Akademia Sztuki Kwantowej — podsumowanie

Piotr Gawron

Instytut Informatyki Teoretycznej i Stosowanej Polskiej Akademii Nauk

01.04.2026

AKADEMIA
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NAUKA DLA
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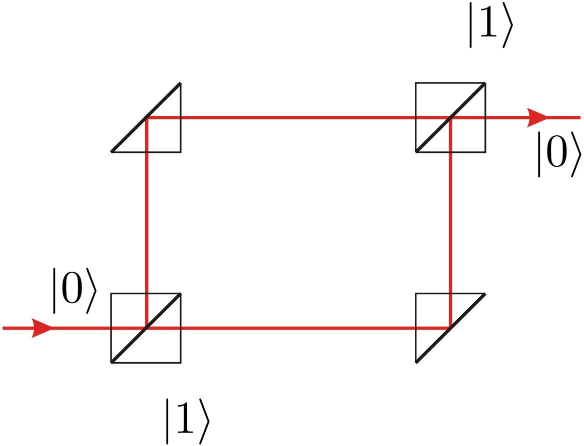
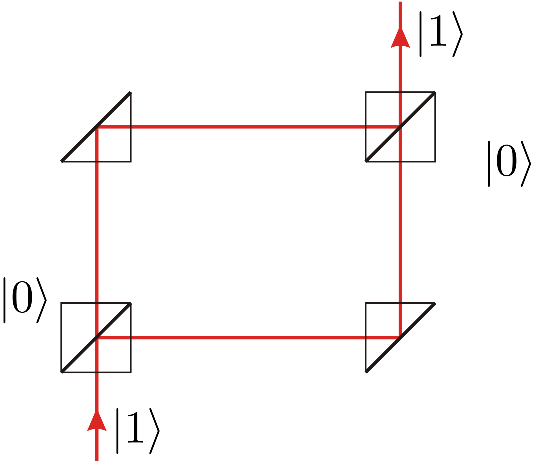
Na smutny Prima Aprilis

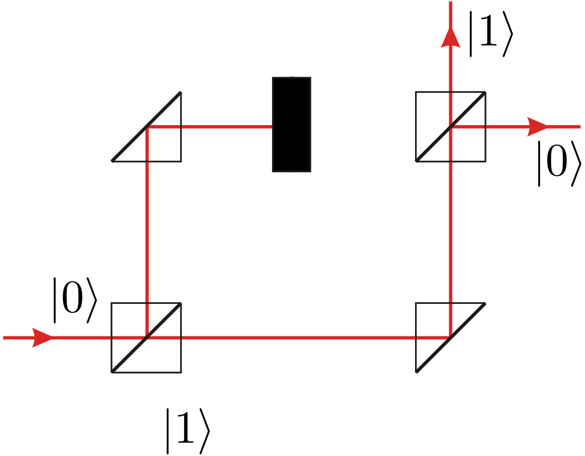
Interferometr Macha-Zendera I



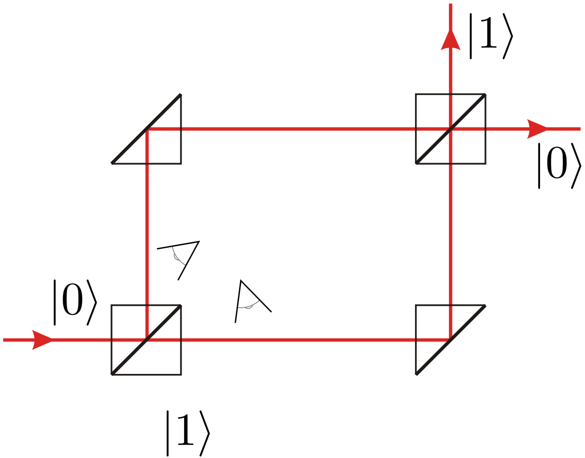
Interferometr Macha-Zendera II



Interferometr Macha-Zendera III

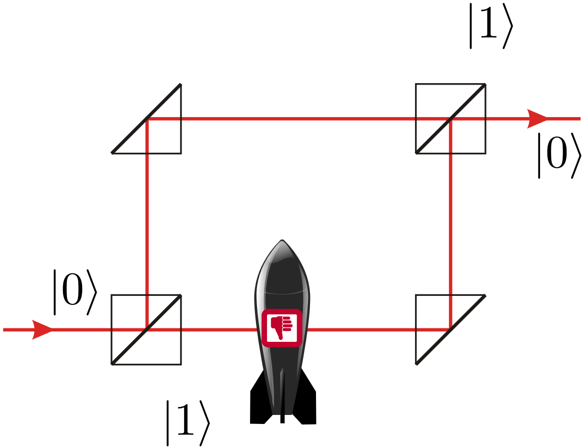


Interferometr Macha-Zendera IV



Problem testowania bomb Elitzura-Vaidmana I

Problem testowania bomb Elitzura-Vaidmana II



Problem testowania bomb Elitzura-Vaidmana III

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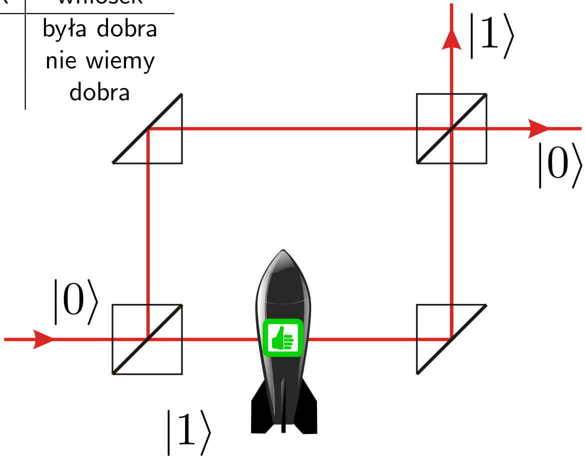
1/4	nie	1	dobra



Biznes

Mapping the global quantum ecosystem

A comprehensive analysis based on innovation, firm, investment, skills, trade and policy data

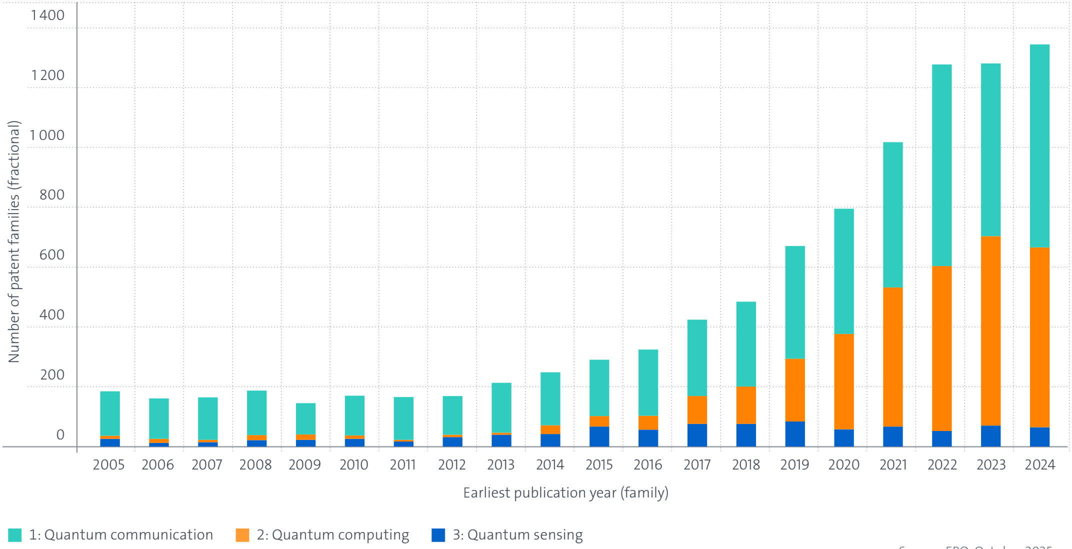
December 2025

Europäisches Patentamt
European Patent Office
Office européen des brevets

OECD

Figure E1

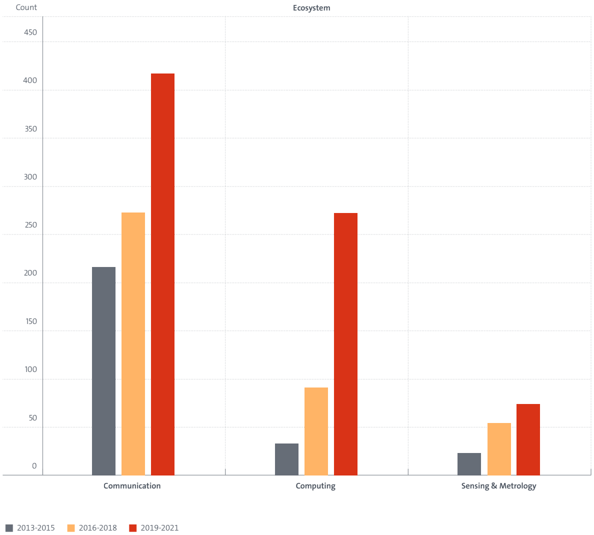
Trends in IPFs in quantum technologies by quantum area



Source: EPO, October 2025.

Figure E2

Quantum ecosystem entries by main technology: 2013-2021



Notes: The figure shows only firms with a quantum patent. Entry is defined as the year of a firm's first quantum patent. The definition of the main technology of a company is based on the technology with the strongest representation in its patent portfolio as of the latest available date (2025). If a firm has the same number of patents across multiple technologies, it is assigned proportionally across the categories.

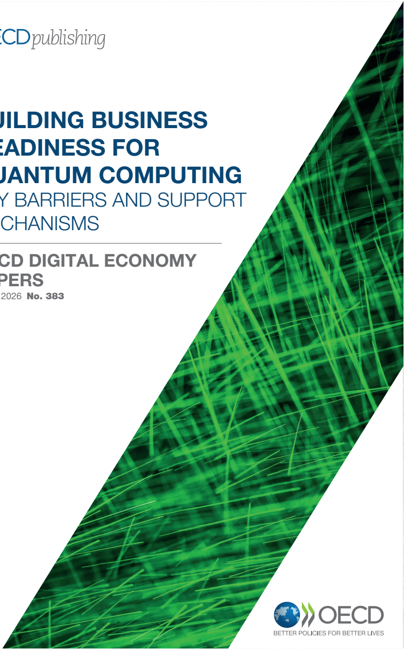
Source: OECD calculations based on OECD, STI Micro-data Lab and Orbis, Bureau van Dijk, October 2025.

OECD*publishing*

BUILDING BUSINESS READINESS FOR QUANTUM COMPUTING

KEY BARRIERS AND SUPPORT MECHANISMS

OECD DIGITAL ECONOMY PAPERS
March 2026 **No. 383**



OECD
BETTER POLICIES FOR BETTER LIVES

Box 1. Quantum computing: Common misconceptions to avoid

Public discussions of quantum technologies sometimes exaggerate their current or near-term capabilities. The following clarifications can help set realistic expectations:

- **Exponential information does not automatically mean exponential speed:** Quantum computers can in principle represent very large amounts of information, but this does not translate into automatic or universal performance gains. Quantum technologies are expected to be useful in resolving only certain problems and progress remains gradual.
- **Superposition is not the same as doing millions of tasks at once:** Quantum states describe probabilities, not parallel calculations. Useful results still require carefully designed algorithms and repeated testing.
- **Quantum machine learning will not replace today's AI soon:** Noise, limited hardware and the difficulty of loading large volumes of data in quantum computers mean that, for most applications, artificial intelligence on classical computers will continue to be more effective for many years.
- **Claims of quantum advantage must be tested against classical approaches:** Several announcements of breakthroughs have been scaled back once faster or cheaper classical solutions were considered. Advantage is meaningful only when demonstrated under fair comparisons.
- **Timelines are uncertain:** Predictions about when quantum computing will be ready for broad commercial use vary widely. Policymakers and firms should treat such forecasts with caution and plan for multiple scenarios.

Source: OECD (2025[1]).

Box 2. Potential commercial applications of quantum computing across business activities

- **Medicine and healthcare**: Quantum computing could accelerate drug discovery and DNA sequencing, as well as contribute to more accurate patient outcome predictions.
- **Materials science**: Quantum computers could help model novel alloys and superconductors, guiding the development of stronger, lighter and more efficiently manufactured materials.
- **Energy**: Quantum simulation and optimisation may help deliver improved carbon-capture processes and energy grid operations.
- **Chemistry**: By simulating molecular reactions such as nitrogenase-based nitrogen fixation and photosynthesis, quantum computers could lead to new, more efficient and less costly processes for chemical manufacturing.
- **Finance**: Quantum algorithms could improve risk analysis, credit scoring and portfolio management, potentially optimising processes such as transaction settlements, arbitrage and crash forecasting.
- **Transportation and logistics**: Quantum computing could help design next-generation batteries and solve vast routing and scheduling problems, thereby increasing efficiency in vehicle fleets and cargo networks.

Source: OECD (2025[1]).

Table 2. Recent survey data on barriers to building quantum readiness

Source	(QuEra, 2025[32])	(Moody's, 2023[28])	(ISED, 2024[30])
Survey year	2024	2023	2024
Focus	Quantum computing	Quantum computing	Quantum technologies
Sample	• 770 quantum computing experts, researchers and decision-makers from 50 countries, primarily in Europe (39.6% of responses), North America (35.6%) and Asia (14.9%).	• 200 data, analytics and innovation leaders in financial services and banking firms from 17 European and North American countries. • Respondents were affiliated with businesses generating annual revenues of USD 100 million or greater.	• 112 individuals in Canada's quantum sector developing quantum technologies, including 66 from industry and 46 academics. • 46% of industry respondents conduct research and development in quantum computing.
Survey question	What challenges would or does your organisation face in adopting quantum computing?	What are the biggest operational challenges for the development of quantum computing in your organisation?	What is the main barrier, if any, preventing end users from adopting quantum solutions?
Question type	Multiple choice	Multiple choice	Single choice
Question sample	Users or potential users of quantum computing (12.7% of survey sample)	Full survey sample	Industry actors developing quantum technologies (50% of survey sample)
Main barriers reported	• High costs of implementation: 39.6% • Lack of skilled workforce: 40.6% • Unclear business value: 39.6% • Technology immaturity: 34.4% • Immaturity of algorithms: 28.1% • Limited access to hardware: 21.9% • Integration with existing systems: 17.7% • Competition with other priorities: 17.7% • Lack of internal buy-in: 15.6% • Security and data privacy: 15.6% • Regulatory compliance concerns: 9.4%	• Technology immaturity: 82% • Lack of C-level executive buy-in: 48% • General scepticism about the potential of quantum computing: 41% • Lack of investment: 37% • Integration with existing systems: 33% • Lack of skills in-house: 32% • Cybersecurity concerns: 22% • No access to partnerships with other expert institutions: 4%	• Use cases still being proven: 21.4% • Technology immaturity: 19.6% • Lack of knowledge: 19.6% • Technology costs: 8.9% • Risk aversion 7.1% • No urgency/incentive for it: 5.4% • Other barriers: 14.3% • No barriers: 3.6%

Nauka

REVIEWS OF MODERN PHYSICS, VOLUME 97, JULY–SEPTEMBER 2025

Nobel Lecture: Boltzmann machines*

Geoffrey Hinton

Department of Computer Science, University of Toronto, Ontario, Canada

(published 25 August 2025)

To solve difficult computational tasks, artificial neural networks need to construct appropriate internal representations by adapting the weights on their connections in the direction that improves performance. In the 1980s, there were two promising techniques for computing the gradients required to adapt the weights. One technique was backpropagation, which is now used in almost all artificial intelligence systems. The other was the Boltzmann machine learning algorithm, which is no longer used. After describing two of the major successes of backpropagation, this Nobel Lecture explains the Boltzmann machine learning algorithm, which uses a property of the Boltzmann distribution to compute gradients in an elegant and unexpected way.

DOI: 10.1103/RevModPhys.97.030502

communications physics

Article

A Nature Portfolio journal

https://doi.org/10.1038/s42005-025-02353-1

Expressive equivalence of classical and quantum restricted Boltzmann machines

Check for updates

Maria Demidik[1,2], Cenk Tüysüz[1,3,4], Nico Piatkowski[5], Michele Grossi[4] & Karl Jansen[1,2]

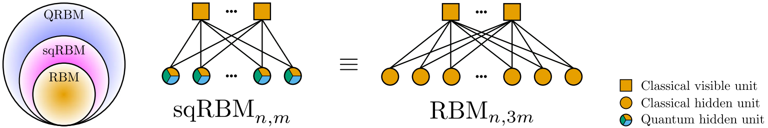


Fig. 1 | Summary of main results. This work introduces semi-quantum restricted Boltzmann machines (sqRBM) as an intermediate model, satisfying the relation QRBM $\supseteq$ sqRBM $\supseteq$ RBM. sqRBMs generalize RBMs by rendering the hidden units *quantum* through the use of non-commuting Hamiltonians. In Theorem 2, we show that sqRBM$_{n,m}$ $\equiv$ RBM$_{n,3m}$, where n and m denote the number of visible and hidden units, respectively, with both models having the same number of parameters. In pedestrian terms, RBMs require three times as many hidden units as sqRBMs to learn the same target distribution.

Spectral methods: crucial for machine learning, natural for quantum computers?

Vasilis Belis, Joseph Bowles, Rishabh Gupta, Evan Peters, and Maria Schuld*
Xanadu Quantum Technologies Inc., Toronto, Ontario, M5G 2C8, Canada
(Dated: March 27, 2026)

This article presents an argument for why quantum computers could unlock new methods for machine learning. We argue that spectral methods, in particular those that learn, regularise, or otherwise manipulate the Fourier spectrum of a machine learning model, are often natural for quantum computers. For example, if a generative machine learning model is represented by a quantum state, the Quantum Fourier Transform allows us to manipulate the Fourier spectrum of the state using the entire toolbox of quantum routines, an operation that is usually prohibitive for classical models. At the same time, spectral methods are surprisingly fundamental to machine learning: A spectral bias has recently been hypothesised to be the core principle behind the success of deep learning; support vector machines have been known for decades to regularise in Fourier space, and convolutional neural nets build filters in the Fourier space of images. Could, then, quantum computing open fundamentally different, much more direct and resource-efficient ways to design the spectral properties of a model? We discuss this potential in detail here, hoping to stimulate a direction in quantum machine learning research that puts the question of "why quantum?" first.

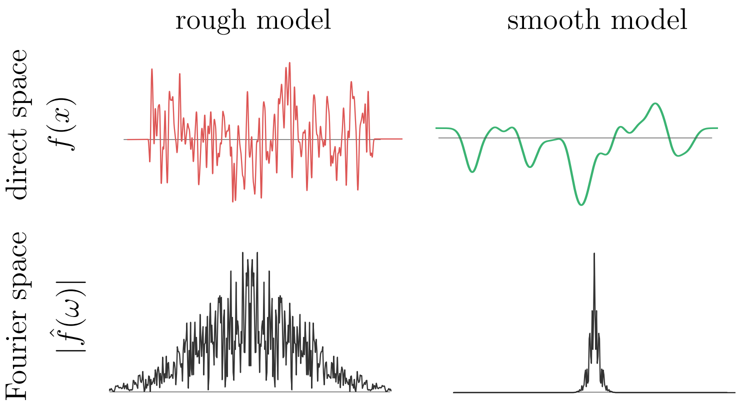


FIG. 1. A common simplicity bias of machine learning models is their smoothness, which is linked to a decay of the model function's Fourier spectrum. But designing such a decay in Fourier space is usually computationally expensive. Can quantum computers help here?

Shor's algorithm is possible with as few as 10,000 reconfigurable atomic qubits

Madelyn Cain[1,*,†], Qian Xu[1,2,*,‡], Robbie King[1], Lewis R. B. Picard[1], Harry Levine[1,3],
Manuel Endres[1,2], John Preskill[1,2], Hsin-Yuan Huang[1,2], Dolev Bluvstein[1,2,§]

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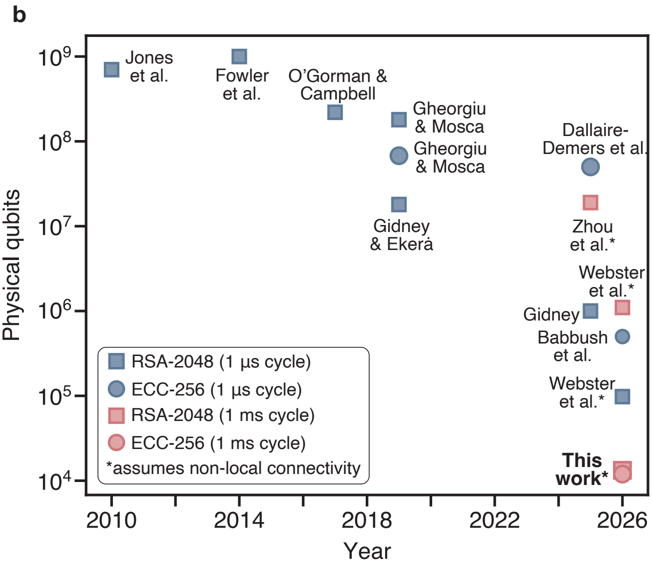
[†] *mcain@oratomic.com*, [‡] *qxu@oratomic.com*, [§] *dbluvstein@oratomic.com*

[*] *These authors contributed equally*

(Dated: March 31, 2026)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Jones et al.
Fowler et al.
O'Gorman & Campbell
Gheorgiu & Mosca
Gheorgiu & Mosca
Gidney & Ekerå
Dallaire-Demers et al.
Zhou et al.*
Webster et al.*
Gidney
Babbush et al.
Webster et al.*
This work*
RSA-2048 (1 µs cycle)
ECC-256 (1 µs cycle)
RSA-2048 (1 ms cycle)
ECC-256 (1 ms cycle)
*assumes non-local connectivity
Physical qubits
Year
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10^6
10^5
10^4
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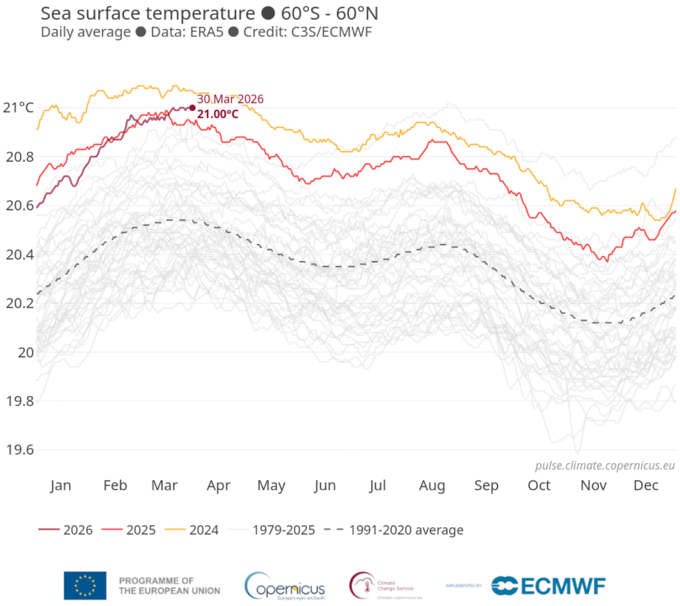
2014
2018
2022
2026

Klimat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Daily average ● Data: ERA5 ● Credit: C3S/ECMWF
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PROGRAMME OF
THE EUROPEAN UNION
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ECMWF

nature reviews earth & environment

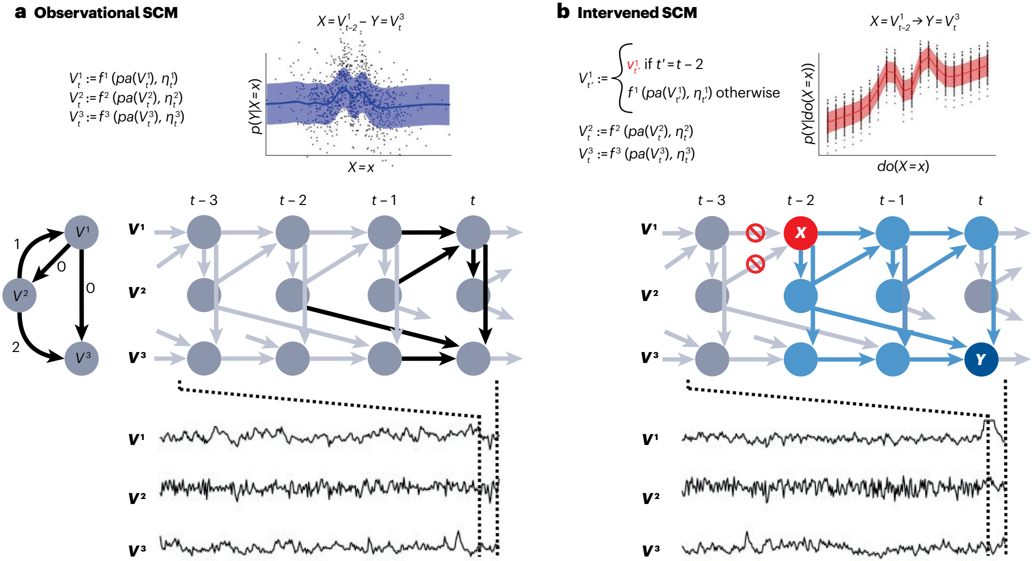
https://doi.org/10.1038/s43017-023-00431-y

Technical review

Check for updates

Causal inference for time series

Jakob Runge [1,2], Andreas Gerhardus [1], Gherardo Varando [3], Veronika Eyring [4,5] & Gustau Camps-Valls [3]



a Observational SCM
$V_t^1 := f^1(pa(V_t^1), \eta_t^1)$
$V_t^2 := f^2(pa(V_t^2), \eta_t^2)$
$V_t^3 := f^3(pa(V_t^3), \eta_t^3)$
$X = V_{t-2}^1 - Y = V_t^3$
$p(Y|X=x)$
$X=x$
1
0
0
2
V^1
V^2
V^3
$t-3$
$t-2$
$t-1$
t
b Intervened SCM
$V_{t'}^1 := \begin{cases} v_{t'}^1 \text{ if } t' = t-2 \\ f^1(pa(V_{t'}^1), \eta_{t'}^1) \text{ otherwise} \end{cases}$
$V_t^2 := f^2(pa(V_t^2), \eta_t^2)$
$V_t^3 := f^3(pa(V_t^3), \eta_t^3)$
$X = V_{t-2}^1 \rightarrow Y = V_t^3$
$p(Y|do(X=x))$
$do(X=x)$
X
Y

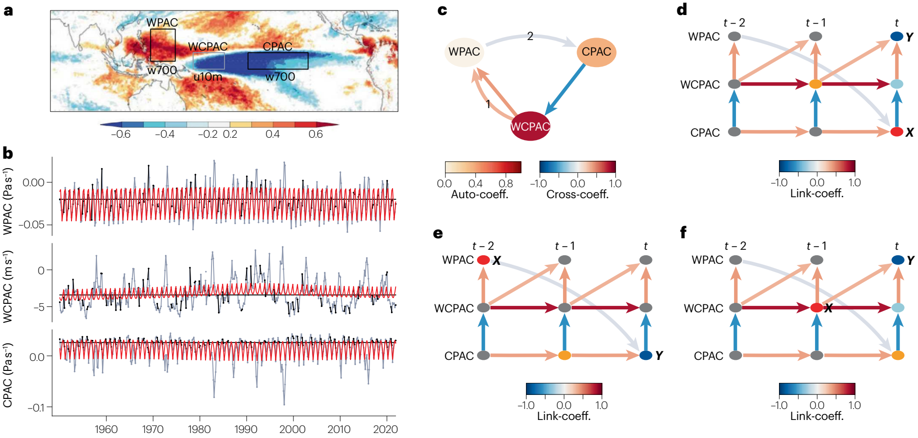


Fig. 3 | Causal inference analysis of the Walker Circulation. a, WPAC and CPAC are spatial averages of the 700mb-height level vertical velocity averaged across the West Pacific [130° E–150° E, 20° N–0°] and Central Pacific [160° W–120° W, 5° N–5° S], respectively, and WCPAC is the 10m zonal wind averaged across the Western-Central Pacific [160° E–180° E, 5° N–5° S]. The underlying contours depict the correlations of the Niño3.4 index with the vertical anomalous January–February velocity field. **b**, Time series (black, masked samples in grey) extracted from ERA5 reanalysis data[146,147]. Red lines represent the 15-year Gaussian kernel smoothed long-term trend plus the seasonal cycle. **c**, Assumed causal graph, collapsed in time, where straight edges are contemporaneous causal links and curved edges are lagged links with the corresponding lags shown as numbers on the curved edges. Edge colours show the link coefficients at the lag with maximum absolute link coefficient (lag label), and the node colours depict the link coefficient of the lag −1 autocorrelation links. **d**, Time series graph for causal effect estimate of X (red) on Y (blue), with mediators in light blue and optimal adjustment set in orange. Edge colours depict link coefficients. **e**, As in panel **d**, but for another X and Y. **f**, As in panel **d**, but for another X and Y. This analysis illustrates the many (pre)processing steps that are necessary to fulfil the assumptions of causal inference methods and to transparently discuss causal conclusions.

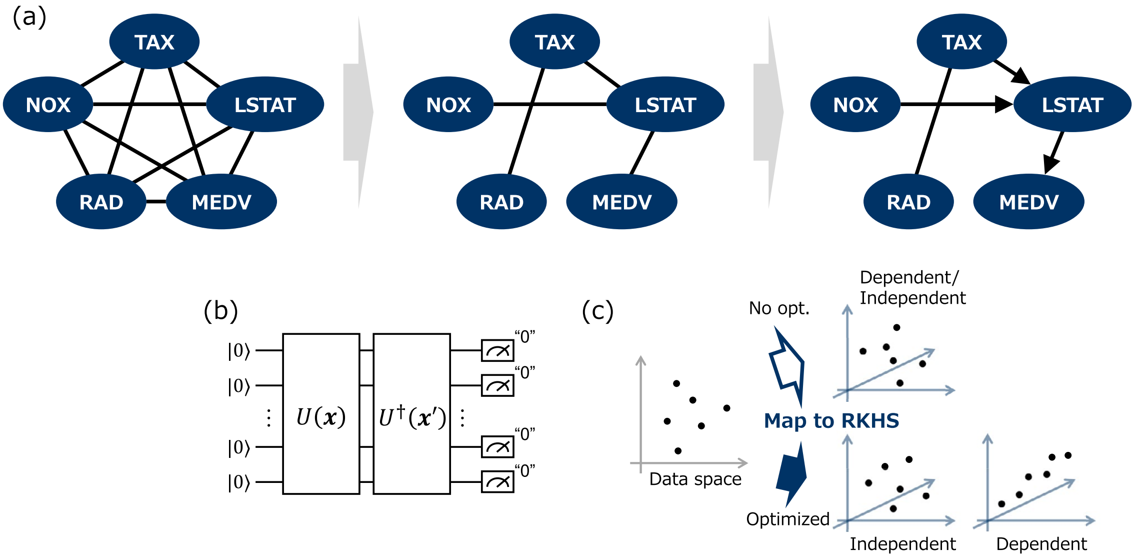
Quantum Machine Intelligence (2026) 8:36
https://doi.org/10.1007/s42484-026-00380-x

RESEARCH ARTICLE

Quantum-enhanced causal discovery for a small number of samples

Yu Terada[1] · Ken Arai[1] · Yu Tanaka[1] · Yota Maeda[1] · Hiroshi Ueno[1] · Hiroyuki Tezuka[1,2]

Received: 4 July 2025 / Accepted: 23 February 2026


(a)
TAX
NOX
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|0⟩
|0⟩
|0⟩
|0⟩
$U(\boldsymbol{x})$
$U^\dagger(\boldsymbol{x}')$
"0"
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"0"
(c)
Data space
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Dependent/
Independent
Map to RKHS
Optimized
Independent
Dependent

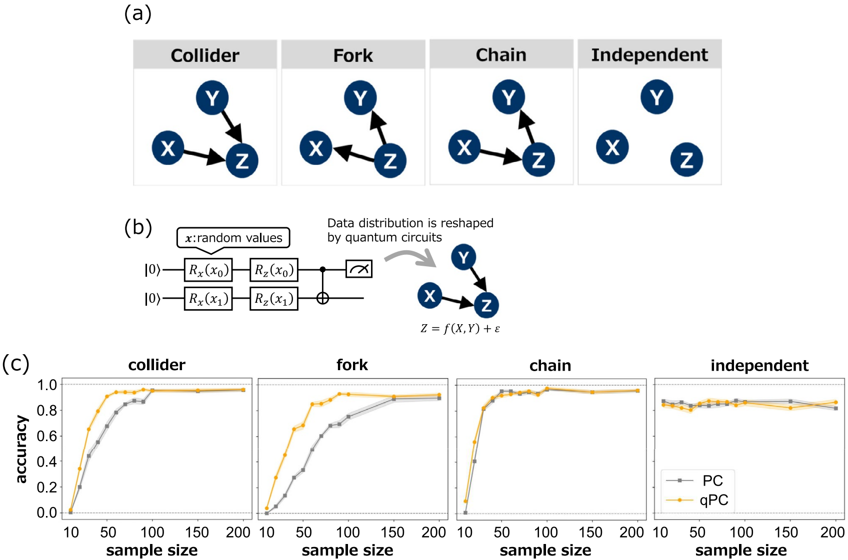
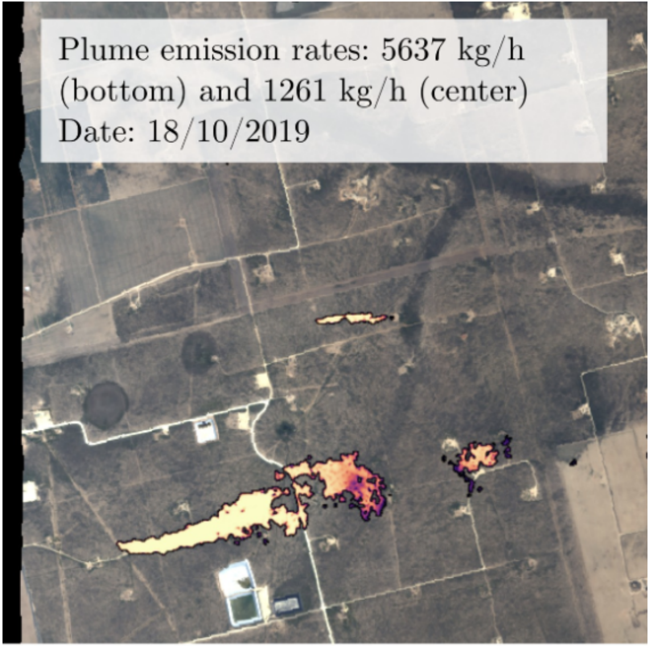


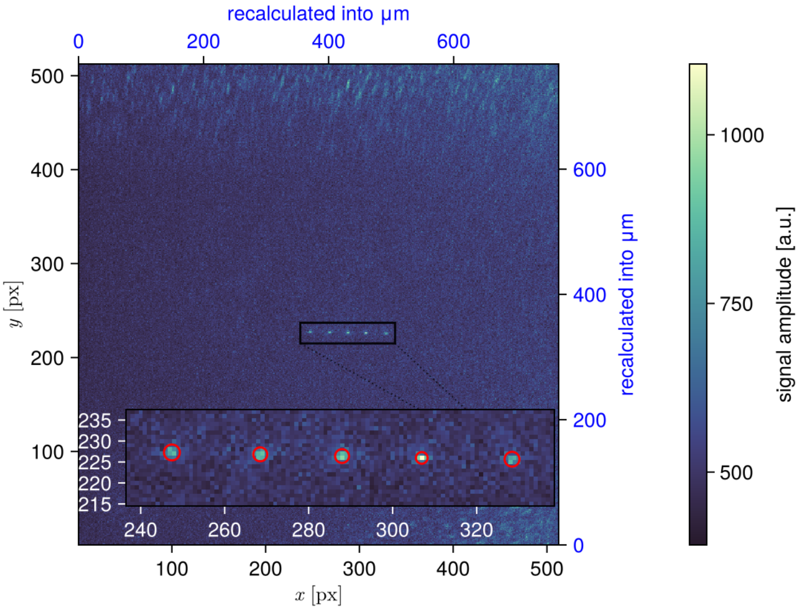
Fig. 3 Characteristic performance of the qPC algorithm. **a** Basic causal graphs under three variables with their corresponding dependent and independent relations. **b** Data generation with quantum models. The source variables were drawn from quantum circuits with random variable inputs, and the other variables were determined by a causal structure. **c** Accuracy of the PC and qPC algorithms for the four causal patterns with different sample sizes. The shaded regions represent the standard errors from 10 different simulations

esa

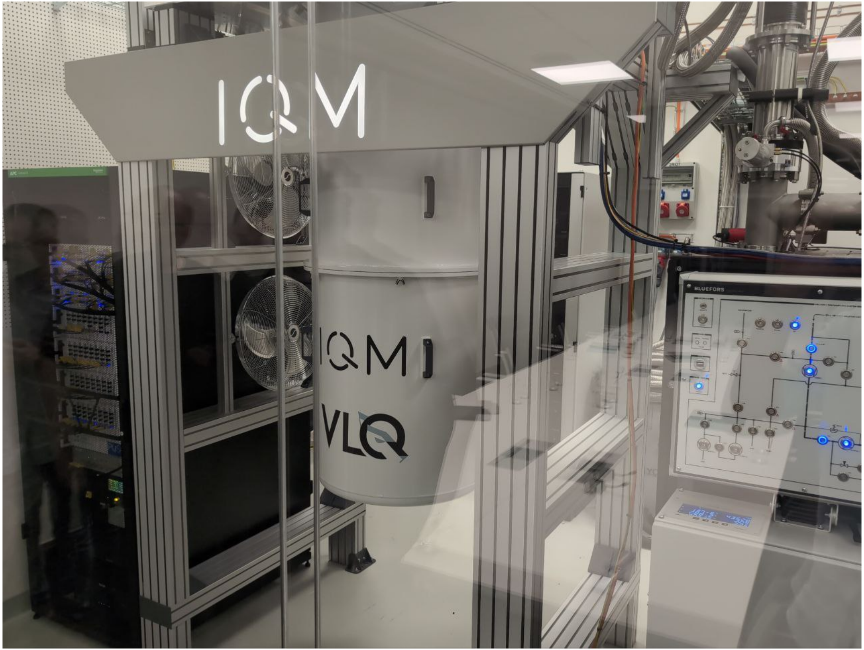



Plume emission rates: 5637 kg/h
(bottom) and 1261 kg/h (center)
Date: 18/10/2019

Komputery



recalculated into µm
0
200
400
600
500
400
300
200
100
y [px]
x [px]
100
200
300
400
500
recalculated into µm
0
200
400
600
235
230
225
220
215
240
260
280
300
320
signal amplitude [a.u.]
1000
750
500


IQM
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VLQ
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Matrix

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