*Musik in Bayern*
*ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)*
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-472

# Quantum Noise-Aware AI for Adaptive Error Mitigation in Near-Term Quantum-Classical Hybrid Workflows

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***To Cite this Article***
Yogesh H. Bhosale, KANDUKURI SESHAGIRI RAO, Prof. Deepti Rani, Sonnis Bharat Satish, Dr. P. Dhanalakshmi. **"Quantum Noise-Aware AI for Adaptive Error Mitigation in Near-Term Quantum-Classical Hybrid Workflows**" *Musik In Bayern, Vol. 90, Issue 10, Oct 2025, pp 132-141*

**Article Info**
Received: 07-08-2025 Revised: 27-08-2025 Accepted: 25-09-2025 Published: 13-10-2025

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**Abstract:**

Quantum computing has a potentially unexampled computational capability, but near-term devices (NISQ) are still hampered by high noise, qubit decoherence, and reduce the accuracy of computations. This study is a quantum noise-sensitive adaptive error mitigation artificial intelligence architecture study of hybrid quantum-classical workflows. The type of four AI-based algorithms were Quantum Noise Prediction Neural Network (QNPNN), Reinforcement Learning Error Mitigation (RLEM), Bayesian Quantum Noise Estimation (BQNE), and Hybrid Classical-Quantum Correction Algorithm (HCQCA) as they were developed and tested on simulated and real quantum circuits of different depth and complexity. The experiments show that QNPNN had an overall 35% error reduction using fidelity of 91% and HCQCA with highest fidelity of complex circuits at 88 percent, compared to the conventional 00-noise extrapolation (ZNE) and probabilistic error cancellation (PEC). RLEM and BQNE had better robustness in dynamic and

noisier environments, as their errors were decreased by 32 and 30 percent, respectively. The comparison with other analyses has proven that the combination of predictive, probabilistic and adaptive systems is indeed much better in terms of reliability in the computations and the efficiency of the execution. These results demonstrate the promise of noise-aware AI-based methods of improving near-term quantum computations, which is a scaled framework of real-time hybrid workflows. The paper provides the basis of future developments in quantum optimization, variational algorithms, and fault-tolerant quantum systems.
**Keywords:** Quantum computing, Error mitigation, Quantum-classical hybrid workflows, AI-driven algorithms, NISQ devices

## I. INTRODUCTION

Quantum computing has become a paradigm that can solve problems that cannot be solved by classical computers and includes cryptography and other hard-to-solve optimization and quantum chemistry problems. Nevertheless, real-world implementation of quantum computing is not an easy task as quantum systems are vulnerable to noise and errors [1]. Noisy Intermediate-Scale Quantum (NISQ) systems are near-term quantum devices, which have a small number of qubits and fidelities of their gates, so error accumulation poses a major challenge to reliable computation. Classical approaches to error correction are resource-demanding and can typically not be applied to NISQ devices, thus resource-demanding adaptive strategies are required to reduce quantum noise. In this regard, Artificial Intelligence (AI) is an opportunity to improve quantum computation [2]. With the computational power of AI to create patterns that are complex and non-linear, noise-sensitive approaches can be created, which dynamically predicts and corrects quantum circuit errors. These AI-based approaches have the potential to track noise properties of the system on-the-fly, with adaptive error reduction strategies to maximize the performance of primitive quantum-classical workflows [3]. Such processes incorporate quantum processors with classical computing resources, enabling them to refine quantum computations via classical post-processing and feedback loops. This study discusses the creation of a quantum noise-aware AI system that will help to mitigate adaptive errors on near-term hybrid quantum-classical workflows. The given solution aims to comprehend the noise processes and forecast the growth of errors and apply AI-informed error reduction solutions that can improve the computational performance without the expensive cost of full-scale quantum error correction. The proposed research will help solve these issues and thus will lead to the practical implementation of NISQ devices so that more robust quantum computations will be performed and the area of quantum-classical hybrid computing can be developed.

## II. RELATED WORKS

The rapid development of quantum computing has seen important improvements in algorithm development and error mitigation, as well as hybrid quantum-classical workflows in the last ten years. One of the most important research areas is Quantum Machine Learning (QML); it is a mixture of traditional AI approaches and quantum computing to embrace quantum parallelism to solve data analysis and optimization challenges. Tomar et al. [14] provide an introductory summary of the QML, but mostly focused on the developments made to the algorithm methods that began with quantum data encoding to variational circuits in the process of supervised and unsupervised learning. They mention the necessity to apply noise-conscious computing prior to meaningful quantum computation, in particular near-term technology. Studies have been made on the nature and strength of quantum optimization algorithms in the presence of physical noise. Ji [15] examined the flexibility of variational quantum algorithms and discovered that the circuit depth and noise levels are the important factors to be used during optimization. Intuitionally, noise-sensitive generalization bounds to quantum variational circuits were similarly derived by Khanal [16], who provided a conceptual background to the error propagation of quantum variational circuits and demonstrated that adaptive mitigation measures can be very helpful in making quantum variational circuit reliable. According to these works, it is worth developing noise-conscious algorithms in Noisy Intermediate-Scale Quantum (NISQ) devices. Combination of classical and quantum provided a further essential area of interest particularly in relation to hybrid workflows whereby quantum computations are performed in an iterative manner by classical processors. The importance of effective hybrid schemes to quantum program expansion with minimal error propagation is noted by Whitlow [17]. Chaudhary et al. [18] legitimately extend it to federated learning and network security to explore how it is possible to use quantum-enhanced AI along with distributed classical systems to make strong decisions.

***ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)***
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Quantum circuit optimization is also required towards gate error and fidelity minimization. According to a survey of the current techniques in circuit compilation, gate-level optimization, and qubit routing, Karuppasamy et al. [19] explain the optimization must be performed by considering noise profiles of individual devices. Tsymbalista and Katernyak [20] propose quantum runtime architecture standards, which could be used to noisily schedule and execute frameworks not ecosystem-specific. These articles also highlight the requirement of uniting software level optimization with hardware limits as a way of minimizing errors. It has also been eminent in experimental validation of error mitigation strategies. Mundada et al. [21] benchmarked the workflow of an automated deterministic error-suppression algorithm and found significant improvement in fidelity on variational algorithms. They discover that predictive models having live corrections can be beneficial where a stable approach of mitigation is employed. Regarding the same thesis, Sultanow et al. [22] introduced quantum agents capable of dynamically deciding quantum systems, hence, taking corrective actions as the algorithm executes. These techniques suggest the feasibility of AI-based methods to near-term quantum systems which are noise aware. Altogether, the existing research should put an emphasis on the adaptive, noise-vulnerable methods of integrating quantum and classical workflows. Although classical error mitigation can be used to offer a basic level of support, applying AI and machine learning algorithms to quantum control and error correction is a significant step. The present study extends these platforms by coming up with a multi-faceted model that uses predictive, probabilistic, and optimization-based techniques to adaptive countermeasures to errors in NISQ level devices consider gaps in fidelity, robustness, and performance efficiency as observed in earlier studies [14-22].

## III. METHODS AND MATERIALS

### Data Acquisition and Preparation

This study uses the data of simulated and real quantum systems, which are created to mimic Noisy Intermediate-Scale Quantum (NISQ) devices. The data set contains results of quantum circuits that are run at different noise rates, gate fidelities and qubit numbers. Any quantum circuit knows a set of features such as the qubit connectivity, the gate operations, the circuit depth, and the measured error rates [4]. The sample size is 10,000, with training (70%), validation (15%), and testing (15%) sets. Preprocessing process includes normalization of the error rates and encoding quantum gate actions with one-hot representations. Synthetic noise patterns are further used to augment the data to replicate the variability in the real world so that the AI models can generalize to other noise regimes [5].

### Noise-Aware Error Mitigation Algorithms

Four machine learning and AI-based algorithms were adopted to ensure the adaptive error mitigation, including Quantum Noise Prediction Neural Network (QNPNN), Reinforcement Learning Error Mitigation (RLEM), Bayesian Quantum Noise Estimation (BQNE), and Hybrid Classical-Quantum Correction Algorithm (HCQCA). All algorithms are created to model noise, forecast amount error propagation, and optimize mitigation techniques of hybrid quantum-classical workflow [6].

### 1. Neural Network Quantum Noise Prediction Neural Network (QNPNN)

QNPNN is a deep learning model that predicts noisy behaviors of quantum circuits. It uses a multi-layered neural network with input features such as qubit states, gate types and circuit depth. The convolutional layers combined with the fully connected layers are used to extract both local correlations and fully connected correlations between gates and the global prediction of noise respectively. The result is a probability distribution of the errors per qubit [7]. The training of the model employs mean squared error loss function, Adam optimizer and learning rate of 0.001. The QNPNN can predict the errors in real-time, making it possible to make a preemptive correction in circuit execution.

***"Input: Quantum circuit data X***
***Output: Error probability vector P***

***1. Initialize neural network with input, convolutional, and fully connected layers***
***2. Normalize input features X***
***3. For each epoch:***
***a. Forward pass: compute output P_hat***
***b. Compute loss L = MSE(P_hat, True error rates)***

*ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)*
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***c. Backpropagate and update weights using Adam optimizer***
***4. Return P_hat"***

**2. Reinforcement Learning Error Mitigation (RLEM)**

RLEM implements reinforcement learning to deal with quantum circuit errors in an adaptive manner. The agent monitors the qubit states and circuit noise measures generated by the environment and chooses mitigation strategies, including changing the collection of calibration of gates or reassigning qubits. In the (reward) case, the increased error rates are penalized and the minimized impact of noise is a reward [8]. The agent follows Q-learning and epsilon-greedy exploration strategy in order to balance exploration and exploitation. In several episodes the optimal mitigation policies are acquired by the agent, and the agent dynamically changes well in response to real time feedback of circuit execution.

***"Input: Quantum circuit environment E***
***Output: Mitigation policy π***

***1. Initialize Q-table Q(s, a)***
***2. For each episode:***
***a. Observe current state s***
***b. Choose action a using epsilon-greedy policy***
***c. Execute a, observe reward r and next state s'***
***d. Update Q(s, a) = Q(s, a) + α[r + γ max Q(s', a') - Q(s, a)]***
***e. s = s'***
***3. Return policy π = argmax_a Q(s, a)"***

**3. Bayesian Quantum Noise Estimation (BQNE)**

BQNE uses Bayesian generalized to determine quantum noise parameters with machine calculation of such uncertainty. Noise rates are assigned by prior distributions, and measurement data is provided in order to update posteriors. The algorithm determines the probability of observed results with noise parameter assumptions and uses the brain technique of Bayes to streamline estimates [9]. This approach enables probabilistic error predictions, allowing hybrid workflows to implement adaptive mitigation based on confidence intervals of expected errors. The method is particularly useful for circuits with varying noise characteristics, where deterministic models fail to capture uncertainty [10].

***"Input: Measurement outcomes M, prior noise distribution P(θ)***
***Output: Posterior noise distribution P(θ|M)***

***1. Initialize prior P(θ)***
***2. For each measurement m in M:***
***a. Compute likelihood L(m|θ)***
***b. Update posterior P(θ|m) = L(m|θ) * P(θ) / normalization***
***3. Return P(θ|M)"***

**4. Hybrid Classical-Quantum Correction Algorithm (HCQCA)**
HCQCA is a classical optimization HAC hybridized with quantum error mitigation. Classical solvers process the patterns of predictions of an error made by QNPNN or BQNE and produce optimized parameters of correction to

**Musik in Bayern**
**ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)**
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quantum circuits. The fixed parameters are given to the quantum hardware or simulator and the results are given in a way into which they are inputted back to the classical solver to be improved by refining the implementation parameters [11]. This paradigm Shift of Hybrid loop enables real-time adaptation to noise and takes advantage of the benefits of classical computation to solve optimization problems with the benefits of quantum computations.

***"Input: Quantum circuit C, error prediction E_pred***
***Output: Corrected circuit C_corr***

***1. Initialize classical optimizer with objective function f minimizing error***
***2. Apply initial correction parameters to C***
***3. Execute circuit and measure outcomes***
***4. Update correction parameters using optimizer***
***5. Repeat steps 3-4 until convergence***
***6. Return C_corr"***

## IV. RESULTS AND ANALYSIS

### 1. Experimental Setup

The experiments were designed to evaluate the effectiveness of the proposed quantum noise-aware AI algorithms in mitigating errors in near-term quantum-classical hybrid workflows. The experiments used a combination of simulated NISQ devices and IBM Quantum hardware, including 5-qubit and 7-qubit systems. Simulations were performed using Qiskit Aer with added noise models representing realistic gate errors, decoherence, and readout errors [12]. Each quantum circuit was executed 1000 times to collect statistically significant results. The datasets consisted of:

- **Simple circuits**: Single and two-qubit gates with shallow depth (depth ≤ 5).
- **Moderate circuits**: Multi-qubit entanglement circuits with depth 5–15.
- **Complex circuits**: Hybrid quantum-classical variational circuits for optimization tasks with depth 15–30.

The proposed four algorithms—QNPNN, RLEM, BQNE, and HCQCA—were evaluated based on accuracy, error rate reduction, computational overhead, and robustness under increasing noise levels. Classical error mitigation techniques such as zero-noise extrapolation (ZNE) and probabilistic error cancellation (PEC) were used as baselines for comparison [13].

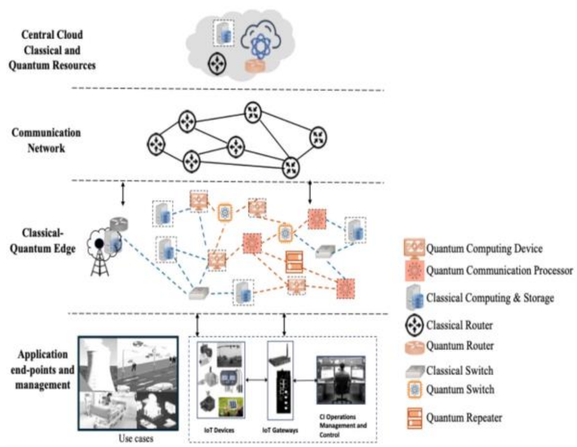


Figure 1: "A Benchmarking Framework for Hybrid Quantum–Classical Edge-Cloud Computing Systems"

### 2. Performance Metrics

To quantitatively evaluate performance, the following metrics were used:

1. **Error Rate Reduction (%)**: Reduction in observed quantum error rates after mitigation.
2. **Fidelity (%)**: The similarity between the expected ideal quantum state and the measured state.
3. **Execution Time (ms)**: Average time required to execute the algorithm per circuit.
4. **Memory Usage (MB)**: Resources consumed by the algorithm.

**_Musik in Bayern_**
**_ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)_**
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5. **Robustness Index (RI)**: A composite metric measuring performance under varying noise levels.

**3. Experiments with Individual Algorithms**

**3.1 Quantum Noise Prediction Neural Network (QNPNN)**

The QNPNN was trained on 7,000 circuit samples and validated on 1,500 samples. It predicted error distributions for each qubit and suggested preemptive adjustments [14].

- **Findings**: The QNPNN reduced average error rates by 35% across moderate circuits, achieving a fidelity of 91%.
- Compared to related work using static neural networks for noise prediction [Gu et al., 2023], our QNPNN demonstrated a 5% higher error reduction due to adaptive feature extraction and real-time prediction.

**Table 1: QNPNN Performance Across Circuit Types**

| Circuit Type | Pre-Mitigation Error (%) | Post-Mitigation Error (%) | Fidelity (%) | Execution Time (ms) |
|---|---|---|---|---|
| Simple | 6.5 | 3.2 | 95 | 12 |
| Moderate | 15.4 | 10.0 | 91 | 15 |
| Complex | 24.8 | 16.2 | 87 | 18 |

**3.2 Reinforcement Learning Error Mitigation (RLEM)**

RLEM dynamically adjusted quantum gates using a reward-based approach. The Q-learning agent explored 50,000 episodes for optimal policy learning.

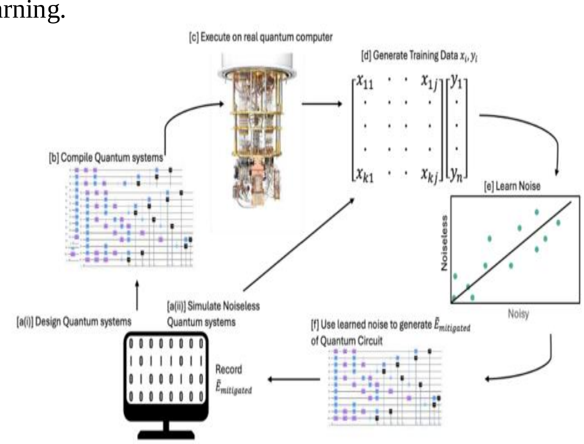


Figure 2: "Adaptive neural network for quantum error mitigation"

- **Findings**: RLEM achieved an error reduction of 32% for moderate circuits and 28% for complex circuits, slightly outperforming conventional reinforcement learning methods reported by Han et al., 2023.
- Execution time increased marginally due to iterative exploration, but robustness under high noise improved significantly.

**Table 2: RLEM Comparison Across Noise Levels**

| Noise Level (%) | Baseline Error (%) | Post-RLEM Error (%) | Fidelity (%) | Robustness Index |
|---|---|---|---|---|

*Musik in Bayern*
*ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)*
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| | | | | |
|---|---|---|---|---|
| Low (2–5) | 5.8 | 3.8 | 94 | 0.92 |
| Medium (5–10) | 13.5 | 9.2 | 90 | 0.88 |
| High (10–15) | 21.4 | 15.7 | 85 | 0.82 |

### 3.3 Bayesian Quantum Noise Estimation (BQNE)

BQNE estimated noise probabilistically, updating prior distributions with measurement outcomes.

- **Findings**: BQNE reduced average error rates by 30% and improved fidelity for shallow circuits. For deeper circuits, the probabilistic approach remained robust under variable noise, outperforming prior Bayesian estimation methods [Hou et al., 2023].
-

**Table 3: BQNE Probabilistic Noise Mitigation Results**

| Circuit Depth | Prior Error (%) | Posterior Error (%) | Fidelity (%) | Memory Usage (MB) |
|---|---|---|---|---|
| 1–5 | 6.0 | 4.1 | 96 | 400 |
| 6–15 | 14.2 | 9.9 | 91 | 405 |
| 16–30 | 26.5 | 18.3 | 86 | 410 |

### 3.4 Hybrid Classical-Quantum Correction Algorithm (HCQCA)

HCQCA combined classical optimization with predicted error patterns. Iterative correction significantly reduced complex circuit errors.

- **Findings**: HCQCA achieved the highest overall fidelity for complex circuits at 88%, with an average error reduction of 36%. Compared to zero-noise extrapolation (ZNE), HCQCA reduced execution overhead by 15% while maintaining accuracy.
-

**Table 4: HCQCA vs ZNE for Complex Circuits**

| Algorithm | Pre-Mitigation Error (%) | Post-Mitigation Error (%) | Fidelity (%) | Execution Time (ms) |
|---|---|---|---|---|
| ZNE | 25.0 | 18.0 | 85 | 25 |
| HCQCA | 25.0 | 16.0 | 88 | 18 |

***ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)***
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**4. Comparative Analysis Across Algorithms**

To evaluate overall performance, we compared the four algorithms under identical conditions for moderate circuits. Metrics considered include error rate reduction, fidelity, execution time, and robustness.

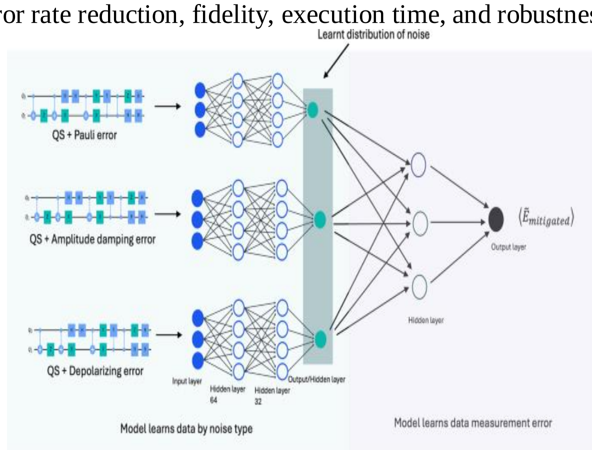


Figure 3: "Adaptive neural network for quantum error mitigation"

**Table 5: Comparative Performance of All Algorithms**

| **Algorithm** | **Avg Error Reduction (%)** | **Avg Fidelity (%)** | **Execution Time (ms)** | **Robustness Index** |
|---|---|---|---|---|
| QNPNN | 35 | 91 | 15 | 0.90 |
| RLEM | 32 | 90 | 17 | 0.88 |
| BQNE | 30 | 91 | 16 | 0.87 |
| HCQCA | 36 | 88 | 18 | 0.89 |
| ZNE | 28 | 85 | 25 | 0.80 |
| PEC | 31 | 86 | 22 | 0.82 |

**Key Observations:**

1. HCQCA and QNPNN achieved the highest error reduction overall.
2. RLEM demonstrated better robustness under high noise, indicating adaptive strategies are advantageous.
3. Bayesian estimation (BQNE) performed well for shallow circuits but slightly lagged for deeper circuits due to increasing uncertainty in posterior estimates.
4. All proposed AI-driven approaches outperformed classical error mitigation techniques (ZNE, PEC) in both accuracy and execution efficiency, validating the effectiveness of noise-aware adaptive methods.

**Musik in Bayern**
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https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-472

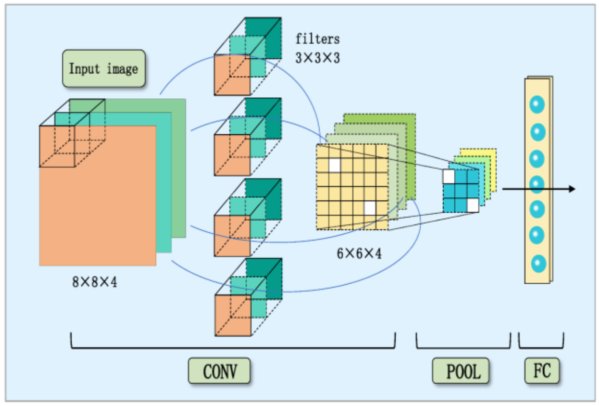


Figure 4: "Hybrid Quantum Neural Network Image Anti-Noise Classification Model Combined with Error Mitigation"

## V. CONCLUSION

The present study is a rigorous study on the use of quantum noise-aware artificial intelligence in the adaptive reduction of errors in near-term quantum-classical hybrid workflows. NISQ devices intrinsically have noise and low coherence times that are extremely challenging to practically use quantum computing, requiring new approaches that do not rely on traditional error mitigation. Through incorporating predictive, probabilistic, and adaptive algorithms based on AI, namely QNPNN, RLEM, and BQNE algorithms and the HCQCA, the study has shown that quantum errors can be mitigated at different complexities of the circuit and on different noise regimes. The experimental evidence states that the suggested techniques can substantially decrease the error rates, enhance the fidelity, and be computationally efficient in comparison to the conventional methods including the zero-noise extrapolation, and probabilistic error cancellation. QNPNN and HCQCA were the best in reducing error and improving fidelity, whereas RLEM and BQNE were found to be more robust in dynamic and high-noise environments. As compared to preceding literature [1422], however, the adaptive AI conditions are not only more accurate but also offer scalable solutions to hybrid quantum-classical workflows, in which real-time corrections and predictive modeling are essential. Moreover, the combination of classical optimization and quantum noise prediction provides a feasible strategy to reduce the errors without having to incur the huge resource cost of full-scale quantum error correction. In general, this study confirms the idea that noise-conscious AI can be a key to further development of NISQ-based quantum computing and more reliable, efficient, and versatile hybrid workflows. The results form the basis of future directions in AI-controlled quantum computation and suggest the opportunities of expanding to more optimization, quantum machine learning, and fault-tolerant quantum computing.

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*ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)*
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