

Quantum Circuit Vision

Cost-Aware Evaluation of Visual AI Agents for Quantum Code Generation

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Motivation & Research Questions (RQs)

Quantum computing is scaling, yet every circuit diagram in papers, textbooks, and courses must still be translated into code by hand — a bottleneck slowing scientific progress.

We ask whether multimodal agents can **read circuit images** and output **executable, unitary-verified** code—and at what cost.

- **RQ 1:** Can agents translate circuit **images** into correct SDK code?
- **RQ 2:** What is the **cost–accuracy** trade-off across model tiers?
- **RQ 3:** Does analyze-then-code (**TV** / CoT) improve visual understanding?

Datasets

QCV fills a gap left by *circuit-only* corpora (e.g., NTangled, QDataSet, MNISQ) and *non-quantum* vision→code suites (e.g., Vis.→Code): it pairs **multimodal diagrams** with **executable ground truth** and **objective verification** (unitary fidelity $F \geq 0.99$). In the taxonomy, QCV stands out on **dataset infra.** (governance + versioning), **cost/deployment** (latency + billing logs), and **trust/monitoring** (annotated failure taxonomy).

Circuit Categories (13)

Group	Examples
Basic	Hadamard, Bell, Toffoli
Intermediate	QFT, Grover, teleportation
Advanced	QAOA, VQE, Bernstein–Vazirani
Blockchain	BB84, VRF, consensus-style protocols
A: Gate coverage	CRy, CCZ, iSWAP (broad gate families)
B: Qubit scaling	GHZ-10, QFT-5, ring entanglers (4–10 qubits)
C: Classical	Deutsch–Jozsa, Simon, Shor
D: Variational	hardware-efficient, UCCSD-style ansatz
E: Error correction	Shor-9, Steane-7, surface-code patch
F: Quantum ML	QCNN, QGAN, kernel methods
G: Blockchain extensions	E91, voting, auction protocols
H: Visual variants	barrier/decomposed/reversed (layout robustness)
I: BTC security	Shor vs ECDSA, Kyber-like PQC defense

Methodology

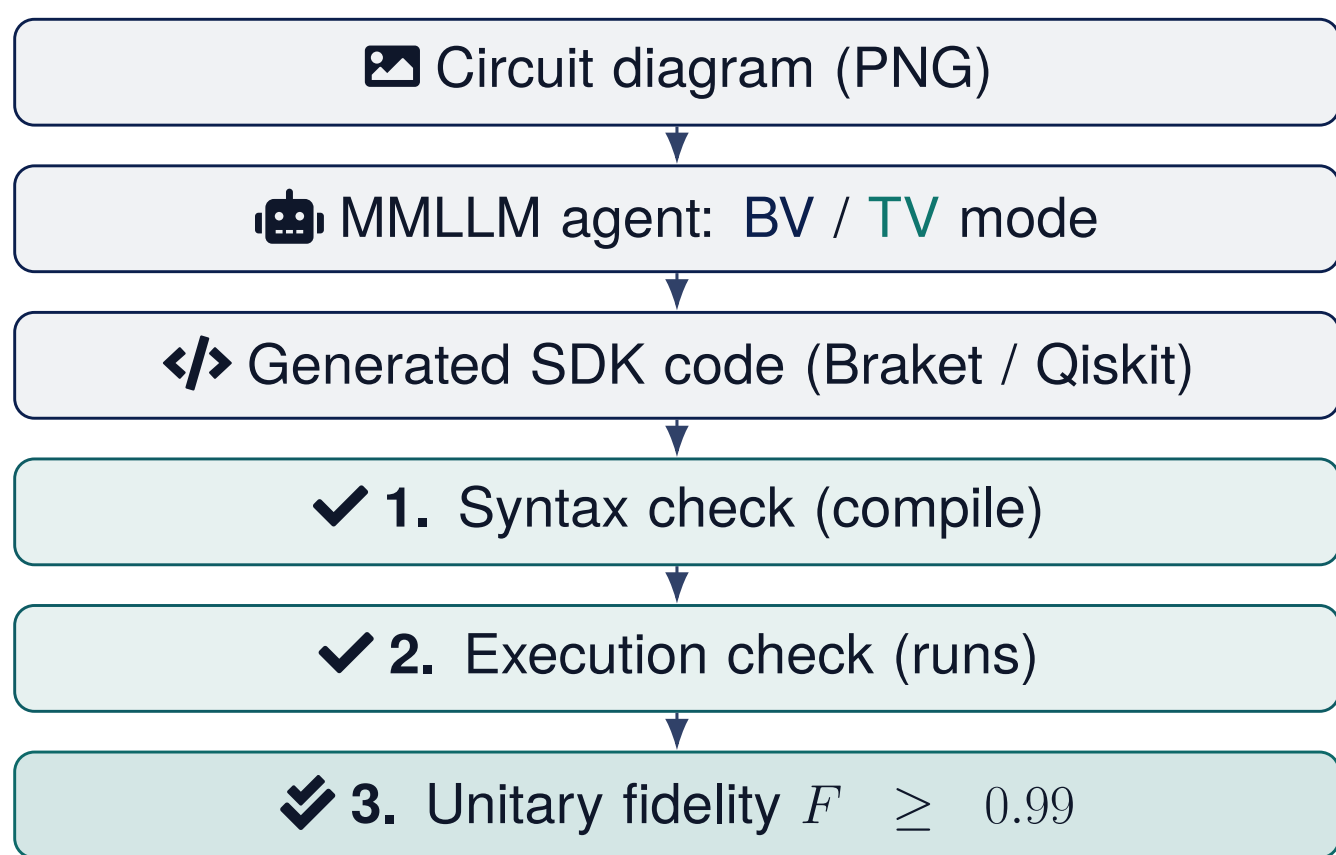
Two visual modes. BV (image→code) and TV (analyze-then-code; CoT).

Objective verification (no LLM-as-judge):

$$F = \frac{|\text{Tr}(U_{\text{gt}}^\dagger U_{\text{gen}})|}{2^n} \geq 0.99$$

Three levels: **syntax** → **execution** → **unitary fidelity**. Unitary comparison is SDK-agnostic in principle (e.g., Qiskit Aer, Cirq, PennyLane).

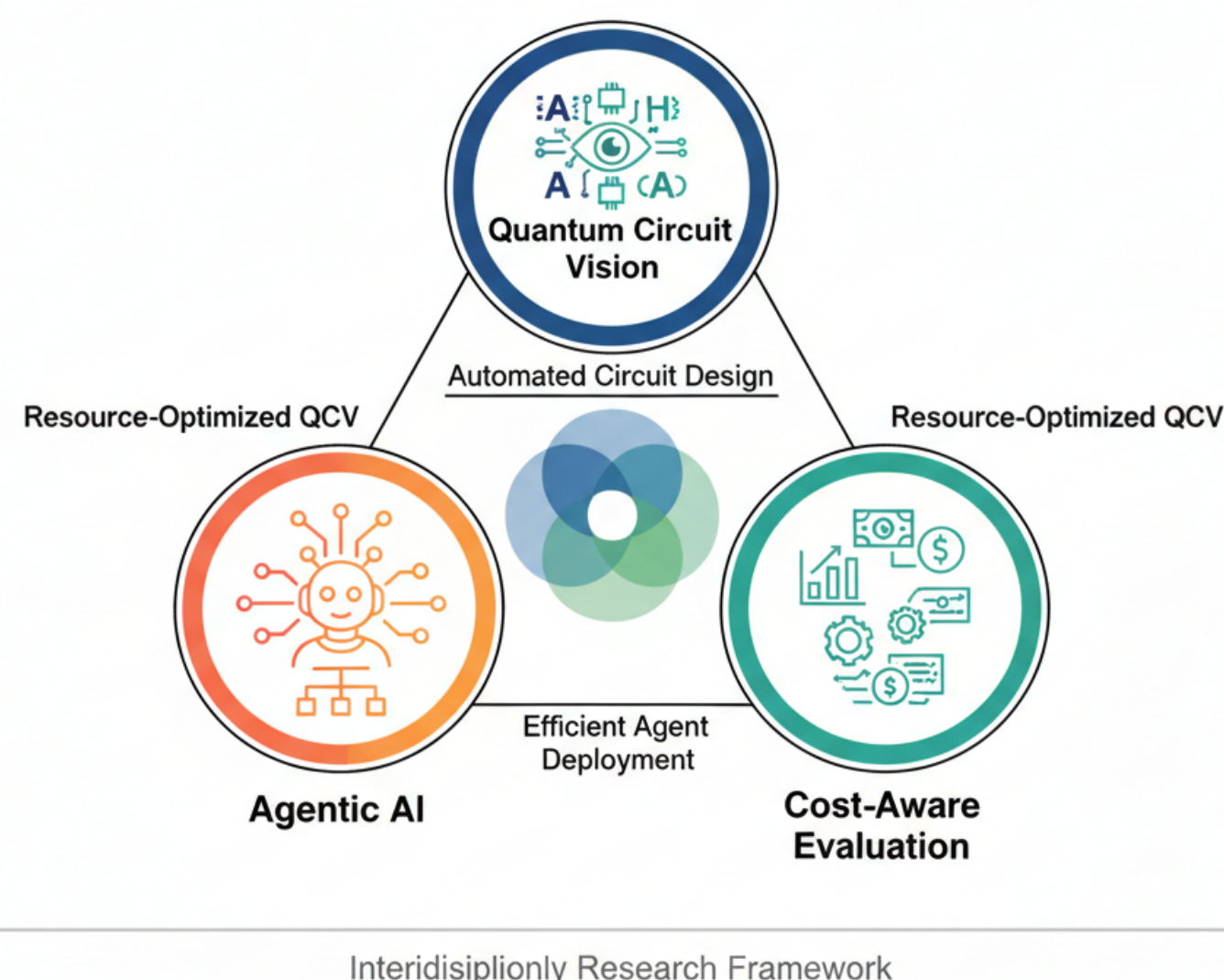
Verification Pipeline



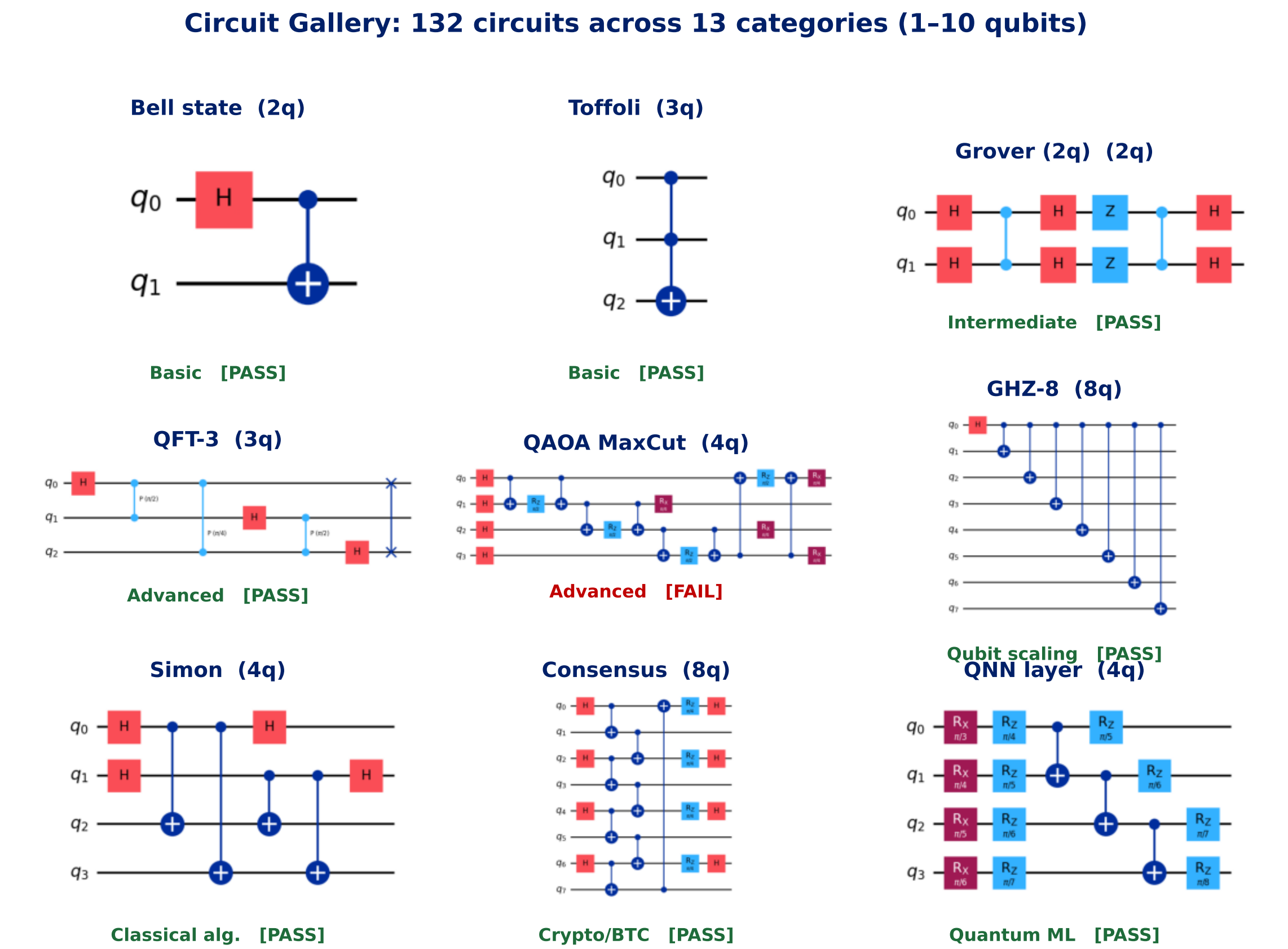
Objective pipeline: no human review and no LLM-as-judge.

Key Contributions

- **Open Assets — QCV-Datasets:** 132 circuits, 13 categories, 5 modalities. Released on Hugging Face & GitHub with Datasheet, CITATION.cff, Croissant-RAI, DOI.
- **Cost-Aware Framework:** model-agnostic & SDK-agnostic evaluation; cascade routing cuts cost by 62% (84% pass @ 38% cost).
- **Agentic AI for Quantum Computing Evaluation:** $n=5$ trials, paired tests, TOST on core subset; full-set results ($n=1$) are indicative; failure analysis + transparent limitations guide future research.

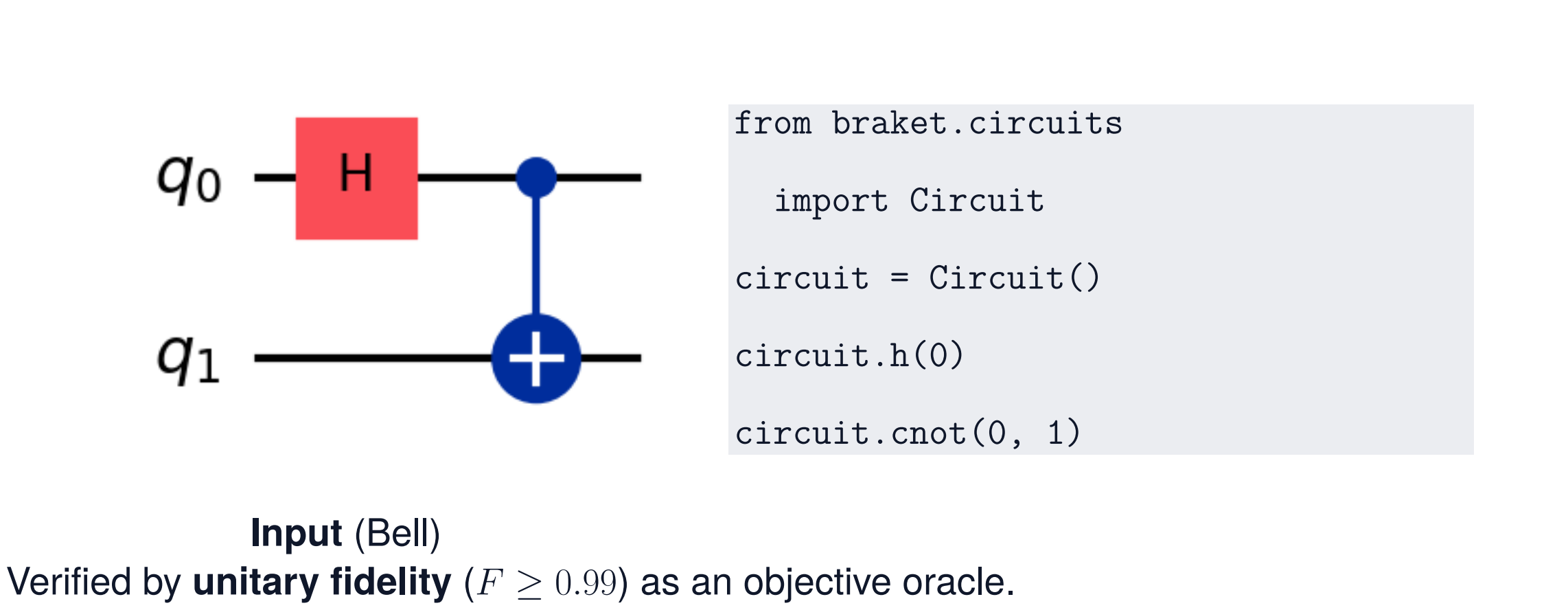


Circuit Gallery (132 circuits, 1–10 qubits)

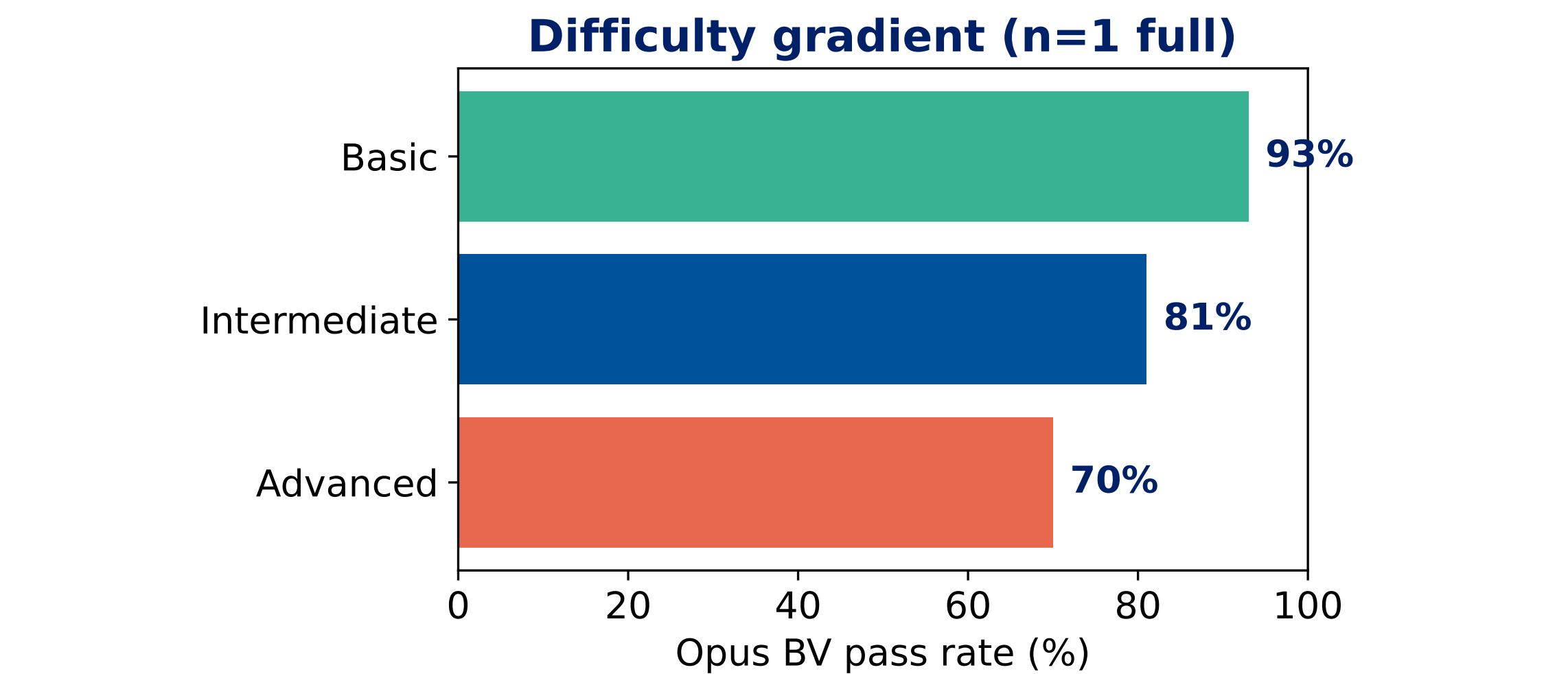


Regular structure can pass even at 8 qubits (**GHZ-8, Consensus PASS**), while a smaller instance (**QAOA, 4q**) can fail—*structure, not size, determines success*.

Example: Image → Verified Code

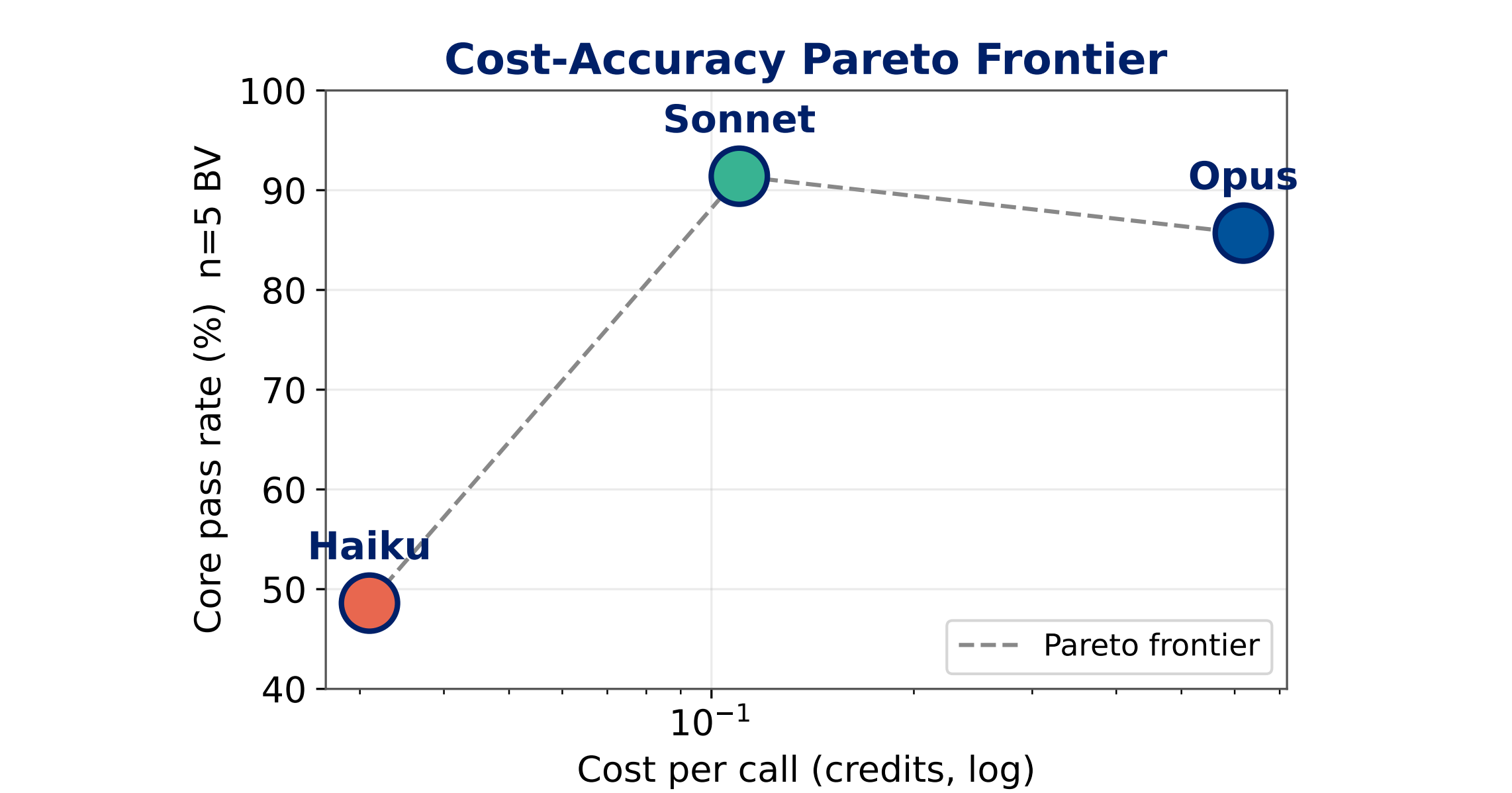


Difficulty Gradient



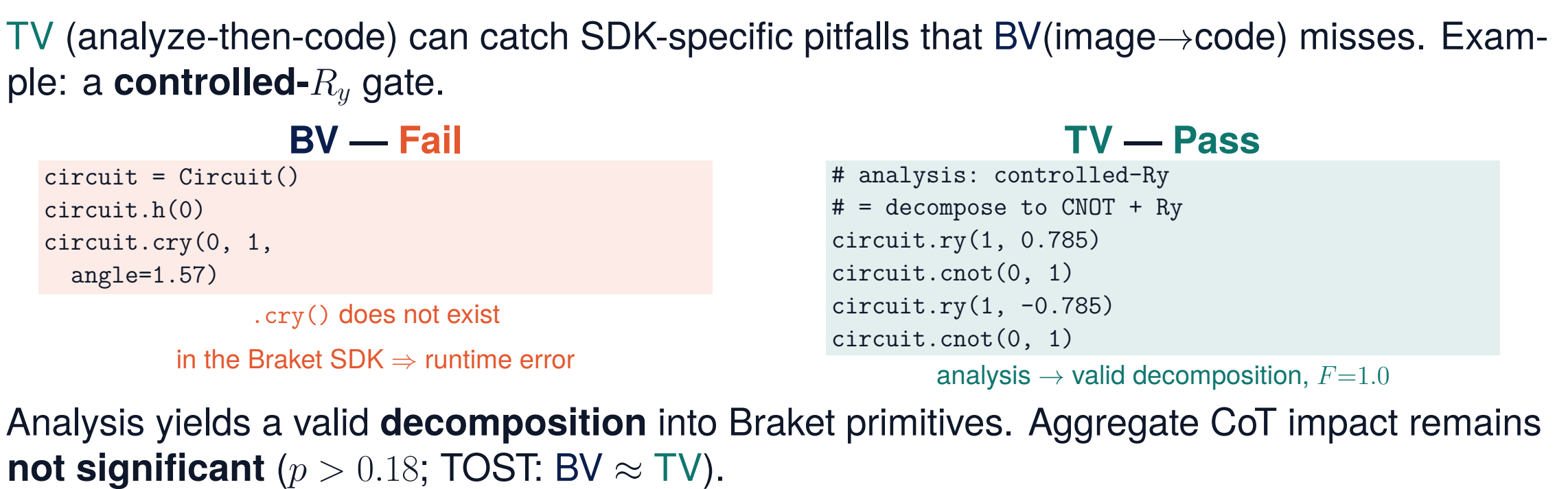
A clear gradient: Basic **93%** → Intermediate **81%** → Advanced **70%** ($n=1$, Opus BV, full set). Hard algorithms and cryptographic protocols remain challenging, while basic gates are near-solved.

Cost–Accuracy Frontier



All three models lie on the **Pareto frontier**: Haiku minimizes cost, Opus maximizes accuracy, and **Sonnet** is the balance point (~97% of Opus accuracy at ~18% of the cost). The Sonnet–Opus gap is **not significant** (paired t : $p=0.083$; Wilcoxon: $p=0.057$) — “optimal” depends on preference.

BV vs TV: A Rescue Example



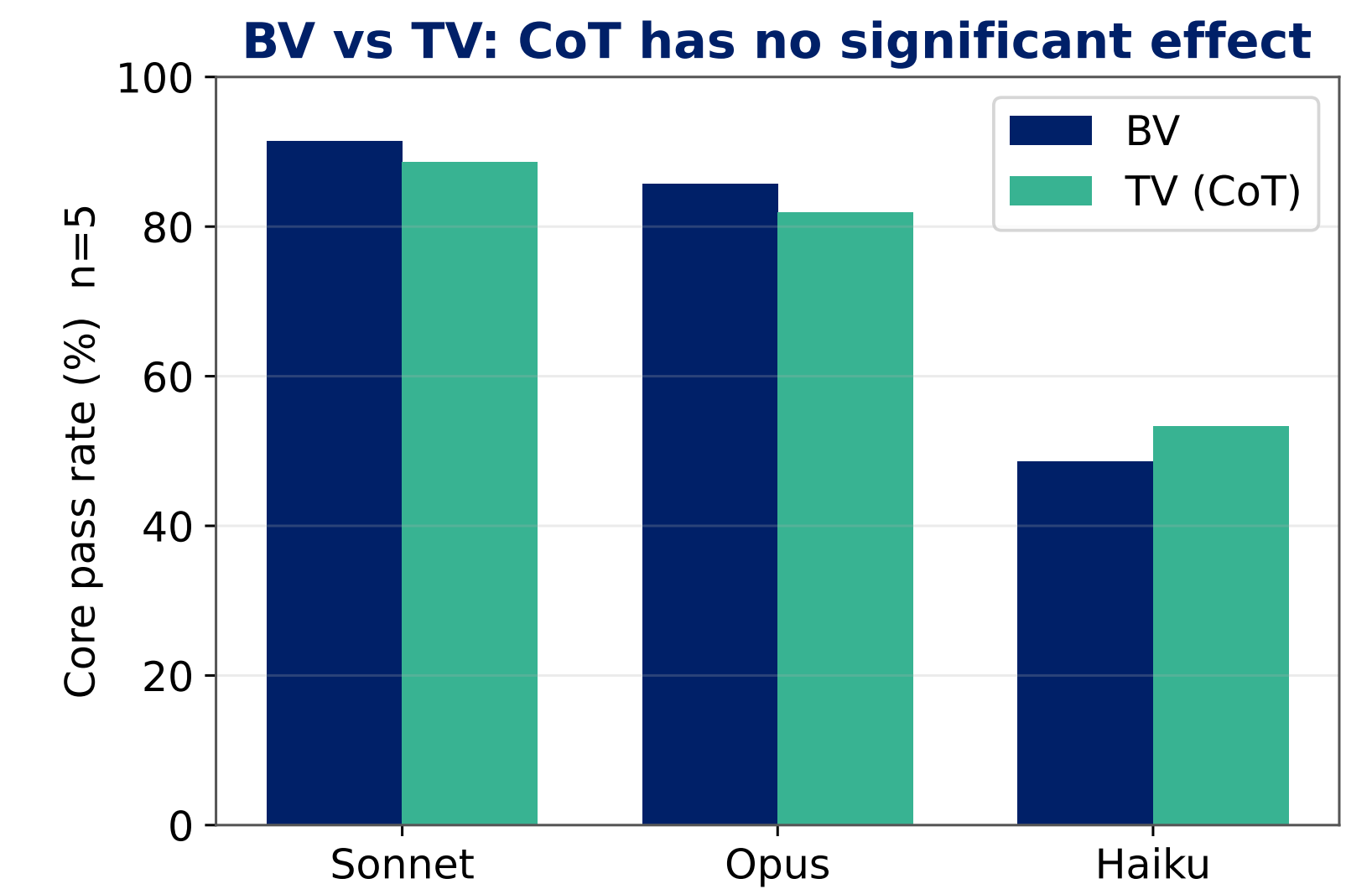
Analysis yields a valid **decomposition** into Braket primitives. Aggregate CoT impact remains **not significant** ($p > 0.18$; TOST: BV $\approx$ TV).

Results & Findings

■ Accuracy ■ Cost ■ Deployment & Failure

CoT has no significant effect

Overall, analyze-then-code (TV / CoT) does not significantly improve accuracy vs BV. Equivalence testing (TOST, $\pm 10\text{pp}$) supports BV $\approx$ TV (see table + $p > 0.18$ overall).



Circuit **depth** ($p < 0.001$) — not qubit count ($p=0.20$) — predicts failure (LR, 13.2% dev., strongest tested).

Full Benchmark (pass rate %)

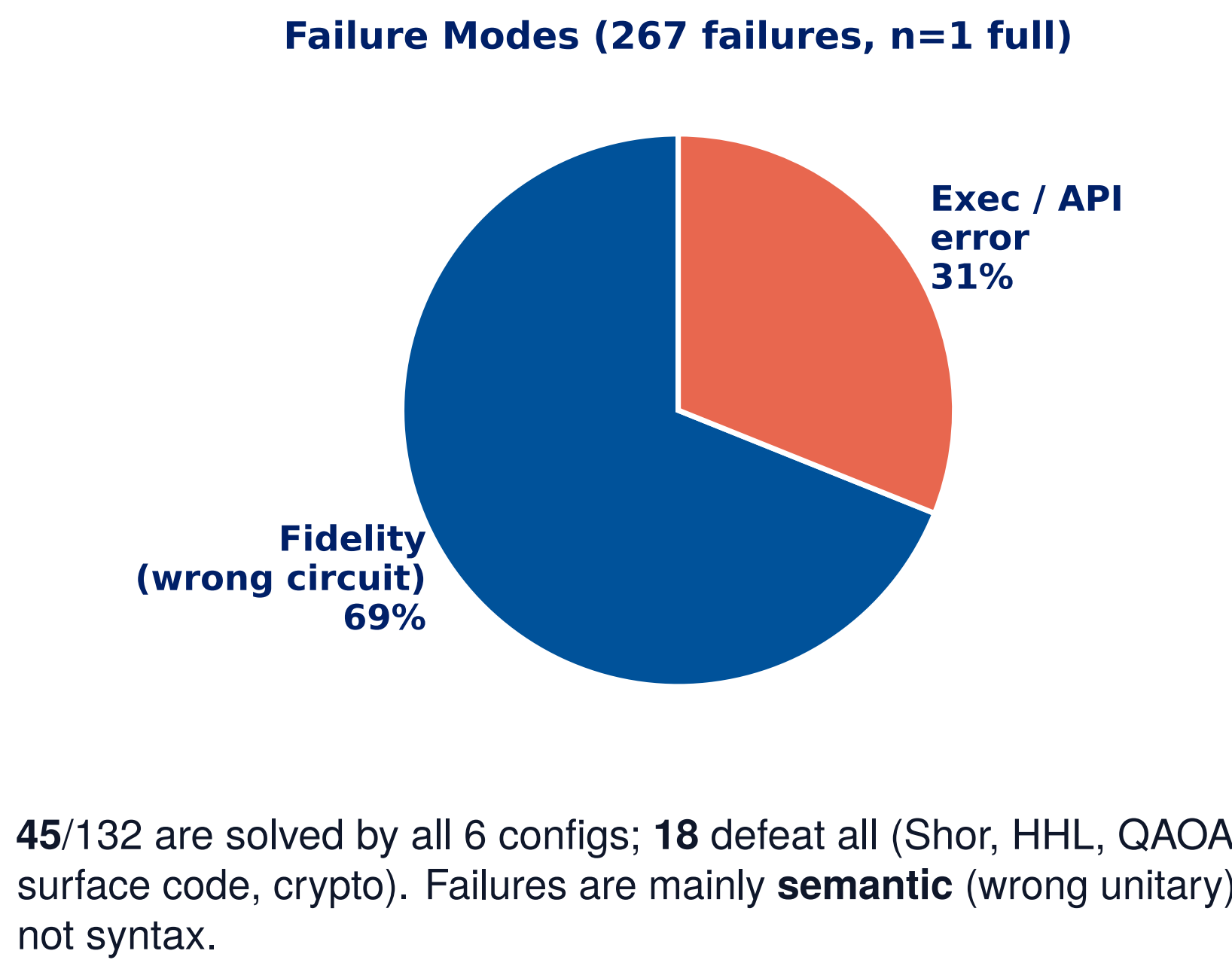
	Full ($n=1$)		Core ($n=5$)				
Model	BV	TV	BV	$\pm\sigma$	TV	$\pm\sigma$	Note
Opus	79	77	85.7	5.8	81.9	7.8	priciest
Sonnet	77	75	91.4	5.2	88.6	4.3	sensible default
Haiku	43	47	48.6	4.0	53.3	9.2	cheapest

Cost & CoT Equivalence (BV mode)

Model	cr/call	cr/correct	$\Delta(\text{TV} - \text{BV})$	TOST	p
Haiku	0.031	0.072	+4.8	0.33	(n.s.)
Sonnet	0.110	0.142	−2.9	0.001	✓
Opus	0.618	0.778	−3.8	0.037	✓

Opus & Sonnet: **TV is statistically equivalent** to BV ($\pm 10\text{pp}$). Sonnet is the cost-efficiency sweet spot.

Failure Analysis



45/132 are solved by all 6 configs; **18** defeat all (Shor, HHL, QAOA, surface code, crypto). Failures are mainly **semantic** (wrong unitary), not syntax.

Cascade Routing

Haiku→Sonnet→Opus yields **84% pass at 38% of single-model cost ($n=1$, indicative)**. Routing > prompting as the main cost lever.

Conclusion & Resources

We introduce a **cost-aware, unitary-verified** benchmark for visual AI agents on quantum code. **Sonnet** is the cost-efficiency sweet spot on the frontier; **routing** beats prompting (84% pass @ 38% cost); and circuit **depth** predicts failure. To handle volatile pricing, we report **tokens** and **price** layers separately. Data, code, and cost logs are released.



GitHub



HF Dataset

BV = Basic Vision (direct image→code); TV = Thinking Vision (chain-of-thought analyze-then-code); CoT = Chain of Thought; EDA = Electronic Design Automation; MLLM = Multimodal Large Language Model.