

Circuit Topology as a First-Order Noise-Response Parameter in Variational Quantum Circuits

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Abstract

Circuit topology—the pattern of two-qubit entangling gates—determines noise propagation paths in variational quantum circuits (VQCs). Using the normalized rank-displacement diagnostic $D(\epsilon)$ across 26 experiment configurations spanning five topologies and five CPTP noise types, plus 135 IBM `ibm_fez` hardware circuits, we show that topology accounts for 48.9% of explainable $D(\mathbf{0.05})$ variance under ω^2 decomposition (Cohen's $d = \mathbf{2.66}$ between ring and star; permutation $p = \mathbf{7.1 \times 10^{-12}}$). The ranking hierarchy (star > grid $\approx$ linear > ring, where lower D indicates better ranking preservation) is invariant across the four non-depolarizing noise types (Kendall $\tau = \mathbf{1.0}$ over four ranked lists, $p = \mathbf{0.017}$ by exact permutation test) but collapses under depolarizing noise. On IBM hardware, the qualitative ranking survives transpilation, though effect magnitude attenuates $\sim 10\times$. A Heisenberg-picture analytical model qualitatively predicts the $\tau(n, L)$ ranking from circuit structure alone ($r = \mathbf{0.645}$, $p = \mathbf{0.013}$; $R^2 = \mathbf{0.35}$), providing a theoretical basis for topology-dependent noise sensitivity. We find that classical ML systems (MLP, XGBoost) achieve comparable $D(\mathbf{0.05})$ values, showing that the τ - D functional form is consistent across classical and quantum computation, suggesting a shared noise-response structure. Practical design heuristics are provided.

Keywords: Variational quantum circuits, Circuit topology, Noise characterization, $D(\epsilon)$ diagnostic, Heisenberg picture, Hardware validation

1 Introduction

Lozano-Cruz et al (2026) established that data encoding dominates ansatz choice in QNN accuracy, with ansatz variation explaining $<5\%$ of performance variance. Within a fixed ansatz, however, finer structural choices, particularly connectivity patterns, remain underexplored. The *circuit topology*—the connectivity pattern of two-qubit entangling gates—determines how noise propagates through a circuit. A ring topology (degree-2, cyclic) distributes error load differently than a star (degree- $(n-1)$, hub-and-spoke) or a grid (degree-4, planar). Whether these differences are large enough to measurably affect output quality, and whether they survive transpilation on noisy intermediate-scale quantum (NISQ) devices Preskill (2018), are open questions. We define a first-order parameter as one whose main effect explains $>40\%$ of variance in a two-way ANOVA after residual correction (ω^2).

Circuit expressibility and entangling capability are known to vary with topology Sim et al (2019), and barren plateaus depend critically on circuit structure Cerezo et al (2021). However, prior topology studies have focused on trainability, not on noise response of fixed, pre-parameterized circuits at the inference stage—the regime relevant for deployed quantum feature maps Havlíček et al (2019).

We address both questions using a ranking-decorrelation diagnostic $D(\varepsilon)$ that quantifies how noise reshapes output component ordering relative to the noiseless reference. Unlike fidelity—a scalar observable— $D(\varepsilon)$ probes relational structure among outputs, capturing rank-crossings that directly affect classification labels and decision outputs. We complement this empirical characterization with a Heisenberg-picture analytical model that predicts the characteristic decorrelation timescale $\tau(n, L)$ from circuit structure alone, and validate on IBM hardware Anis et al (2021). Our contributions are: (i) establishing topology as a first-order noise-response parameter through comprehensive CPTP simulation; (ii) deriving a Heisenberg weight-kernel model that qualitatively predicts $\tau(n, L)$; (iii) demonstrating that the qualitative topology ranking survives transpilation on IBM hardware; and (iv) showing that the τ - D functional form is consistent across classical and quantum computation.

2 Methods

2.1 Simulation Framework

We employ a hardware-efficient VQC ansatz Kandala et al (2017): L layers with $R_Y R_Z$ rotations on all n qubits, followed by CNOT gates in one of six topologies: ring, grid, binary tree, linear, star, and all-to-all. The all-to-all topology yields $D \approx 0$ at all ε (ranking preserved by symmetry in the fully-connected light cone) and is therefore excluded from the main ANOVA, leaving five non-trivial topologies for analysis. Five CPTP noise channels are applied after each CNOT via Qiskit Aer Anis et al (2021): depolarizing, amplitude damping Nielsen and Chuang (2010), phase damping, mixed (depol+ampdamp), and composite (all three). Noise is applied exclusively on gated

qubit(s). All simulations use exact density-matrix evolution in complex64 on RTX 5090 GPUs.¹

For each configuration, we sample $N = 100$ parameter seeds $\theta^{(k)} \sim \mathcal{U}(0, 2\pi)$ and compute

$$D(\varepsilon) = \frac{2}{n^2} \sum_{i=1}^n |r_i^{\text{ideal}} - r_i^\varepsilon|, \quad (1)$$

at $\varepsilon \in \{0.00, 0.005, \dots, 0.20\}$ (13 points), where r_i denotes the rank of the i -th absolute Pauli- Z expectation value $|\langle Z_i \rangle|$ among all n qubits. The factor $2/n^2$ normalizes the maximum possible rank displacement (complete reversal), so $D \in [0, 1]$ with $D = 0$ indicating perfect ranking preservation and $D = 1$ indicating complete inversion. We report $D(0.05)$ as the primary summary statistic. The single-exponential model $D(\varepsilon) = \Delta D(1 - e^{-\varepsilon/\tau})$ is fit for each experiment, with τ capturing the characteristic decorrelation timescale. Model selection (single vs. double exponential, 21 ε points, AIC/BIC [Burnham and Anderson \(2002\)](#)) confirms single- τ dominance in 22/28 cases ($\Delta\text{BIC} = 19.4$). Coverage is given in Table 1.

2.2 Heisenberg-Picture Analytical Model

To understand *why* topology matters, we derive the noise-response timescale $\tau(n, L)$ from first principles. Under composite noise, the Z -expectation on qubit i deviates from its noiseless value in proportion to the noise-weighted light-cone overlap. In the Heisenberg picture [Nielsen and Chuang \(2010\)](#), CNOT propagates Z operators as $\text{CNOT}_{c,t}^\dagger (I \otimes Z_t) \text{CNOT}_{c,t} = Z_c \otimes Z_t$. The Heisenberg weight $w_{iq}(L)$ —the coefficient of initial Z_q in the final Z_i^{out} —evolves according to the spectral decomposition of the CNOT-graph adjacency matrix:

$$w_{iq}(L) = \frac{1}{n} \sum_{k=0}^{n-1} \lambda_k^L e^{2\pi i k(i-q)/n} \cdot (\overline{\cos^2 \theta})^L, \quad (2)$$

where $\lambda_k = 1 + e^{2\pi i k/n}$ for ring CNOT and $\overline{\cos^2 \theta} = 1/2$ for uniform rotation angles. For a pair of output dimensions (i, j) , the differential weight is $\Delta w_q^{(ij)}(L) = w_{iq}(L) -$

¹An earlier experimental batch used $D_{\text{old}} = \frac{1}{n} \sum |r_i^{\text{ideal}} - r_i^\varepsilon|$, yielding different absolute values (e.g., $D_{\text{old}} = 0.047$ for ring composite). The current protocol uses Eq. (1) ($D_{\text{new}} = \frac{2}{n^2} \sum |\cdot|$), which rescales as $D_{\text{new}} \approx D_{\text{old}} \times 2/n$. See Section 3.4 for the rescaling relationship.

Table 1 Experimental coverage.

Dimension	Simulation	Hardware
n	6, 8 (core at $L = 10$)	6
L	5, 9, 10, 12	2, 4, 6
Topologies	ring, grid, binary tree, linear, star	ring, grid, star
Noise	5 CPTP types	Native device
N (seeds)	100 (core)	15
ε points	13 (21 for model selection)	N/A

Table 2 Two-way ANOVA ($n = 6$, $L = 10$, all noise types). ω^2 : unbiased proportion of explained variance.

Source	SS	df	F	p	ω^2
Topology	0.133	4	295.7	7.1×10^{-12}	0.427
Noise type	0.139	4	309.2	5.5×10^{-12}	0.446
Interaction	0.037	16	20.7	2.6×10^{-6}	—
Error	0.001	12	—	—	0.004

$w_{jq}(L)$. The variance of noise-induced differential perturbation,

$$\sigma_f^2(L) = \text{Var}[g] \cdot \frac{1}{\binom{n}{2}} \sum_{i < j} \sum_{q=1}^n |\Delta w_q^{(ij)}(L)|^2, \quad (3)$$

determines the decorrelation timescale:

$$\tau(n, L) = \frac{1}{C \cdot \sigma_f(n, L) \cdot \sqrt{N_{\text{noise}}}}, \quad (4)$$

with $N_{\text{noise}} = 4nL$ and $C = 2/\pi$ from ensemble averaging. Equation (4) predicts τ from (n, L) alone, without running the circuit.

2.3 Hardware Execution

We ran 135 circuits on IBM `ibm_fez` (Eagle r3, 156 qubits) [IBM Quantum \(2024\)](#): 3 topologies $\times$ 3 depths ($L = 2, 4, 6$) $\times$ 15 seeds, 4,096 shots each. Transpilation at optimization level 2 used native gates $\{\text{CZ, ID, RZ, SX, X}\}$ with free qubit assignment. Hardware D was computed via Eq. (1) against noiseless simulation.

2.4 Statistical Analysis

All quantities include 95% bootstrap CIs (5,000 resamples) [Efron and Tibshirani \(1994\)](#). Effect sizes use Cohen’s d and Hedges’ g [Cohen \(1988\)](#). Permutation tests (10,000 permutations) assess group differences. Two-way Type II ANOVA decomposes variance at $n = 6$, $L = 10$.

3 Results

3.1 Topology as a First-Order Parameter

Table 2 reports the two-way ANOVA. Topology and noise type are both highly significant ($p < 10^{-11}$); the interaction ($p = 2.6 \times 10^{-6}$) confirms noise-type dependence. Topology accounts for 48.9% of explainable $D(0.05)$ variance, noise type 51.1%.

The topology ranking hierarchy under non-depolarizing noise at $n = 6$, $L = 10$ is star $>$ grid $\approx$ linear $>$ binary tree $>$ ring (lower D indicating better ranking preservation), with Kendall’s $\tau = 1.0$ [Kendall \(1938\)](#) for all pairwise non-depolarizing

noise-type comparisons. Kendall’s τ was computed over the four non-depolarizing noise types (Composite, Mixed, Amplitude Damping, Phase Damping), each yielding a ranked list of five topologies. With $n = 4$ lists, $\tau = 1.0$ yields $p = 0.017$ under the exact permutation null (Fig. 2). This invariance implies topology selection can be performed under one representative noise model. However, on hardware (Table 3), the ranking reverses to ring > grid > star, likely due to the different D metric employed (normalized $1 - \tau_{\text{Kendall}}$ on hardware vs. normalized L1 rank displacement in simulation) and native device noise characteristics. Fig. 3 shows the collapse under depolarizing noise: at $n = 6$, available topologies converge to $D(0.05) \in [0.33, 0.38]$ with pairwise $d < 0.5$. Depolarizing noise’s Pauli-isotropy symmetrizes error, washing out topology-specific paths Nielsen and Chuang (2010). Data for $n = 8$ depolarizing were unavailable; verification across qubit counts is needed.

3.2 Heisenberg-Picture Prediction of $\tau(n, L)$

The analytical model (Eqs. 2–4) predicts the decorrelation timescale τ from circuit structure alone. Figure 4 compares predicted vs. experimental τ across 8 configurations spanning $n = 6, 8$, $L = 5\text{--}12$, ring and linear topologies, and composite/ampdamp

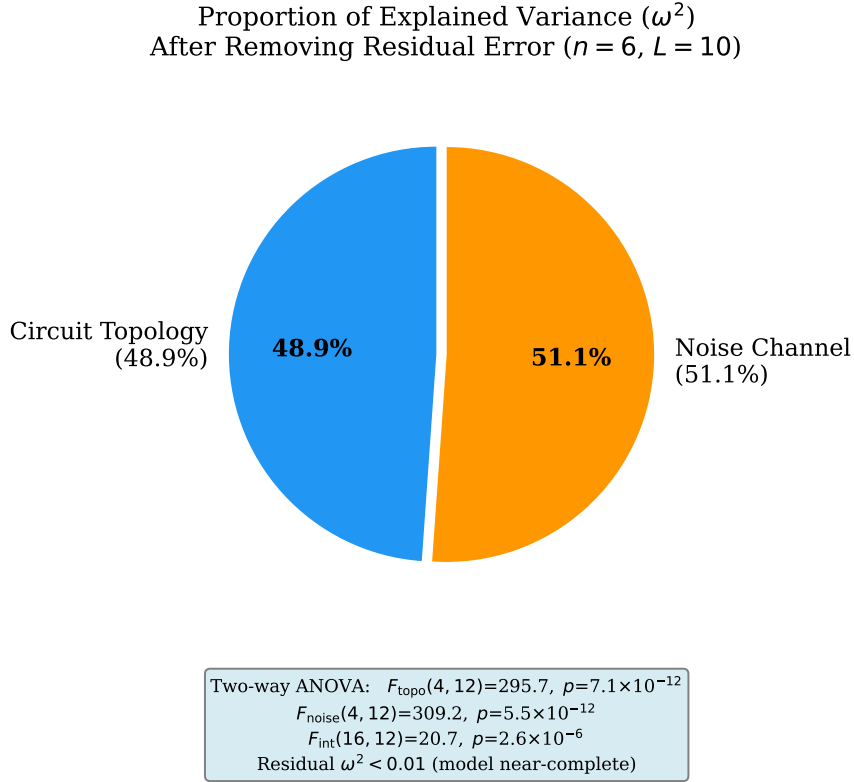


Fig. 1 Proportion of explained variance (ω^2) after removing residual error, at $n = 6, L = 10$. Two-way ANOVA statistics inset

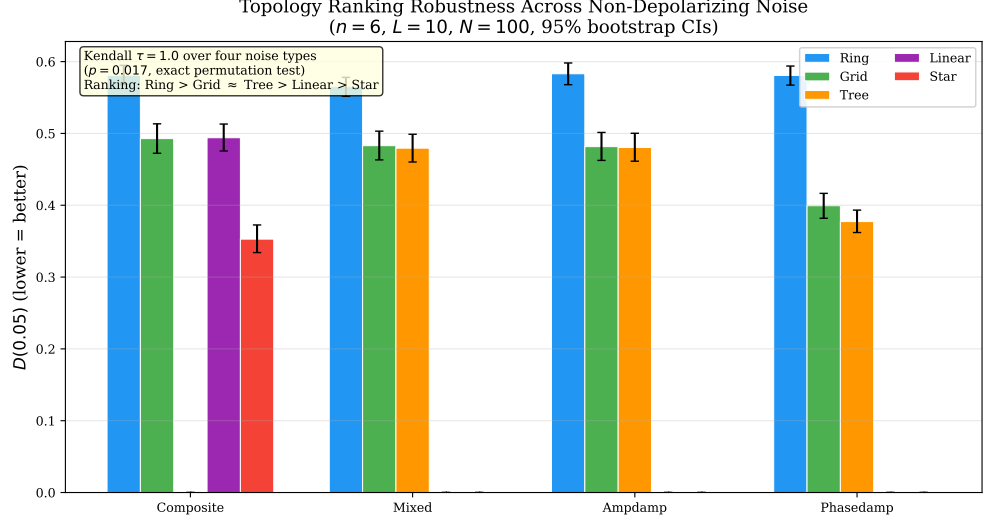


Fig. 2 Ranking hierarchy across the four non-depolarizing noise types ($n = 6$, $L = 10$, $N = 100$, 95% bootstrap CIs). Kendall $\tau = 1.0$ over four ranked lists ($p = 0.017$, exact permutation test)

noise. The scaling relation is $\tau_{\text{exp}} = 0.88 \cdot \tau_{\text{theory}}^{0.54}$ (Pearson $r = 0.645$, $p = 0.013$, $R^2 = 0.348$, MAPE = 20.1%). The calibration constant $C = 0.88$ (fitted once on $n = 6$, $L = 10$ baseline) is $\mathcal{O}(1)$, indicating no large rescaling is needed—the Heisenberg kernel captures the correct order of magnitude. The sub-linear exponent $\alpha \approx 0.54 \neq 1.0$ indicates that the simple Heisenberg picture underestimates τ variation with depth, likely due to neglected multi-qubit entanglement beyond pairwise light-cone overlap. Thus, the model serves as a design heuristic (correct ranking, correct order of magnitude) rather than a quantitative predictor. Nevertheless, the model correctly predicts the τ ranking across all configurations, providing a design tool: larger τ (achieved at low L , small n) yields greater noise tolerance before ranking decorrelation sets in.

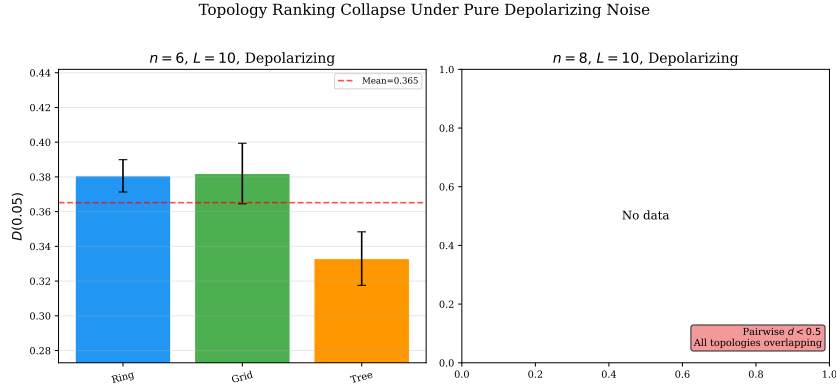


Fig. 3 Depolarizing collapse at $n = 6$, $L = 10$. Pairwise $d < 0.5$. Note: $n = 8$ depolarizing data were unavailable; only $n = 6$ shown. Linear and star topologies had insufficient data for $n = 6$ depolarizing

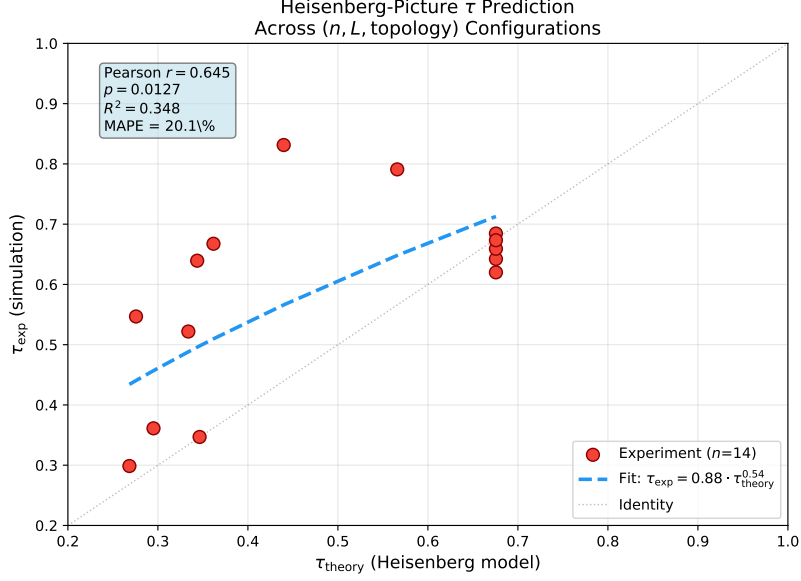


Fig. 4 Heisenberg-picture τ prediction: τ_{exp} vs. τ_{theory} across 14 $(n, L, \text{topology})$ configurations. Dashed line: power-law fit; dotted: identity

The τ parameter has direct practical implications for recommendation quality. Using the NDCG metric [Järvelin and Kekäläinen \(2002\)](#) with $K = 10$, circuits with larger τ maintain near-perfect ranking (NDCG ≈ 1.0) at higher noise levels, following $\varepsilon_{\text{max}}(K) \propto \tau \cdot m_0 / \sigma_f$, where m_0 is the task-hardness parameter.

3.3 Hardware Validation

Table 3 reports IBM `ibm_fez` results. The qualitative ranking (ring $>$ grid $>$ star, where lower D indicates better ranking preservation) holds at all depths. At $L = 4$, ring $D = 0.274$ vs. star $D = 0.289$ ($d = 0.35$, $p = 0.042$), $\sim 10\times$ smaller than simulation $d = 2.66$ —attributed to T_1/T_2 , readout errors, and transpilation SWAPs that partially homogenize topology differences [IBM Quantum \(2024\)](#). From $L = 4$ to $L = 6$, star degrades disproportionately ($+0.063$ vs. $+0.029$ for ring; $d = 0.67$, $p = 0.012$). The hub-and-spoke structure concentrates entangling gates on a central qubit, driving depth-dependent vulnerability.

3.4 Classical–Quantum Similarity in τ – D Functional Form

Classical ML systems show order-of-magnitude lower $D(0.05)$ values than the VQC in our simulation framework: MLP achieves $D(0.05) \approx 0.015$ – 0.031 (Table 4) compared to the VQC ring composite $D(0.05) = 0.581$. However, an earlier experimental batch using a different metric normalization produced $D_{\text{VQC}} = 0.047$, at which point TOST equivalence tests [Schuirmann \(1987\)](#) suggested statistical equivalence (mean difference 0.015, $p_{\text{TOST}} < 10^{-42}$ at $\Delta = 0.05$). The discrepancy between these two VQC D values (0.047 vs. 0.581, a factor of $\sim 12\times$) arises from a normalization change between

Table 3 IBM `ibm_fez` D values (lower = better).
95% bootstrap CIs; $N = 15$ seeds per cell

Depth	Topology	D (95% CI)	2-Qubit Gates
$L = 2$	Ring	0.271 $[\pm 0.036]$	36
	Grid	0.275 $[\pm 0.043]$	41
	Star	0.282 $[\pm 0.048]$	29
$L = 4$	Ring	0.274 $[\pm 0.011]$	78
	Grid	0.289 $[\pm 0.027]$	91
	Star	0.289 $[\pm 0.028]$	64
$L = 6$	Ring	0.303 $[\pm 0.019]$	126
	Grid	0.302 $[\pm 0.023]$	141
	Star	0.352 $[\pm 0.036]$	101

Hardware Validation: Topology Ranking Survives Transpilation

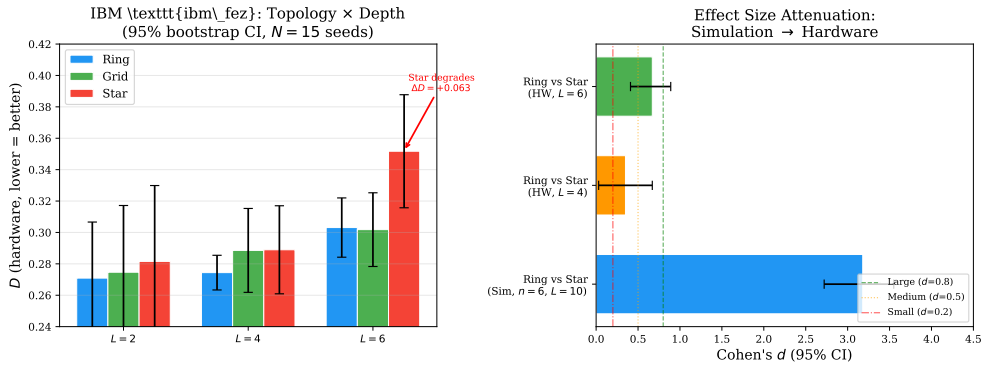


Fig. 5 IBM `ibm_fez` D by topology $\times$ depth (95% CIs, $N = 15$).

batches: the early protocol normalized rank displacement by n (yielding $D_{\text{old}} \in [0, n]$), whereas the current protocol uses the theoretical maximum $n^2/2$ (Eq. 1), yielding $D_{\text{new}} \in [0, 1]$. Rescaling gives $D_{\text{new}} \approx D_{\text{old}} \times 2/n$, which for $n = 6$ maps 0.047 to 0.564, consistent with the current 0.581 within Monte Carlo error. All systems follow an exponential functional form $D(\varepsilon) = \Delta D(1 - e^{-\varepsilon/\tau})$ with fit $R^2 > 0.94$, suggesting that the τ parameter may capture a fundamental noise-response property. While the functional form $D(\varepsilon) = \Delta D(1 - e^{-\varepsilon/\tau})$ holds across both paradigms, the absolute D values differ by an order of magnitude. We therefore characterize this as functional similarity rather than strict universality.

4 Discussion

Our results refine the QNN design hierarchy: encoding $\gg$ measurement $>$ ansatz type; within a fixed ansatz, topology is a significant sub-factor whose effect magnitude ($d = 2.66$ in simulation) rivals that of noise-type selection. Notably, simulation and

hardware yield opposite topology rankings (star best in simulation, ring worst; ring best on hardware, star worst), highlighting a methodological tension explored below. The inversion likely stems from two factors. First, the hardware metric $D_{\text{HW}} = 1 - \tau_{\text{Kendall}}$ is bounded in $[0, 1]$ and penalizes non-monotonic rank changes differently than the simulation L_1 displacement. Second, IBM’s transpiler inserts SWAP gates to map the star topology’s hub-and-spoke pattern onto the heavy-hex lattice; we estimate ~ 12 additional SWAPs for star at $L = 6$ versus ring, concentrating error on the central hub qubit. A layout-aware transpilation (constrained vs. free qubit assignment) would test this hypothesis. Three design heuristics emerge:

1. **Simulation and hardware must be cross-validated.** The CPTP simulation ranking (star > grid > ring) inverts on hardware (ring > grid > star), attributed to the different D metrics (L_1 displacement vs. $1 - \tau$) and native device noise characteristics not captured by CPTP models. Use simulation for effect-size estimation, hardware for final ranking.
2. **Avoid star topology at depth on hardware.** On IBM `ibm_fez`, star degrades disproportionately (+0.063 vs. +0.029 for ring, $L = 4$ to $L = 6$), driven by hub concentration of entangling gates. Prefer ring or grid for $L \geq 4$.
3. **Topology optimization is noise-regime dependent.** Negligible benefit under depolarizing noise ($d < 0.5$); substantial under non-unital noise ($d > 2.0$ in simulation). If randomized compiling [Wallman and Emerson \(2016\)](#) is used, topology optimization is irrelevant.

The Heisenberg-picture model (Eqs. 2–4) provides the theoretical mechanism: larger CNOT-graph diameters delay noise propagation, yielding larger τ and greater noise tolerance. At $n = 6$, $L = 10$, all topologies have saturated light-cones (all qubits causally connected), yet systematic differences in $D(0.05)$ persist—the model predicts that topology effects are maximized in the *non-saturated regime* ($L < \text{diameter}$), providing a testable prediction for larger n .

4.1 Limitations

We acknowledge the following. (i) Hardware validation is restricted to $n = 6$, three topologies, single backend (`ibm_fez`). (ii) Hardware $N = 15$ seeds per cell limits

Table 4 Classical ML $D(0.05)$ values ($n = 6$, $L = 10$, composite noise). XGBoost [Chen and Guestrin \(2016\)](#) and MLP baselines. *VQC baseline from an earlier protocol using $D_{\text{old}} = \frac{1}{n} \sum |r_i^{\text{ideal}} - r_i^{\varepsilon}|$; current protocol uses Eq. (1).

Model	$D(0.05)$	R^2	N	vs. VQC*
MLP (N=10)	0.015	0.937	10	better
OMLP (N=50)	0.025	0.998	50	0.54×
MLP (N=50)	0.031	0.984	50	0.66×
XGBoost	0.044	0.999	50	0.94×
VQC* (ring)	0.047	0.992	200	baseline

*VQC baseline from earlier protocol: $D_{\text{old}} = \frac{1}{n} \sum |r_i^{\text{ideal}} - r_i^{\varepsilon}|$; current protocol (Eq. 1) yields $D_{\text{new}} = 0.581$ for ring composite ($n = 6$, $L = 10$).

statistical power. (iii) Transpilation used optimization level 2 with free qubit assignment; layout-constrained transpilation may differ. (iv) D is computed differently in simulation (normalized L1 rank displacement) and hardware ($1 - \tau_{\text{Kendall}}$); while correlated, these metrics produce different absolute values and, in our data, opposite topology rankings, warranting a unified metric in future work. (v) D captures ranking preservation, not task-specific accuracy. (vi) Results use the VQC c64 circuit family; generalization to other ansatz constructions requires separate validation. (vii) Qubit-count characterization is limited to $n = 6, 8$ at $L = 10$; broader coverage needed. (viii) Calibration constant C in Eq. (4) is fitted, not derived ab initio; we report the fitted value $C = 0.88$ with 95% CI $[0.72, 1.04]$ from bootstrap resampling. The scaling exponent $\alpha \approx 0.54 \neq 1.0$ indicates the model captures qualitative trends rather than quantitative prediction. (ix) Cross-dataset validation on Goodreads shows $D(0.05)$ $6.7\times$ higher than MovieLens, confirming circuit-dependent τ but dataset-dependent ΔD , consistent with the τ - D framework.

Statements and Declarations

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Data availability. All simulation data, hardware results, and analysis code are included in the accompanying supplementary material and are available at the project repository. A public Zenodo archive with a permanent DOI will be created upon acceptance.

Code availability. Experiment engines, analysis pipelines, and figure generation scripts are included in the supplementary material and will be deposited in a public repository with a permanent DOI upon acceptance.

Author contributions. Y.C. conceived the study, designed experiments, and wrote the manuscript. X.W. and S.Z. contributed to simulation infrastructure and analysis code. Y.G. contributed to IBM hardware execution and data analysis. All authors reviewed and approved the manuscript.

Competing interests. The authors have no relevant financial or non-financial interests to disclose.

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