Quantum Information and Computing at EPFL

Laboratory of Quantum Information and Computation (QIC) · Zoë Holmes · 2023-2026

Why quantum computing?

1 — Nature is quantum

Many systems, like molecules, materials and magnets, obey quantum mechanics. The cost of simulating them scales very fast with size.

2 — A quantum computer speaks that language

It could solve chemistry, materials or optimization problems beyond the means of supercomputers. Building it requires solving many engineering problems.

3 — Many theoretical challenges

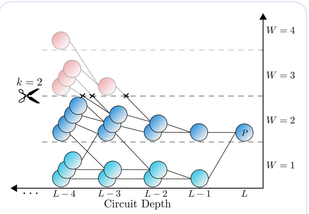
Where does it genuinely win over classical? How do we get there on noisy hardware? Can quantum algorithms learn from data?

33 Preprints — **11 in Nature journals, PRL & PRX Quantum** in 2025-2026

Co-authors at **MIT · Caltech · Google · IBM · Harvard**

2025 Zonta Prize — Zoë Holmes

Quantum Simulations

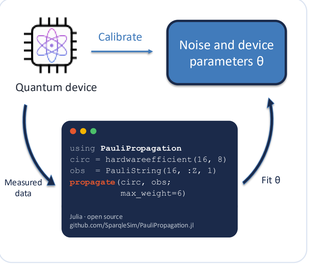


Paths that climb to high Pauli weight are cut (scissors) with small error.

Classically estimating observables of quantum circuits

Observables of typical circuits, noisy or not, are efficiently estimated classically, including the 127-qubit Ising dynamics from a well-known quantum advantage publication.

Angrisani, Schmidhuber, Rudolph, Cerezo, Holmes, Huang · PRL 135, 170602 (2025) · arXiv:2409.01706
With noise: Angrisani, Mele, Rudolph, Cerezo, Holmes · PRX Quantum 7, 020313 (2026)



Pauli Propagation: A Computational Framework for Simulating Quantum Systems

The method behind these proofs, packaged as PauliPropagation.jl, is used beyond simulation to benchmark and calibrate quantum processors against measured data across the field.

Rudolph, Jones, Teng, Angrisani, Holmes · PRX Quantum 7, 032001 (2026)
LOWESA: Rudolph, Fontana, Holmes, Cincio · arXiv:2308.09109 (2023)

Quantum-enhanced classical simulation, surrogate and measurement based.

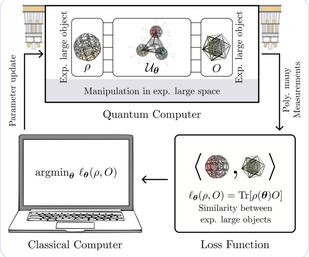
- **Trainability vs simulability.** Barren-plateau-free models are often simulable.
  Cerezo, Larocca et al. (with Rudolph, Thanasilp, Holmes) · Nature Communications 16, 7907 (2025) · arXiv:2312.09121
- **Landscape patches.** Hardware data lets a surrogate simulate a training region.
  Lerch, Puig, Rudolph, Angrisani, Jones, Cerezo, Thanasilp, Holmes · PRX Quantum 7, 020359 (2026) · arXiv:2411.19896

Thermal, open and bosonic systems. Propagation beyond closed qubit circuits.

- **Thermal and open systems.** Gibbs states and dissipative many-body dynamics.
  Rudolph, Angrisani et al. · arXiv:2602.04878 (2026) · Angrisani, Puig, Teng, Holmes · arXiv:2609.40174 (2026)
- **Bosonic circuits.** Coherent-state propagation for photonic systems.
  Guseynov, Holmes, Angrisani · arXiv:2604.19625 (2026) · Upreti, Chabaud, Holmes, Angrisani · arXiv:2510.07264 (2025)

- **Utility-scale dynamics.** IBM-led benchmark of hardware against classical methods.
  Barron et al. (IBM, with Holmes, Rudolph, Teng) · arXiv:2607.25998 (2026)

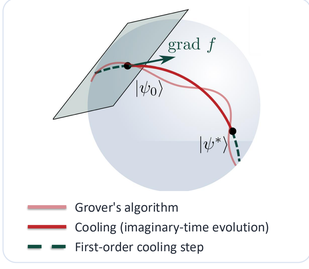
Quantum Algorithms



Barren plateaus in variational quantum computing

Gradients vanish exponentially in variational algorithms for ground states and dynamics: we connect the cause to expressivity, entanglement, noise and global costs.

Larocca, Thanasilp, Wang, Sharma, Biamonte, Coles, Cincio, McClean, Holmes, Cerezo · Nature Reviews Physics 7, 174 (2025) · arXiv:2405.00781



Grover's famous algorithm for search is 'cooling' in disguise

The most famous quantum algorithm turns out to approximate imaginary-time evolution, a thermodynamic process. This explains its magic angles and our understanding yields faster variants.

Suzuki, Gluza, Son, Tiang, Ng, Holmes · arXiv:2507.15065 (2025)

Double-bracket algorithms: ground and thermal states from cooling circuits.

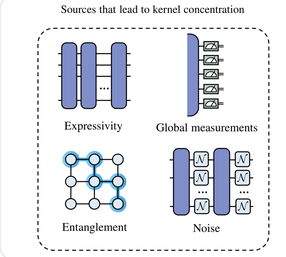
- **Imaginary-time evolution.** Ground-state preparation with an explicit circuit.
  Gluza, Son, Tiang, Zander, Seidel, Suzuki, Holmes, Ng · PRL 136, 020601 (2026) · arXiv:2412.04554
- **Thermal-state preparation** with guarantees for Gibbs states of many-body models.
  Wright, Aghaei Saem, Thanasilp, Suzuki, Holmes · arXiv:2606.05947 (2026)

- **Warm starts.** Initialization near the answer for variational ground states and dynamics.
  Puig, Drudis, Thanasilp, Holmes · PRX Quantum 6, 010317 (2025) · arXiv:2404.10044 · Puig et al. · arXiv:2602.06137 (2026)
- **High-energy physics.** Review on applications in lattice gauge theory and scattering.
  Di Meglio, Jansen, Tavernelli et al. (CERN-led roadmap, with Holmes) · PRX Quantum 5, 037001 (2024) · arXiv:2307.03236

Where quantum hardware pays off: operator dynamics, practical cost of circuits.

- **Heisenberg-picture simulation.** Operator spreading understood as a hardware task.
  Chiew, Angrisani, Holmes, Carleo · arXiv:2602.20154 (2026)
- **Resource costs.** Costs of quantum runs compared to classical simulation.
  Chang, Thanasilp, Holmes, Cerezo · arXiv:2609.11847 (2026)

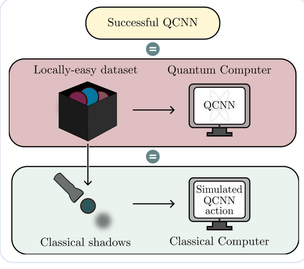
Quantum Learning



Exponential concentration in quantum kernel methods

Kernel values concentrate exponentially with qubit number through expressivity, entanglement, global measurements or noise.

Thanasilp, Wang, Cerezo, Holmes · Nature Communications 15, 5200 (2024) · arXiv:2208.11060
Dequantization: Sahebi, Barthe, Suzuki, Holmes, Grossi · arXiv:2505.15902 (2025)



Quantum CNNs are effectively classically simulable

Many quantum networks look successful because they are tested on easy data. The classical copy matches all results, up to 1024 qubits. At the same time, this technique opens up hybrid approaches with classical training and quantum deployment.

Bermejo, Braccia, Rudolph, Holmes, Cincio, Cerezo · PRX Quantum 7, 020304 (2026) · arXiv:2408.12739

Learning quantum dynamics, including unitaries, correlators and OTOCs.

- **Out-of-distribution learning.** Unitary dynamics learned from few input states.
  Favre, Angrisani, Holmes · arXiv:2610.03690 (2026) · Caro, Huang et al. · Nat. Commun. 14, 3751 (2023) · arXiv:2204.10268
- **Operator shadows.** Extraction of all local OTOCs and two-point correlators at once.
  Chiew, Angrisani, Holmes · arXiv:2607.15493 (2026)

Quantum models in practice: reservoirs and generative models.

- **Quantum reservoirs.** Scrambling and noise bound memory for time series.
  Xiong, Holmes, Angrisani, Suzuki, Chotibut, Thanasilp · arXiv:2505.10080 (2025)
- **Extreme learning machines.** What fixed quantum feature maps can and cannot learn.
  Xiong, Facelli, Sahebi, Agnel, Chotibut, Thanasilp, Holmes · Quantum Mach. Intell. 7, 20 (2025) · arXiv:2312.15124
- **Quantum generative models.** Trainability barriers, and where training can work.
  Rudolph, Lerch, Thanasilp, Kiss, Shaya, Vallecorsa, Grossi, Holmes · npj Quantum Inf. 10, 116 (2024) · arXiv:2305.02881
- **IQP Born machines.** Generative models with data-dependent initialisation.
  Lerch, Bowles, Puig, Armengol, Holmes, Thanasilp · arXiv:2603.14576 (2026)

Where it matters

✓ **Discerning quantum advantage**

Our proofs and simulations help the field understand in which scenarios quantum computers can win, so effort and money go where they count.

✓ **Algorithms for the present and the near future**

Cooling, warm-start and Heisenberg-picture methods are designed for today's noisy machines, whereas Double-bracket algorithms keep an eye on the fault-tolerant devices of the future.

✓ **Great community impact**

Presence in steering committees (QIP; QCTiP), collaborations in many institutes across the globe (France, Germany, UK, Spain, Singapore, Thailand, US…) and the industry (Google, IBM, Algorithmiq…), and strong adoption of our tools (16 contributors on PauliPropagation.jl)

Team: Zoë Holmes (PI) · Armando Angrisani, Maite Arcos Enriquez, Sergi Masot Llima, Yudai Suzuki, Yanting Teng, Slimane Thabet (Postdocs) · Reyhaneh Aghaei Saem, Sacha Lerch, Ricard Puig, Manuel Rudolph, Mehrad Sahebi, Weijie Xiong (PhDs) · and recent members and visitors.