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Review article

Assessing the potential of quantum computing in agriculture

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ABSTRACT

With increasing computational demands in agriculture and life sciences, quantum computing is emerging as a potential alternative to classical computing. Unlike classical computers, which utilize binary bits, quantum computers utilize quantum bits (qubits) with unique properties such as superposition and entanglement, enabling them to solve certain computational problems more efficiently and achieve significant speed-ups in specific applications.

In this manuscript, we evaluate the potential of quantum computing in agriculture and life sciences by reviewing computational challenges suitable for quantum computing and exploring exemplary domain applications. We examine optimization problems in agrifood supply chains, large-scale linear equation systems in animal breeding, quantum-based network architectures for machine learning in classifying satellite images for land-use analysis, quantum simulations for resource recovery from agriculture waste streams, and quantum search algorithms for genome assembly. Each computational problem type presents unique opportunities and challenges, underscoring the need for tailored quantum algorithms.

Furthermore, we provide a critical assessment of the broader potential of quantum computing, discussing its challenges, limitations, and how to facilitate a potential implementation. While current quantum hardware remains limited, developing quantum algorithms is still valuable — not only to prepare for future advancements but also to foster innovation through interdisciplinary collaboration. Rather than replacing traditional computing, we foresee quantum computing complementing classical systems, offering novel solutions to previously intractable problems. Continued research and interdisciplinary collaborations are essential to realize the full potential of quantum computing, paving the way for pioneering advancements in agriculture and life sciences.

Contents

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1. Introduction

Computational demands across research areas have rapidly increased in recent years, driving the need for faster computing. For over 50 years, computing power has doubled approximately every two years - a phenomenon commonly referred to as Moore's Law (Moore, 1965). However, as the physical size of transistors approaches its natural limits, interest has grown in alternative computing options (Möller and Vuik, 2019).

Quantum computing has attracted interest since the first provable speedups in quantum algorithms and theoretical algorithms proposed in the 1980s and 1990s (Feynman, 1982; Deutsch, 1985), the development of quantum hardware has only recently surged. This growth is fueled by investments from major companies like IBM and Google, alongside government funding initiatives (Hassija et al., 2020). In 2021, the Netherlands invested 615 million Euros to advance quantum technology through their National Growth Fund (QuTech, 2021).

Conventional computers process bits, represented as a 0 or a 1, through a series of logical gates. Applying these operations to bits allows a computer to run programs and solve problems. Physically, logical gate operations are created using transistors that require a bit or an electrical signal. Quantum computers differ fundamentally from classical ones but share the concept of processing information using logical operations. A quantum bit, or a qubit (Vedral and Plenio, 1998), is a piece of quantum information that may exhibit two intrinsic quantum properties: *superposition*, allowing them to exist in multiple states simultaneously, and *entanglement*, enabling links between qubits that facilitate novel computational techniques.

In this manuscript, we mostly omit the technical details of quantum computing, but in short: For the basis states $|0\rangle$ and $|1\rangle$, which are the quantum equivalents of bits $|0\rangle$ and $|1\rangle$, a superposition quantum state is given by a wavefunction $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$, where $|\alpha|^2$ is the probability that the observed value after measurement is 0 and $|\beta|^2$ is the probability that the measured value is 1. Hence, the act of measuring in quantum computing changes the state to the observed state. For this reason, to obtain an accurate representation, one must prepare a state and perform measurements multiple times. Entanglement describes the potential of two or more qubits to be interconnected. Hence, a measurement on qubit A determines the measurement on qubit B and vice versa. This allows a qubit to include substantially more information and allows for new computing techniques that make use of this entangled storage structure. Popular examples of this are given by the Greenberger–Horne–Zeilinger state (Greenberger et al., 1989) and the Bell State (Nielsen and Chuang, 2010). In simpler terms, entanglement can be compared to enabling parallel or coordinated computing in traditional hardware, whereas superposition introduces entirely novel computational possibilities.

Quantum computers have grown rapidly, with the largest universal quantum computer having 127 qubits in 2021 (IBM, 2021) to 433 qubits in 2022 (IBM, 2022), and reaching 1,121 qubits in 2024 (IBM, 2024). This rapid growth in qubit count is crucial, as each additional qubit effectively doubles computing power, offering an exponential increase in performance while computing power in traditional computing only increases linearly in the number of bits (Cooper et al., 2022). However, this also comes with issues, including unwanted interactions between entangled qubits (Steane, 1997; O'brien, 2007) and coherence decay limiting the time horizon in which computations can be performed accurately (Rahman et al., 2021). Physical constraints in qubit implementation, combined with the need for error correction, impose significant overhead on qubit count and computation time, limiting the construction of reliable logical qubits (Bravyi et al., 2024; Preskill, 2018). The current stage of quantum computing is referred to as the *Noisy Intermediate-Scale Quantum* (NISQ) era, characterized by the availability of accessible cloud-based quantum hardware that operates with a significant level of noise (Ritter, 2019).

Quantum computing does not inherently accelerate all tasks by performing the same computations faster as a GPU does compared to a CPU (Freudenberg et al., 2023). Instead, the promise of quantum computing also lies in utilizing the unique properties and storage structure of qubits to reduce the number of operations, thereby achieving a 'quantum advantage' (Ristè et al., 2017). One of the most well-known applications for quantum computing is Shor's algorithm (Shor, 1994) to efficiently calculate the prime factors of large integers, which would render conventional encryption methods vulnerable once reliable and high-power quantum computers become available. The interested reader is referred to Bernhardt (2019) for an in-depth introduction to the software and technical side of quantum computing associated with Shor's algorithm.

Quantum advantage does not necessarily need to be realized in a quantum system. Quantum algorithms often require linear algebraic formulations of a problem for an application or use case. If an algorithm does not rely on the unique properties of superposition and entanglement, it may achieve a speedup on classical hardware as well. This approach, known as *dequantization*, involves reformulating the problem to run on a classical computer and forms the basis of quantum-inspired methods (Cotler et al., 2023). These techniques usually involve stochastic processes and dimension-reducing schemes to achieve poly-logarithmic scaling with dimensions instead of exponential scaling (Chia et al., 2018).

Applied research in agriculture and life sciences has immense computational demands, ranging from estimating genetic merits for millions of livestock animals (Meuwissen et al., 2001) to global supply chain management (Nguyen et al., 2018), and to land-surface dynamics classification by machine learning from terabytes of Earth observation data (Hoeser and Kuenzer, 2020). The complexity of biological systems and agricultural processes, combined with the sheer volume of data generated, underscores the need for high-performance computing. With this, scientists continually strive to develop more efficient algorithms to match increasing computational needs. Naturally, method development is constrained by the computational feasibility of existing hardware and software.

While quantum computing has been explored in specific life science applications, its broader potential remains largely underexplored. In this manuscript, we review potential use cases of quantum computing across domains of agriculture and life science, focusing on computational challenges where quantum computing could provide advantages and discussing strategies for its implementation. Our goal is not to delve into the technical details of specific applications, but rather highlight the broader computational problem types that arise across multiple domains. Additionally, we provide a critical assessment of the broader potential of quantum computing, examining its challenges, limitations, and the steps necessary to facilitate its implementation.

2. Use cases in quantum computing

In the following, we examine various domains in agriculture and life sciences that could be suitable for quantum computing, with a schematic overview of topics and potentially suitable quantum algorithms given in Fig. 1. This list by no means has the claim to be exhaustive. The ordering of applications used is based on the type of computational problem and not by domain.

While the focus in this section will be on existing applications, it is important to recognize that quantum computing could also enable

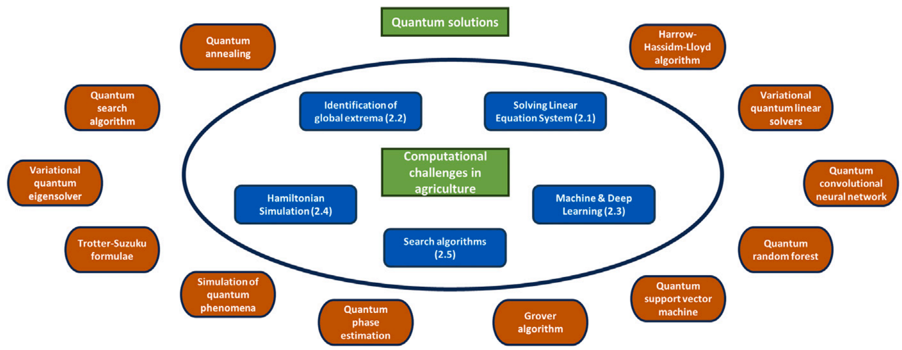

Fig. 1. Overview of potential use cases of quantum computing in agriculture.

tasks previously deemed too costly and thus overlooked. As the development of quantum hardware is still in its infancy and with a limited number of available research articles in agriculture, no systematic review (Page et al., 2021) with a formal keyword search or similar was conducted (Denney and Tewksbury, 2013). Instead, domain experts identified key computational challenges in their respective fields, which were then used as the basis for discussion with quantum experts to identify potential suitable quantum algorithms for the given computational problem. Although experts from various domains were involved, this approach may introduce a reporting bias towards the domain of the experts involved. As the types of computational problems are quite universal, this bias should mainly be towards the chosen exemplary application and not the problem types themselves.

2.1. Linear equation systems

Efficient and reliable solving of linear equation systems is of fundamental importance in various domains. In animal breeding, it is a common task to estimate the genetic merits of millions of animals and multiple characteristics of interest. The gold standard for this is the mixed model (Meuwissen et al., 2001), resulting in a system with billions of equations (Vandenplas et al., 2023). The computational complexity will continue to increase, as the number of animals (or plants/humans) with phenotypic and genetic records rises and additional data dimensions like transcriptomics (Li et al., 2019), methylation (Hu et al., 2015), or environmental information (Gillberg et al., 2019) are added to prediction models. Quantum algorithms developed to date, such as the Harrow–Hassidim–Lloyd (HHL) algorithm (Harrow et al., 2009) offer speed-ups under specific conditions of the linear system, such as sparsity, efficient data representation using qubits, or being well-conditioned. Hence, they are not applicable to any linear equation system, but only to those with a low rank of the coefficient matrix or only provide the solution of the systems as a quantum state in cases where full knowledge of the solution vector is not required. Although the traditional optimization problem with the current models might not be suitable to be solved on a quantum computer, reformulating the task to instead only rely on a simplification or subset of the current output or focus might be beneficial. From the theoretical side, Kitaev (1995) showed massive benefits of quantum computing when only calculating the eigenvalues of the solution matrix. A practical application of this concept was subsequently developed by Möller and Vuik (2019). In addition to quantum algorithms themselves, quantum-inspired algorithms (Arrazola et al., 2020), that try to mimic a quantum computer on a traditional computing device, should be considered with exemplary algorithms from other domains improving both condition number (Jethwani et al., 2019; Bakshi and Tang, 2024) and subsequently solve low-rank linear equation systems (Chia et al., 2020; Shao and Montanaro, 2022). In addition, hybrid approaches, such as variational quantum linear solver (Bravo-Prieto et al., 2023), using quantum heuristics and classical optimizers may offer future speed-ups.

2.2. Identification of global extrema

Optimization, and more broadly the identification of the global extrema, is a pivotal computational challenge. Exemplarily, we will discuss the use of quantum computing to optimize agri-food supply chains. As perishable food products, such as fruits and vegetables, form a crucial part of the modern food systems with various regional, national, and transnational actors, management of post-harvest operations is a highly complex optimization problem (Marvin et al., 2022) (NP-hard problem (Chouhan et al., 2021)).

Supply chain management (Blackburn and Scudder, 2009) nowadays requires the use of heuristic algorithms and/or simplifying assumptions (Chouhan et al., 2021; Nourbakhsh et al., 2016) about various factors such as farm locations, harvest conditions, transport infrastructure, factory locations, storage and handling conditions, route planning, modes of transport, weather, traffic conditions, retailer demands, inventory availability, and more. Optimization techniques include, among others, stochastic programming, linear programming, dynamic programming, stochastic dynamic programming, mixed integer programming, and fuzzy programming (see review by Ahumada and Villalobos (2009)).

Advances in quantum computing are expected to provide solutions to these and similar optimization problems as the number of parameters in optimization problems continue to increase (Popa et al., 2019). A quantum algorithm for solving the traveling salesman optimization problems (Laporte, 1992) and finding global extrema of functions have already been proposed (Srinivasan et al., 2018). Depending on the application, hybrid algorithms such as the variational quantum eigensolver or a quantum approximate optimization algorithm (Farhi et al., 2014; Farhi and Harrow, 2016), may be applicable. Hybrid solutions that take advantage of quantum annealing/tunneling for resource optimization have already been investigated for grocery optimization solutions by D-Wave (Thom, 2021), however, these solutions are just heuristic with non-universal applicability. The scientific literature has not yet reached a conclusion on whether current quantum annealing approaches can outperform advanced optimization methods on classical computing approaches, however, the quantum annealing field is evolving rapidly with advances anticipated in quantum speedup from novel protocols, new encoding strategies for quantum annealing, and novel hardware architectures (Hauke et al., 2020).

2.3. Machine & deep learning

Machine learning and convolutional neural networks (CNNs) have revolutionized the analysis of image and video data (Rawat and Wang, 2017). The suggested benefits from quantum computing are improvements in run time, learning capacity, and learning efficiency (Abbas et al., 2021). Active research in quantum machine learning includes work on variational quantum circuits (Farhi and Neven, 2018; Abohashima et al., 2020), for which parameters can be trained similarly to traditional neural networks, enabling hybrid network architectures with both classical and quantum layers. An exemplary application for this is the quantum convolutional neural network (QCNN) described in Cong et al. (2019). In agriculture and life science, image and video analysis are used in various fields, including high throughput phenotyping in plant (Gill et al., 2022) and animal breeding (Berckmans, 2017; Koltes et al., 2019), with the use of QCNNs for plant disease detection proposed by Genemo (2023).

Quantum computing can also enhance the analysis of Earth Observation data from satellite missions, to develop novel computer vision algorithms to classify land use, vegetation, crops, deforestation, fires, and other phenomena using multispectral, hyperspectral, and radar imagery. While still in early development, positive results with QCNN to classify satellite images are described in Otgonbaatar and Datcu (2021), with a hybrid network displaying good performance on a typical land use classification benchmark data set. Dutta et al. (2024) and Fan et al. (2023) performed similar exploratory studies leveraging hybrid quantum–classical deep learning approaches, also showing the potential for increased prediction accuracy.

Quantum computing combined with Artificial Intelligence (AI), Internet of Things (IoT), and Big Data can greatly enhance food safety (Cravero et al., 2022). AI and IoT can gather data from different data sources and types such as weather, soil moisture, and plant growth (Ramachandran et al., 2022). As suggested by a recent review (Maraveas et al., 2024), this data can be processed by quantum computers to help farmers monitor crop health, detect early signs of crop contamination, and optimize the use of fertilizers, and pesticides, reducing the reliance on harmful pesticides.

Although traditional linear regression models are often the first tested and compared against, more and more applications investigate the use of more sophisticated Machine Learning approaches like decision trees (Lu and Braunstein, 2014), simulated annealing (Manouchehri et al., 2020), and the support vector machine (Zhao et al., 2020) with a first extension of these approaches being developed into respective quantum-based algorithms (Nielsen and Chuang, 2010; Liu et al., 2021; Srikumar et al., 2022).

2.4. Hamiltonian simulation

One of the most natural applications of quantum computing is in processes that occur on the scale of quantum phenomena (Cirac and Zoller, 2012; Georgescu et al., 2014; Daley et al., 2022). This is the case for resource recovery from agriculture waste streams, e.g., animal manure. From these streams, a variety of resources, such as nutrients, organic compounds, water, and energy can be recycled and reused (Saliu and Oladoja, 2021). The value from their reuse can derive benefits beyond eliminating the environmental impact of these wastes by providing a pathway towards a circular economy. However, one of the challenges of resource recovery is the low efficiency and selectivity of the separation technologies used to remove the valuable component, which is often diluted in a complex matrix containing several other elements (Xie et al., 2016).

Membrane processes, pressure and electrically driven, such as reverse osmosis and electrodialysis, are technologies commonly used for resource recovery (Pismenskaya et al., 2022). Hamiltonian simulations can leverage resource recovery with these technologies by (i) providing insights about membrane selectivity on a molecular level where interactions between mobile components and the membrane structure can be described, (ii) identifying the design of new materials, and (iii) theoretically testing those new materials under different process conditions to achieve higher recoveries. The main quantum algorithms of interest here are the Trotter-Suzuku formulae (Somma, 2016), quantum phase estimation (Cruz et al., 2020) and variational quantum eigensolvers (Cervera-Lierta et al., 2021) could allow for exponential speed-ups for computing e.g., the groundstates of complex electronic structures.

2.5. Search algorithms

Another field where quantum computing could offer an advantage is search algorithms, such as those based on the Grover algorithm (Grover, 1997), which is used for searching specific objects in a large database providing a quadratic speed-up over brute force search algorithms. In life sciences, a natural application for this is *de novo* genome assembly to efficiently piece together short strings of DNA segments (reads) into the full genome. Proof-of-concept studies for this process using quantum computing have already been provided by Boev et al. (2021), Sarkar et al. (2021) and Fang et al. (2024). This is of particular interest as the cost of the generation of genomic data has been steadily decreasing since the first assembly of a human genome (Sboner et al., 2011). In 10 years, cheap data and assembly algorithms with run times of minutes, instead of days or weeks, could enable the generation of whole genome assemblies for all individuals of interest in a breeding population and use in personalized medicine. This will lead to new analytical methods for computational and molecular genomics, resulting in a much deeper functional understanding of underlying biology and trait architectures. For example, early screening for deleterious mutations and analysis of genetic diversity via pan genomes (Crysnanto and Pausch, 2020; Crysnanto et al., 2021) could substantially enhance breeding efforts, e.g., to increase livestock welfare. Combined with concepts of Hamiltonian simulation, the application of quantum computing has been proposed to further computational molecular biology applications such as protein folding (Babej and Fingerhuth, 2018; Robert et al., 2021) and identification of transcription factors (Li et al., 2018). The interested reader is referred to Outeiral et al. (2021) and Pal et al. (2024) for an in-depth review of potential applications in computational molecular biology.

3. Discussion

In this manuscript, we discuss various potential applications of quantum computing in the fields of life science and agriculture. These applications are either in very early stages of development or illustrate how established quantum algorithms might be used in the future, even though no concrete investigations that we are aware of have yet been conducted.

Given that quantum computers are currently extremely costly, error-prone, and only suitable for very specific tasks, we do not foresee practical use for most applications in the near future. For example, the application of Shor's algorithm to calculate a prime factor decomposition (Shor, 1994) on numbers as small as 35 is still far from being reliably solved on quantum hardware (Cai, 2024). As technology advances rapidly, raising awareness and investigating opportunities is crucial for future readiness. Some first implementations exist, e.g., quantum machine learning algorithms have been integrated as a modular component within a machine learning pipeline for satellite image recognition tasks (Aguilera et al., 2023).

As agriculture is also rapidly evolving, research focuses may include computational problems not currently considered, as the availability of reliable large-scale quantum hardware is expected to take at least another ten years (Groenland, 2024). Therefore, quantum computing should not only be viewed as a tool to accelerate the computationally challenging problems of today but also as a means to enable methodologies currently infeasible. This could include broader use for whole-genome alignment (Boev et al., 2021; Fang et al., 2024) or more complex linear equation systems (Gillberg et al., 2019) and optimization problems (Samadi et al., 2018) than those currently solvable on traditional hardware.

In addition to quantum computers themselves, there is also technology developed for traditional hardware to simulate quantum computers such as the Intel Quantum Simulator (IQS, (Guerreschi et al., 2020)) or QisKit simulation kit (Aleksandrowicz et al., 2019), which strive to adhere to the same input and output schemes as quantum systems, as shown by Arrazola et al. (2020) for solving linear equation systems. While not yet applicable to large-scale problems like the estimation of genetic merits (Meuwissen et al., 2001), this enables near-term development of quantum algorithms by testing small-scale problems on simulators. It should be possible to swap the computational backend, replacing the simulator with a quantum computer, being particularly valuable as a potential quantum advantage should not be unique to a NISQ era quantum computer (Ritter, 2019) but also applicable to further developments of quantum hardware.

Quantum computing could mark a paradigm shift (Preskill, 1998), requiring novel coding styles designed for a single very specific application. Thus, quantum computers are unlikely to replace traditional computers. Instead, they should be seen as an additional high-performance computing tool that could be integrated into computing clusters. Changes to computing architecture, efficient programming, and computational possibilities should be expected to be greater than the introduction of GPUs in high-performance computing. The use of GPUs already showed massive improvements in selected fields ranging from deep learning for video and image analysis (Rawat and Wang, 2017) to solving large linear equation systems when estimating genetic merits (Freudenberg et al., 2023) and AI applications (Webb, 2018).

Managing quantum computers requires cryogenic cooling (close to zero Kelvin) and specialized materials, leading to logistical and management challenges as well as high costs. Since the technology is in its infancy, uncertainties in scalability, labor, and accessibility complicate non-research implementation (Brin, 2022; Martens et al., 2024). Interoperability between traditional processing units (CPUs and GPUs) and quantum processing units remains suboptimal, limiting practical speedup. Current research is therefore focused on unifying or integrating the physical information flow to enhance communication and data transfer between these systems (Elsharkawy et al., 2024).

More broadly, applying quantum computing to existing problems might spark a deeper understanding of computational problems and provide new ways of approaching existing problems. Implementing quantum algorithms requires collaboration with physicists and mathematicians, as the necessary background exceeds typical bioinformatics or computational biology scope, while researchers working in quantum will lack the necessary knowledge of the structure of data and problems within the domain itself. For example, in the context of the estimation of the genetic merits of livestock (Meuwissen et al., 2001), a quantum advantage will most likely be achievable by using a novel preconditioning technique (Vandenplas et al., 2018), finding structure in the genetic data or similar instead of speeding up matrix and vector operations overall. For this, quantitative genetics researchers can provide the necessary knowledge on genetic inheritance and the structure of genetic data while researchers in the field of quantum computing can provide technical expertise on quantum. Furthermore, a different view of methods on its own can already spark innovation and have a short-term impact beyond what quantum computing on its own can provide in the future.

While this manuscript focuses on agriculture and life sciences, we do not see major domain-specific risks of quantum computing beyond general concerns associated with intensive agriculture, ecosystems, and biotechnology that need to be monitored with any technical advancement in the field to ensure food security, biodiversity, and public health (Gaffney et al., 2019; Flöther, 2023). These challenges will also be relevant for other sectors exploring quantum computing.

Quantum's impact on life science is unlikely to be as severe as in cryptography, where time is needed to adapt encryption and security protocols before suitably strong quantum hardware is available (Brassard, 1994). In contrast, applications in agriculture and life science are less pressing to be investigated before quantum computers become available, as the changes are likely to only improve specific aspects rather than transform the entire field. Consequently, once quantum computers become viable, most researchers will likely shift their focus to these highly pressing fields. Therefore, investigation in agriculture and life science beforehand is required to provide information on which applications could expect the most promise from the new technology. Therefore, early empirical assessment of quantum computing for agriculture is crucial for identifying opportunities, limitations, and challenges associated with the practical interoperability of data pre-processing, NISQ computation, and post-processing.

3.1. Conclusions

Quantum computing in agriculture and life science remains a niche due to limited near-term applicability. However, with quantum computers becoming more reliable and performant in the future, research presents great opportunity, with quantum computing providing potentially pioneering advancements in computing and enabling the application of analyses that are currently not possible. We strongly advocate for continued and expanded research into quantum computing for agriculture and life science as it not only sparks innovation by quantum computing but also fosters innovation and interdisciplinary collaboration.

CRediT authorship contribution statement

Torsten Pook: Writing – review & editing, Writing – original draft, Methodology, Investigation. **Jeremie Vandenplas:** Writing – review & editing, Investigation. **Juan Carlos Boschero:** Writing – review & editing, Investigation. **Esteban Aguilera:** Writing – review & editing, Investigation. **Koen Leijnse:** Writing – review & editing, Investigation. **Aneesh Chauhan:** Writing – review & editing, Investigation. **Yamine Bouzembrak:** Writing – review & editing, Investigation. **Rob Knapen:** Writing – review & editing, Investigation. **Michael Aldridge:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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