



Thermodynamic Cost of Learning in Variational Quantum Machines: An Information-Theoretic Framework

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Abstract

The emergence of variational quantum machines (VQMs) has introduced new paradigms for quantum learning by combining quantum computational advantages with classical optimization strategies. However, the physical resources required during the learning process remain insufficiently understood, particularly from the perspective of thermodynamic efficiency. This study develops an information-theoretic framework to analyze the thermodynamic cost of learning in variational quantum systems by establishing relationships between information acquisition, parameter optimization, entropy variation, and energy dissipation. The proposed framework integrates principles from quantum information theory and nonequilibrium thermodynamics to quantify the minimum energetic requirements associated with updating quantum models during training. The analysis demonstrates that learning efficiency in VQMs is fundamentally constrained by information processing limits, where reductions in uncertainty and improvements in model performance correspond to measurable thermodynamic expenditures. The framework provides a theoretical foundation for evaluating the sustainability and scalability of future quantum learning architectures. This research contributes a new perspective by linking quantum machine learning performance with physical resource consumption, offering insights for designing energy-efficient quantum artificial intelligence systems.

Keywords: Information Theory, Quantum Machine Learning, Thermodynamic Cost



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INTRODUCTION

The rapid development of quantum computing has significantly transformed the landscape of artificial intelligence by introducing computational paradigms that exploit the fundamental principles of quantum mechanics (Maimaitiabdulla et al., 2027; Ur Rehman & Lin, 2026; W. Wang et al., 2026). Unlike classical computing systems that process information through binary states, quantum systems utilize superposition, entanglement, and quantum interference to represent and manipulate information within high-dimensional spaces. These unique characteristics have stimulated the emergence of quantum machine learning (QML), an interdisciplinary research field that integrates quantum information processing with machine learning methodologies. Among various approaches in QML, variational quantum machines (VQMs) have attracted substantial attention because of their compatibility with current noisy intermediate-scale quantum (NISQ) technologies. By combining parameterized quantum circuits with classical optimization algorithms, VQMs provide a flexible framework for addressing complex computational problems, including classification, optimization, generative modeling, and quantum simulation. However, despite significant advances in improving computational performance, the fundamental physical resources required during the quantum learning process remain insufficiently understood.

The evaluation of learning systems has traditionally emphasized computational performance indicators, such as accuracy, convergence speed, model complexity, and scalability. In conventional artificial intelligence research, optimization efforts have mainly focused on increasing predictive capability while reducing computational requirements. Nevertheless, the rapid expansion of large-scale machine learning models has revealed that computational efficiency cannot be separated from energy consumption and physical resource limitations. Modern artificial intelligence infrastructures require enormous amounts of electricity for computation, storage, and cooling, creating concerns regarding sustainability and long-term technological feasibility (Aamir et al., 2026; Hong & Medina, 2026; Liu et al., 2026). This situation has encouraged researchers to reconsider the relationship between information processing and physical resources, emphasizing the importance of thermodynamic perspectives in understanding the fundamental limitations of intelligent systems.

The relationship between information and thermodynamics was fundamentally established through Landauer's principle, which demonstrated that information processing has unavoidable physical consequences. According to this principle, the irreversible erasure of information requires a minimum amount of energy dissipation proportional to the environmental temperature (Chelikowsky et al., 2026; Delhibabu, 2026; Guo et al., 2026). This discovery challenged the traditional view that information exists independently from physical reality and established information as a physical quantity governed by thermodynamic laws. Subsequent developments in nonequilibrium thermodynamics, stochastic thermodynamics, and information theory have further demonstrated that processes such as inference, adaptation, and learning involve energetic costs associated with uncertainty reduction and information transformation. These theoretical developments provide a foundation for investigating whether artificial learning systems, including quantum-based architectures, operate under similar physical constraints.

Variational quantum machines represent a particularly important domain for examining the thermodynamic implications of learning because their operational mechanisms involve continuous cycles of information processing and physical transformation (Abeng, 2026; Adel et al., 2026; Ebere Enyoh & Wang, 2025). During the training process, VQMs repeatedly prepare quantum states, perform measurements, evaluate objective functions, and update circuit parameters through classical optimization procedures. Each optimization iteration contributes to improving the informational representation of the model while simultaneously involving physical operations that may generate entropy and energy dissipation. Although parameter optimization improves learning performance, the associated physical costs remain largely

unexplored. Therefore, investigating the thermodynamic characteristics of VQM learning processes is essential for determining whether quantum machine learning systems can achieve sustainable scalability in practical applications.

Existing research in quantum machine learning has primarily concentrated on algorithmic development, quantum advantage, circuit optimization, and error mitigation techniques. Numerous studies have explored how variational quantum algorithms can improve computational efficiency and overcome limitations associated with classical machine learning approaches (Hosamo et al., 2025; Z.-H. Wang et al., 2026; Xiao et al., 2026). However, these investigations frequently evaluate performance based on computational outcomes without considering the energetic implications of the learning process. The assumption that quantum computing inherently provides greater efficiency may not always be valid because quantum systems introduce additional requirements, including quantum state preparation, measurement overhead, environmental control, and optimization complexity. Consequently, a comprehensive evaluation of quantum learning systems requires a broader perspective that integrates computational capability with physical resource consumption.

A significant theoretical gap exists in the absence of a systematic framework that connects quantum learning dynamics with thermodynamic principles. Although information theory has been extensively applied to analyze uncertainty, representation learning, and model optimization, its relationship with energy expenditure in quantum learning environments remains underdeveloped (Biswas et al., 2026; Han et al., 2026; Muttumthala & Kiani, 2026). Current approaches often examine quantum information properties and thermodynamic characteristics as separate domains rather than as interconnected processes. However, learning fundamentally involves reducing uncertainty, extracting meaningful information, and modifying internal representations based on acquired knowledge. These transformations suggest that quantum learning should be understood not only as an algorithmic process but also as a physical information-processing phenomenon.

An information-theoretic perspective provides a valuable approach for analyzing the thermodynamic cost of learning because it allows learning processes to be interpreted as transformations of information states (Akrom et al., 2026; Sai et al., 2026; Selvaraj et al., 2026). Concepts such as entropy reduction, mutual information, and information compression have been widely used to describe how machine learning systems extract relevant patterns from complex datasets. When combined with thermodynamic principles, these concepts provide a theoretical pathway for quantifying the relationship between information gain and energy consumption. In the context of variational quantum machines, such an approach may reveal how improvements in learning performance correspond to physical costs associated with quantum state manipulation and parameter optimization.

The analysis of thermodynamic processes in quantum systems presents additional challenges due to the unique characteristics of quantum information (Bathula & Misra, 2026; Huang et al., 2026; Zhang et al., 2026). Unlike classical systems, quantum states cannot be directly observed without measurement-induced disturbance, and information is encoded through probabilistic amplitudes rather than deterministic variables. Furthermore, quantum coherence and entanglement introduce complex relationships between information content, entropy variation, and physical energy exchange. These properties require theoretical approaches that integrate quantum information theory with thermodynamic analysis. Developing such approaches is necessary to understand the fundamental principles governing the efficiency of quantum learning mechanisms.

The importance of studying thermodynamic costs in variational quantum machines extends beyond theoretical considerations and has practical implications for future quantum artificial intelligence development (Jayan K. & Babu, 2025; Rahmati et al., 2026; Xin & Xing, 2025). As quantum technologies progress toward larger-scale implementations, energy efficiency will become a critical factor affecting deployment and sustainability. Quantum

processors may provide computational advantages, but these benefits must be evaluated alongside the physical requirements of cooling systems, control mechanisms, and repeated measurement operations. Understanding the energetic foundations of quantum learning can assist researchers in designing architectures that achieve optimal balance between computational performance and physical efficiency.

Furthermore, incorporating thermodynamic considerations introduces a new dimension for evaluating learning efficiency (Choudhury & Ghosh, 2025; Kherra et al., 2025; Thomas et al., 2026). Conventional machine learning evaluation generally focuses on predictive accuracy and computational complexity, yet two models with comparable accuracy may require substantially different physical resources during training. Therefore, evaluating quantum learning systems solely through performance metrics provides an incomplete understanding of their efficiency. Thermodynamic indicators offer an alternative perspective by examining the relationship between information improvement and energy expenditure. This approach enables the development of more sustainable learning architectures that optimize not only computational results but also resource utilization.

This study addresses the existing theoretical limitation by proposing an information-theoretic framework for analyzing the thermodynamic cost of learning in variational quantum machines (Chen et al., 2026; Chern et al., 2026; Shi et al., 2026). The framework conceptualizes quantum learning as a physical information transformation process in which knowledge acquisition, uncertainty reduction, and parameter optimization are accompanied by measurable thermodynamic consequences. By integrating principles from quantum information theory and nonequilibrium thermodynamics, this research seeks to establish a theoretical foundation for understanding the minimum physical resources required during quantum learning processes.

The novelty of this research lies in positioning thermodynamic cost as an intrinsic component of quantum learning rather than merely an external engineering constraint. Previous studies have primarily investigated how quantum algorithms improve computational capability, whereas this study examines how learning itself is physically constrained by information and energy relationships. Through the integration of entropy analysis, information measures, and thermodynamic principles, the proposed framework provides a new perspective for evaluating the sustainability and efficiency of quantum artificial intelligence systems.

The development of such a framework contributes to broader discussions regarding responsible artificial intelligence and sustainable computing. As artificial intelligence systems become increasingly powerful, concerns regarding energy consumption, environmental impact, and computational sustainability continue to grow. Quantum computing is often regarded as a promising solution for overcoming classical computational limitations; however, its long-term success depends on understanding its physical requirements. A thermodynamic perspective enables researchers to evaluate quantum intelligence not only according to computational power but also according to its ability to process information efficiently within fundamental physical constraints.

Based on these considerations, this study aims to investigate the thermodynamic cost of learning in variational quantum machines from an information-theoretic perspective. Specifically, the research explores the conceptual relationship between information acquisition, entropy variation, parameter optimization, and energy dissipation during quantum learning processes. By establishing connections between quantum information theory and thermodynamic principles, this study provides a theoretical foundation for future empirical investigations and algorithmic developments in energy-efficient quantum machine learning.

Ultimately, this research advances the understanding of quantum artificial intelligence by emphasizing that learning capability should be evaluated through both computational effectiveness and physical efficiency. The integration of thermodynamics and information theory offers a comprehensive paradigm for analyzing quantum learning systems as physical

processes governed by fundamental laws. Through the proposed framework, this study contributes to the development of sustainable quantum machine learning architectures capable of balancing intelligence, computational performance, and energetic responsibility.

RESEARCH METHOD

Research Design

This research was conducted from January to August 2026 through theoretical investigation, analytical modeling, and synthesis of scientific literature related to quantum machine learning, quantum information theory, and thermodynamics. Since this study is conceptual and theoretical in nature, it does not involve a specific physical research location or experimental laboratory (Altuijri & Abdel-Aty, 2026; Kurban et al., 2026; Li et al., 2026). The research activities were carried out through systematic examination of scientific publications, theoretical frameworks, and mathematical formulations obtained from internationally recognized journals, conference proceedings, and academic databases focusing on quantum computing and artificial intelligence.

Research Target/Subject

The research target of this study is the learning mechanism of variational quantum machines, particularly the relationship between information processing and thermodynamic expenditure during model optimization. The primary subject of analysis is the variational learning process, which includes quantum state preparation, parameter adjustment, measurement operations, and iterative optimization procedures.

The research does not involve human participants, experimental subjects, or biological samples. Instead, the object of study consists of theoretical constructs, including quantum states, information entropy, optimization parameters, and thermodynamic variables associated with quantum learning processes. The selection of VQMs as the research subject is based on their significant role in current quantum machine learning development and their suitability for analyzing the interaction between computational learning mechanisms and physical resource limitations.

Research Procedure

The research procedure was conducted through several sequential stages to construct the proposed information-theoretic framework. The first stage involved identifying fundamental concepts and theoretical assumptions related to variational quantum machines, quantum learning mechanisms, entropy, information processing, and thermodynamic constraints. Relevant theories were reviewed to establish the conceptual foundation of the research.

The second stage involved analyzing the relationship between learning dynamics and thermodynamic principles. In this stage, the study examined how information acquisition, uncertainty reduction, and parameter optimization within VQMs can be interpreted as physical information-processing activities. The analysis focused on identifying possible relationships between changes in informational states and corresponding thermodynamic costs.

The third stage involved developing a conceptual mathematical framework that integrates information-theoretic measures with thermodynamic quantities. Variables such as entropy change, information gain, energy dissipation, and optimization progress were examined to formulate a theoretical representation of learning cost. The framework was then evaluated through theoretical consistency analysis by comparing the proposed relationships with established principles in quantum information theory and nonequilibrium thermodynamics.

The final stage involved interpreting the theoretical implications of the framework and identifying its potential contributions to the development of energy-efficient quantum artificial intelligence systems. This stage also included identifying limitations and proposing directions for future empirical studies.

Instruments, and Data Collection Techniques

The instruments used in this research consist of theoretical analysis frameworks, mathematical formulations, and scientific literature review protocols. Since this study does not involve experimental data collection, the primary data source consists of secondary theoretical data obtained from peer-reviewed scientific articles, academic books, and research reports related to quantum computing, quantum machine learning, information theory, and thermodynamics.

Data collection was conducted through a systematic literature analysis approach. Relevant publications were identified based on their contribution to understanding quantum learning mechanisms, thermodynamic principles of information processing, and theoretical models of computational efficiency. The collected literature was analyzed to extract fundamental concepts, mathematical relationships, and theoretical assumptions necessary for constructing the proposed framework.

The main categories of collected information include: (1) principles of variational quantum algorithms and parameter optimization, (2) quantum information measures such as entropy and mutual information, (3) thermodynamic concepts related to energy dissipation and irreversible computation, and (4) previous approaches for evaluating computational efficiency in artificial intelligence systems.

Data Analysis Technique

The data analysis technique employed in this study is qualitative theoretical analysis combined with conceptual synthesis and mathematical interpretation. The collected theoretical information was analyzed through comparative examination to identify relationships between quantum learning processes and thermodynamic principles. The analysis focused on determining how information changes occurring during learning can be interpreted as thermodynamic transformations.

The analytical process involved three main steps. First, theoretical concepts from quantum machine learning and thermodynamics were examined separately to identify their fundamental assumptions and limitations. Second, these concepts were integrated to establish a relationship between information gain and thermodynamic cost during the optimization process of variational quantum machines. Third, the resulting framework was evaluated based on theoretical coherence, consistency with existing scientific principles, and its potential contribution to sustainable quantum artificial intelligence research.

The interpretation of findings was conducted by assessing how the proposed framework explains the physical requirements of learning processes in VQMs. Through this analysis, the study aims to provide a theoretical foundation for understanding the minimum energetic requirements of quantum learning and supporting the future development of thermodynamically efficient quantum machine learning architectures.

RESULTS AND DISCUSSION

The analysis conducted in this study resulted in an information-theoretic framework that conceptualizes learning in variational quantum machines (VQMs) as a physical process involving information acquisition, uncertainty reduction, and thermodynamic transformation. Unlike conventional machine learning perspectives that primarily evaluate learning based on predictive accuracy and computational complexity, the proposed framework considers learning efficiency as a relationship between the amount of useful information acquired by the system and the physical resources required to achieve such improvement.

The theoretical analysis indicates that the learning process in VQMs can be represented as a sequence of transformations involving quantum state preparation, parameter optimization,

measurement, and information updating. Each stage contributes to the reduction of uncertainty within the model while simultaneously producing physical consequences associated with entropy change and energy dissipation. Therefore, learning improvement cannot be considered independent from thermodynamic limitations because every modification of the quantum system represents a physical transition between informational states.

The relationship between informational gain and thermodynamic expenditure is formulated through the principle that increased knowledge acquisition requires corresponding physical resources. In this framework, the efficiency of quantum learning is not determined solely by the final performance of the model but also by how effectively the system converts available energy into useful information. The proposed conceptual relationship can be expressed as the ratio between information gain (ΔI) and thermodynamic cost (ΔE), where higher values indicate more efficient learning processes.

$$\eta_L = \frac{\Delta I}{\Delta E}$$

where η_L represents learning thermodynamic efficiency, ΔI represents the improvement in informational content obtained during training, and ΔE represents the energy expenditure required for achieving such improvement.

The formulation demonstrates that an optimal quantum learning system should maximize information acquisition while minimizing unnecessary energy dissipation. This perspective introduces a new criterion for evaluating VQMs by extending traditional machine learning evaluation metrics toward physically grounded efficiency measurements.

Table 1. Relationship Between Learning Components and Thermodynamic Variables in Variational Quantum Machines

o.	Learning Component		Information-Theoretic Aspect		Thermodynamic Implication	
	Quantum Preparation	State Initial encoding	information		Energy requirement for quantum state initialization	
	Parameter Optimization	Reduction of uncertainty	of model		Entropy modification during learning	
	Quantum Measurement	Information extraction			Physical disturbance and energy expenditure	
	Parameter Updating	Knowledge adaptation			Irreversible information processing cost	
	Model Convergence	Information stabilization			Minimum thermodynamic requirement for learning	

The results presented in Table 1 demonstrate that each learning component in VQMs has a corresponding thermodynamic implication. Quantum state preparation requires physical energy to establish the initial computational condition, while parameter optimization represents a continuous process of information refinement accompanied by entropy transformation. Measurement operations, although essential for extracting information from quantum states, introduce additional physical costs because quantum measurement is inherently associated with state disturbance.

The second major finding of this research is the identification of entropy reduction as a fundamental indicator of learning progress in VQMs. In machine learning systems, successful learning generally involves reducing uncertainty regarding patterns contained within data. From an information-theoretic perspective, this process corresponds to a decrease in entropy as the model becomes increasingly capable of representing relevant information.

In quantum learning environments, entropy reduction is closely connected with the modification of quantum states during optimization. As the variational parameters approach

optimal configurations, the uncertainty associated with model predictions decreases. However, according to thermodynamic principles, such reduction of uncertainty cannot occur without physical consequences. The transformation of information states requires energy exchange between the quantum system and its surrounding environment.

The relationship between entropy variation and energy cost can be theoretically represented through:

$$\Delta E \geq k_B T \Delta S$$

where ΔE represents the minimum energy requirement, k_B represents Boltzmann’s constant, T represents absolute temperature, and ΔS represents entropy variation. This relationship indicates that greater entropy manipulation during learning may require greater thermodynamic resources.

This finding challenges the assumption that improved computational performance automatically corresponds to improved efficiency. A quantum model may achieve high accuracy while still operating inefficiently if excessive energy is consumed during the learning process. Therefore, thermodynamic analysis provides an additional dimension for evaluating quantum learning architectures.

The third finding of this study is the integration of information bottleneck principles into the analysis of thermodynamic costs in VQMs. Traditional information bottleneck theory explains learning as a process of preserving relevant information while eliminating unnecessary information from input representations. This principle is highly relevant for quantum learning because quantum systems possess extremely large state spaces that may introduce unnecessary computational complexity.

The proposed framework suggests that efficient quantum learning requires selective information retention rather than maximum information processing. Excessive information manipulation may increase thermodynamic costs without providing meaningful improvements in learning performance. Therefore, an efficient VQM should identify the minimum informational representation necessary for achieving optimal task performance.

The relationship between information compression and thermodynamic efficiency is summarized in Table 2.

Table 2. Information Compression and Thermodynamic Implications in VQM Learning

o.	Information Process	Learning Effect		Thermodynamic Consequence	
	Information Encoding	Representation of input patterns		Initial energy consumption	
	Feature Selection	Removal of irrelevant information		Reduction of unnecessary computation	
	Parameter Optimization	Improvement of representation quality		Additional energy expenditure	
	Information Compression	Efficient knowledge storage		Reduced thermodynamic cost	
	Final Representation	Stable learned state		Minimum requirement	operational

The results indicate that information compression has an important role in reducing thermodynamic costs. Unlike approaches that attempt to maximize computational capacity, the proposed framework emphasizes that efficient quantum intelligence depends on achieving an optimal balance between information preservation and physical resource consumption.

Based on the previous analyses, this study proposes an integrated framework for evaluating the thermodynamic cost of learning in variational quantum machines. The framework combines three fundamental dimensions: information gain, learning complexity,

and energy expenditure. These dimensions provide a broader perspective for understanding quantum learning efficiency.

The proposed framework can be described as follows:

$$TC_L = f(\Delta, S, \Delta, ICE)$$

where TC_L represents the thermodynamic cost of learning, ΔS represents entropy variation, ΔI represents information gain, C represents computational complexity, and E represents energy expenditure.

The framework suggests that thermodynamic cost is influenced not only by physical energy consumption but also by the amount of information transformation required during learning. A quantum model requiring extensive parameter updates and repeated measurements may achieve high accuracy but incur greater thermodynamic costs.

This theoretical contribution represents the primary novelty of the research because previous studies have generally examined quantum machine learning from algorithmic and computational perspectives. The proposed framework extends existing discussions by introducing thermodynamics as a fundamental evaluation dimension for quantum intelligence.

The findings of this research have important implications for the future development of sustainable quantum artificial intelligence. As quantum computing technologies continue to advance, the ability to evaluate systems based on both computational performance and physical efficiency will become increasingly important. The proposed framework provides a foundation for designing quantum learning architectures that minimize unnecessary energy expenditure while maintaining effective information processing.

The results also suggest that future quantum algorithms should incorporate thermodynamic awareness during optimization (Aurangzeb et al., 2025; Bueno, 2025; Xiong & Yin, 2026). Instead of focusing exclusively on reducing circuit depth or improving accuracy, researchers should consider strategies that optimize the relationship between information gain and energy consumption. Such approaches may contribute to the development of environmentally sustainable quantum computing technologies.

Furthermore, the framework provides theoretical guidance for future empirical studies. Experimental investigations may validate the proposed relationships by measuring energy consumption, entropy variation, and information improvement during actual VQM training processes (Jaouane et al., 2026; Khan et al., 2026; Raja et al., 2026). Therefore, this study establishes a conceptual bridge between quantum information theory, thermodynamics, and practical quantum machine learning implementation.

The main novelty of this study lies in introducing an information-theoretic framework that interprets learning in variational quantum machines as a thermodynamic process (Goumri-Said & Kanoun, 2026; Sibille et al., 2026; Zhou & Gao, 2026). While previous research has mainly focused on improving quantum algorithm performance, this study emphasizes that learning efficiency must also consider the physical cost required to acquire and process information.

The proposed framework contributes three theoretical advances. First, it integrates quantum learning mechanisms with thermodynamic principles by conceptualizing parameter optimization as a physical information transformation process. Second, it introduces thermodynamic efficiency as an additional criterion for evaluating quantum learning performance. Third, it provides a foundation for developing energy-aware quantum artificial intelligence systems.

Therefore, the findings demonstrate that the future of quantum machine learning should not only pursue computational superiority but also address fundamental questions regarding physical sustainability. Understanding the thermodynamic cost of learning represents an essential step toward developing quantum systems capable of achieving intelligence within the constraints imposed by the laws of physics.

CONCLUSION

This study developed an information-theoretic framework to analyze the thermodynamic cost of learning in variational quantum machines (VQMs). The findings demonstrate that quantum learning should not be evaluated solely based on computational performance, accuracy, or convergence capability, but also through the perspective of physical resource consumption. The proposed framework shows that learning in VQMs represents a physical information transformation process in which information acquisition, entropy reduction, parameter optimization, and energy dissipation are fundamentally interconnected.

The theoretical analysis reveals that improvements in quantum learning performance are accompanied by thermodynamic consequences because reducing uncertainty and increasing information representation require physical resources. The relationship between information gain and energy expenditure provides a new perspective for measuring learning efficiency, where an optimal quantum learning system should maximize useful information acquisition while minimizing unnecessary energy dissipation. Furthermore, the integration of information bottleneck principles indicates that efficient quantum intelligence does not depend on processing the maximum amount of information but rather on extracting and preserving the most relevant information with minimum physical cost.

The main contribution of this research is the introduction of thermodynamic cost as an intrinsic dimension of quantum machine learning evaluation. Unlike previous approaches that mainly emphasize algorithmic improvement and computational advantages, this study expands the evaluation framework by incorporating fundamental physical constraints governing information processing. The proposed model provides a conceptual foundation for developing energy-aware quantum learning architectures and offers theoretical insights into the sustainability of future quantum artificial intelligence systems.

Although this research provides a theoretical framework, further empirical validation is required through experimental implementation on quantum hardware platforms. Future studies may investigate measurable relationships between quantum circuit operations, energy consumption, entropy variation, and learning performance. Additionally, the proposed framework can be extended by incorporating real-time thermodynamic measurements and optimization algorithms designed specifically to minimize the energetic cost of quantum learning. Such developments will contribute to the advancement of sustainable quantum computing technologies that balance computational intelligence with physical efficiency.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the authors used ChatGPT, developed by OpenAI, to assist with language refinement, grammatical correction, academic writing organization, and improvement of the clarity and coherence of the manuscript. All AI-assisted content was carefully reviewed, verified, and revised by the authors. The authors take full responsibility for the accuracy, originality, integrity, and final content of this publication.

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AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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