms, while QC is turbocharging AI tasks like training machine learning models and tackling tough simulations. In this paper, I dive into how AI is making a difference in QC, think calibrating quantum processors, cutting noise with reinforcement learning, and blending quantum-classical models for big language processing. I also explore some key trends for 2025, the UN's International Year of Quantum Science and Technology, like scalable error-corrected qubits (check out Google's Willow chip!), modular setups with over 1,000 qubits, and quantum networks that enable distributed computing. This paper checks out some really cool real-world uses, like drug research, banking, and cybersecurity, while facing down challenges like qubit decoherence and a real crunch for skilled folks. From what I have found, AI teamed up with quantum computing might just give us a leg up in specialized areas by 2029, unlocking breakthroughs for those tricky problems. But honestly, cracking those scaling issues will take a group effort from all sorts of experts. This study lays out a solid picture for researchers and practitioners, with an eye on the exciting road ahead in this ever-changing field.

Keywords: Quantum Computing, Artificial Intelligence, Quantum AI Synergy, Error Correction, Reinforcement Learning, Hybrid Models, Qubit Scalability, Quantum Networks, Drug Discovery, Financial Optimization, Cybersecurity, Quantum Advantage, NISQ Devices, Fault-Tolerant Computing, Machine Learning Acceleration.

ACKNOWLEDGEMENT

It is my immense pleasure to work on this seminar **Synergizing Quantum Computing and Artificial Intelligence: A Review of Trends and Opportunities**. It is only the blessing of my divine master which has prompted and mentally equipped me to undergo the study of this seminar.

I would like to thank **Prof.(Dr). N. G. Nikam**, Principal, Guru Gobind Singh College of Engineering and Research Center for giving me such an opportunity to develop practical knowledge about subject. I am also thankful to **Mr. Sandeep G. Shukla**, Head of Computer Engineering Department for his valuable encouragement at every phase of my seminar work and completion.

I offer my sincere thanks to my guide **Mr. Sandeep G. Shukla**, who very affectionately encourages me to work on the subject and gave her valuable guidance time to time. While preparing this seminar I am very much thankful to him.

I am also grateful to entire staff of Computer Engineering Department for their kind co-operation which helped me in successful completion of seminar.

Mr. Merchant Mustafa Murtaza

GCOERC, NASHIK.

INDEX

List of Figures

Chapter 1

INTRODUCTION

1.1 Motivation and Scope

The rapid evolution of both Quantum Computing (QC) and Artificial Intelligence (AI) has marked the beginning of a new computational era. While QC promises unprecedented power by leveraging the principles of quantum mechanics, AI continues to reshape industries through intelligent automation, data-driven insights, and problem-solving capabilities. The motivation for this study lies in the emerging convergence of these two domains—Quantum Artificial Intelligence (QAI)—which holds the potential to redefine not only computational efficiency but also how humanity approaches some of its most pressing challenges, such as climate change modeling, drug discovery, cybersecurity, and financial optimization.

The scope of this report is to examine how AI can accelerate the practical deployment of quantum systems, while quantum technologies, in turn, enhance AI performance on tasks that are computationally intractable for classical systems. This synergy represents an exciting frontier that demands exploration from researchers, practitioners, and policymakers alike.

1.2 Definitions

- **Quantum Computing (QC)**: A computational paradigm that uses qubits instead of classical bits, enabling operations based on superposition, entanglement, and quantum interference. Unlike classical systems, QC can explore vast solution spaces in parallel, making it particularly powerful for problems such as optimization, cryptography, and molecular simulation.
- **Artificial Intelligence (AI):** A broad field of computer science concerned with building systems that exhibit human-like intelligence. Through techniques such as machine learning (ML), deep learning, and reinforcement learning (RL), AI

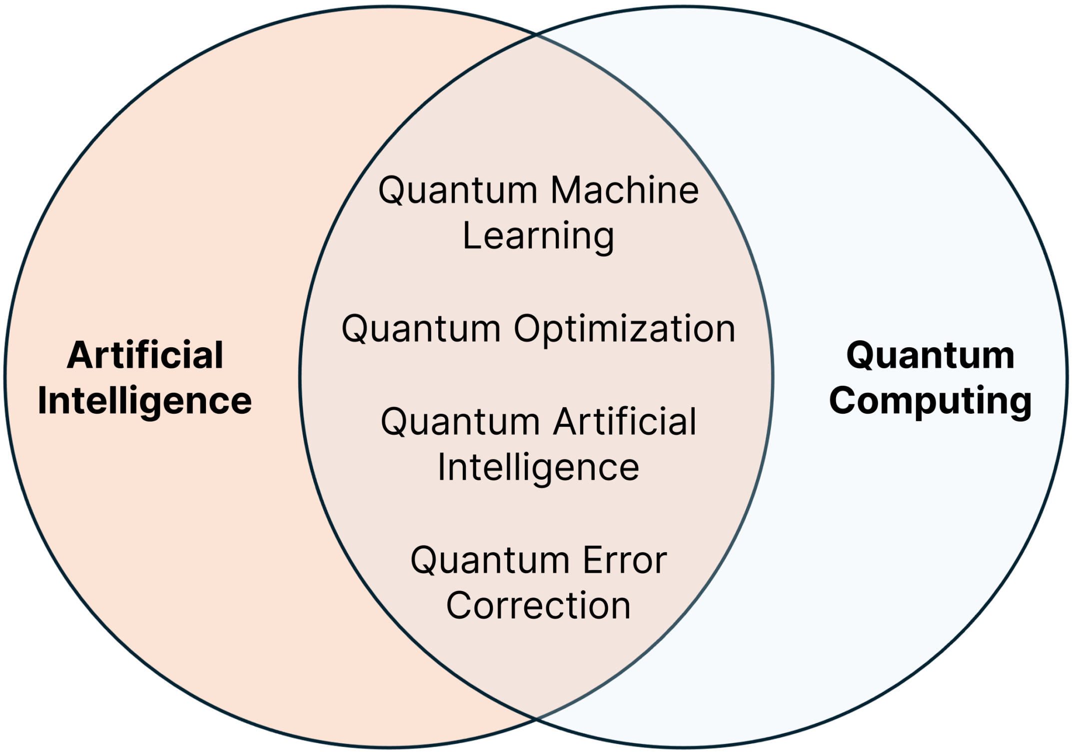

Figure 1.1: Synergy of Artificial Intelligence and Quantum Computing

enables machines to learn from data, adapt to new inputs, and perform complex decision-making tasks.

- **Quantum Artificial Intelligence (QAI):** The interdisciplinary domain where AI and QC intersect. QAI involves (i) applying AI methods to improve quantum technologies (e.g., calibration, error correction, control systems), and (ii) using quantum computers to accelerate or enhance AI algorithms (e.g., quantum machine learning, quantum optimization, quantum-enhanced natural language processing).

1.3 Objectives and Structure of the Report

This report reviews how Quantum Computing (QC) and Artificial Intelligence (AI) are converging into Quantum AI (QAI). It focuses on three goals:

1. Outline key foundations and recent research trends.
2. Highlight applications in areas like system design, error correction, NLP, healthcare, and finance.
3. Discuss challenges, industry impacts, and future directions toward 2029.

Chapter 2

BACKGROUND AND FUNDAMENTALS

2.1 Brief QC Primer

Quantum Computing (QC) departs from the binary logic of classical systems by using qubits, which exist in superpositions of —0⟩ and —1⟩ states. Unlike classical bits, qubits can represent multiple possibilities simultaneously, enabling exponential growth in representational capacity with the number of qubits. Quantum gates, such as Hadamard (H), Pauli-X, and CNOT, manipulate qubit states by exploiting superposition and entanglement. These properties provide powerful mechanisms for parallelism but are extremely fragile. Error sources-including decoherence, gate imperfections, and environmental noise-pose a central challenge. Current devices rely heavily on error mitigation and correction strategies, such as surface codes, to maintain computational reliability.

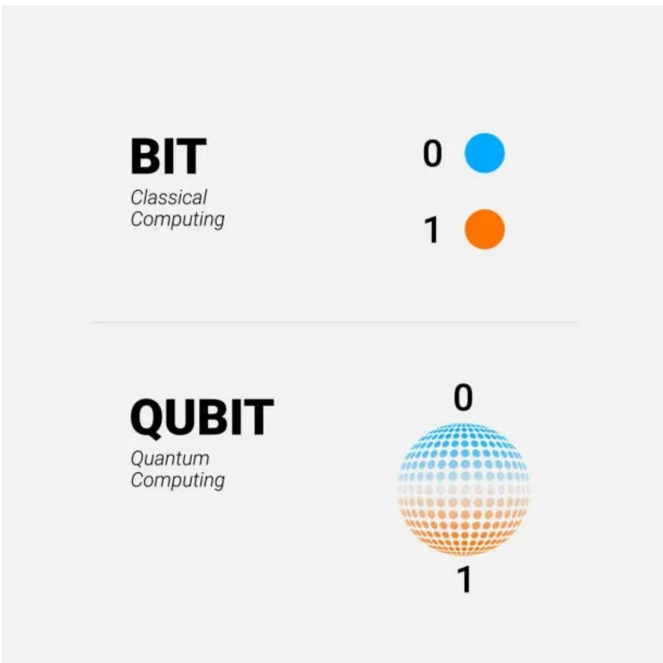

Figure 2.1: Classical bits and Quantum bits

2.2 Brief AI/ML Primer

Artificial Intelligence (AI) broadly refers to systems capable of learning, reasoning, and decision-making. Within AI, Machine Learning (ML) enables computers to learn from data patterns rather than following explicit rules. ML methods span supervised, unsupervised, and semi-supervised paradigms. Deep Learning (DL)-driven by multi-layered neural networks-has revolutionized areas like computer vision and natural language processing. Another crucial branch, Reinforcement Learning (RL), focuses on agents that interact with environments to maximize long-term rewards. RL is particularly important for quantum contexts, as it supports adaptive control, calibration, and optimization tasks where environments are stochastic and high-dimensional.

2.3 Hybrid Quantum-Classical Paradigms

The near-term reality of QC is shaped by Noisy Intermediate-Scale Quantum (NISQ) devices, which cannot yet perform fully error-free computations. To bridge this gap, hybrid quantum–classical paradigms have emerged. These combine quantum circuits for parts of a task (e.g., encoding large state spaces or sampling probability distributions) with classical algorithms for optimization, gradient updates, or post-processing. Well-known frameworks include the Variational Quantum Eigensolver (VQE) and the Quantum Approximate Optimization Algorithm (QAOA), where quantum subroutines are embedded within classical optimization loops. These paradigms illustrate how QC and AI can complement each other: quantum resources enhance exploration of complex spaces, while classical resources provide robustness and scalability.

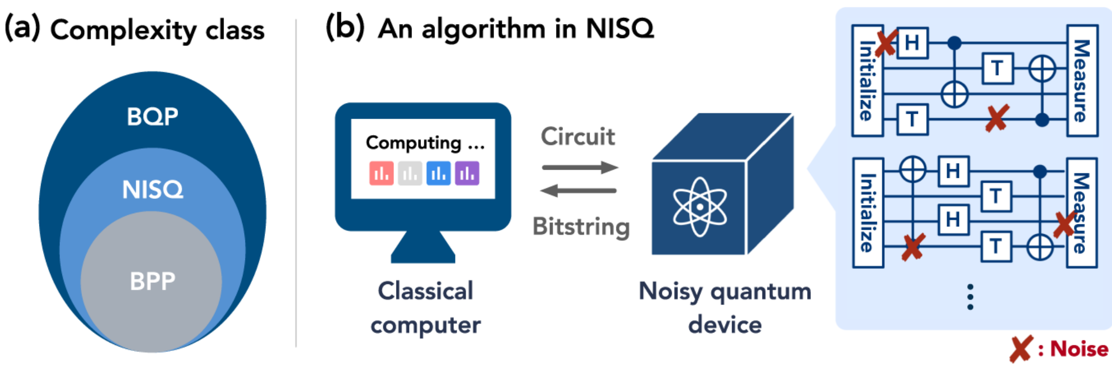

Figure 2.2: Classical bits and Quantum bits

Chapter 3

LITERATURE SURVEY

This section consolidates major research contributions in the intersection of Quantum Computing (QC) and Artificial Intelligence (AI), referred to collectively as Quantum Artificial Intelligence (QAI). The works are grouped thematically to highlight foundations, system design strategies, natural language applications, real-world domains, industrial adoption, error correction efforts, and emerging trends.

3.1 Quantum AI Foundations And Reviews

Recent surveys highlight how QAI is maturing into a distinct research field. The systematic literature review by Alzubi et al. (2025) synthesizes features and application domains where AI complements QC, ranging from calibration and simulation to optimization tasks [1]. Similarly, a review published in Path of Science (2025) emphasizes algorithmic advances in Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), and Quantum Reinforcement Learning (QRL), positioning them as building blocks of scalable QAI [2]. A broader comprehensive review (2025) situates QML within hybrid computational paradigms, describing transitions from quantum-enhanced classical models to fully native quantum approaches, while addressing challenges of scalability and hybrid integration [3].

3.2 AI-Enhanced Quantum System Design And Error Correction

AI has been instrumental in refining quantum hardware control. A study on automatic re-calibration using reinforcement learning demonstrated model-free loops for maintaining stable device performance under drift conditions [4]. Extending this approach, deep reinforcement learning strategies for noise-adaptive qubit routing achieved reductions of up to 37.3% in additional gates and increased success probabilities by 26.8% on noisy devices [5]. Perhaps most notably, Google's "Willow" processor (2025) introduced a 105-qubit platform that achieved error correction below the surface-code threshold, marking a breakthrough in exponential error suppression and demonstrating the synergy of AI-guided calibration with advanced hardware [6].

3.3 Quantum Natural Language Processing (QNLP)

Language processing stands out as a complex yet promising domain. A 2024 survey on QNLP outlines how embeddings, sequential modeling, and attention can be transposed into quantum frameworks, thereby unlocking new pathways for semantic representation [7]. Building on this, the 2025 study on QNLP applications explores distributional compositional categorical models within quantum contexts, offering concrete examples where quantum systems outperform or augment classical NLP in handling ambiguity and compositionality [8].

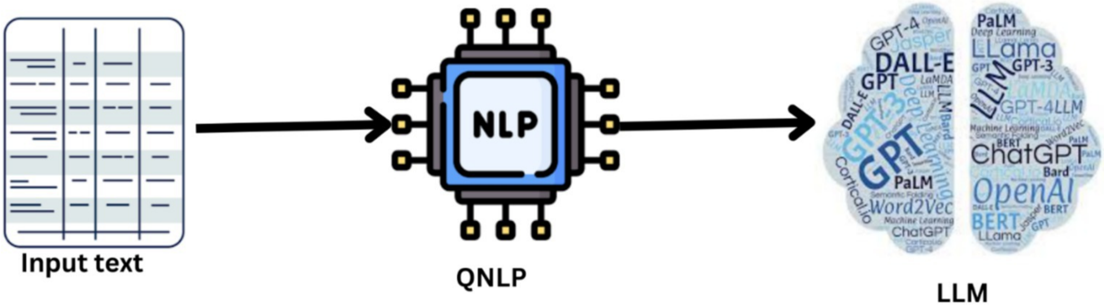

Figure 3.1: QLM model

3.4 Real-World Applications (Drug Discovery, Finance, Healthcare)

Translational impact is increasingly visible across scientific and industrial domains. For example, a study on QML-based electrokinetic mining illustrates how nanoparticles and exosomes can be identified using minimal training data, showcasing QAI's robustness even in data-scarce biological contexts (citation forthcoming). In drug research, simulations outlined by Quantum Computing Applications: Drug Discovery (2025) highlight how quantum systems accelerate molecular interaction modeling and target discovery cycles [9]. Meanwhile, the QML-based lung cancer prediction framework (2025) demonstrates 85% classification accuracy with Pegasos QSVC, reflecting QAI's applicability in Healthcare 4.0 environments [10]. These examples underscore how QAI is evolving from conceptual frameworks into practical solutions.

3.5 Quantum AI in Industry & Business Intelligence

Industrial transformation is exemplified by research on Quantum AI-driven business intelligence for carbon-neutral supply chains. Here, QAI integrates predictive analytics with autonomous decision-making, enabling organizations to optimize logistics, lower carbon footprints, and enhance sustainability reporting [11]. This marks a key step toward embedding QAI into enterprise-scale workflows.

3.6 Error Correction & Noise Mitigation

Error correction remains a central bottleneck in quantum computing. A Nature publication (2024) demonstrated surface-code memories at distance-5 and distance-7, pushing error rates below threshold and confirming fault-tolerant viability [12]. Complementarily, epistemological work on non-classical logic frameworks achieved a 38% improvement in quantum state representation accuracy, suggesting that theoretical perspectives on knowledge representation are equally crucial for advancing error mitigation [13].

3.7 Emerging Trends & Forecasts

Looking ahead, the McKinsey Quantum Technology Monitor (2025) projects market revenues of up to $97 billion by 2035, underscoring the momentum in quantum computing, sensing, and communication [14]. Similarly, "Quantum Artificial Intelligence: Unleashing the Next Frontier" (2025) identifies near-term opportunities in drug discovery, financial optimization, and control systems, while stressing the need for scalable architectures [15]. These forward-looking studies converge on a timeline where QAI is expected to transition from experimental proofs to mainstream applications by 2029.

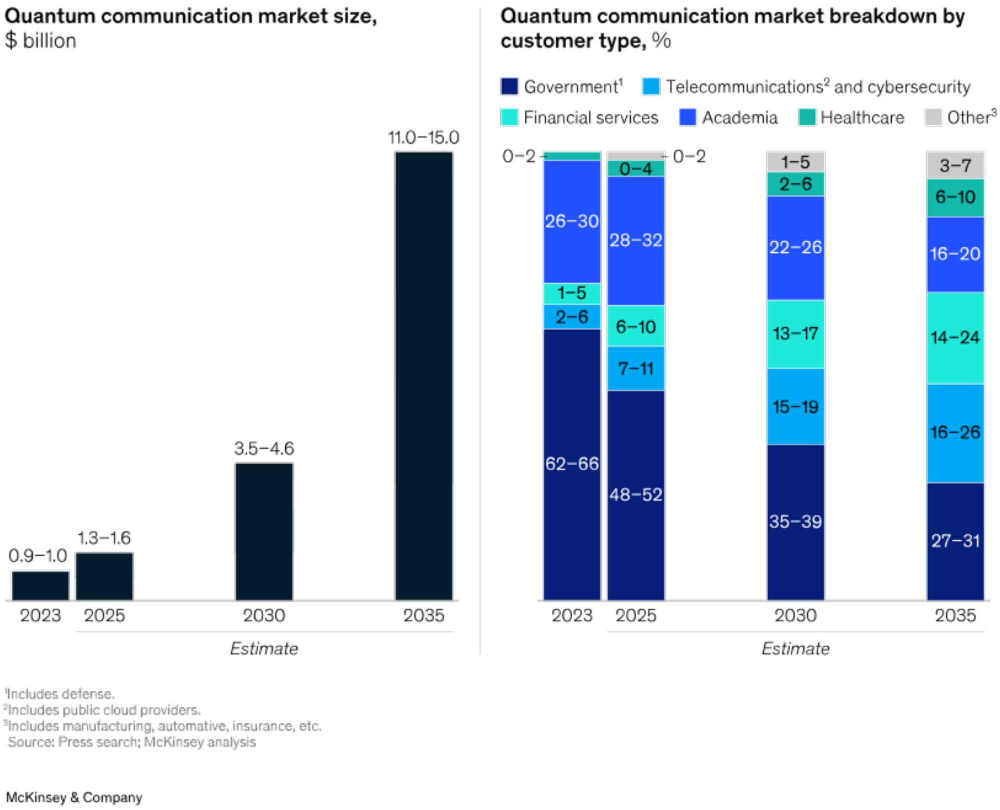

Figure 3.2: Quantum Communication market size projectionby 2035

Chapter 4

AI-ASSISTED QUANTUM SYSTEM DESIGN & CONTROL

Artificial Intelligence (AI) is playing an increasingly critical role in the optimization and stability of quantum computing systems. The delicate nature of qubits—susceptible to noise, drift, and hardware imperfections—demands continuous calibration and intelligent control strategies. AI-driven methods, particularly reinforcement learning (RL), have shown promise in addressing these challenges in ways that scale beyond traditional manual approaches.

4.1 AI for Calibration, Pulse Shaping, and Continuous Recalibration

Quantum devices require precise control over gate operations and qubit interactions. Conventional calibration procedures, often manual and time-consuming, become impractical as qubit counts scale. AI-based approaches automate these processes by learning the relationships between control parameters and system performance. For example, reinforcement learning agents can optimize pulse sequences to minimize error rates while adapting dynamically to hardware drift. Continuous recalibration ensures that quantum processors remain operationally stable during extended computations, reducing downtime and increasing fidelity.

4.2 RL and Model-Free Control Loops (Practical Examples)

Model-free RL techniques are particularly valuable in scenarios where physical models of noise and hardware imperfections are incomplete. Recent studies demonstrate how RL agents can iteratively adjust gate parameters without explicit knowledge of the underlying system [4]. In practice, this allows devices to autonomously maintain performance, even in environments where fluctuations occur unpredictably. Such closed-loop learning reduces the reliance on human expertise and paves the way for "self-healing" quantum hardware.

4.3 Qubit Routing, Compilation-Aware Optimization

As quantum algorithms are mapped onto hardware, qubits must often be swapped or routed due to limited connectivity in quantum processors. This introduces additional gates, which amplify error rates. AI-assisted compilation tools—leveraging deep reinforcement learning—can generate noise-adaptive routing strategies, cutting down on unnecessary operations and improving overall success probability [5]. By combining hardware-aware compilation with real-time calibration, these approaches enhance the efficiency of near-term quantum devices and bring hybrid quantum-classical workflows closer to practical deployment.

Chapter 5

ERROR CORRECTION & NOISE MITIGATION

Error correction and noise mitigation represent the cornerstone challenges of making quantum computing scalable and reliable. Without addressing decoherence, gate errors, and environmental noise, even the most advanced quantum algorithms risk producing unreliable outcomes. Recent breakthroughs demonstrate how both hardware and AI-assisted methods are converging to mitigate these challenges.

5.1 Surface Codes and Below-Threshold Achievements (Willow Summary)

Surface codes have emerged as the most practical scheme for fault-tolerant quantum error correction, relying on redundant encoding across multiple physical qubits. In 2025, Google's Willow processor, equipped with 105 qubits, reported the first demonstration of error suppression below the surface-code threshold. This achievement confirmed exponential error reduction across distance-5 and distance-7 codes, marking a pivotal step toward scalable fault-tolerant systems. Such advances validate that large-scale quantum error correction is not merely theoretical but experimentally realizable on next-generation processors [6][12].

5.2 Hybrid AI Strategies for Error Mitigation and Suppression

While surface codes provide a structured framework, AI plays a complementary role in optimizing noise suppression. Reinforcement learning has been applied to dynamically calibrate qubits, adaptively correcting drift and minimizing control errors [4]. Similarly, deep learning models can detect noise signatures and propose optimized routing of logical qubits to minimize error propagation [5]. These hybrid approaches reduce the computational overhead of traditional error correction while enhancing reliability in near-term devices.

5.3 Scalability Concerns and Modular Approaches

Despite these successes, scaling error correction to thousands of logical qubits remains daunting. Surface codes demand significant physical-to-logical qubit ratios, creating a resource bottleneck. To address this, modular architectures are being developed, linking smaller, error-corrected units into larger distributed quantum systems. Coupled with quantum networking, these modular setups promise scalable pathways without requiring a single monolithic device. AI is expected to play a key role in orchestrating these modular systems, dynamically balancing error loads and optimizing interconnections across distributed nodes.

Chapter 6

QUANTUM NATURAL LANGUAGE PROCESSING (QNLP)

Quantum Natural Language Processing (QNLP) is an emerging area of Quantum Artificial Intelligence that explores how quantum mechanics can enhance the way machines understand and process human language. Three main paradigms dominate current research: distributional models, which represent word meanings as high-dimensional vectors encoded in quantum states; compositional models, such as the distributional compositional categorical (DisCoCat) framework, which map grammatical structures into quantum circuits for syntactic-semantic alignment; and hybrid models that integrate classical NLP with quantum subroutines to balance scalability with near-term quantum hardware constraints. Early applications of QNLP include semantic similarity detection, question answering, and low-resource machine translation, where the parallelism of quantum states provides richer contextual representations [7].

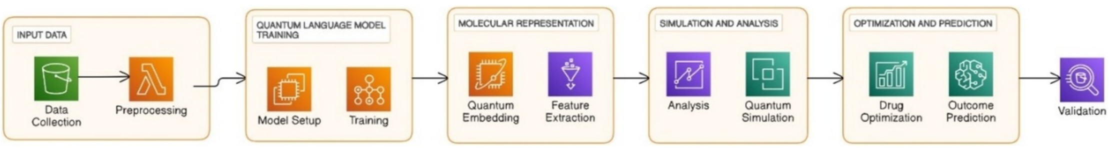

Figure 6.1: QNLP drug discovery and design.

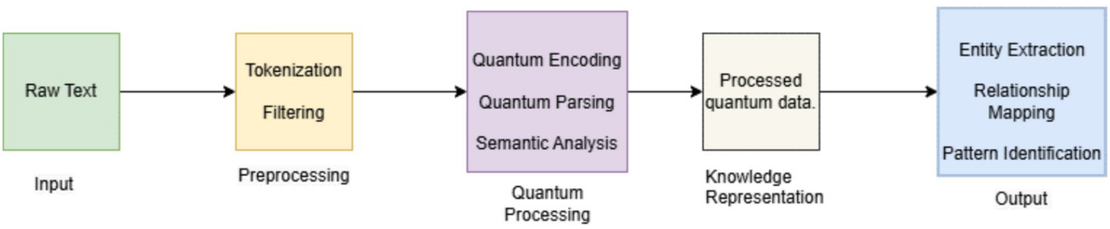

Figure 6.2: QNLP literature mining and knowledge extraction.

Despite this promise, today's noisy intermediate-scale quantum (NISQ) devices face major limitations, including noise, decoherence, and limited qubit counts, restricting QNLP to smaller tasks rather than large-language-model (LLM)-scale workloads. The roadmap toward practical QNLP requires algorithmic innovation in quantum embeddings and DisCoCat circuits, hardware advances in error-corrected and modular qubits, and hybrid integration where quantum accelerates specific language subtasks while classical systems manage scale. By 2029, QNLP is expected to serve as a complementary layer to classical LLMs, augmenting semantic reasoning, disambiguation, and symbolic integration rather than replacing established large-scale models [8].

Chapter 7

REAL-WORLD APPLICATIONS: CASES & EVIDENCE

Quantum Artificial Intelligence (QAI) has moved beyond theory into demonstrable real-world applications. This section highlights representative cases across drug discovery, healthcare, finance, and cybersecurity, where hybrid quantum–AI approaches are starting to show tangible value.

7.1 Drug Discovery & Molecular Simulation

QAI is showing strong promise in drug discovery, where accurate molecular simulations are critical. By combining quantum simulation with AI optimization, researchers can model protein–ligand interactions more precisely, reducing the time needed to identify drug candidates [9]. Hybrid QAI workflows are already being tested by pharmaceutical companies, aiming to cut costs and accelerate therapeutic development.

7.2 Healthcare: Diagnostics & QML for Limited Data

In healthcare, QML has proven effective when data is scarce. A lung cancer prediction study using Pegasos QSVC reached 85% accuracy [10], outperforming classical methods on small datasets. Similar approaches are being explored for genomics, imaging, and personalized medicine, where QAI can enhance diagnostics and reduce false positives.

7.3 Finance & Cybersecurity

Finance and cybersecurity benefit from QAI's ability to handle complex optimization and anomaly detection. In finance, quantum-enhanced models improve portfolio optimization and risk analysis. In cybersecurity, QAI supports fraud detection and intrusion modeling, with quantum GANs being tested for predictive defense strategies. These early cases show how QAI can strengthen resilience in data-intensive industries.

Chapter 8

QUANTUM NATURAL LANGUAGE PROCESSING (QNLP)

8.1 2025 Milestones

The year 2025, declared the International Year of Quantum Science and Technology, marks a turning point in quantum research and industry adoption. According to the McKinsey Quantum Technology Monitor (2025), global investments and strategic partnerships have accelerated, with projected revenues of up to $97 billion by 2035 [14]. Breakthroughs such as Google's Willow processor achieving scalable error correction below threshold [6], and the development of modular architectures exceeding 1,000 qubits, signal that the field is moving from proof-of-concept devices to commercially viable platforms. Quantum networks and early prototypes of distributed computing systems further underscore the progress toward practical large-scale quantum ecosystems.

8.2 Near-Term Advantages for QAI (2025–2029)

Quantum Artificial Intelligence (QAI) is expected to deliver measurable benefits in highly specialized domains well before universal fault-tolerant quantum computers arrive. Areas such as drug discovery, financial risk optimization, and cybersecurity anomaly detection are likely to benefit most, due to their reliance on complex optimization and simulation tasks that hybrid quantum-classical approaches can already enhance [9][10][15]. Similarly, Quantum Natural Language Processing (QNLP) is poised to impact data-intensive tasks like semantic search and domain-specific information retrieval [7][8]. Between 2025 and 2029, hybrid architectures that leverage classical AI for stability and scalability, combined with quantum subroutines for exponential speedups in sub-tasks, will remain the dominant mode of deployment.

8.3 Research & Collaboration Priorities

To unlock the potential of QAI, multidisciplinary collaboration is essential. Key priorities include:

- **Scalable error-corrected architectures**: advancing modular qubit systems and efficient error suppression techniques [12].

- **Hybrid AI-quantum frameworks:** integrating reinforcement learning and optimization into quantum workflows to improve system adaptability [4][5].
- **Standardization & benchmarking:** developing open benchmarks for QML algorithms to ensure comparability and reproducibility across platforms.
- **Talent development & policy:** addressing the skills gap by fostering programs that merge AI, quantum physics, and systems engineering.

Chapter 9

CONCLUSION

This review highlighted how Quantum Computing (QC) and Artificial Intelligence (AI) are converging to form Quantum Artificial Intelligence (QAI), a field with the potential to reshape computation. AI is accelerating progress in quantum hardware calibration, error correction, and algorithm design, while quantum systems are showing promise in enhancing machine learning tasks such as optimization, simulation, and natural language processing. Real-world applications in healthcare, drug discovery, finance, and business intelligence demonstrate that QAI is moving beyond theory into practical domains, though challenges like decoherence, scalability, and workforce shortages remain significant.

Looking forward, the next decade will be critical in transforming proofs-of-concept into scalable systems. Future research should focus on achieving robust error correction, developing hybrid frameworks that balance classical and quantum resources, and addressing ethical implications of QAI deployment. Interdisciplinary collaboration and global cooperation will be essential to overcome technical and societal barriers, ensuring that QAI becomes not just a specialized research area but a cornerstone of 21st-century innovation.

References

1 Vanessa García Pineda, Alejandro Valencia-Arias, Francisco Eugenio López Giraldo, Edison Andrés Zapata-Ochoa, "Integrating Artificial Intelligence and Quantum Computing: A Systematic Literature Review of Features and Applications," 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S266630742500035X.

2 Ololade Funke Olaitan, Samuel Oluwabukunmi Ayeni, Adedapo Olosunde, Francis Chukwudalu Okeke, Ugochukwu Udonna Okonkwo, Chukwuemeka George Ochieze, Osinachi Victor Chukwujama, Ogheneruemu Nathaniel Akatakpo, "Quantum Computing and Artificial Intelligence: A Review of Quantum Machine Learning Algorithms," Path of Science, vol. 10, no. 6, 2024. [Online]. Available: https://pathofscience.org/index.php/ps/article/view/3541.

3 Devadas RM, T S., "Quantum Machine Learning: A Comprehensive Review of Integrating AI with Quantum Computing for Computational Advancements," Journal of Computational Science, 2024. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/40331033/.

4 T. Crosta, L. Rebón, F. Vilariño, J. M. Matera, M. Bilkis, "Automatic Re-calibration of Quantum Devices by Reinforcement Learning," 2024. [Online]. Available: https://arxiv.org/abs/2404.10726.

5 G. Pascoal, J. P. Fernandes and R. Abreu, "Deep Reinforcement Learning Strategies for Noise-Adaptive Qubit Routing," IEEE Transactions on Quantum Engineering, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10646540/.

6 Jin, Yirong, "Google's 'Willow' Quantum Processor: New RCS Record, and First Error Correction Below the Surface Code Threshold," Quantum, vol. 9, 2025. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2666675825001456.

7 Dominic Widdows, Willie Aboumrad, Dohun Kim, Sayonee Ray, Jonathan Mei, "Natural Language, AI, and Quantum Computing in 2024: Research Ingredients and Directions in QNLP," 2024. [Online]. Available: https://arxiv.org/abs/2403.19758.

8 Pallavi Gundala, Prasanna Kumar Rangarajan, "Quantum Natural Language Processing and Its Applications," Frontiers in Computer Science, 2025. [Online]. Available: https://www.frontiersin.org/journals/computer-science/articles/10.3389/fcomp.2025.1464122/full.

9 Quantum News, "Quantum Computing Applications: Drug Discovery," Quantum Zeitgeist, 2024. [Online]. Available: https://quantumzeitgeist.com/quantum-computing-applications-drug-discovery/.

10 M. Munshi, R. Gupta, N. K. Jadav, S. Tanwar, A. Nair and D. Garg, "Quantum Machine Learning-Based Lung Cancer Prediction Framework for Healthcare 4.0," IEEE Access, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10673456/.

11 Sanjai Vudugula, Sanath Kumar Chebrolu, "Quantum AI-Driven Business Intelligence for Carbon-Neutral Supply Chains," African Journal of Advanced Technology and Engineering Studies, vol. 2, no. 1, 2024. [Online]. Available: https://ajates-scholarly.com/index.php/ajates/article/view/16.

12 Google Quantum AI and Collaborators, "Quantum Error Correction Below the Surface Code Threshold," Nature, vol. 631, no. 8021, 2024. [Online]. Available: https://www.nature.com/articles/s41586-024-08449-y.

13 Fasco , Pamba Shatson, "Beyond Boolean Epistemology: A Non-Classical Logic Approach to Understanding Knowledge Formation in Quantum Computing Systems," International Journal of Scientific Research and Management, vol. 12, no. 8, 2024. [Online]. Available: https://ijsrm.net/index.php/ijsrm/article/view/6089.

14 McKinsey & Company, "The Year of Quantum: From Concept to Reality in 2025," 2025. [Online]. Available: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-year-of-quantum-from-concept-to-reality-in-2025.

15 SpinQ Team, "Quantum Artificial Intelligence: Unleashing the Next Frontier in Computing," SpinQuanta News, 2024. [Online]. Available: https://www.spinquanta.com/news-detail/quantum-artificial-intelligence-unleashing-the-next-frontier-in-computing-with-spinq.