

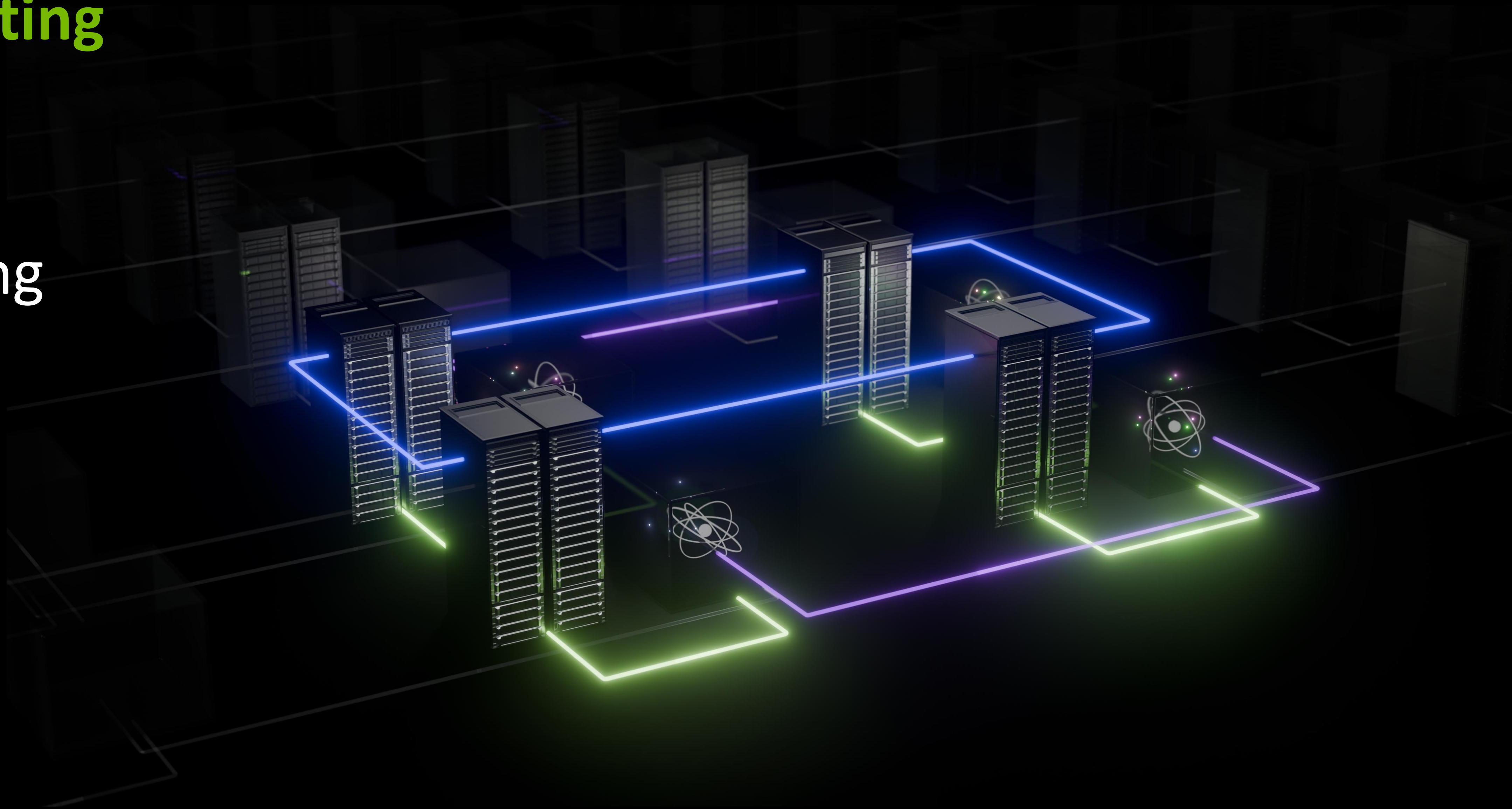


AIが生成する量子プログラムとその実行

Ikko Hamamura / NVIDIA

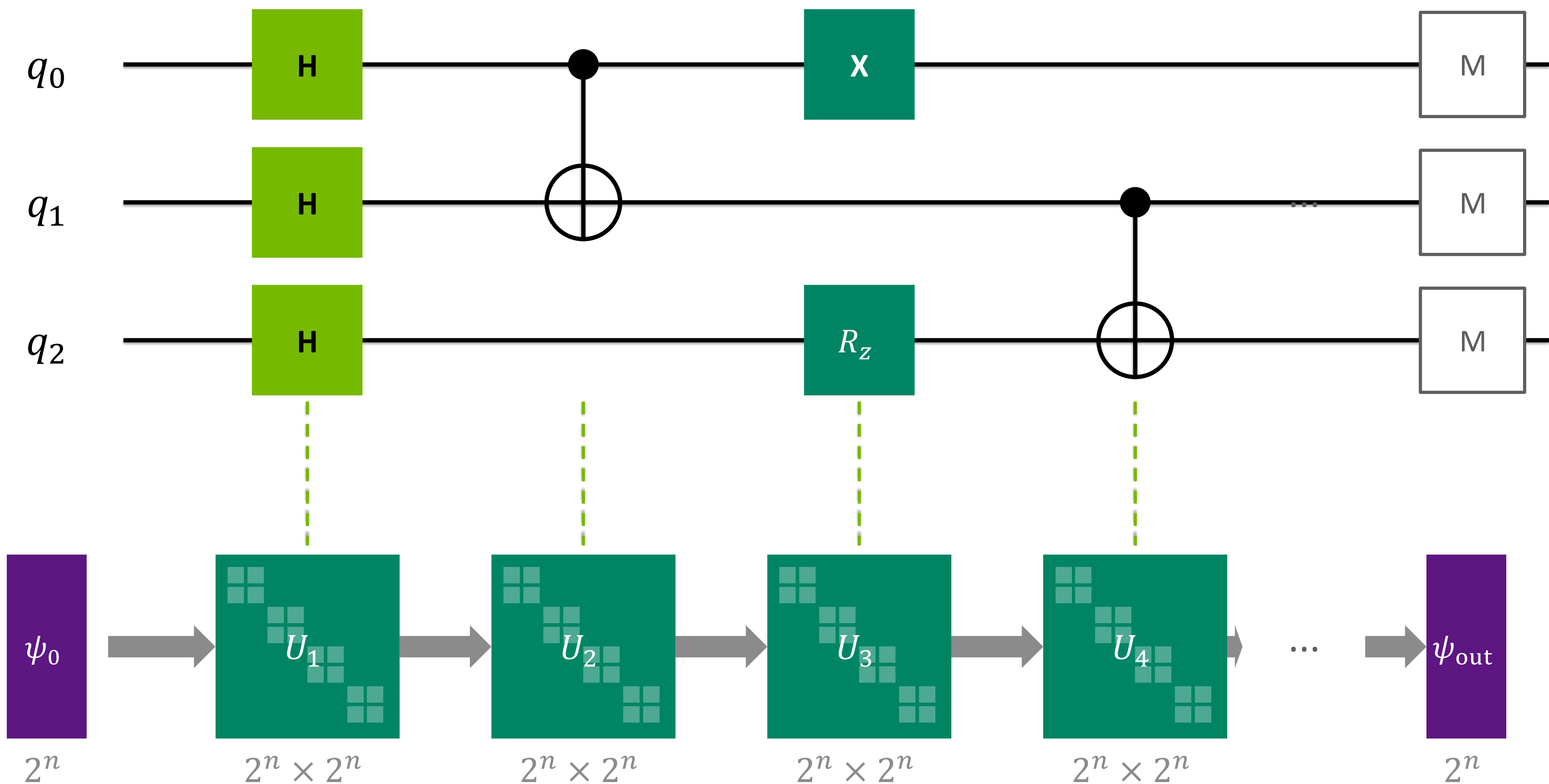
Quantum-GPU Supercomputing

- Supercomputing architecture **connecting quantum hardware**
- Ability to run **hybrid algorithms** - using GPUs and QPUs
- A **software platform** that seamlessly connects hybrid applications
- The ability to perform **qubit-agnostic** development of control and error correction



Quantum Circuits: Sparse Matrix-Vector Products

Quantum circuit (the program you write)



Linear algebra (what the machine does)

$$\psi_{\text{out}} = U_k \cdots U_2 U_1 \psi_0$$

Each U_i is sparse with 2^m nonzeros per row

k up to $\text{poly}(n)$ gates $\Rightarrow O(k \cdot 2^n)$ flops in total



In Computational Terms

State

State vector $\psi \in \mathbb{C}^{2^n}$. At $n = 30$ that is $2^{30} \times 16 \text{ B} \approx 17 \text{ GB}$, and each extra qubit doubles it.

Gate

Each gate is a sparse unitary $U \in \mathbb{C}^{2^n \times 2^n}$ with only 2^m nonzeros per row for an m -qubit gate.

Circuit

A circuit of depth k is k sparse mat-vec products in sequence, with k up to $\text{poly}(n)$.

Output

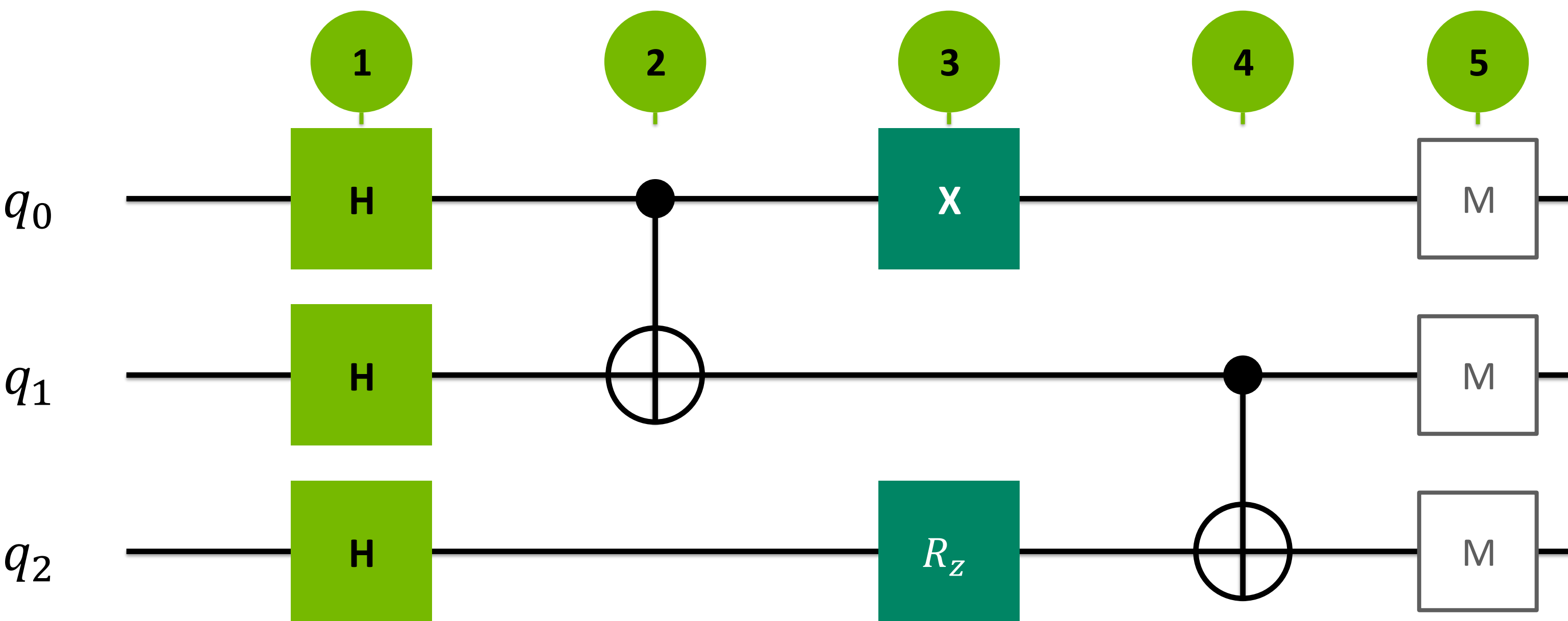
Measurement returns a single index i with probability $\text{Pr}(i) = |\psi_i|^2$.

Quantum Kernels: The Circuit as a Program

Quantum kernel written in CUDA-Q (Python)

```
@cudaq.kernel
def circuit(theta: float):
    q = cudaq.qvector(3)      # state |000>
    h(q)                      # H on every qubit
    x.ctrl(q[0], q[1])         # CNOT q0 -> q1
    x(q[0]); rz(theta, q[2])   # X and Rz
    x.ctrl(q[1], q[2])         # CNOT q1 -> q2
    mz(q)                     # measure all
    counts = cudaq.sample(circuit, 0.3, shots_count=1000)
```

Quantum circuit drawn from the same program



Kernel line order = circuit column order = matrix product order



Device code

Written on the host and launched on a target, like a CUDA kernel. The body is a real program with arguments, function calls, loops and branches.



Qubit-agnostic

One source is compiled for the chosen hardware, whether a QPU of any qubit modality or a simulator such as state vector or tensor network.



Line = matrix

Each gate call applies one sparse $2^n \times 2^n$ unitary to the state, so the listing is $U_k \cdots U_1$ written out one factor per line.



sample = histogram

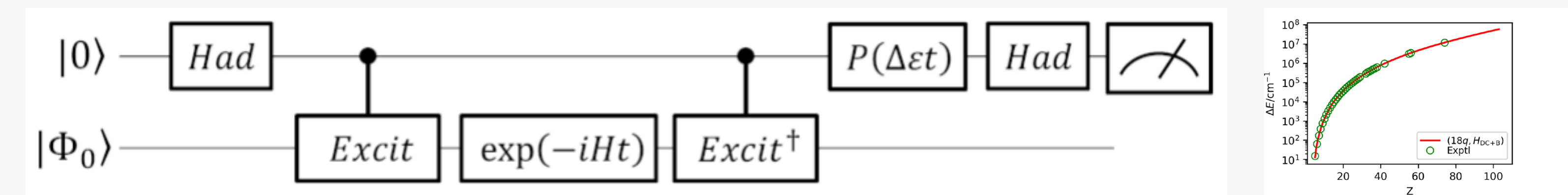
The kernel is launched 1000 times and each run returns one bitstring. The result is a histogram of outcomes. The 2^n vector entries never leave the device.

Quantum Algorithms: Time Evolution and Eigenvalue Problems

Time evolution

$$\psi(t) = e^{-iHt}\psi(0)$$

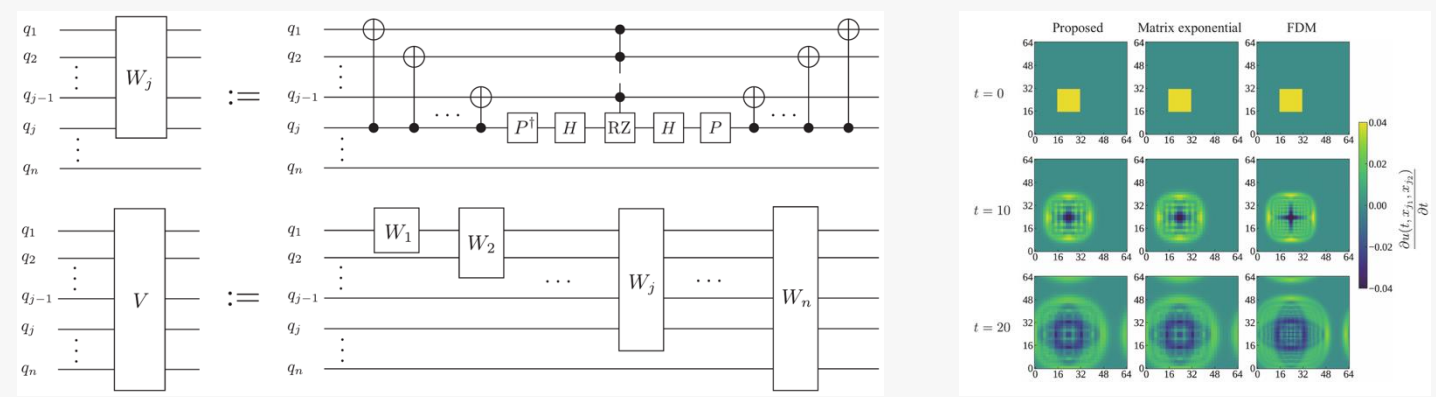
Quantum simulation



Energy gaps of boron-like ions, $Z = 5$ to 103 , from Bayesian phase difference estimation on 18 qubits, simulated with cuQuantum.

Sugisaki et al., Electron. Struct. 5, 035006 (2023)

Quantum CAE



For the wave equation, finite-difference operators become explicit gates, giving a circuit for e^{-iHt} with depth $O(\log_2 N)$ for N cells.

Sato et al., Phys. Rev. Research 6, 033246 (2024)

Eigenvalue problems

$$H\psi = E\psi$$

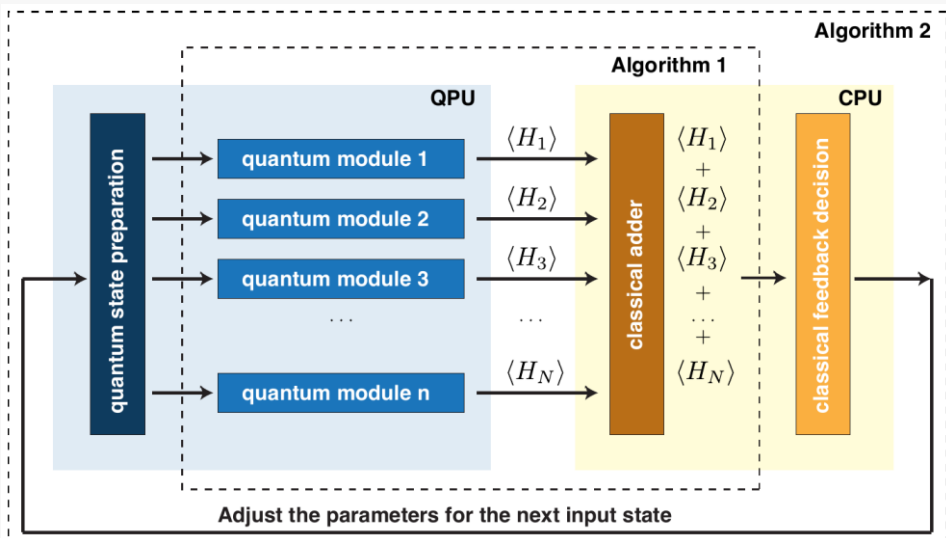


VQE

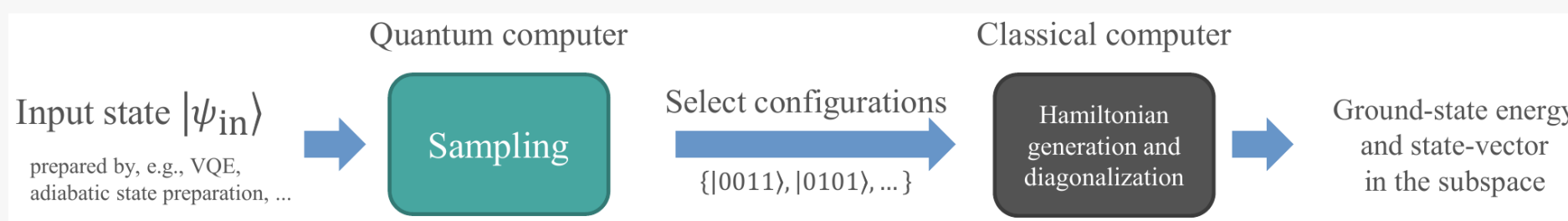
$$E_0 \approx \min_{\theta} \langle \psi(\theta) | H | \psi(\theta) \rangle$$

The QPU prepares $\psi(\theta)$ and measures the energy, a classical CPU/GPU optimizer updates θ .

Peruzzo et al., Nat. Commun. 5, 4213 (2014)

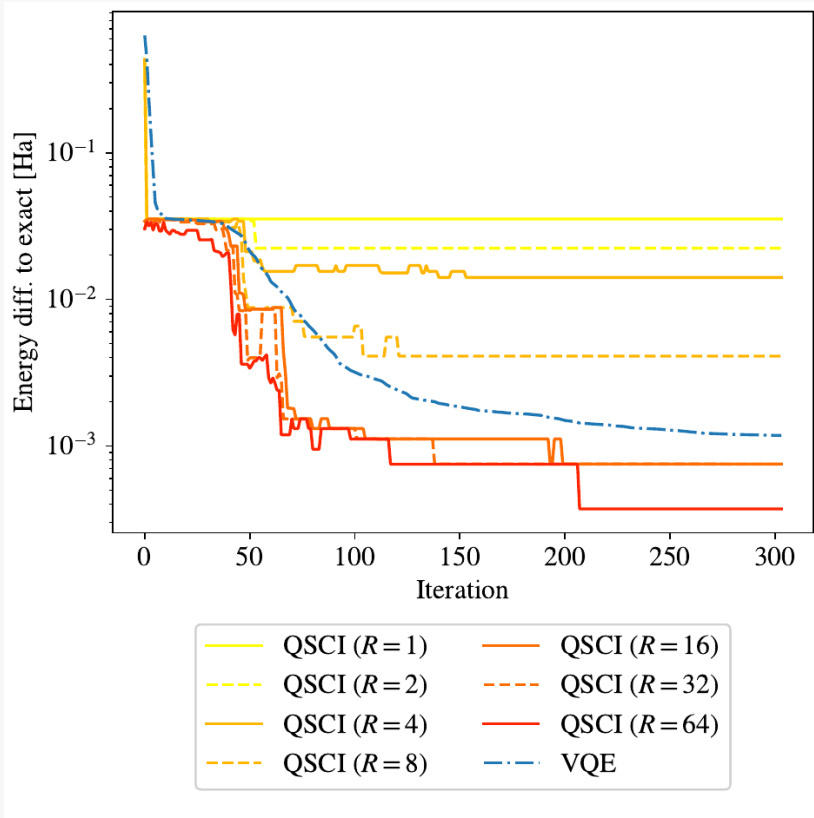


QSCI / SQD



Sample ψ on the QPU, keep frequent configurations, diagonalize H in that subspace on CPU/GPU. Variational and noise-robust.

Kanno et al., Phys. Rev. Research 8, 023268 (2026)



The Generative Quantum Eigensolver

First demonstration of GPT-generated circuits in the literature

Find a circuit producing e.g. ground state

Optimization of circuits for desired output

GPT-QE specifically employs a GPT model

- Recent advances in attention-based transformer models can be leveraged

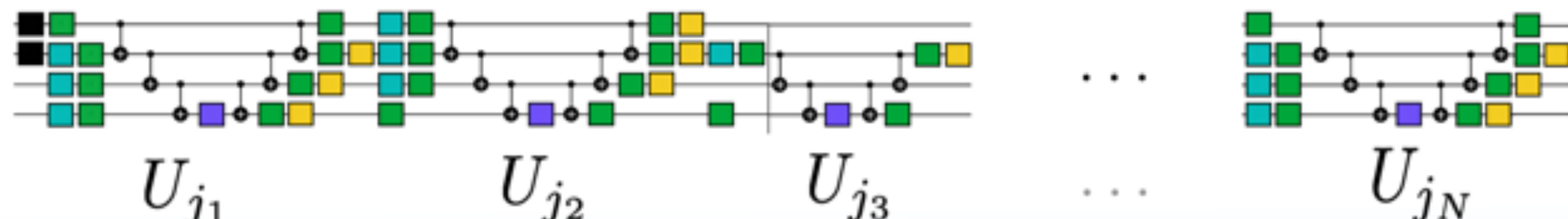
Analogy to Large Language Models (LLMs)

- Quantum operations are analogous to words
- Quantum circuits analogous to sentences
- When trained, GPT-QE generates a sequence of operations to form a circuit

Training learns weights in GPT model

- Cost function compares current prediction to measure of desired circuit output

$\vec{j} \sim$ "Once upon a time . . . happily ever after"
word_{j₁} word_{j₂} word_{j₃} word_{j₄} . . . word_{j_{N-2}} word_{j_{N-1}} word_{j_N} **LLM**

$\vec{j} \sim$

GPT-QE



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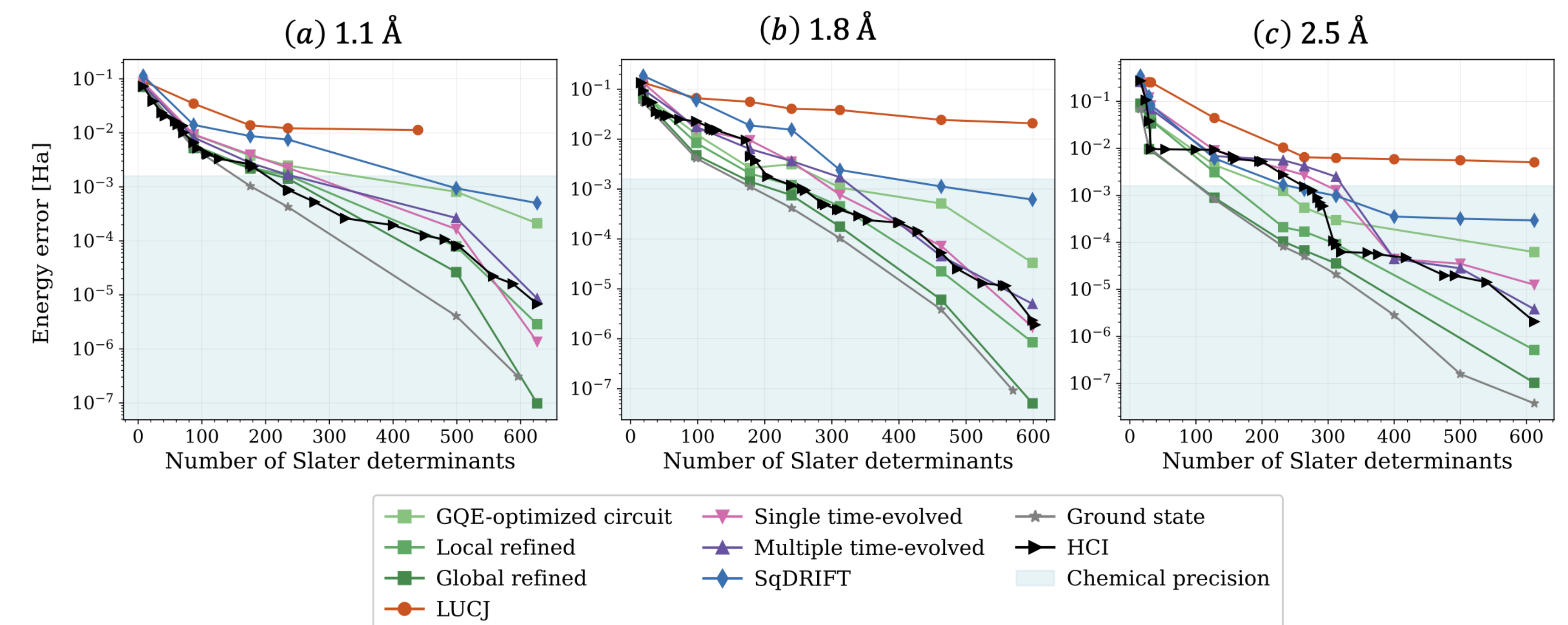
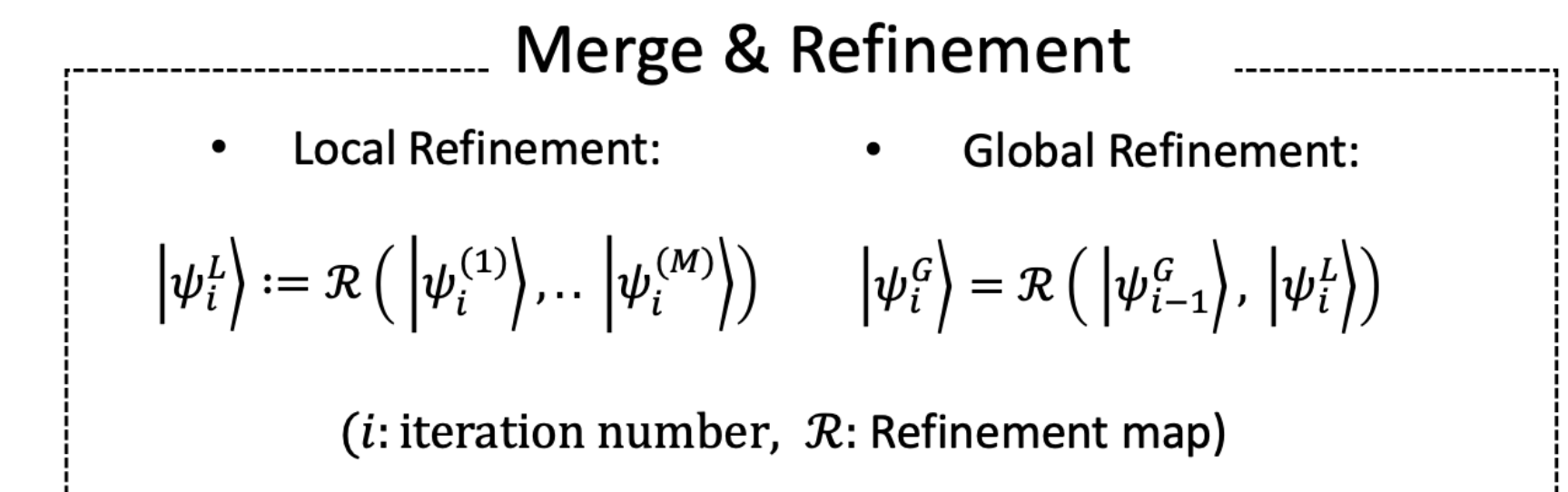
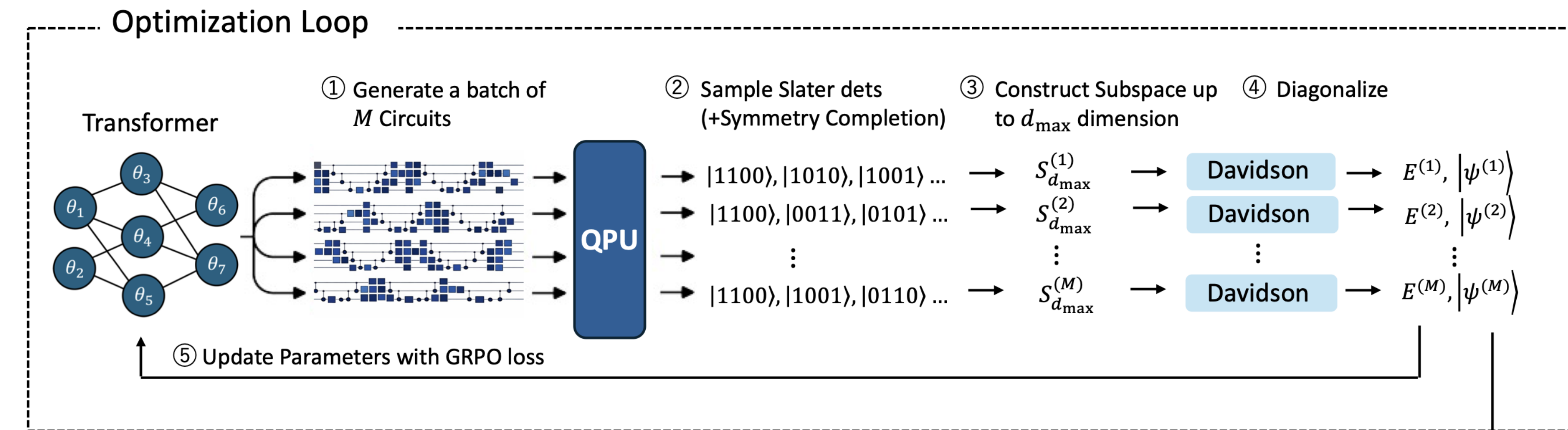
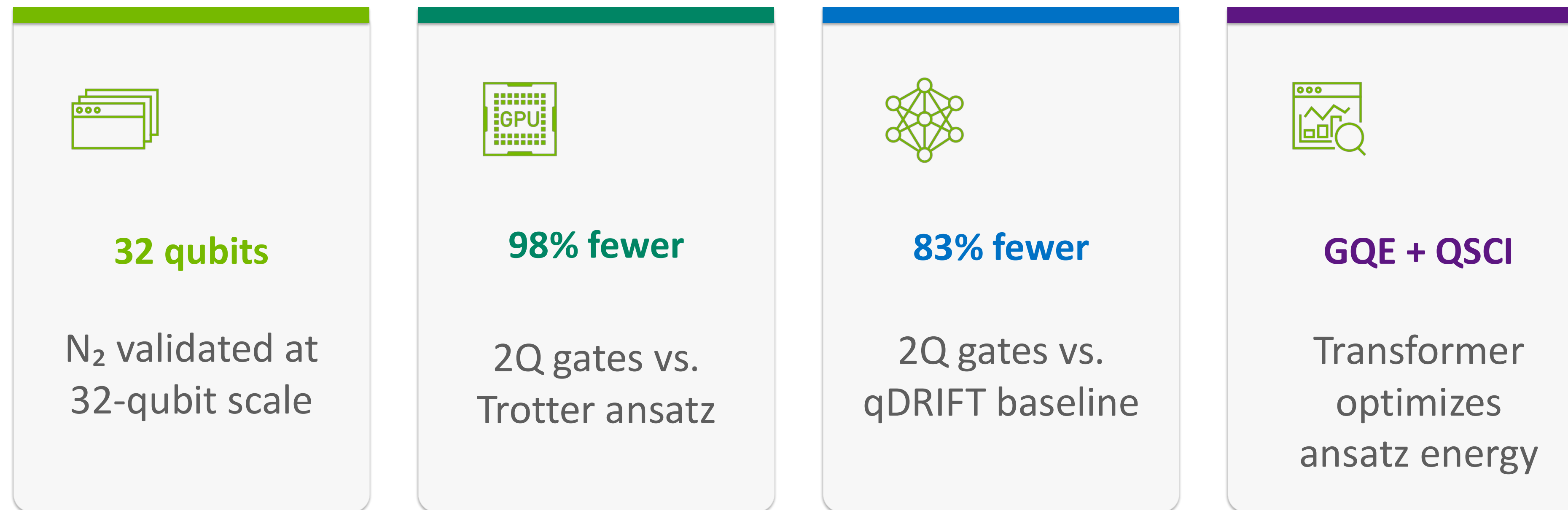
<https://arxiv.org/abs/2401.09253>



Generative Circuit Design for QSCI

First GPT-designed circuits validated at 32-qubit scale

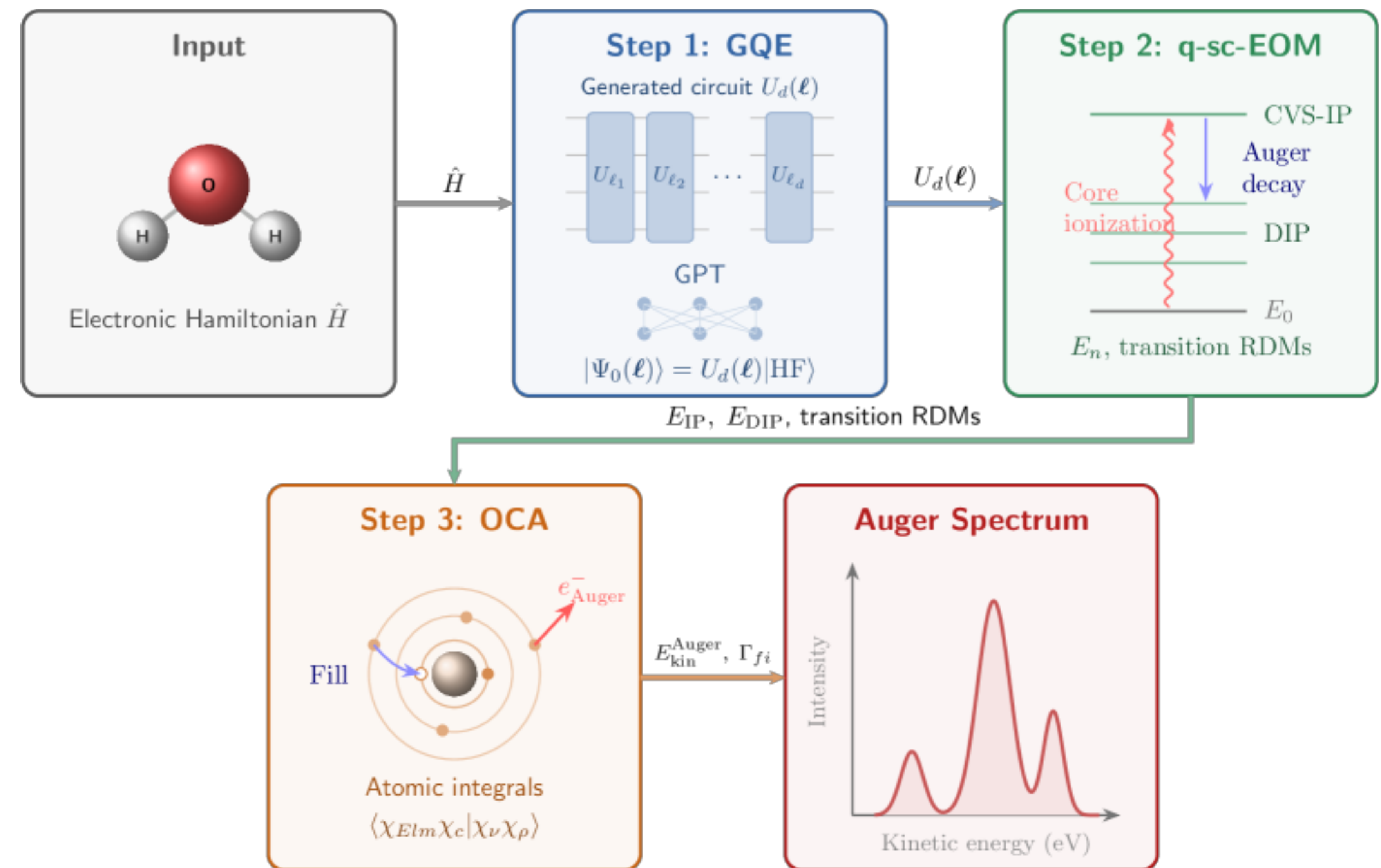
- QSCI needs **well-designed circuits** under hardware noise
- GQE** — Transformer optimizes ansatz via QSCI energy
- QSCI** — Samples determinants, diagonalizes in subspace



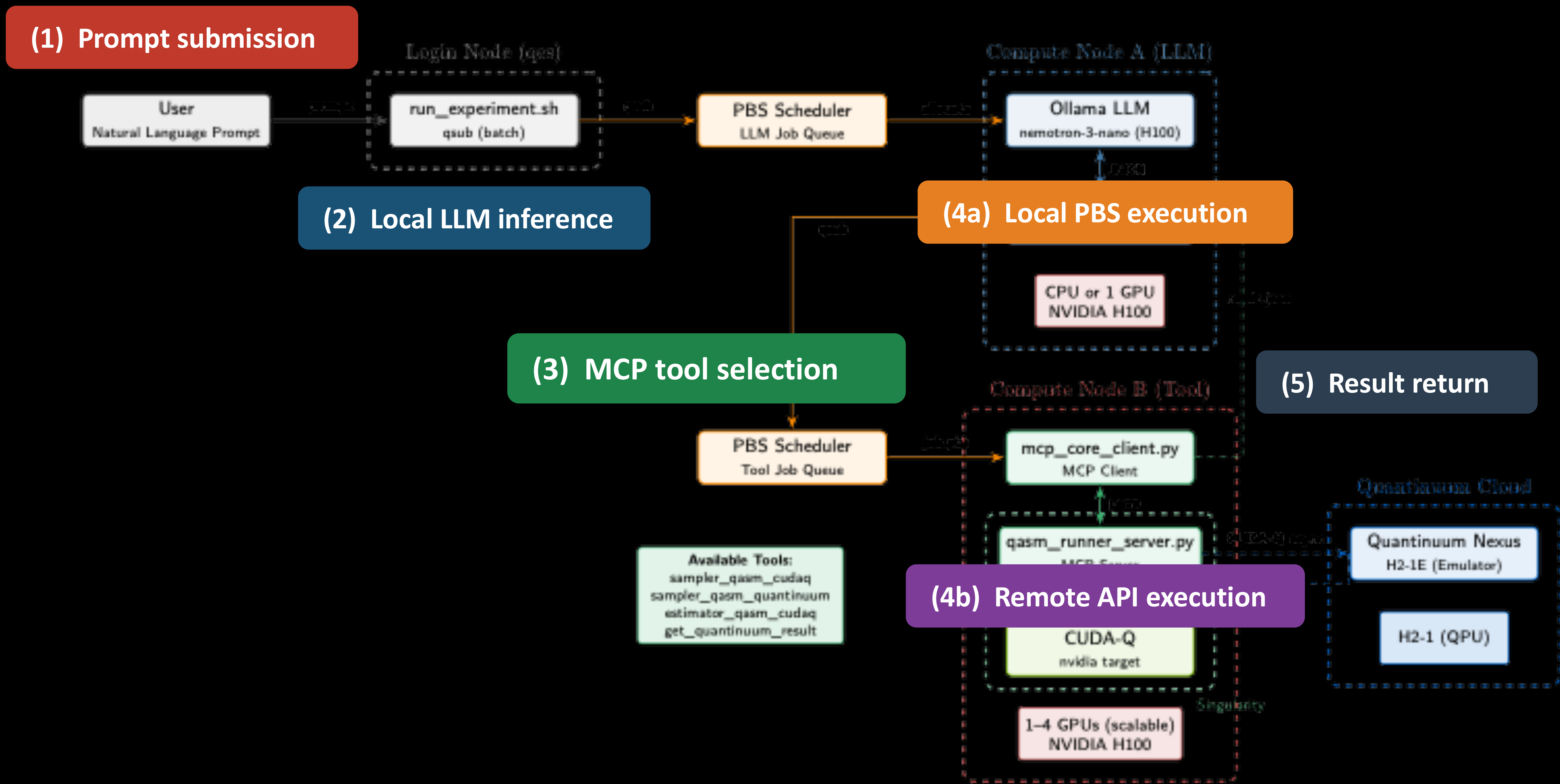
Auger Spectroscopy via GQE

Generated circuits match FCI and experiment for H₂O Auger spectra

- Auger spectroscopy needs **many excited states**
- **Hybrid quantum-classical**
 - GQE + q-sc-EOM + OCA
- GPU-accelerated via **CUDA-Q**
- Validated on **H₂O** — matches FCI & experiment
- **GQE halves gate count** vs. VQE



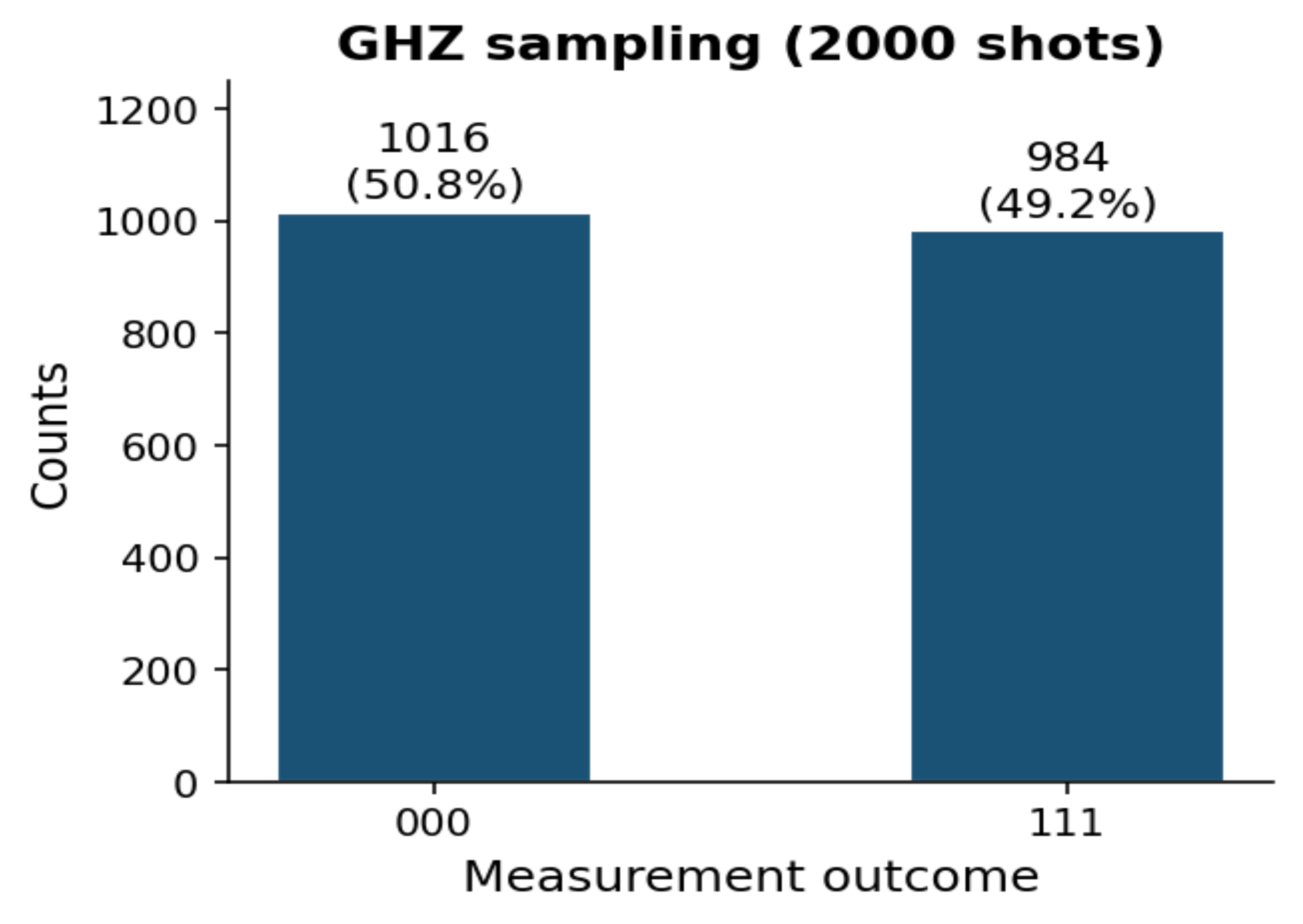
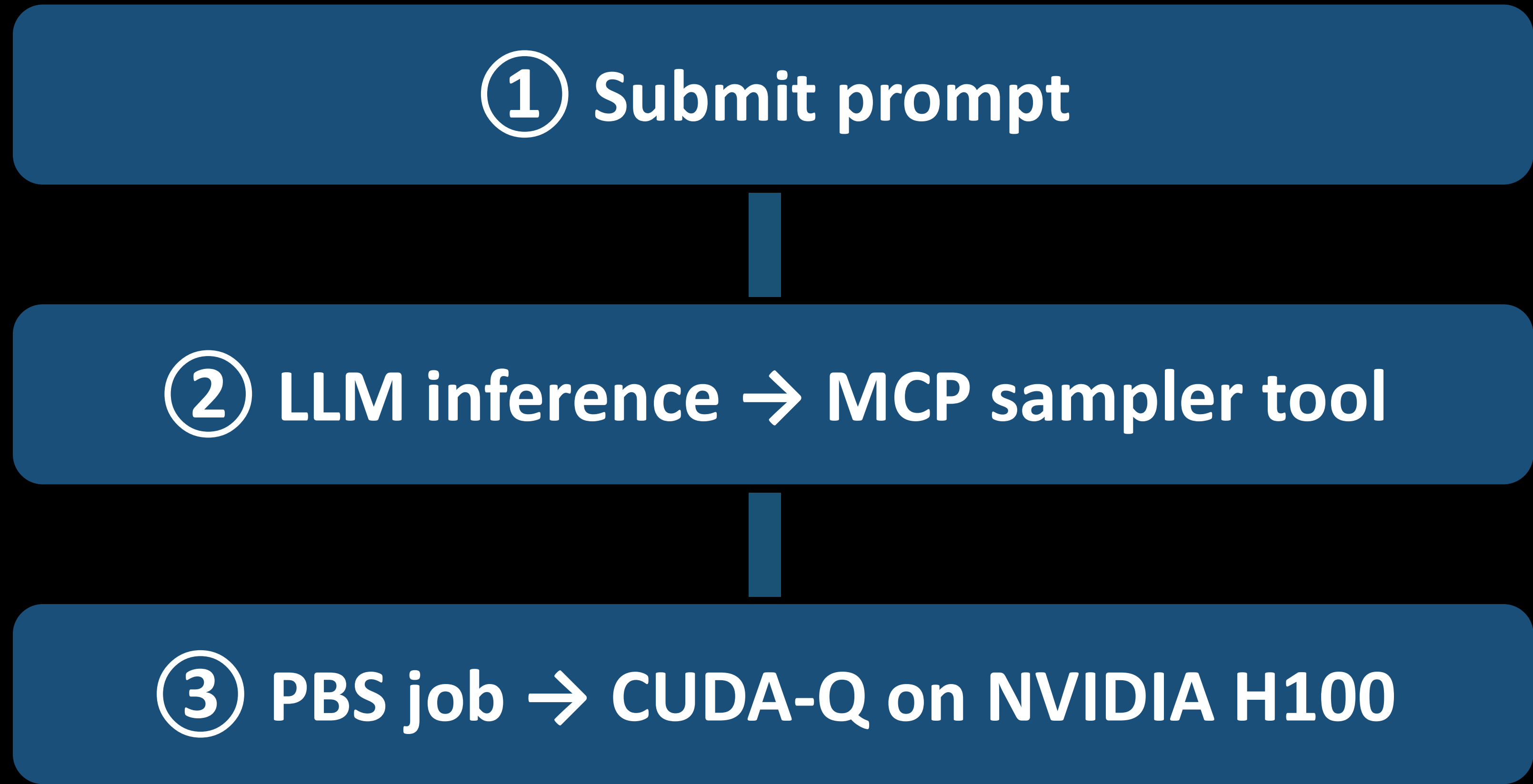
Our system: Local LLM + MCP + hybrid quantum backends



Local LLM inside ABCI-Q
MCP-based tool
dispatch
Unified local / remote
execution

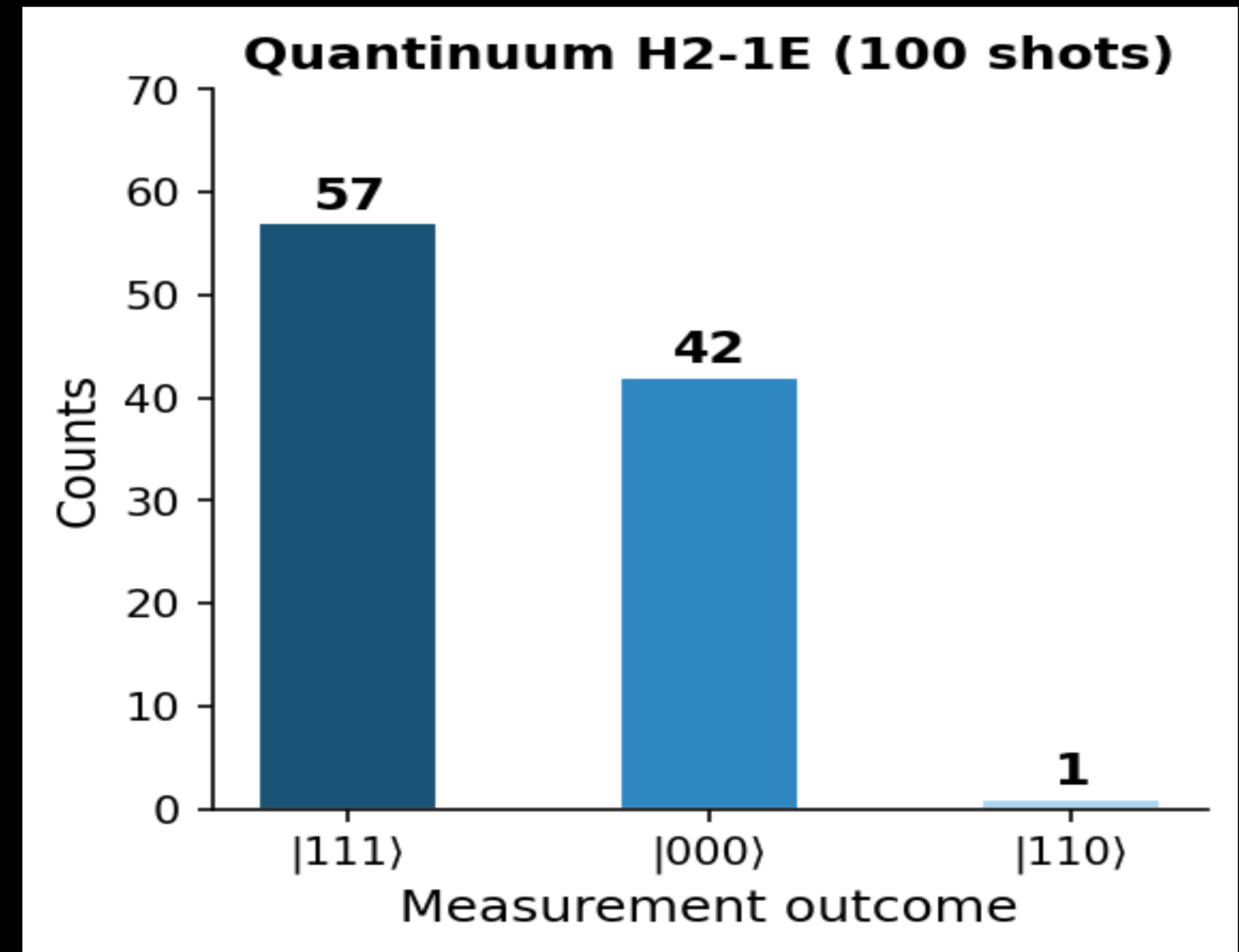
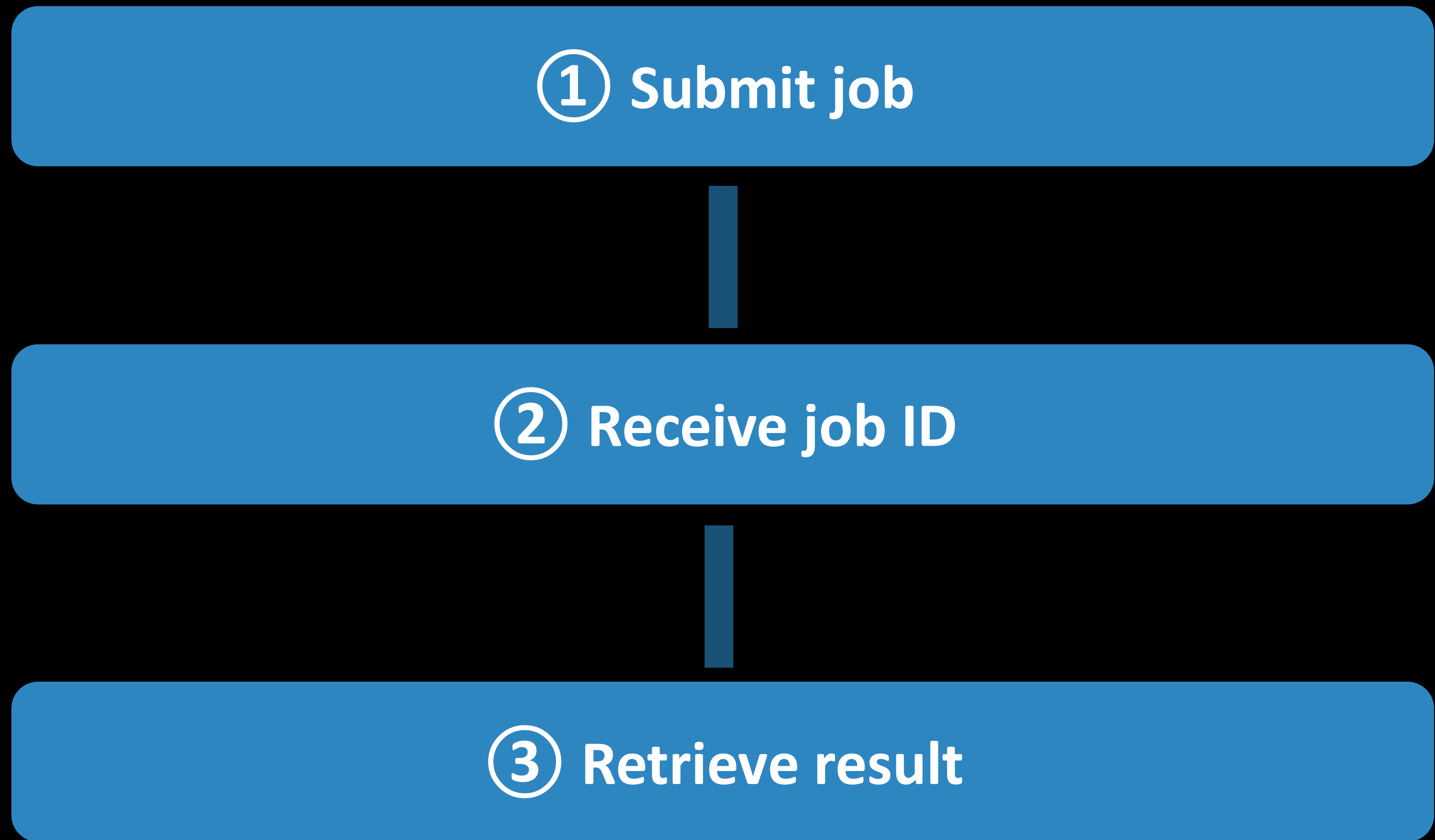
Local deployment keeps execution inside ABCI-Q

Result 1: Automated GHZ sampling on ABCI-Q Supercomputer (GPU Nodes*)



$|000\rangle \approx 0.50, |111\rangle \approx 0.50$

Result 2: Asynchronous execution on Quantinuum (Emulator)



Result 2': IBM Quantum Platform from ABCI-Q

LLM resources: rt_QG=1, walltime=01:00:00
Tool resources: rt_QG=1, walltime=00:20:00

Submitted: 141325.qjcm

Waiting for job to complete...

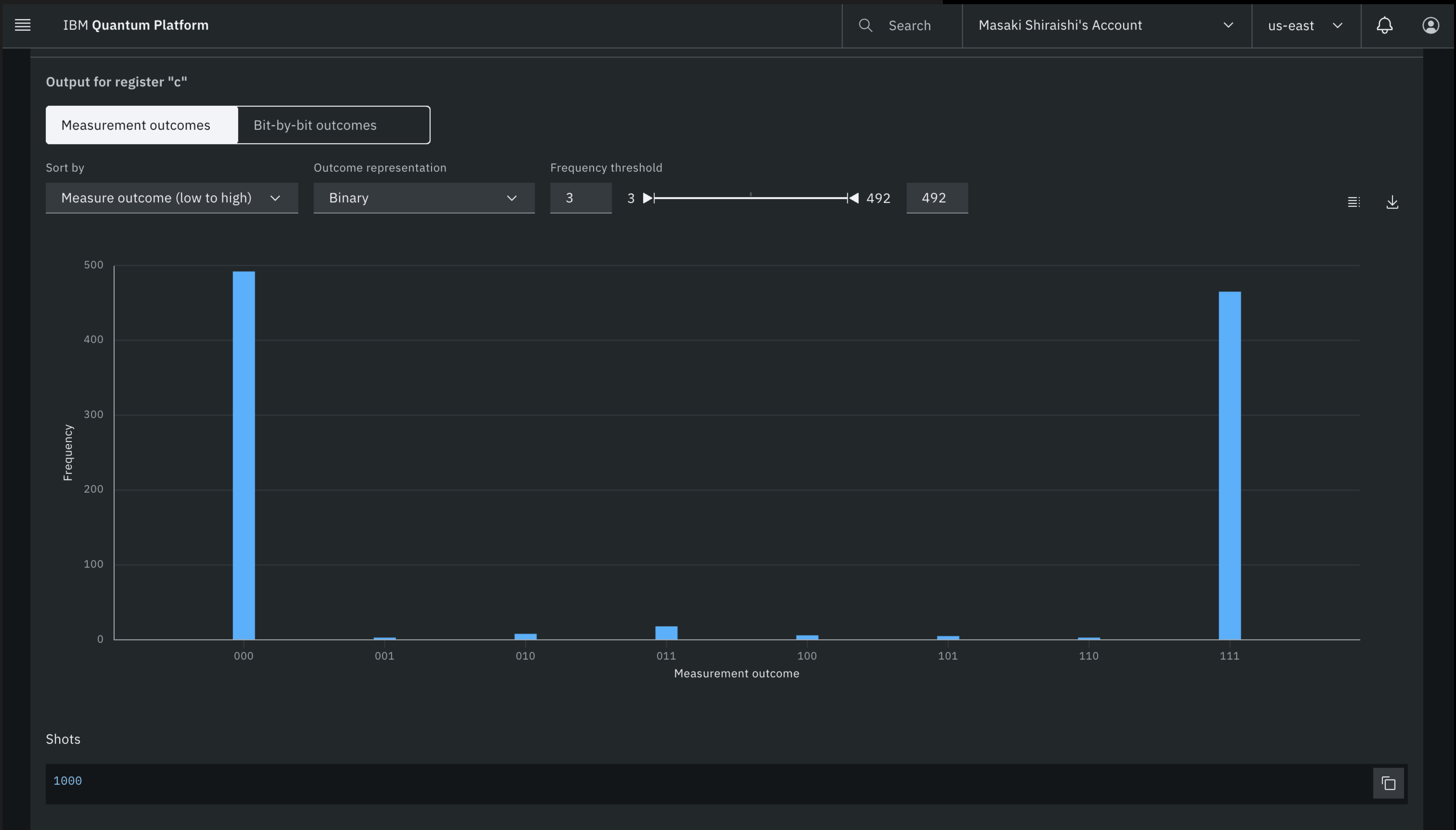
=== LLM Job Started on qh238 ===
Job ID: 141325.qjcm
Date: Sat May 23 12:42:00 AM JST 2026

Starting Ollama server...
Ollama PID: 2991794
Ollama is ready (attempt 2)

=== Running MCP Host ===

=== Job Completed ===
Exit code: 0

Result:
{
 "job_id": "d887kk5g7okc73en70eg",
 "device": "ibm_kingston",
 "shots": 1000,
 "counts": {
 "000": 492,
 "111": 465,
 "010": 8,
 "011": 18,
 "110": 3,
 "100": 6,
 "101": 5,
 "001": 3
 },
 "probabilities": {
 "000": 0.492,
 "111": 0.465,
 "010": 0.008,
 "011": 0.018,
 "110": 0.003,
 "100": 0.006,
 "101": 0.005,
 "001": 0.003
 }
}



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