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Perspective

Integrated Photonic Computing beyond the von Neumann Architecture

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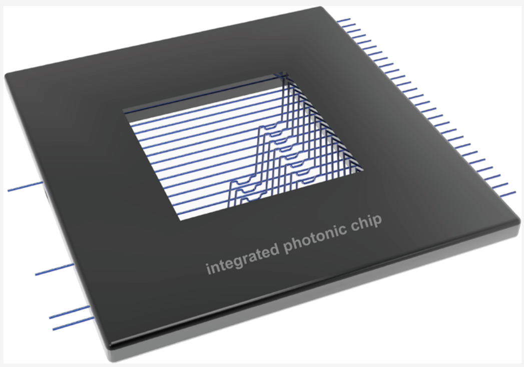

ABSTRACT: In the context of a doomed end of the Moore's law, various new types of computing architectures have been emerging, aiming to meet the demands of intractable computation and artificial intelligence. Photonic computing is a competitive candidate, in light of the inherent properties of photons, including high propagation speed, strong robustness, and multiple degrees of freedom to encode information. Also, the progress of integrated photonics continues to provide novel possibilities, apart from boosting the scalability and stability of photonic computing architectures. Moreover, an introduction of quantum technology might open a new chapter for photonic computing, from the view of single photons. In this Perspective, we highlight the unique features and advances of integrated photonic platforms, whose roles in constructing a non-von Neumann computing architecture are also outlined. We show their potential in solving problems beyond the reach of traditional computers and in machine learning and further discuss the conceivable challenges and opportunities.

KEYWORDS: *photonic computing, integrated photonics, NP-hard problem, quantum technology, time-of-flight storage*

■ INTRODUCTION

With Moore's law faltering in recent years, the improvement of the computing power of modern electronic computer is expected to encounter a bottleneck in the near future.[1] The stagnation is due to the inevitable physical and technical limitations during the miniaturization of transistors, such as heat dissipation and quantum tunneling.[2] Meanwhile, lots of practical problems belonging to the NP-complete class,[3−5] related to scheduling, drug discovery, etc., are hard to solve efficiently on even the most powerful electronic computer.[6,7] Besides, machine learning, which usually involves the processing of mega data, can easily lead to massive time and energy consumption owing to the von Neumann bottleneck,[8,9] i.e., the separation between processor and memory. In light of the wide correlation between NP-complete problems and the real world and the extensive application of artificial intelligence, it is thus of great significance to find a novel computing architecture, which could be a complement of the conventional computer in the fields of specific computation, not necessary to be a replacement.

A variety of non-von Neumann computing paradigms have been reported, including quantum computation,[10,11] mem-computing,[12,13] neuromorphic computing,[14] molecular computing,[15−17] optical computing,[18,19] etc. On the long journey of seeking a powerful computing paradigm, light-based computation showcases as an active player. Actually, inspired by the inherent strengths of light, such as high propagation speed and vast parallelism, the investigation of light-based computation has started at about 70 years ago.[20] At the early and middle stage, classical light was treated as a basic information carrier, and there was no application of quantum technology in the computing paradigms. Therefore, we would like to call it "optical computing". Obviously, optical computing is a very old topic, which can even date back to the Fourier transform with optical lens. However, today's significant development of integrated photonic technology could offer new possibilities. Compared with bulk optics, integrated photonics provides a monolithic, miniaturized, and physically scalable platform, enabling the realization of large-scale complex computation with high accuracy.[21] Further, an introduction of quantum technology could also open a new chapter for light-based computation, like the demonstration of the quantum computational advantage using a photonic system.[22−24]

In this Perspective, "photonic computing" refers to the computing paradigms where single photons are regarded as independent information carriers and quantum technology could play a part. In the following sections, we first highlight the unique features and advances of different integrated photonic platforms, and briefly discuss their roles in photonic

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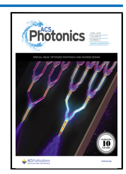

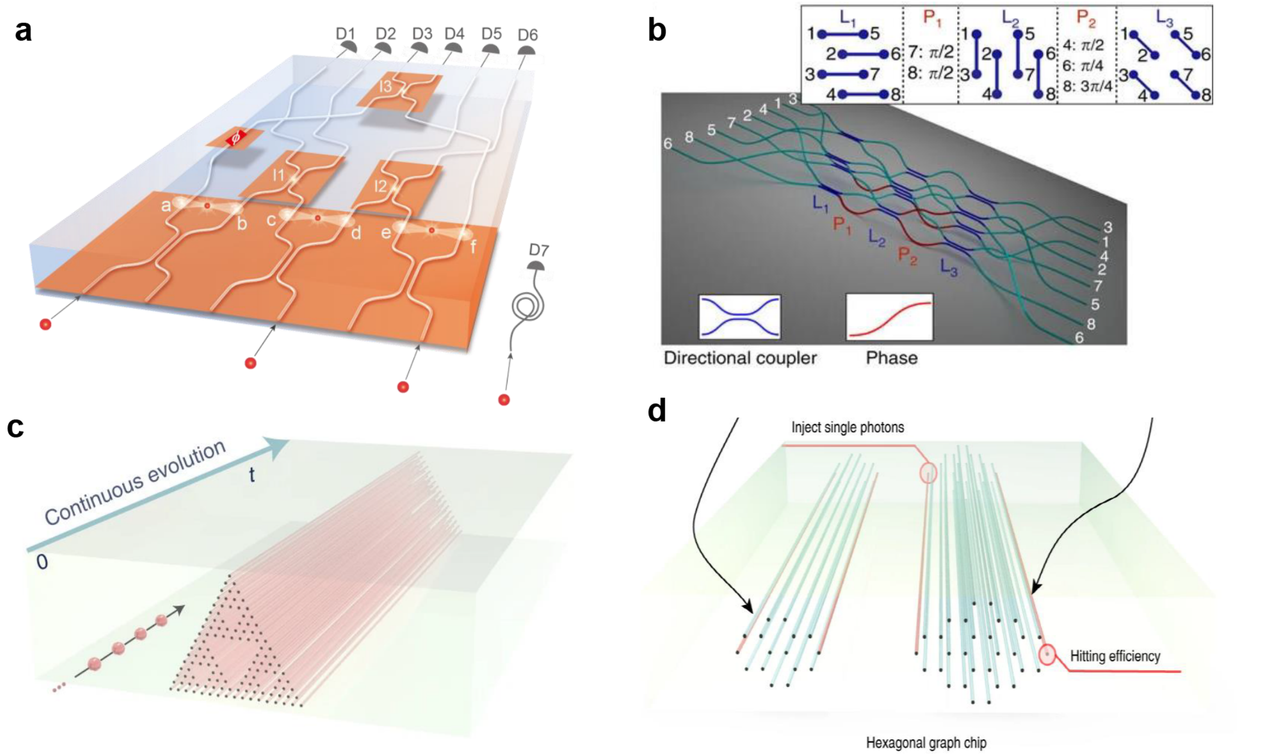

Figure 1. Photonic chips based on femtosecond laser written-silica. (a, b) Embedded photonic circuits, made of basic components such as a directional coupler, enable three-dimensional complicated interconnects. (c, d) Buried photonic lattices, which couple continuously along the longitudinal direction, have cross sections with fractal and hexagonal geometries, respectively. (a) Reproduced with permission from ref 27. Copyright 2021 American Physical Society. (b) Adapted with permission from ref 28. Copyright 2016 Nature Publishing Group, https://creativecommons.org/licenses/by/4.0/. (c) Adapted with permission from ref 29. Copyright 2021 Nature Publishing Group. (d) Adapted with permission from ref 30. Copyright 2018 Nature Publishing Group.

computing. Then, specific applications in solving NP-hard problems and machine learning are introduced to show the potential advantages of integrated photonic computing. We also conceive a possible application of quantum technology in photonic computing. Finally, we make a conclusion and discuss challenges for the future.

■ INTEGRATED PHOTONIC PLATFORM

Femtosecond Laser-Written Silica. A femtosecond laser irradiated into glass can induce a positive refractive index change in the region of its focus spot.[25] In this sense, the movement trajectory of the laser spot in silica forms an optical waveguide where light can be confined, which is known as a femtosecond laser writing technique.[26] Distinguished from other photonic platforms, femtosecond laser-written silica supports a three-dimensional structure. This unique feature can be used to achieve photonic circuits with a highly complicated topology[27,28] and to realize photonic lattices with complex geometry such as fractal and honeycomb,[29,30] as shown in Figure 1. The third dimensionality provides new degrees of freedom for the design of photonic computing architecture since nonadjacent photonic components are allowed to directly connect with each other. Also, the extra loss brought by the planar waveguide intersection could be avoided.

Reconfigurability is a critical criterion for a computing architecture to meet practical demands. A programmable laser-written photonic circuit can be implemented through an integration of Mach–Zehnder interferometers (MZIs) driven by thermal-optical phase shifters. In combination with an appropriate circuit design,[31] such as the universal linear circuits proposed by Reck[32] and Clements,[33] different configurations can be obtained on a photonic circuit, consequently leading to a realization of diverse functions. As presented in Figure 2a, the construction of thermal phase shifters is compatible with the system used to inscribe the waveguide,[34] which indicates that the chip fabrication flow is completely maskless and gets rid of the redundant steps of traditional lithography. So far, photonic circuits with up to 12 phase shifters have been reported,[35−37] making the first steps toward reconfigurable silica photonic chips. To further enhance the scale and performances of the photonic circuits, isolation trenches are utilized to reduce the thermal crosstalk between phase shifters (see Figure 2b),[38] and meanwhile, the geometry of the phase shifters is elaborately optimized to increase their heating efficiency.[39] Recently, programmability can even be demonstrated on a three-dimensional continuously coupled photonic circuit, regardless of an absence of MZI,[40] as shown in Figure 2c.

It is also worth stressing that the propagation of light in laser-written silica can be visible by taking advantage of fluorescence,[41] as displayed in Figure 3a, which makes path-encoding and position-encoding computation possible. Besides, the transmission and generation of orbital angular momentum are supported by the silica platform (Figure 3b), enabling high-capacity information encoding.[42,43] In terms of the on-chip generation and detection of quantum light, 128 identical quantum source (Figure 3c)[44] and an array of superconducting nanowire single-photon detectors (Figure 3d) have been successfully implemented on a silica substrate,[45] suggesting the possibility of applying quantum technology to

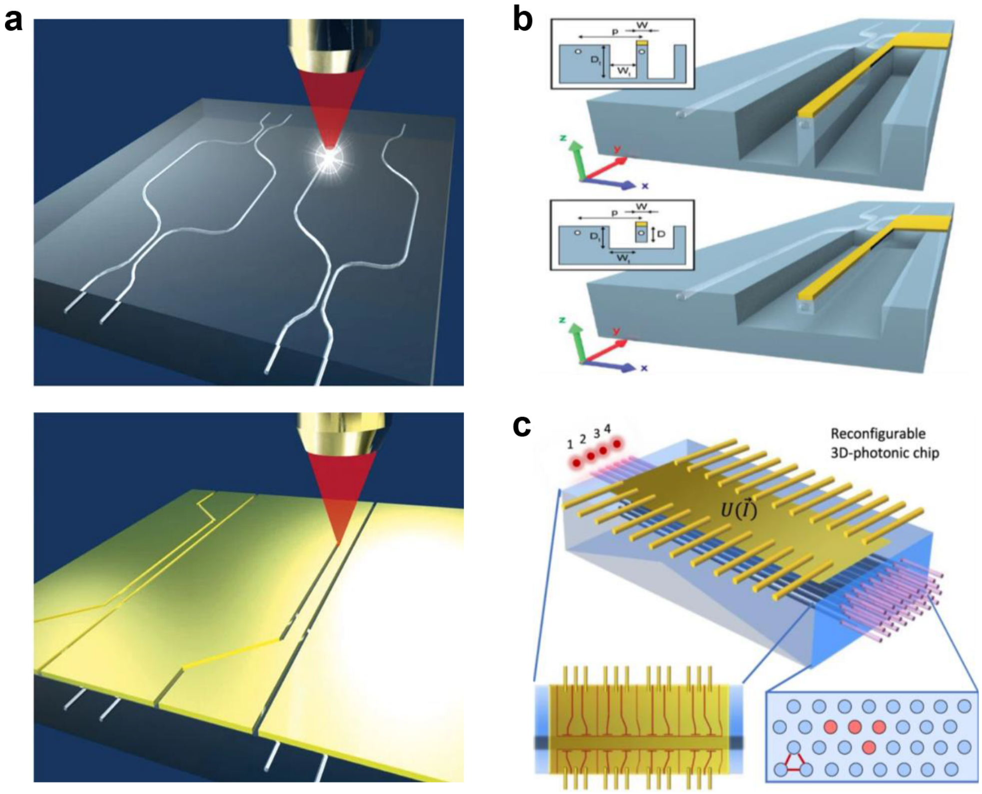

Figure 2. Selected progress of a programmable silica photonic chip. (a) Waveguides and phase shifters can be fabricated with the same femtosecond laser writing system. Waveguides are written into the chip first, and phase shifters are later formed by ablating the metal thin films deposited on the chip surface. (b) Isolation trenches are employed to lower the heat dissipation of the phase shifter to neighboring waveguides, reducing on-chip thermal crosstalk. (c) Three-dimensional photonic lattices, consisting of coupled straight waveguides, can be reconfigured through a combination of multiple phase shifters that are elaborately arranged. (a) Reproduced with permission from ref 34. Copyright 2015 Nature Publishing Group, https://creativecommons.org/licenses/by-nc-sa/4.0/. (b) Adapted with permission from ref 38. Copyright 2020 The Authors, https://creativecommons.org/licenses/by/4.0/. (c) Adapted with permission from ref 40. Copyright 2022 Nature Publishing Group, https://creativecommons.org/licenses/by/4.0/.

large-scale photonic computation, where the amplitudes of output signals probably decay to a very low level.

Silicon-on-Insulator. Silicon-on-insulator (SOI) is prevalent for its compatibility with complementary metal-oxide-semiconductor (CMOS) technology. Thanks to the solid foundation laid by silicon electronics, a large variety of integrated photonic devices have been developed, with wide applications in both classical and quantum signal processing.[46,47] The existing abundance of silicon photonic devices can be conveniently used to construct a photonic computing architecture. Meanwhile, due to the high refractive index contrast between silicon waveguide and the substrate, light can be tightly confined, thus enabling high-density integration, as demonstrated in Figure 4a.[48] The reported state-of-the-art 32 × 32 optical switches contain up to 1024 integrated MZIs and hundreds of intersection components,[49,50] which demonstrates the leadership of SOI platform in building large-sized photonic circuits. Given that MZI is the key building block of many programmable photonic circuits,[31] the impressive achievements confirm the possibility of dealing with photonic computation at large scale. In addition to common thermo-optic and electro-optic modulation, SOI allows a novel way of modulation based on nonvolatile phase-change materials, which has less energy consumption and exhibits promising application in neuromorphic computing.[51]

Lithium Niobate-on-Insulator. Another attractive integrated photonic platform is lithium niobate-on-insulator (LNOI).[52] Different from bulk lithium niobate, LNOI enables the fabrication of waveguides with high refractive index contrast, leading to an enjoyment of many advantages possessed by other thin-film semiconductor counterparts, such as high integration density. On the other hand, LNOI inherits the unique properties of bulk lithium niobate, including wide transparency window, large electric-optic coefficient, and strong nonlinearity. These advantages allow LNOI to support a wide range of passive and active devices,[53] as illustrated in Figure 4b. By taking advantages of the high electric-optic coefficient, on-chip modulators achieve a modulation frequency of 110 GHz,[54,55] far ahead of the counterparts based on other platforms. Also, with an employment of the strong nonlinearity, optical switching can be performed within an ultrashort time of ∼76 fs (Figure 4c).[56] These achievements make LNOI a promising candidate in ultrafast photonic information processing and computing. For example, it always takes a certain amount of time to configure a large-scale programmable photonic chip for particular computation tasks, given the vast number of tunable devices in the photonic chip. LNOI enables electro-optic modulator that is several orders of magnitude faster than thermo-optic modulator, providing a possibility of ultrafast reconfiguration of programmable photonic chips. In many cases, the computing results of a photonic chip could be obtained through only one-shot detection (e.g., the photonic computer for subset sum problem in the next section). On these

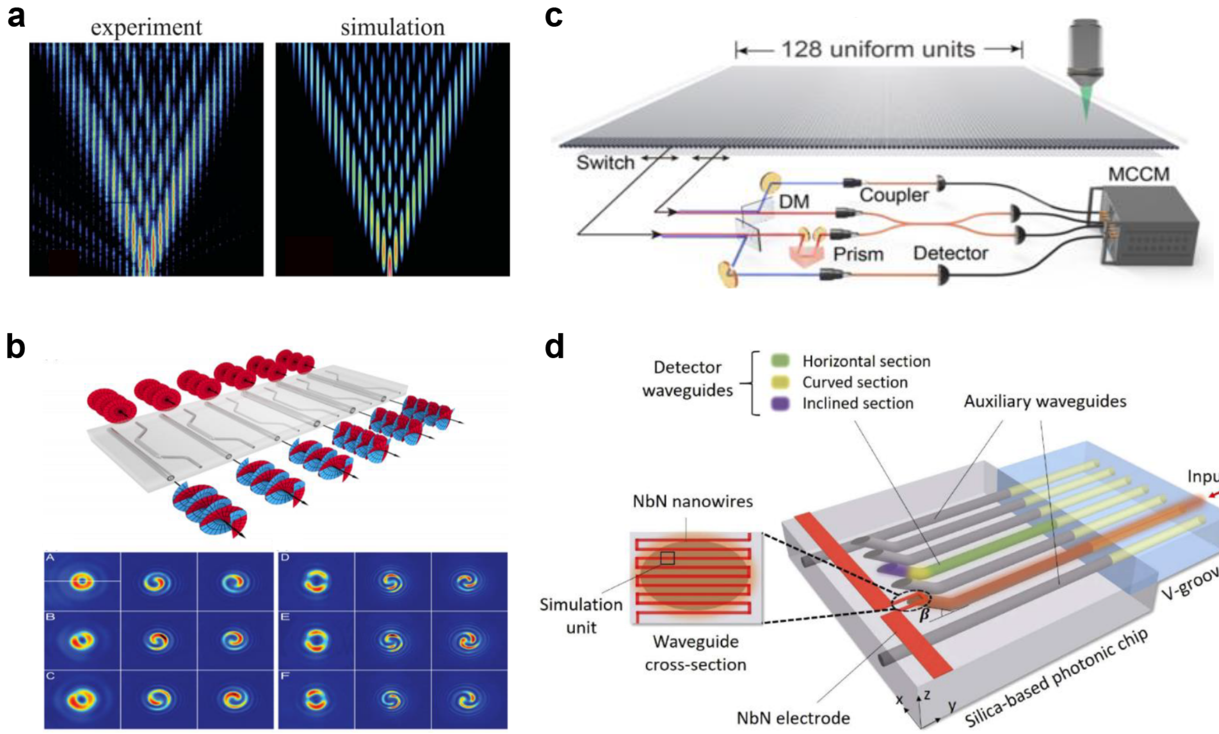

Figure 3. Other functions available on laser written-silica platform. (a) The propagation of light can be directly observed through fluorescent imaging. (b) Orbital angular momentum can be generated on a silica photonic chip. (c) 128 on-chip identical quantum sources are realized through a nonlinear process of spontaneous four-wave mixing. (d) Superconducting nanowire single-photon detector arrays are successfully deposited on the silica substrate. (a) Adapted with permission from ref 41. Copyright 2008 The Optical Society. (b) Reproduced with permission from ref 43. Copyright 2020 American Physical Society. (c) Reproduced with permission from ref 44. Copyright 2021 American Physical Society. (d) Reproduced with permission from ref 45. Copyright 2021 The Optical Society.

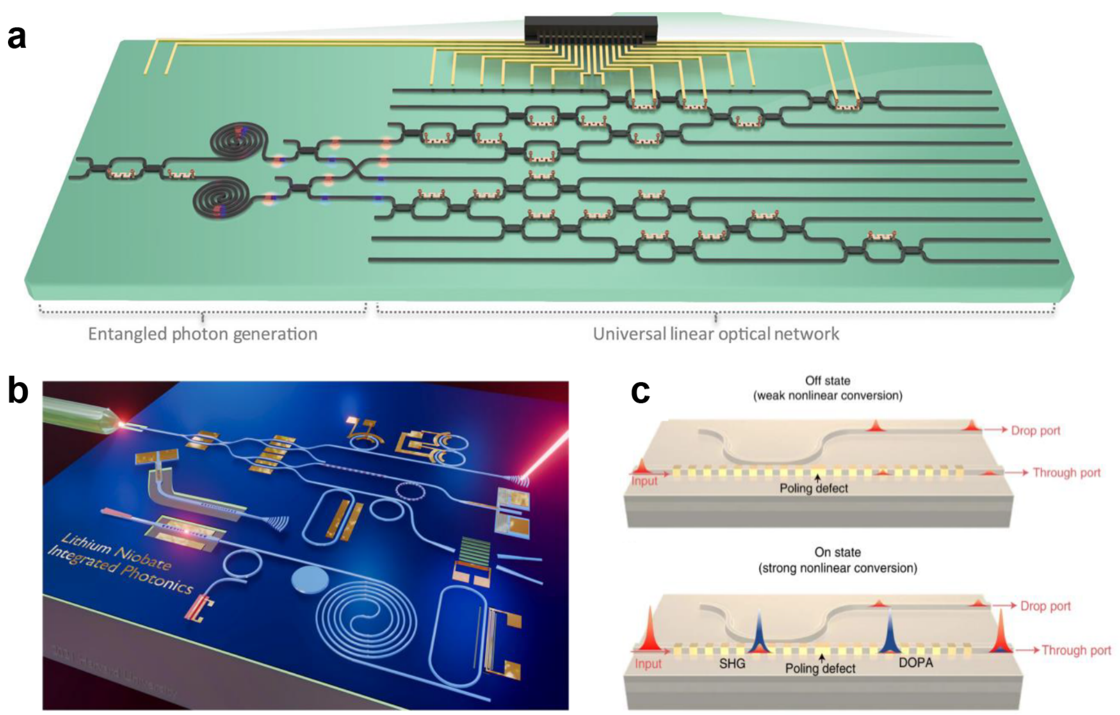

Figure 4. SOI and LNOI. (a) SOI is featured by a high-density integration of photonic components even in the context of programmability. (b) Photonic components ranging from passive to active can be potentially implemented on LNOI. (c) An ultrafast and energy-efficient optical switch based on the strong nonlinearity of lithium niobate. (a) Adapted with permission from ref 48. Copyright 2021 American Association for the Advancement of Science, https://creativecommons.org/licenses/by-nc/4.0/. (b) Reproduced with permission from ref 53. Copyright 2021 The Optical Society. (c) Reproduced with permission from ref 56. Copyright 2022 Nature Publishing Group.

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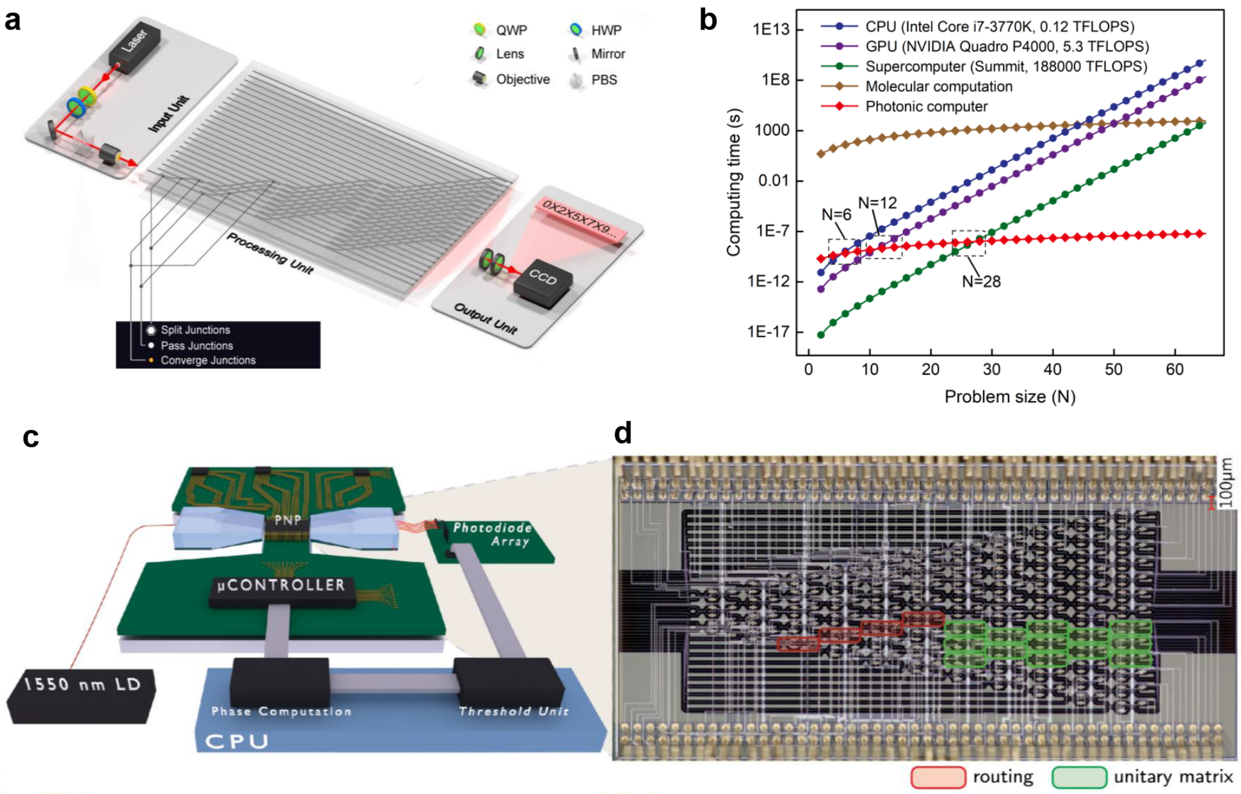

Figure 5. Applications of integrated photonic platform in solving NP-hard problems. (a) A photonic computer for the subset sum problem (SSP) consists of three parts, at the heart of which is the processing unit realized with a three-dimensional silica photonic chip. (b) The photonic computer for SSP is comparable to Intel i7−3770k and shows a potential computational advantage with the problem size growing. (c) An Ising machine accelerated by the use of a silicon photonic chip, which is magnified and presented in (d), provides another way to deal with NP-hard problems. (a) Adapted and (b) reproduced with permission from ref 21. Copyright 2020 American Association for the Advancement of Science, https://creativecommons.org/licenses/by-nc/4.0/. (c, d) Reproduced with permission from ref 60. Copyright 2020 The Optical Society.

occasions, single-photon detectors are not necessary to operate at ultrahigh speed and thus could be taken advantages in the computation.

Moreover, the electrical 3 dB bandwidth of commercially available photodetectors now can be up to 100 GHz,[57] which is comparable to the modulation frequency enabled by LNOI. These photodetectors are obviously fast enough to match the LNOI platform when real-time detection and feedback are required during the computation process, therefore enabling high-speed photonic computing. Though the detection sensitivity of the photodetectors is not as high as a single-photon detector, the high-speed property of the LNOI platform can still be made full use in the cases where optical signals are beyond the detection threshold of the photo-detectors. In addition, ingenious techniques could be developed to reduce the energy consumption of photonic computing,[58] which might be beneficial to mitigating the decay of optical signal and relieving the harsh requirements on photodetectors.

■ COMPUTING ARCHITECTURES BASED ON INTEGRATED PHOTONIC PLATFORM

Application in Solving NP-Hard Problems. NP-hardness is used to describe the time complexity of a computational problem that is much beyond the capability of electronic computers.[6,7] More specifically, the time taken to solve a NP-hard problem by a deterministic Turing machine grows exponentially with the problem size, resulting in unacceptable time consumption in practice. In the class of NP-hard, NP-complete is an important category closely related to the real world. As mentioned in the Introduction, solving NP-complete problems with higher efficiency is one of the crucial motivations of searching for a novel and powerful computing architecture. On the other hand, NP-complete problems can be treated as testbeds for the evaluation of a computing architecture.

Despite the rapid development of integrated photonic platforms, the implementation of a universal photonic computer still remains elusive. Compared with a universal photonic computer, a specific-purpose one is more accessible. In recent years, photonic computers designed for particular kinds of NP-complete problems have been emerging, such as a subset sum problem and a Hamiltonian path problem.[21,59] As demonstrated in Figure 5a, a typical photonic computer is generally made of three parts, i.e., an input unit, a processing unit, and an output unit. The input unit is in charge of the generation of desirable incident light. The processing unit is responsible for computation and usually appears as a chip with embedded photonic circuits where integrated photonics plays a key role. The output unit is used to read out the computation results.

From the aspect of a working principle, one of the core ideas of the photonic computer is to search the entire solution space of the problem, which is mapped to the photonic circuits. Individual photons propagate in parallel in the photonic circuits to execute computation. The ultimate computation results can be encoded by either the intrinsic features of

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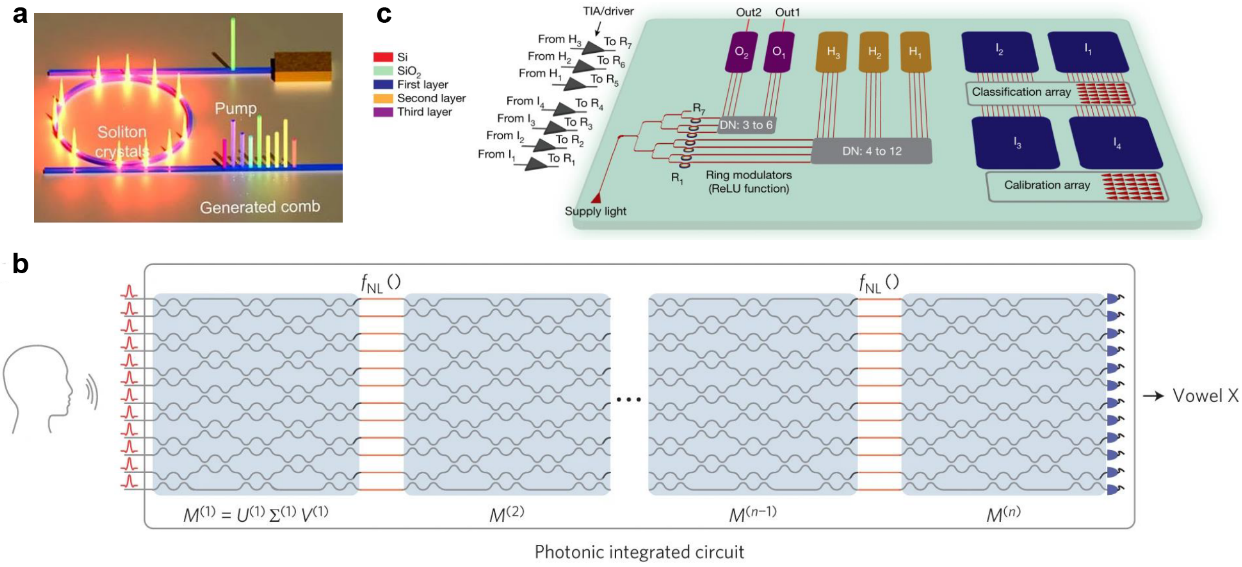

Figure 6. Applications of an integrated photonic platform in artificial intelligence. (a) An integrated Kerr mirocomb is used as an accelerator for the convolutional optical neural network. (b) A fully optical neural network based on an integrated photonic circuit is used for vowel recognition. (c) A deep neural network is implemented on a photonic chip, enabling image classification with high accuracy. (a) Reproduced with permission from ref 64. Copyright 2021 Nature Publishing Group. (b) Reproduced with permission from ref 66. Copyright 2017 Nature Publishing Group. (c) Reproduced with permission from ref 67. Copyright 2022 Nature Publishing Group.

photons, like frequency and polarization, or the status of photons such as delay time and spatial position. We notice that the feasibility of proposals based on delay time-encoding have been demonstrated by a proof-of-principle experiment performed with a laser-written silica photonic chip.[59] Meanwhile, a three-dimensional physically scalable photonic chips, where position-encoding is employed, show potential strengths in solving the subset sum problem by trading space for time.[21] Apart from the parallel computation, Ising machine provides another way to solve NP-complete problems (Figure 5c,d), where integrated photonics could play a part in accelerating computation.[60,61]

One of the most concerned performances of a computing architecture is time consumption. A straightforward evaluation method is to compare with representative electronic processors or computers, whose computational power can be roughly characterized by floating point operations per second (FLOPS). There is evidence showing that, under particular conditions, a photonic computer built with a laser-written silica chip has already beaten the electronic processors released in an early stage, and it can potentially outperform state-of-the-art electronic computers when the problem size becomes considerably large.[21] As displayed in Figure 5b, the laser-written silica-based photonic computer for subset sum problem appears to outperform the supercomputer Summit (with a FLOPS of 10^{17}) when the problem size becomes larger than 28.[21] The photonic superiority is attributed to the parallel computing architecture and fast single-threaded operation speed of the photonic computer. The parallel computing architecture leads to a slower growth of computing time than the electronic counterparts. The single-threaded operation speed is determined by the size of the photonic circuit and the propagation speed of light.

Apparently, an ultracompact photonic circuit is the key to get close to the photonic computational advantage. First of all, an improvement of compactness can enhance the single-threaded operation speed of the photonic computer, resulting in a smaller problem size at which the supercomputer is surpassed. Second, the smaller problem size is beneficial to lowering the complexity of physical implementation and reducing power consumption. For example, when the circuit size decreases by 50 times (compared with the reported silica photonic circuit[21]), the photonic computer will be able to beat the supercomputer at $N = 22$ (see Figure S1 in the Supporting Information), and meanwhile, the circuit will have a reasonable size (the maximum side is shorter than 30 mm). Note that the circuit size can be reduced through an optimization of both the computing architecture and the photonic component design (such as waveguide bending).

In terms of laser power budget and detector requirement, they could be estimated by analyzing the photon loss in the longest path in the photonic circuit, because the optical signal passing through the longest path is in principle the weakest. The probability of a photon reaching the output through the longest path is given by the following equation:[21]

$$\theta(N) = 10^{(c_1 N + c_2 S)/10} \tag{1}$$

where N is the problem size and S is sum of the set involved in the subset sum problem. Constants c_1 and c_2 are determined by the specific parameters of the photonic circuit, including splitting ratio of beam splitters, propagation loss and insertion loss of the components. For the reported silica photonic circuit, c_1 and c_2 are equal to −3.212 and −0.0252, respectively.[21] Therefore, the intensity at the output port corresponding to the longest path can be calculated by

$$I_{out} = I_{in} \times \theta(N) \times \eta \tag{2}$$

where I_{in} is the power of the incident laser and η is the detection efficiency of the detector. To ensure the photonic computer is working normally, I_{out} should be beyond the detection threshold of the detector and larger than the dark noise of the detector. Also, I_{out} decays with the growth of the problem size, resulting in a requirement of larger input power

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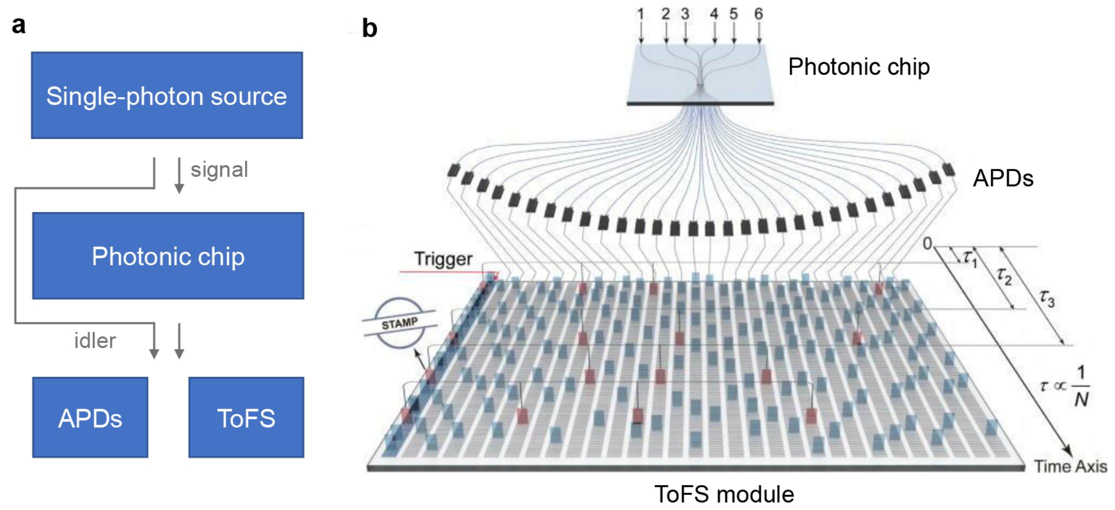

Figure 7. Constitution of the proposed photonic computing system and a sketch of experimental setup. (a) The photonic computing system contains a heralded single-photon source, a photonic chip and a readout unit composed of avalanche photodiodes (APDs) and time-of-flight storage (ToFS) module. The correlated photon pairs from the single-photon source are termed as signal photons and idler photons, respectively. (b) A photonic chip is bonding to an array of APDs, which are connected to the ToFS module.[70] Signal photons are injected into the photonic chip. Idler photons act as triggers. The arrival time of the photons (i.e., the timestamp τ) is recorded by the ToFS module. Signal photons are validated through the coincidences with the triggers. (b) Adapted with permission from ref 70.

or a photodetector with higher performances[62] (e.g., low dark noise, high sensitivity, and high detection efficiency).

Application in Artificial Intelligence. Computing architectures based on an artificial neural network mimic the working manner of the human brain, which are beyond the framework of a von Neumann architecture. There are many kinds of neural networks, such as spiking neural network, recurrent neural network, and convolutional neural network, which differ in the arrangement of neurons or the degree of similarity to human brain.[8] It should be stressed that photonic circuits are well suited for the implementation of artificial neural networks, owing to their strengths in matrix multiplication and interconnects.[63] Particular photonic components or modules, such as a Kerr comb (Figure 6a), can be used as an accelerator in deep learning.[64,65] Furthermore, a deep neural network can be achieved with reconfigurable integrated photonic circuits,[66,67] which could be either fully optical (Figure 6b) or optoelectronically hybrid (Figure 6c). Based on the photonic chips, machine learning tasks, image classification and vowel recognition, are demonstrated with considerable accuracy and computing speed.[66,67]

ROLE OF QUANTUM TECHNOLOGY IN PHOTONIC COMPUTING

We conceive a potential application scenario where quantum technology could bring a reduction in energy consumption of a photonic computer. As shown in Figure 7, the photonic computing system consists of a heralded single-photon source, a photonic chip, and a readout unit that is composed of avalanche photodiodes (APDs) and a time-of-flight storage (ToFS) module.[68−70] The single-photon source generates correlated photon pairs, which are labeled as signal photons and idler photons, respectively. Signal photons are coupled into the photonic chip and evolve in the embedded photonic circuits to execute a computation task. Idler photons, acting as triggers, do not go through the chip. The photons are finally detected by the APDs and meanwhile their arrival time (i.e., the timestamp τ) are recorded by the ToFS module with high accuracy (picosecond level). We validate the detection of signal photons through their coincidences with the triggers.

Generally, the time stamp of the validated signal photons reflects the probability of photons arriving at the output ports of the photonic chip. The relation is given by the following equation:[70]

$$p_i = \frac{\tau_i^{-1}}{\sum_i \tau_i^{-1}} \tag{3}$$

where τ_i is the time stamp of the photon detected at the output port i, and p_i is the normalized probability. In our proposed protocol, the time stamps of the first (few) photons can be used to reconstruct the probability distribution according to eq 3, which greatly reduces the number of photons needed to accumulate at the output in comparison with the photon-counting protocol. In addition, the low dark noise and high sensitivity of single-photon detectors enable the capture of extremely weak optical signals. Therefore, intractable problems, whose computing results can be mapped to the probability distribution of photonic chips, are possible to solve in an energy-efficient regime.

DISCUSSION AND CONCLUSION

The rapid progress of electronic computers in the past once led to an occasion that there is no more room left for light-based computation in the area of high-performance computation. With the coming of the information age and artificial intelligence era, developed photonic technology and advanced quantum technology open a new chapter for light-based computation, bringing photonic computing to the race. Since scalability is a critical criterion for a computing architecture to move out of the laboratory and into practical application, photonic computing based on integrated platforms has attracted much attention. There is diversity in the integrated photonic platforms, from the aspects of material (including silicon, silica, silicon nitride, lithium niobate, etc.) or

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fabrication technology (including femtosecond laser writing, lithography, etc.). The diverse platforms enable the availability of various photonic components, which are featured by three-dimensionality, high compactness, ultrafast modulation, and strong nonlinearity. However, it is hard to implement all the unique devices on a single platform. Hybrid or heterogeneous integration might be the solution.[71,72] Unlike other photonic platforms, the integration of laser-written silica with other photonic materials mostly remains elusive. Conceivable schemes might include high-precision bonding and three-dimensional nanoprinting[73] (see Figure S2 in the Supporting Information).

Despite the technical difficulties, various integrated photonic computing regimes have been proposed and applied to solve NP-hard problems or to perform machine learning tasks. In view of the long-term development, large-scale reconfigurable photonic circuits are essential. Though integrated photonics enables the construction of physically scalable photonic architectures, the computation might suffer from accumulated loss, which increases with the depth of the neural network or the problem size of NP-complete problems. The decay of optical signals in large-scale computation could have a significant influence on the computing results. An employment of single-photon detectors and quantum detection techniques might greatly enhance the scale of photonic computation that can be handled in reality.

Compared with bulk optics, photonic system based on integrated photonics are obviously compact. Besides the inherent compactness, lots of effort has been devoted to device design to meet the demand of an ultracompact large-scale photonic circuit. Inverse design methods, which in principle allow a search of the full parameter space of a device, get rid of the dependence on the designers' experience and have been widely adopted to achieve small-footprint photonic devices with challenging properties. Traditional optimization algorithms (e.g., genetic algorithm and gradient-based algorithms), artificial intelligence algorithms (e.g., deep learning algorithm and reinforcement learning algorithm), or a hybrid model consisting of the two forms could be applied to the inverse design process.[74] So far, a variety of photonic devices with excellent compactness, such as wavelength demultiplexer,[75] polarization rotator,[76] waveguide bends,[77] beam splitter,[78,79] and so on, have been enabled by inverse design. These design techniques and their future development could be helpful for further boosting the scalability of integrated photonic platforms and paving the way to large-scale photonic computation.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsphotonics.2c01543.

Estimated computation time with a change in the photonic circuit size and the possible scheme of integrating laser-written silica with other materials (PDF)

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Notes

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■ REFERENCES

(1) Waldrop, M. M. The Chips are Down for Moore's Law. *Nature* **2016**, *530*, 144−147.

(2) Kumar, S. Fundamental Limits to Moore's law. *arXiv:1511.05956 [cond-mat.mes-hall]* **2015**, na.

(3) Reinelt, G. *The Traveling Salesman: Computational Solutions for TSP Applications*; Springer, 2003; Vol. *840*.

(4) Smith, A.; Veneris, A.; Ali, M. F.; Viglas, A. Fault Diagnosis and Logic Debugging Using Boolean Satisfiability. *IEEE T. Comput. Aid. D* **2005**, *24*, 1606−1621.

(5) Eghdami, M.; Naghibzadeh, M. SSA: Subset Sum Approach to Protein β-sheet Structure Prediction. *Comput. Biol. Chem.* **2021**, *94*, 107552.

(6) Garey, M. R.; Johnson, D. S. *Computers and Intractability: a Guide to the Theory of NP-Completeness*; W.H. Freeman, 1979.

(7) Sipser, M. *Introduction to the Theory of Computation*; Cengage Learning, 2012.

(8) Schuman, C. D.; Kulkarni, S. R.; Parsa, M.; Mitchell, J. P.; Kay, B.; et al. Opportunities for Neuromorphic Computing Algorithms and Applications. *Nat. Comput. Sci.* **2022**, *2*, 10−19.

(9) Wei, S.-T.; Gao, B.; Wu, D.; Tang, J.-S.; Qian, H.; Wu, H.-Q. Trends and Challenges in the Circuit and Macro of RRAM-based Computing-in-memory Systems. *Chip* **2022**, *1*, 100004.

(10) Farhi, E.; Goldstone, J.; Gutmann, S.; Lapan, J.; Lundgren, A.; Preda, D. A Quantum Adiabatic Evolution Algorithm Applied to Random Instances of an NP-complete Problem. *Science* **2001**, *292*, 472−475.

https://doi.org/10.1021/acsphotonics.2c01543
ACS Photonics 2023, 10, 1027−1036

(11) Chang, W.-L.; Yu, Q.; Li, Z.; Chen, J.; Peng, X.; Feng, M. Quantum Speedup in Solving the Maximal-clique Problem. *Phys. Rev. A* **2018**, *97*, 032344.
(12) Traversa, F. L.; Ramella, C.; Bonani, F.; Di Ventra, M. Memcomputing NP-complete Problems in Polynomial Time using Polynomial Resources and Collective States. *Sci. Adv.* **2015**, *1*, No. e1500031.
(13) Yan, X.; Ma, J.; Wu, T.; Zhang, A.; Wu, J.; Chin, M.; Zhang, Z.; Dubey, M.; Wu, W.; Chen, M. S.-W.; et al. Reconfigurable Stochastic Neurons Based on Tin Oxide/MoS2 Hetero-memristors for Simulated Annealing and the Boltzmann Machine. *Nat. Commun.* **2021**, *12*, 5710.
(14) Lee, Y.-J.; On, M. B.; Xiao, X.; Yoo, S. B. Energy-efficient Photonic Spiking Neural Network on a Monolithic Silicon CMOS Photonic Platform. *2021 Optical Fiber Communications Conference and Exhibition*; OFC, 2021; pp 1−3.
(15) Adleman, L. M. Molecular Computation of Solutions to Combinatorial Problems. *Science* **1994**, *266*, 1021−1024.
(16) Braich, R. S.; Chelyapov, N.; Johnson, C.; Rothemund, P. W.; Adleman, L. Solution of a 20-variable 3-SAT Problem on a DNA Computer. *Science* **2002**, *296*, 499−502.
(17) Nicolau, D. V., Jr; Lard, M.; Korten, T.; Van Delft, F. C.; Persson, M.; Bengtsson, E.; Månsson, A.; Diez, S.; Linke, H.; Nicolau, D. V. Parallel Computation with Molecular-motor-propelled Agents in Nanofabricated Networks. *Proc. Natl. Acad. Sci. U. S. A.* **2016**, *113*, 2591−2596.
(18) Wu, K.; Garcia de Abajo, J.; Soci, C.; Ping Shum, P.; Zheludev, N. I An Optical Fiber Network Oracle for NP-complete Problems. *Light Sci. Appl.* **2014**, *3*, No. e147.
(19) McMahon, P. L.; Marandi, A.; Haribara, Y.; Hamerly, R.; Langrock, C.; Tamate, S.; Inagaki, T.; Takesue, H.; Utsunomiya, S.; Aihara, K.; et al. A Fully programmable 100-spin Coherent Ising Machine with All-to-all Connections. *Science* **2016**, *354*, 614−617.
(20) Ambs, P. Optical Computing: a 60-year Adventure. *Adv. Opt. Technol.* **2010**, *2010*, 372652.
(21) Xu, X.-Y.; Huang, X.-L.; Li, Z.-M.; Gao, J.; Jiao, Z.-Q.; Wang, Y.; Ren, R.-J.; Zhang, H.; Jin, X.-M. A Scalable Photonic Computer Solving the Subset Sum Problem. *Sci. Adv.* **2020**, *6*, No. eaay5853.
(22) Zhong, H.-S.; Wang, H.; Deng, Y.-H.; Chen, M.-C.; Peng, L.-C.; Luo, Y.-H.; Qin, J.; Wu, D.; Ding, X.; Hu, Y.; et al. Quantum Computational Advantage Using Photons. *Science* **2020**, *370*, 1460−1463.
(23) Madsen, L. S.; Laudenbach, F.; Askarani, M. F.; Rortais, F.; Vincent, T.; Bulmer, J. F.; Miatto, F. M.; Neuhaus, L.; Helt, L. G.; Collins, M. J.; et al. Quantum Computational Advantage with a Programmable Photonic Processor. *Nature* **2022**, *606*, 75−81.
(24) Gao, J.; Wang, X.-W.; Zhou, W.-H.; Jiao, Z.-Q.; Ren, R.-J.; Fu, Y.-X.; Qiao, L.-F.; Xu, X.-Y.; Zhang, C.-N.; Pang, X.-L.; et al. Quantum Advantage with Membosonsampling. *Chip* **2022**, *1*, 100007.
(25) Davis, K. M.; Miura, K.; Sugimoto, N.; Hirao, K. Writing Waveguides in Glass with a Femtosecond Laser. *Opt. Lett.* **1996**, *21*, 1729−1731.
(26) Osellame, R.; Cerullo, G.; Ramponi, R. *Femtosecond Laser Micromachining: Photonic and Microfluidic Devices in Transparent Materials*; Springer, 2012; Vol. *123*.
(27) Qiao, L.-F.; Jiao, Z.-Q.; Xu, X.-Y.; Gao, J.; Zhang, Z.-Y.; Ren, R.-J.; Zhou, W.-H.; Wang, X.-W.; Jin, X.-M. Multistage Quantum Swapping of Vacuum-one-photon Entanglement. *Phys. Rev. A* **2021**, *104*, 022415.
(28) Crespi, A.; Osellame, R.; Ramponi, R.; Bentivegna, M.; Flamini, F.; Spagnolo, N.; Viggianiello, N.; Innocenti, L.; Mataloni, P.; Sciarrino, F. Suppression Law of Quantum States in a 3D Photonic Fast Fourier Transform Chip. *Nat. Commun.* **2016**, *7*, 10469.
(29) Xu, X.-Y.; Wang, X.-W.; Chen, D.-Y.; Smith, C. M.; Jin, X.-M. Quantum Transport in Fractal Networks. *Nat. Photonics* **2021**, *15*, 703−710.
(30) Tang, H.; Di Franco, C.; Shi, Z.-Y.; He, T.-S.; Feng, Z.; Gao, J.; Sun, K.; Li, Z.-M.; Jiao, Z.-Q.; Wang, T.-Y.; et al. Experimental Quantum Fast Hitting on Hexagonal Graphs. *Nat. Photonics* **2018**, *12*, 754−758.
(31) Bogaerts, W.; Pérez, D.; Capmany, J.; Miller, D. A.; Poon, J.; Englund, D.; Morichetti, F.; Melloni, A. Programmable Photonic Circuits. *Nature* **2020**, *586*, 207−216.
(32) Reck, M.; Zeilinger, A.; Bernstein, H. J.; Bertani, P. Experimental Realization of any Discrete Unitary Operator. *Phys. Rev. Lett.* **1994**, *73*, 58−61.
(33) Clements, W. R.; Humphreys, P. C.; Metcalf, B. J.; Kolthammer, W. S.; Walmsley, I. A. Optimal Design for Universal Multiport Interferometers. *Optica* **2016**, *3*, 1460−1465.
(34) Flamini, F.; Magrini, L.; Rab, A. S.; Spagnolo, N.; D'ambrosio, V.; Mataloni, P.; Sciarrino, F.; Zandrini, T.; Crespi, A.; Ramponi, R.; et al. Thermally Reconfigurable Quantum Photonic Circuits at Telecom Wavelength by Femtosecond Laser Micromachining. *Light Sci. Appl.* **2015**, *4*, No. e354.
(35) Dyakonov, I.; Pogorelov, I.; Bobrov, I.; Kalinkin, A.; Straupe, S.; Kulik, S.; Dyakonov, P.; Evlashin, S. Reconfigurable Photonics on a Glass Chip. *Phys. Rev. Appl.* **2018**, *10*, 044048.
(36) Polino, E.; Riva, M.; Valeri, M.; Silvestri, R.; Corrielli, G.; Crespi, A.; Spagnolo, N.; Osellame, R.; Sciarrino, F. Experimental Multiphase Estimation on a Chip. *Optica* **2019**, *6*, 288−295.
(37) Chang, Y.-J.; Lu, Y.-H.; Wang, Y.; Xu, X.-Y.; Zhou, W.-H.; Cui, W.-H.; Wang, X.-W.; Gao, J.; Qiao, L.-F.; Jin, X.-M. Symmetry-induced Error Filtering in a Photonic Lieb Lattice. *Phys. Rev. Lett.* **2021**, *126*, 110501.
(38) Ceccarelli, F.; Atzeni, S.; Pentangelo, C.; Pellegatta, F.; Crespi, A.; Osellame, R. Low Power Reconfigurability and Reduced Crosstalk in Integrated Photonic Circuits Fabricated by Femtosecond Laser Micromachining. *Laser Photonics Rev.* **2020**, *14*, 2000024.
(39) Ceccarelli, F.; Atzeni, S.; Prencipe, A.; Farinaro, R.; Osellame, R. Thermal Phase Shifters for Femtosecond Laser Written Photonic Integrated Circuits. *J. Light. Technol.* **2019**, *37*, 4275−4281.
(40) Hoch, F.; Piacentini, S.; Giordani, T.; Tian, Z.-N.; Iuliano, M.; Esposito, C.; Camillini, A.; Carvacho, G.; Ceccarelli, F.; Spagnolo, N.; et al. Reconfigurable Continuously-coupled 3D Photonic Circuit for Boson Sampling Experiments. *npj Quantum Inf* **2022**, *8*, 55.
(41) Dreisow, F.; Szameit, A.; Heinrich, M.; Pertsch, T.; Nolte, S.; Tünnermann, A. Second-order Coupling in Femtosecond-laser-written Waveguide Arrays. *Opt. Lett.* **2008**, *33*, 2689−2691.
(42) Chen, Y.; Gao, J.; Jiao, Z.-Q.; Sun, K.; Shen, W.-G.; Qiao, L.-F.; Tang, H.; Lin, X.-F.; Jin, X.-M. Mapping Twisted Light into and out of a Photonic Chip. *Phys. Rev. Lett.* **2018**, *121*, 233602.
(43) Chen, Y.; Xia, K.-Y.; Shen, W.-G.; Gao, J.; Yan, Z.-Q.; Jiao, Z.-Q.; Dou, J.-P.; Tang, H.; Lu, Y.-Q.; Jin, X.-M. Vector Vortex Beam Emitter Embedded in a Photonic Chip. *Phys. Rev. Lett.* **2020**, *124*, 153601.
(44) Ren, R.-J.; Gao, J.; Zhou, W.-H.; Jiao, Z.-Q.; Qiao, L.-F.; Wang, X.-W.; Jin, X.-M. 128 Identical Quantum Sources Integrated on a Single Silica Chip. *Phys. Rev. Appl.* **2021**, *16*, 054026.
(45) Hou, X.; Xu, X.-Y.; Xu, G.; You, L.; Jin, X.-M.; Li, H.; Zhang, W.; Ren, R.-J.; Huang, X.-L.; Wang, Z. Waveguide-coupled Superconducting Nanowire Single-photon Detectors Based on Femtosecond Laser Direct Writing. *Opt. Express* **2021**, *29*, 7746−7756.
(46) Feng, L.; Zhang, M.; Wang, J.; Zhou, X.; Qiang, X.; Guo, G.; Ren, X. Silicon Photonic Devices for Scalable Quantum Information Applications. *Photonics Res.* **2022**, *10*, A135−A153.
(47) Wang, J.; Long, Y. On-chip Silicon Photonic Signaling and Processing: a Review. *Sci. Bull.* **2018**, *63*, 1267−1310.
(48) Qiang, X.; Wang, Y.; Xue, S.; Ge, R.; Chen, L.; Liu, Y.; Huang, A.; Fu, X.; Xu, P.; Yi, T.; et al. Implementing Graph-theoretic Quantum Algorithms on a Silicon Photonic Quantum Walk Processor. *Sci. Adv.* **2021**, *7*, No. eabb8375.
(49) Suzuki, K.; Konoike, R.; Hasegawa, J.; Suda, S.; Matsuura, H.; Ikeda, K.; Namiki, S.; Kawashima, H. Low-insertion-loss and Power-efficient 32× 32 Silicon Photonics Switch with Extremely High-Δ Silica PLC Connector. *J. Light. Technol.* **2019**, *37*, 116−122.

(50) Qiao, L.; Tang, W.; Chu, T. 32 × 32 Silicon Electro-optic Switch with Built-in Monitors and Balanced-status Units. *Sci. Rep.* **2017**, *7*, 42306.

(51) Quan, Z.; Wan, Y.; Ma, X.; Wang, J. Nonvolatile Multi-level Adjustable Optical Switch Based on the Phase Change Material. *Opt. Express* **2022**, *30*, 36096−36109.

(52) Zhang, M.; Wang, C.; Kharel, P.; Zhu, D.; Lončar, M. Integrated Lithium Niobate Electro-optic Modulators: When Performance Meets Scalability. *Optica* **2021**, *8*, 652−667.

(53) Zhu, D.; Shao, L.; Yu, M.; Cheng, R.; Desiatov, B.; Xin, C.; Hu, Y.; Holzgrafe, J.; Ghosh, S.; Shams-Ansari, A.; et al. Integrated Photonics on Thin-film Lithium Niobate. *Adv. Opt. Photonics* **2021**, *13*, 242−352.

(54) Mercante, A. J.; Yao, P.; Shi, S.; Schneider, G.; Murakowski, J.; Prather, D. W. 110 GHz CMOS Compatible Thin Film LiNbO3Modulator on Silicon. *Opt. Express* **2016**, *24*, 15590−15595.

(55) Pan, B.-C.; Liu, H.-X.; Xu, H.-C.; Huang, Y.-S.; Li, H.; Yu, Z.-J.; Liu, L.; Shi, Y.-C.; Dai, D.-X. Ultra-compact Lithium Niobate Microcavity Electro-optic Modulator Beyond 110 GHz. *Chip* **2022**, *1*, 100029.

(56) Guo, Q.; Sekine, R.; Ledezma, L.; Nehra, R.; Dean, D. J.; Roy, A.; Gray, R. M.; Jahani, S.; Marandi, A. Femtojoule Femtosecond All-optical Switching in Lithium Niobate Nanophotonics. *Nat. Photonics* **2022**, *16*, 625−631.

(57) High-Speed Detectors. https://ii-vi.com/product-category/products/optical-communications/communication-components/high-speed-detectors-and-receivers/ (accessed 2023-1-26).

(58) Wang, T.; Ma, S.-Y.; Wright, L. G.; Onodera, T.; Richard, B. C.; McMahon, P. L. An Optical Neural Network Using Less than 1 photon per Multiplication. *Nat. Commun.* **2022**, *13*, 123.

(59) Vázquez, M. R.; Bharadwaj, V.; Sotillo, B.; Lo, S.-Z. A.; Ramponi, R.; Zheludev, N. I.; Lanzani, G.; Eaton, S. M.; Soci, C. Optical NP problem Solver on Laser-written Waveguide Platform. *Opt. Express* **2018**, *26*, 702−710.

(60) Prabhu, M.; Roques-Carmes, C.; Shen, Y.; Harris, N.; Jing, L.; Carolan, J.; Hamerly, R.; Baehr-Jones, T.; Hochberg, M.; Čeperić, V.; Joannopoulos, J. D.; Englund, D.; Soljačić, M. Accelerating Recurrent Ising Machines in Photonic Integrated Circuits. *Optica* **2020**, *7*, 551−558.

(61) Roques-Carmes, C.; Shen, Y.; Zanoci, C.; Prabhu, M.; Atieh, F.; Jing, L.; Dubček, T.; Mao, C.; Johnson, M. R.; Čeperić, V.; Joannopoulos, J. D.; Englund, D.; Soljačić, M. Heuristic Recurrent Algorithms for Photonic Ising Machines. *Nat. Commun.* **2020**, *11*, 249.

(62) Hu, T.; Zhang, R.; Li, J.-P.; Cao, J.-Y.; Qiu, F. Photodetectors Based on Two-dimensional MoS_2 and Its Assembled Heterostructures. *Chip* **2022**, *1*, 100017.

(63) Shastri, B. J.; Tait, A. N.; Ferreira de Lima, T.; Pernice, W. H.; Bhaskaran, H.; Wright, C. D.; Prucnal, P. R. Photonics for Artificial Intelligence and Neuromorphic Computing. *Nat. Photonics* **2021**, *15*, 102−114.

(64) Xu, X.; Tan, M.; Corcoran, B.; Wu, J.; Boes, A.; Nguyen, T. G.; Chu, S. T.; Little, B. E.; Hicks, D. G.; Morandotti, R.; Mitchell, A.; Moss, D. J. 11 TOPS Photonic Convolutional Accelerator for Optical Neural Networks. *Nature* **2021**, *589*, 44−51.

(65) Shiflett, K.; Wright, D.; Karanth, A.; Louri, A. PIXEL: Photonic Neural Network Accelerator. *2020 IEEE International Symposium on High Performance Computer Architecture*; HPCA, 2020; pp 474−487.

(66) Shen, Y.; Harris, N. C.; Skirlo, S.; Prabhu, M.; Baehr-Jones, T.; Hochberg, M.; Sun, X.; Zhao, S.; Larochelle, H.; Englund, D.; Soljačić, M. Deep Learning with Coherent Nanophotonic Circuits. *Nat. Photonics* **2017**, *11*, 441−446.

(67) Ashtiani, F.; Geers, A. J.; Aflatouni, F. An On-chip Photonic Deep Neural Network for Image Classification. *Nature* **2022**, *606*, 501−506.

(68) Eisaman, M. D.; Fan, J.; Migdall, A.; Polyakov, S. V. Invited Review Article: Single-photon Sources and Detectors. *Rev. Sci. Instrum.* **2011**, *82*, 071101.

(69) Liu, C.; Ye, H.-F.; Shi, Y.-L. Advances in Near-infrared Avalanche Diode Single-photon Detectors. *Chip* **2022**, *1*, 100005.

(70) Zhou, W.-H.; Gao, J.; Jiao, Z.-Q.; Wang, X.-W.; Ren, R.-J.; Pang, X.-L.; Qiao, L.-F.; Zhang, C.-N.; Yang, T.-H.; Jin, X.-M. Timestamp Boson Sampling. *Appl. Phys. Rev.* **2022**, *9*, 031408.

(71) Kaur, P.; Boes, A.; Ren, G.; Nguyen, T. G.; Roelkens, G.; Mitchell, A. Hybrid and Heterogeneous Photonic Integration. *APL Photonics* **2021**, *6*, 061102.

(72) Elshaari, A. W.; Pernice, W.; Srinivasan, K.; Benson, O.; Zwiller, V. Hybrid Integrated Quantum Photonic Circuits. *Nat. Photonics* **2020**, *14*, 285−298.

(73) Pattison, T. G.; Wang, S.; Miller, R. D.; Liu, G.-y.; Qiao, G. G. 3D Nanoprinting via Spatially Controlled Assembly and Polymerization. *Nat. Commun.* **2022**, *13*, 1941.

(74) Deng, L.; Xu, Y.; Liu, Y. Hybrid Inverse Design of Photonic Structures by Combining Optimization Methods with Neural Networks. *Photonics Nanostruct* **2022**, *52*, 101073.

(75) Piggott, A. Y.; Lu, J.; Lagoudakis, K. G.; Petykiewicz, J.; Babinec, T. M.; Vučković, J. Inverse Design and Demonstration of a Compact and Broadband On-chip Wavelength Demultiplexer. *Nat. Photonics* **2015**, *9*, 374−377.

(76) Chang, W.; Xu, S.; Cheng, M.; Liu, D.; Zhang, M. Inverse Design of a Single-step-etched Ultracompact Silicon Polarization Rotator. *Opt. Express* **2020**, *28*, 28343−28351.

(77) Sun, S.; Dong, P.; Zhang, F.; Wang, J.; Zhu, N.; Shi, Y. Inverse Design of Ultra-compact Multimode Waveguide Bends Based on the Free-form Curves. *Laser Photonics Rev.* **2021**, *15*, 2100162.

(78) Shen, B.; Wang, P.; Polson, R.; Menon, R. An Integrated-nanophotonics Polarization Beamsplitter with 2.4× 2.4 μm2 Footprint. *Nat. Photonics* **2015**, *9*, 378−382.

(79) Ren, Y.; Zhang, L.; Wang, W.; Wang, X.; Lei, Y.; Xue, Y.; Sun, X.; Zhang, W. Genetic-algorithm-based Deep Neural Networks for Highly Efficient Photonic Device Design. *Photonics Res.* **2021**, *9*, B247−B252.

https://doi.org/10.1021/acsphotonics.2c01543
ACS Photonics 2023, 10, 1027−1036