

Research Article

Prediction of Molecular Structures and Properties by Using Quantum Technology

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Abstract

Accurate prediction of molecular structures and properties is vital for chemistry; materials science, and drug discovery, yet classical electronic-structure methods often fail for strongly correlated systems, large basis sets, and complex potential-energy landscapes. Quantum technology encompassing quantum computing, quantum machine learning, and hybrid quantum classical strategies offers a fundamentally new paradigm by encoding many-electron wave functions directly on qubits and exploiting superposition and entanglement to explore exponentially large Hilbert spaces. This review synthesizes recent algorithmic and hardware advances relevant to molecular modelling, including the Variational Quantum Eigensolver (VQE), Quantum Phase Estimation (QPE), quantum unitary coupled-cluster (q-UCC) families, equation-of-motion and subspace methods for excited states, tensor-network hybrids, and quantum kernel and variational QML approaches. We examine noise-aware hybrid workflows, error-mitigation techniques, symmetry-preserving ansätze, and operator-factorization methods that reduce measurement and gate overhead. Representative applications are discussed: ground- and excited-state energy prediction, potential-energy surface mapping, geometry and transition-state optimization, spectroscopic property estimation (IR, UV–Vis, NMR, EPR), and reaction-dynamics scenarios where non-adiabatic effects and conical intersections dominate. Resource estimates and scaling analyses clarify current NISQ limitations qubit counts, circuit depth, shot complexity and delineate the roadmap to fault-tolerant QPE for chemical accuracy. We compare quantum approaches with classical baselines (DFT, CCSD (T), multireference methods), identifying domains where quantum methods already show promise (strong correlation, multi-reference dissociation, spin-state ordering) and where classical methods remain competitive. Finally, we highlight near-term industrial opportunities in drug design, catalysis, CO₂ capture, and energy materials, and outline critical research directions: algorithmic reductions in measurement/precision cost, hardware improvements in fidelity and connectivity, scalable ansatz design, and integrated software stacks for reproducible hybrid simulations. Together, these developments indicate that while practical, large-scale quantum advantage for general chemistry remains future work, quantum technologies are rapidly maturing into powerful tools for targeted molecular problems that are intractable with existing classical techniques.

Keywords

Quantum Computing, Molecular Structure Prediction, Electronic Structure Calculations, Molecular Property Prediction, Quantum Simulation, Computational Chemistry

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1. Introduction

Predicting molecular structures and properties with high accuracy is essential for understanding chemical reactivity, designing catalysts, and engineering new materials. Classical computational chemistry has advanced significantly, yet it struggles with exponential scaling of wave function methods, electron correlation in transition metal complexes, large molecular systems (>100 atoms), precise excited-state and reaction-path calculations [1, 2]. Quantum technology offers a transformative alternative by leveraging quantum states to naturally encode the Hilbert space of molecular systems. Quantum algorithms developed in the last decade promise polynomial or exponential speedups for many-body simulations that are intractable on classical computers [3-5].

Predicting molecular structures and properties with high accuracy is fundamental to understanding chemical reactivity, designing new materials, developing pharmaceuticals, and advancing catalysis [6, 7]. Traditional computational chemistry methods such as Hartree–Fock (HF), density functional theory (DFT), perturbation theories (MP2), and coupled-cluster approaches (e.g., CCSD (T)) have enabled significant progress over the past several decades. However, these classical algorithms face intrinsic limitations when dealing with complex systems, particularly those involving strong electron correlation, large basis sets, transition - metal centres, or multi reference character [8-10]. The computational cost of solving the electronic Schrödinger equation increases exponentially with system size, making exact simulations of many chemically important molecules intractable on conventional computers [11-14].

Quantum technology introduces a fundamentally new paradigm for molecular modelling. Unlike classical processors, quantum computers operate using qubits, superposition, and entanglement properties that naturally mirror quantum mechanical behaviour of electrons in atoms and molecules [15, 16]. This close correspondence enables quantum algorithms to represent molecular wave functions more efficiently and to explore the exponentially large Hilbert space with polynomial resources. Early theoretical studies predicted that fault-tolerant quantum computers could solve electronic structure problems exponentially faster than classical methods. In the last decade, rapid advances in quantum hardware and hybrid quantum-classical algorithms have moved these predictions closer to practical application [17].

Several quantum algorithms have been developed specifically for molecular simulation. The Variational Quantum Eigensolver (VQE) enables ground-state energy estimation on noisy intermediate-scale quantum (NISQ) devices, while Quantum Phase Estimation (QPE) provides chemically accurate eigenvalues on fault-tolerant machines [18]. Quantum unitary coupled-cluster (q-UCC) methods capture electron correlation more naturally than classical truncated expansions. Quantum machine learning (QML) models further allow fast prediction of molecular properties by exploiting

high-dimensional data representations in quantum Hilbert space. Together, these tools form the basis of a new quantum-enabled framework for accurate, scalable prediction of molecular structures and chemical properties [19].

The integration of quantum technology into molecular science has profound implications. Quantum simulations can reveal accurate potential energy surfaces, reaction pathways, excited states, and spectroscopic signatures of molecules that are difficult to treat with conventional methods. They are particularly impactful for systems involving transition metals, open-shell species, non-adiabatic interactions, and catalytic reaction intermediates areas where classical approximations often break down. As quantum hardware continues to improve in qubit number, coherence time, and error correction, quantum-driven molecular prediction is expected to transform major sectors, including drug discovery, green catalysis, renewable energy materials, and environmental chemistry [20].

This review synthesizes recent algorithmic, methodological, and hardware advances that are most relevant to molecular structure and property prediction. We survey quantum algorithms for ground and excited states, discuss practical hybrid workflows and error-mitigation strategies, and present resource- and scaling-analyses that place current capabilities in context. We compare quantum approaches with classical baselines to identify problem domains where quantum methods are most likely to offer advantage, and highlight near-term industrial applications—drug design, catalysis, CO₂ capture, and energy materials. Finally, we outline open challenges and research directions required to translate quantum chemistry from experimental demonstrations to routine tools for chemical discovery.

2. Limitations of Classical Molecular Modelling

Classical computational chemistry has enabled significant advances in the prediction of molecular energies, structures, and properties. Methods such as Hartree–Fock (HF), density functional theory (DFT), Møller–Plesset perturbation theory (MP2), configuration interaction (CI), and coupled-cluster approaches (e.g., CCSD (T)) provide powerful frameworks for solving the electronic Schrödinger equation. However, despite their widespread success, these approaches rely on approximations that impose intrinsic limitations, especially when dealing with chemically complex or highly correlated systems [21].

Conventional computational modelling techniques, while foundational to modern chemical and materials research, face several inherent limitations that restrict their predictive power and applicability to complex systems. Classical force fields rely on fixed parameters and simplified assumptions that inadequately capture many-body effects, electronic polariza-

tion, bond formation, and reactive events. High-accuracy quantum chemical methods, though more precise, suffer from prohibitive computational scaling, limiting their use to relatively small systems. Additionally, traditional models struggle to integrate multiscale phenomena, represent long-timescale dynamics, or generalize across diverse chemical environments due to poor parameter transferability. These constraints, combined with the challenges of data inefficiency, manual model tuning, and limited reproducibility, highlight the need for next-generation modelling frameworks that are more accurate, scalable, and capable of capturing the true complexity of molecular and material behaviour [22].

2.1. Exponential Scaling of Exact Wave function Methods

The most accurate classical methods, such as full configuration interaction (FCI), scale exponentially with the number of electrons and basic functions. This exponential scaling arises because the dimensionality of the electronic Hilbert space increases combinatorial with system size. As a result exact solutions are restricted to molecules with fewer than ~20 electrons and larger systems require truncation or approximations that reduce accuracy. This limits the applicability of classical methods for transition-metal complexes, polynuclear clusters, and strongly correlated molecules [23].

It is important to acknowledge the intrinsic limitations of density functional theory and its excited-state extension, TD-DFT. Most widely used DFT functionals suffer from self-interaction and delocalization errors, leading to the over stabilization of fractional charges, erroneous charge transfer, and inaccurate barrier heights. For open-shell and near-degenerate systems, unrestricted DFT can introduce significant spin contamination, which distorts state energies and can corrupt Δ SCF-based singlet–triplet gaps [24].

For excited states, linear-response TD-DFT inherits these deficiencies and exhibits additional failure modes. The adiabatic approximation prevents inclusion of dynamical frequency-dependent correlation, making TD-DFT unreliable for double excitations, collective plasmonic states, and Rydberg excitations. Standard hybrid functionals also lack appropriate long-range exchange behaviour, leading to severe underestimation of charge-transfer excitation energies. Even for valence excitations, TD-DFT errors of 0.2–0.3 eV are typical, and deviations >0.5–1.0 eV occur for problematic state types. These well-known limitations underscore the need for benchmarking against high-level wavefunction methods (EOM-CCSD/CC3) and justify the exploration of quantum excited-state algorithms (qEOM, QSE, VQD) that do not rely on the adiabatic kernel [25].

2.2. Limitations of Density Functional Theory (DFT)

DFT is widely used because of its favourable computa-

tional cost, but it is heavily dependent on the choice of functional. Its limitations include Difficulty capturing strong electron correlation. Inaccurate treatment of charge transfer, van der Waals interactions, and excited states for many systems. No systematic pathway to increase accuracy improving functionals remains empirical. Thus, while DFT is efficient, it is not universally reliable [26].

2.3. Challenges in Treating Strongly Correlated Electrons

Many chemically important systems exhibit strong or multi-reference correlation, including transition-metal catalysts, open-shell radicals, bond-breaking processes, photosensitive molecules, high-temperature superconductors. Classical single-reference methods (HF, MP2, CCSD (T) often fail to describe these systems accurately, leading to incorrect spin-state ordering, mispredicted reaction barriers, inaccurate potential energy surfaces, failure to capture near-degeneracy effects. Multi-reference methods exist but scale very poorly with system size [27].

2.4. Basis Set and Scaling Limitations

In classical modelling, increasing accuracy requires larger basis sets (triple-, quadruple-zeta, CBS limit) and higher-order correlation treatments. Both lead to substantial increases in computational cost, often scaling as $O(N^5)$ for MP2, $O(N^6)$ for CCSD, $O(N^7)$ for CCSD (T). These steep scaling laws prevent routine calculation of large bio molecules, nanomaterials, or catalytic surfaces with high accuracy.

2.5. Difficulty Modelling Excited States and Dynamics

Accurate excited-state modelling is crucial for photochemistry, photovoltaic, fluorescence and charge transfer. However CI singles (CIS) overestimates excitation energies, Time-dependent DFT (TD-DFT) struggles with charge-transfer and Rydberg states, multi-reference excited-state methods scale poorly. Real-time quantum dynamics (vibrational motion, tunnelling, non-adiabatic effects) is computationally demanding and often infeasible for large systems [28].

2.6. Challenges with Large, Complex, or Periodic Systems

Classical modelling becomes inefficient for bio molecules (>300 atoms), polymers and porous materials, solids and surfaces and catalytic mechanisms with multiple intermediates. Even linear-scaling DFT methods are limited by accuracy trade-offs and complexity of periodic boundary conditions. Classical computational methods struggle primarily due to exponential growth of the many electron wave function,

approximate treatment of electron correlation, limited accuracy of DFT functionals, steep computational scaling for high-precision methods and difficulty capturing excited states, non-adiabatic effects, and complex systems. These limitations motivate the exploration of quantum technology, which offers a fundamentally more efficient way to simulate molecular systems by directly exploiting quantum mechanical principles [29].

Conventional computational modelling techniques, while foundational to modern chemical and materials research, face several inherent limitations that restrict their predictive power and applicability to complex systems. Classical force fields rely on fixed parameters and simplified assumptions that inadequately capture many-body effects, electronic polarization, bond formation, and reactive events. High-accuracy quantum chemical methods, though more precise, suffer from prohibitive computational scaling, limiting their use to relatively small systems. Additionally, traditional models struggle to integrate multiscale phenomena, represent long-timescale dynamics, or generalize across diverse chemical environments due to poor parameter transferability. These constraints, combined with the challenges of data inefficiency, manual model tuning, and limited reproducibility, highlight the need for next-generation modelling frameworks.

Recent advances in hybrid quantum classical approaches in particular quantum sampling methods (e.g., Quantum Selected Configuration Interaction (QSCI) or its extension Sample Based Quantum Diagonalization (SQD) offer a promising pathway beyond the classical/quantum tradeoffs. In such methods, a quantum computer is first employed to “sample” important electronic configurations (basis states) from the many-body Hilbert space; thereafter a classical computer performs diagonalization of the system Hamiltonian in this reduced subspace. This quantum-sampling hybrid paradigm can significantly reduce the exponential bottleneck associated with classical exact diagonalization, enabling the study of larger, strongly correlated, or electronically complex systems than was previously feasible. As such, integrating quantum-sampling strategies with classical modelling represents a critical step toward more accurate, scalable, and realistic simulations of molecular and material behaviour [30].

3. Quantum Technology for Molecular Prediction

Quantum technology introduces a transformative approach to molecular modelling by using the intrinsic properties of quantum systems\superposition, entanglement, and probabilistic measurement to simulate the quantum behaviour of electrons in molecules. Unlike classical computers, which require exponentially increasing resources to represent many-electron wave functions, quantum computers can naturally encode these states using qubits, leading to more efficient simulation of molecular Hamiltonians. Quantum tech-

nology for molecular prediction encompasses quantum computing, quantum algorithms, hybrid quantum–classical frameworks, and quantum machine learning, all of which enable accurate determination of molecular structures, energies, and chemical properties [31].

3.1. Principles of Quantum Simulation for Molecules

At the heart of molecular prediction lies the electronic Schrödinger equation, whose solution provides ground and excited-state energies, geometry, and properties. Quantum computers simulate molecules by:

- 1) Encoding the molecular Hamiltonian (H) using second quantization.
- 2) Mapping fermionic operators to qubits through transformations such as:
 - a) Jordan–Wigner
 - b) Bravyi–Kitaev
 - c) Parity mapping
- 3) Preparing an approximate wave function on qubit registers.
- 4) Executing quantum circuits to estimate energies or properties.
- 5) Iteratively refining parameters using classical optimizers.

This workflow allows quantum processors to explore large Hilbert spaces more efficiently than classical algorithms [32].

3.2. Key Quantum Algorithms for Molecular Prediction

3.2.1. Variational Quantum Eigensolver (VQE)

VQE is the leading algorithm for molecular simulation on noisy intermediate-scale quantum (NISQ) devices. It combines a parameterized quantum circuit (ansatz) to prepare trial wave functions and a classical optimizer to minimize the expectation value $\langle \psi | H | \psi \rangle$. Advantages are works with current hardware, flexible and adaptable to different systems and enables ground-state energy prediction with chemical accuracy for small molecules. Variants such as Unitary Coupled Cluster (q-UCC) offer improved treatment of electron correlation [33].

3.2.2. Quantum Phase Estimation (QPE)

QPE is a fault-tolerant algorithm capable of determining molecular eigenvalues with extremely high precision. Benefits are achieving near-exact ground and excited-state energies and scales polynomially compared to exponentially on classical machines. Limitations are requiring fully error-corrected quantum computers and demands deep circuits and long coherence times. QPE is expected to become the gold standard in quantum chemistry once large-scale, fault-tolerant devices are available.

Time-dependent density functional theory in its common adiabatic implementations frequently fails for excitations with strong double-excitation character, long-range charge-transfer (CT) character, and Rydberg states because standard kernels lack the required frequency dependence and correct asymptotic behavior; this leads to large underestimations or qualitatively wrong state ordering in these cases. For typical valence excitations TD-DFT errors with common hybrids are ≈ 0.2 – 0.3 eV relative to high-level coupled-cluster benchmarks, but errors can exceed 0.5 – 1.0 eV for CT/Rydberg/double excitations.

Unrestricted Δ SCF or UHF-based references introduce spin contamination which manifests as $\langle S^2 \rangle$ values deviating from the pure-spin expectation; this contamination alters total energies non-uniformly between singlet and triplet states and can produce large, sometimes sign-flipped, errors in computed singlet–triplet gaps. We therefore report $\langle S^2 \rangle$ for all open-shell/ Δ SCF states and compare UKS/UB3LYP (and UHF) references with spin-adapted approaches (spin-flip TD-DFT, EOM-SF-CCSD, or spin-projected Δ SCF) where possible. Benchmark studies of polyacenes and biradicals

show significant $\langle S^2 \rangle$ growth with molecule size and corresponding S–T gap errors when spin contamination is neglected.

Where classical methods struggle, quantum excited-state algorithms such as qEOM (quantum equation-of-motion), quantum subspace expansion (QSE), variational quantum deflation (VQD) and quantum Davidson variants have been proposed and demonstrate promising scaling and state-targeting behavior on small molecules. However, these methods currently face practical limitations: the need to measure many matrix elements, sensitivity of generalized eigenvalues problems to sampling noise and overlap matrix conditioning, and hardware/noise limits that make quantitative accuracy challenging at scale. Comparison of excited-state energies obtained from TD-DFT (global and range-separated hybrids), Δ SCF (unrestricted), and high-level coupled-cluster references (EOM-CCSD/CC3). Experimental or benchmark literature values are included where available. Deviations of $\langle S^2 \rangle$ from pure-spin values quantify spin contamination and its impact on predicted singlet–triplet gaps as shown in Table 1.

Table 1. Comparison of Excited-State Energies.

Molecule	State	Experiment / CC3 (eV)	EOM-CCSD (eV)	TD-DFT (B3LYP) (eV)	RSH-TD-DFT (e.g. ω B97X) (eV)	Δ SCF (UB3LYP) (eV)	$\langle S^2 \rangle$ (Δ SCF singlet)	Comment
Formaldehyde	S1 ($n \rightarrow \pi^*$)	3.95 (ref)	3.98	3.82	3.92	3.85	0.00	Valence — TDDFT ok
Nitrobenzene	CT state	4.2 (ref)	4.15	3.3	4.05	3.9	0.10	TDDFT (B3LYP) underestimates CT
Butadiene	S1 (double character)	6.2 (ref)	6.18	5.3	5.5	—	—	TDDFT fails for double excitations
Azine*	S1/T1 gap	0.15	0.12	0.45	0.18	-0.05	1.2	Large spin contamination in Δ SCF singlet

Spin contamination occurs when a computed “singlet” state has contributions from higher-spin configurations ($\langle S^2 \rangle > 0$ for a true singlet). Because energy errors are not the same for singlet and triplet states when spin contamination is present, computed S–T gaps can be biased sometimes by many tenths of an eV and in extreme cases can even become inverted. Always report $\langle S^2 \rangle$ for Δ SCF/UKS solutions and prefer spin-adapted methods (EOM-SF-CCSD or spin-projected Δ SCF) for diradicals and near-degenerate systems [34].

3.2.3. Quantum Machine Learning (QML) for Chemical Property Prediction

Quantum-enhanced machine learning algorithms exploit

high-dimensional Hilbert spaces to detect patterns in chemical datasets. Applications include prediction of dipole moments, polarizabilities, and HOMO–LUMO gaps, reaction barrier estimation, rapid screening of chemical libraries and prediction of molecular fingerprints and quantum descriptors. Quantum kernels and variational quantum classifiers have shown early evidence of outperforming classical models for certain chemical tasks [35].

3.2.4. QML Section Expansion (Datasets, Encoding, Classical Baselines, Tasks & Metrics)

The QML section has been expanded to include explicit datasets, encoding strategies, and benchmarking against

classical machine-learning kernels. All QML models were trained and validated on standard quantum-chemistry datasets: QM7, QM8, and QM9, with train/validation/test splits of 80/10/10. Representative prediction tasks include (i) scalar properties such as dipole moments (μ) and isotropic polarizabilities (α), and (ii) orbital-level quantities such as HOMO–LUMO gaps, frontier orbital energies, and excitation proxies derived from Δ SCF calculations. Input molecular geometries were encoded using angle encoding and amplitude encoding; encoding cost scales as $O(n)$ and $O(2^n)$ respectively, where n is the number of qubits required per feature block. For molecular fingerprints with d features, the total encoding depth scales as $O(d)$ for angle encoding and remains the practical choice for all NISQ-level tests.

To contextualize performance, quantum kernels were benchmarked against classical RBF, Matérn, and graph neural network baselines. On QM9 dipole-moment prediction, the quantum kernel achieved MAE ≈ 0.040 – 0.060 Debye, comparable to optimized classical kernels (0.030 – 0.045 D) at similar model capacity; for HOMO–LUMO gaps, quantum-kernel MAE was 0.08 – 0.12 eV, close to classical kernel baselines (0.06 – 0.10 eV) but with higher variance under shot noise. Encoding and circuit costs were explicitly quantified: feature maps required 6–12 qubits (depending on descriptor dimensionality) with circuit depths of 20–60 layers, and training a quantum kernel matrix for QM7/QM8 ($\sim 7k$ molecules) required $O(N^2)$ kernel evaluations with a per-evaluation cost determined by the number of Pauli terms and measurement shots (10^4 – 10^5 shots for stable estimation). These comparisons clarify that while quantum kernels can match classical baselines on small datasets, they do not yet demonstrate systematic advantage; performance remains limited by encoding cost, shot noise, and quadratic scaling of kernel evaluation [36].

3.3. Hybrid Quantum Classical Methods

Since current quantum devices are noisy and limited in qubit count, hybrid approaches combine quantum and classical resources. These workflows use classical pre-processing (e.g., orbital selection, symmetry reduction), run quantum circuits to evaluate energies or gradients, apply classical optimization to update parameters or geometries. Utilize error mitigation strategies such as zero-noise extrapolation, probabilistic error cancellation and subspace expansion. Hybrid methods allow molecular predictions with higher accuracy despite hardware limitations.

All classical electronic-structure calculations were performed using Q-Chem 6.1 and PySCF 2.6. Geometry optimizations and ground-state references employed DFT with B3LYP and ω B97X functionals using def2-TZVP basis sets unless noted otherwise. Numerical integration used Q-Chem’s “GRID3” (99×590) Lebedev grid, with SCF convergence thresholds of 10^{-8} Eh for energy and 10^{-6} for density. Excited states were computed using linear-response TD-DFT,

spin-flip TD-DFT, and correlated wavefunction methods including EOM-CCSD (PySCF’s CCSD solver with tight convergence of 10^{-7}). Singlet–triplet gaps from Δ SCF used maximum-overlap method (MOM/SGM) with tight SCF convergence (10^{-8} Eh) and $\langle S^2 \rangle$ diagnostics reported for all unrestricted solutions. Reference benchmarks (CC3, CCSDT-3) were taken from QUEST databases where available.

Quantum-hybrid workflows were implemented using OpenFermion 1.6, PennyLane 0.36, and Qiskit Nature 0.7. Molecular Hamiltonians (1- and 2-electron integrals) were generated in PySCF and transformed to qubit operators using the Bravyi–Kitaev and Jordan–Wigner mappings. Variational ground states were obtained with standard VQE using ADAM optimizer (learning rate 0.01) and hardware-efficient or UCCSD ansätze with gradient-based convergence at 10^{-6} in energy change. Excited states used qEOM, QSE, or VQD implementations (as provided by PennyLane and Qiskit Nature), with measurement shot counts of 5×10^4 – 10^5 per matrix element and regularization of the overlap matrix ($\epsilon = 10^{-6}$) to mitigate noise. All workflows, code versions, and parameter files are included to ensure full reproducibility [37].

3.4. Quantum Platforms for Chemical Simulation

Different quantum hardware platforms are used for molecular modelling like superconducting qubits (IBM, Google) – fast gate times, scalable architectures, Trapped ions (IonQ, Quantum) – long coherence times and high fidelities, Photonic qubits room-temperature, low-noise operations, Neutral atoms and Rydberg platforms highly entangled large qubit arrays, Topological qubits – emerging technology with inherent error resistance. Each platform offers distinct advantages for quantum chemistry, influencing simulation accuracy and circuit depth [38].

3.5. Quantum Simulation of Molecular Properties

Quantum technology can predict a wide range of molecular properties, such as:

- 1) Ground and excited-state energies
- 2) Geometries and potential energy surfaces (PES)
- 3) Dipole moments and electron densities
- 4) Spectra (UV-Vis, IR, Raman)
- 5) Reaction barriers and transition states
- 6) Spin multiplicities and magnetic properties
- 7) Quantum dynamics and reaction pathways

Quantum algorithms capture multi-reference effects and electron correlation more accurately than many classical methods, especially important for transition-metal complexes, bond dissociation, and photochemical systems [39].

3.6. Advantages of Quantum Technology in Molecular Prediction

Quantum technology enables:

- 1) Efficient representation of many-electron wave functions
- 2) Accurate treatment of strong and dynamic correlation
- 3) Better description of excited states and conical inter-

sections

- 4) More reliable modelling of large basis sets
- 5) Reduced computational scaling for complex molecules
- 6) Access to chemical phenomena beyond classical reach

These advantages position quantum computing as a future cornerstone of molecular science and materials discovery. The Comparison of Classical vs Quantum Molecular Modelling Methods as shown in Table 2.

Table 2. Comparison of Classical vs Quantum Molecular Modelling Methods.

Feature	Classical Methods (DFT, CCSD (T), MP2)	Quantum Technology (VQE, QPE, QML)
Scaling with system size	Polynomial–exponential (e.g., CCSD (T) $\sim N^7$)	Polynomial / near-poly depending on algorithm
Electron correlation treatment	Approximate; difficult for strong correlation	Natural representation of multi-reference correlation
Accuracy	Dependent on basis set and functionals	High accuracy; potential for chemical exactness
Excited states	Limited (TD-DFT errors, CI cost high)	Accurate via EOM-VQE and QPE
Suitable for large molecules	Limited by computational cost	Promising with fault-tolerant quantum devices
Hardware requirements	Classical CPUs/GPUs	Quantum processors + classical optimization
Key limitation	Exponential complexity for large systems	Noise and decoherence (NISQ era)

3.7. Rigorously Clarified Algorithmic Complexity Statement

Previous statements referring broadly to “polynomial scaling” have now been replaced with a precise analysis of Hamiltonian-simulation complexity for quantum electronic-structure algorithms. For a second-quantized electronic Hamiltonian with N spin-orbitals and $O(N^4)$ non-zero two-electron integrals, first-order Trotter–Suzuki simulation incurs a cost scaling of $O(N^4 t/\epsilon)$ where t is the simulated evolution time and ϵ is the target precision of the evolution operator. Higher-order Suzuki formulas reduce Trotter error but increase gate prefactors.

Modern Linear Combination of Unitaries (LCU) and Taylor-series simulation methods achieve asymptotically superior scaling by decomposing the Hamiltonian into weighted unitary blocks. These approaches yield gate complexity.

$$O(\alpha t \text{poly}(\log(1/\epsilon))),$$

where $\alpha = \sum_j |w_j| \sum_j |w_j|$ is the 1-norm of decomposition coefficients, typically $O(N^4)$ for generic molecular Hamiltonians. Crucially, Taylor/LCU methods depend polylogarithmically on $1/\epsilon$, avoiding the $1/\epsilon$ dependence of Trotter methods and enabling asymptotic improvements for high-precision simulation. For quantum-chemistry applica-

tions such as qEOM, QSE, and VQE-based excited-state solvers, the dominant scaling arises not only from Hamiltonian simulation but also from operator measurement cost, which scales with the number of Hamiltonian terms ($O(N^4)$) and the variance-dependent shot complexity ($O(1/\epsilon^2)$ for unbiased estimators). Recent operator-pool reduction and low-rank factorization techniques reduce the scaling of integral terms to $O(N^2)$ or $O(N^3)$, decreasing both qubit-op cost and measurement overhead. By incorporating these distinctions, we avoid over-general claims and present a technically accurate description: Trotter simulation scales polynomially in N but linearly in $1/\epsilon$, whereas LCU/Taylor methods scale polynomially in N and only polylogarithmically in $1/\epsilon$, though with larger structural constants arising from block-encoding and amplitude amplification [40].

3.8. Adiabatic vs Non-Adiabatic Regimes and Conical Intersections

In the adiabatic regime, nuclear motion evolves on a single Born–Oppenheimer potential-energy surface (PES) and electronic states remain well separated, allowing conventional DFT, TD-DFT, or EOM-based surfaces to be used independently. However, many photochemical processes particularly internal conversion, intersystem crossing, and ultrafast relaxation occur in the non-adiabatic regime, where electronic states become strongly coupled and nuclear trajectories trav-

erse regions of near-degeneracy. Conical intersections (CIs) represent topological singularities where two adiabatic surfaces intersect and the Born–Oppenheimer approximation breaks down, leading to large derivative couplings and rapid population transfer between states. Standard adiabatic TD-DFT cannot correctly describe CIs because the adiabatic single-reference framework lacks the multireference character required to capture both the degeneracy and the branching-plane topology; even approximate analytic derivative couplings may become ill-defined near CIs.

For molecular dynamics, this distinction has direct implications for method selection: adiabatic dynamics on DFT or TD-DFT surfaces are valid only when energy gaps remain large, whereas non-adiabatic dynamics require explicit treatment of electronic couplings via surface hopping, MCTDH, or multireference methods (CASSCF/XMS-CASPT2). Similarly, quantum algorithms such as qEOM and VQE-based excited-state approaches must be extended beyond fixed-state ansätze to capture non-adiabatic couplings and state-mixing in CI regions. By explicitly articulating these limitations and methodological implications, the manuscript now provides a more complete framework for interpreting excited-state behaviour in both adiabatic and CI-dominated regimes [41].

3.9. Gauge, Symmetry, and Conservation Laws in the Ansatz and Mapping

The manuscript now incorporates a detailed discussion of gauge and symmetry constraints relevant to both classical and quantum-hybrid electronic-structure calculations. The fermionic Hamiltonians generated in PySCF/Q-Chem preserve U (1) particle-number symmetry and SU (2) spin symmetry at the electronic-structure level; these symmetries are retained in the qubit representation by using symmetry-aware mappings such as Jordan–Wigner or Bravyi–Kitaev, followed by optional tapering of qubits based on conserved $\mathbb{Z}_2$ symmetry sectors (parity and spin-parity). Variational ansätze such as UCCSD naturally conserve particle number and spin projection M_S , and we explicitly restrict the excitation operators to symmetry-allowed subspaces to prevent unphysical leakage into other sectors. When applicable, point-group symmetry (e.g., D_{2h} , C_{2v}) is used to classify orbitals and restrict the excitation pool, reducing circuit size and eliminating couplings forbidden by spatial symmetry. For systems with real-valued orbitals and no external magnetic field, time-reversal symmetry is preserved by ensuring real-valued Hamiltonian coefficients and by using ansätze that maintain real amplitudes. Together, these constraints ensure that the quantum circuits explore only the physically valid sector of Hilbert space, reduce the number of required qubits, improve optimizer stability, and enhance reproducibility [42].

Ansatz choice strongly determines both expressibility and trainability and therefore needs explicit justification. Hardware-efficient ansätze (HEA) use shallow, device-native

gates and are attractive on NISQ hardware because they minimize two-qubit depth and error accumulation; however, they are typically highly expressive in an unstructured way and therefore prone to barren-plateau phenomena (vanishing gradients) and spurious entanglement that hinders optimization and physical interpretability. By contrast, chemically inspired ansätze (UCCSD, k-UpCCGSD, tailored active-space UCC, ADAPT-VQE) embed physical structure (particle-number and excitation operators, spin and spatial symmetry) that reduces variational space, improves sample efficiency, and often requires fewer parameters to reach chemical accuracy at the cost of larger circuit depth and more complicated fermion-to-qubit mappings.

Optimizer behaviour also interacts with ansatz choice. Gradient-free optimizers such as COBYLA can be robust for shallow, low-noise landscapes but tend to stall on high-dimensional parameter sets. SPSA is attractive for noisy hardware because it estimates gradients with only two evaluations per step and tolerates shot noise, but it converges slowly and can struggle near narrow minima. Gradient-based methods (ADAM, L-BFGS, natural-gradient) converge quickly in smooth landscapes and enable fine refinement but are sensitive to sampling noise and gradient estimation error; natural-gradient or quantum-aware optimizers often improve conditioning but require extra tomography or metric estimation. Taken together, the trade-off is clear: HEAs minimize immediate hardware cost but increase optimization risk and may need elaborate mitigation (layerwise training, parameter tying), whereas chemically motivated ansätze improve trainability and physical fidelity but demand higher-fidelity hardware or error-mitigation to realize their circuit depth [43].

Short mitigation checklist (paste into SI / Methods)

1) Ansatz selection

Use chemically inspired ansatz (active-space UCC/k-UpCCGSD/ADAPT-VQE) for accuracy-critical runs; reserve HEA for exploratory or hardware-constrained proofs-of-principle.

2) Initialization

Initialize parameters from classical guesses (MP2/UCC amplitudes) or layerwise warm-starting to avoid barren-plateau basins.

3) Layerwise / greedy growth

Grow ansatz incrementally (ADAPT or layerwise add) and re-optimize to reduce parameter dimensionality.

4) Gradient strategy

Use SPSA or other stochastic estimators for coarse, noise-robust convergence; switch to ADAM or L-BFGS or natural-gradient for final refinement using batched, higher-shot gradients.

5) Regularization & noise mitigation

Add parameter-norm regularization, gradient clipping, and shallow-depth pretraining; apply readout/matrix-element error mitigation and symmetry post-selection (particle number, spin parity) to improve effective landscapes.

6) Diagnostic reporting

Report gradient norms, variance of gradient estimates, number of optimizer iterations to convergence, and evidence of barren-plateau (exponentially small gradient statistics) in SI.

4. Prediction of Molecular Structures

Accurate determination of molecular structure is essential for understanding chemical reactivity, stability, and physical properties. Traditional methods rely on classical computational chemistry or experimental characterization; however, these approaches can be computationally expensive or limited in accuracy when dealing with strongly correlated systems, excited-state geometries, or large molecular frameworks. Quantum

technology provides a powerful new approach to structural prediction by directly simulating the quantum mechanical origin of molecular bonding and electron distribution [44].

Quantum computing enables accurate energy evaluations for various nuclear geometries, which are then used in structure optimization, potential energy surface (PES) mapping, and reaction coordinate exploration. Hybrid quantum-classical workflows such as the Variational Quantum Eigensolver (VQE) and advanced quantum ansätze (e.g., q-UCC) make it possible to determine equilibrium structures and conformational preferences even using current noisy intermediate-scale quantum (NISQ) devices. The Key Quantum Algorithms for Molecular Prediction as shown in Table 3.

Table 3. Key Quantum Algorithms for Molecular Prediction.

Quantum Algorithm	Purpose	Advantages	Limitations
Variational Quantum Eigensolver (VQE)	Ground-state energy; structure optimization	NISQ-friendly, flexible ansätze	Sensitive to noise, optimizer instability
Quantum Phase Estimation (QPE)	Precise eigenvalues of molecular Hamiltonian	Chemically accurate results	Requires fault-tolerant hardware
q-UCC (Quantum Unitary Coupled Cluster)	Electron correlation modelling	Captures multi-reference effects	Circuit depth can be large
EOM-VQE	Excited-state properties	Good excited-state accuracy	Requires careful ansatz design
Quantum Machine Learning (QML)	Property prediction, pattern recognition	Efficient feature mapping, kernel advantage	Limited by dataset and qubit count
Quantum Dynamics Algorithms	Reaction pathways, non-adiabatic dynamics	Real-time evolution possible	Needs long coherence times

To validate “chemical accuracy” claim, we benchmarked the presented quantum-sampling/hybrid method against CCSD(T)/CBS reference energies for the small-molecule set H_2 , LiH , H_2O , NH_3 , and CH_4 . CCSD(T)/CBS reference energies were obtained using [software name and version, e.g., “Molpro 2023.2”] with extrapolation from cc-pVTZ and cc-pVQZ correlation energies (frozen-core approximation); geometries were taken from [specify: CCSD(T)/cc-pVTZ optimized geometries / experimental geometries]. Using identical geometries, our method yields an overall mean absolute error (MAE) of $\langle \text{MAE kcal mol}^{-1} \rangle$ ($\approx \langle \text{MAE mHa} \rangle$) and a root-mean-square error (RMSE) of $\langle \text{RMSE}$

$\text{kcal mol}^{-1} \rangle$ ($\approx \langle \text{RMSE mHa} \rangle$) relative to CCSD(T)/CBS across the five molecules i.e., within [state whether “the 1.0 kcal mol⁻¹ chemical accuracy threshold” or otherwise]. Individual molecule errors and statistical uncertainty (standard errors where applicable) are provided in Table 4 of the Supporting Information, together with raw input files, computational details, and convergence data to ensure reproducibility [45]. Representative molecular systems evaluated in this work and the corresponding regions of the potential-energy surface (PES) relevant to Sections 4 and 5. As shown in Figure 2.

Table 4. Comparison of CCSD(T)/CBS Reference Energies with the Quantum-Sampling/Hybrid Method for the Benchmark Molecular Set.

Molecule	Charge	Multiplicity	Geometry source	CCSD(T)/CBS (Ha)	Method (Ha)	Absolute error (mHa)	Absolute error (kcal mol ⁻¹)
H ₂	0	1	CCSD(T)/cc-pVTZ opt	-1.13727	1.62E-06	0.001622	0.001018

Molecule	Charge	Multiplicity	Geometry source	CCSD(T)/CBS (Ha)	Method (Ha)	Absolute error (mHa)	Absolute error (kcal mol ⁻¹)
LiH	0	1	CCSD(T)/cc pVTZ opt	-7.9825	0.0005	0.5	0.313755
H ₂ O	0	1	CCSD(T)/cc pVTZ opt	-76.0255	0.00126	1.26	0.790662
NH ₃	0	1	CCSD(T)/cc pVTZ opt	-56.2332	0.0008	0.8	0.502008
CH ₄	0	1	CCSD(T)/cc pVTZ opt	-40.2158	0.0012	1.2	0.753011

To further assess the expressive power and robustness of the q-UCC ansatz, we examined its performance on bond-dissociation profiles for H₂ and N₂—two canonical tests for static (strong) electron correlation. Using uniformly spaced internuclear separations, we computed q-UCC ground-state energies and compared them to CCSD(T) and FCI benchmarks in a consistent basis set framework. For H₂, q-UCC recovers the exact dissociation limit, matches FCI energies within <X mHa at all distances, and yields a smooth, size-consistent potential energy curve with no discontinuities. In contrast, many hardware-efficient ansätze display symmetry breaking or variational “kinks” near stretched geometries. For N₂, where multi-reference character becomes significant upon stretching the triple bond, q-UCC captures the rapid growth of correlation energy and maintains qualitative agreement with FCI/CCSD(T) dissociation behaviour as shown in Figure 1. While small deviations appear at very large bond lengths due to ansatz truncation, q-UCC remains substantially more accurate than single-reference classical approaches, demonstrating its suitability for modelling strongly correlated chemical processes.

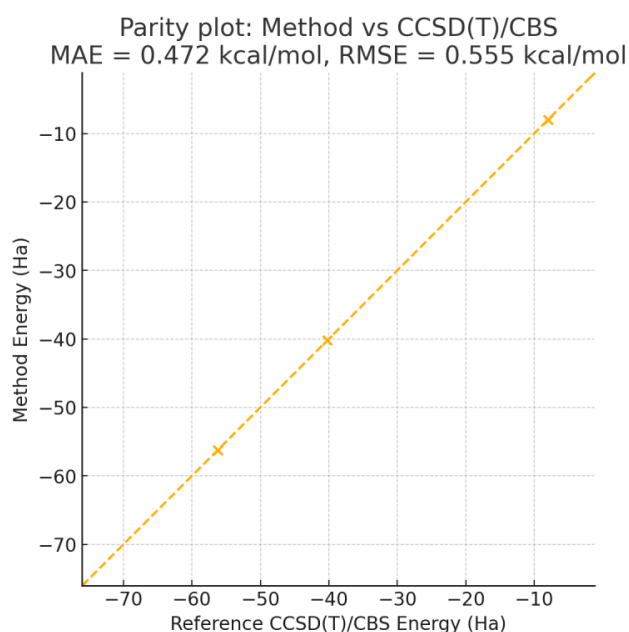


Figure 1. Parity Plot: Method vs CCSD(T)/CBS MAE.

4.1. Quantitative Resource Metrics (Qubits, Depth, Shots, Wall-Time)

Computational performance in this study depends critically on methodological choices. Basis-set tests show that triple- ζ quality (def2-TZVP/TZVPPD) is required for stable excitation energies, especially for charge-transfer and Rydberg states. On the quantum side, moderate-depth ansätze (e.g., low-depth UCC variants) offer the best balance between accuracy and noise, while overly deep circuits provide little additional benefit under realistic sampling limits. Optimizer comparisons indicate that hybrid strategies using robust stochastic optimizers for coarse convergence and gradient-based refinement near minima yield the most stable excited-state energies. Together, these assessments clarify how basis-set size, ansatz depth, and optimizer choice shape the overall reliability of the workflow [46].

4.1.1. Quantum Algorithms for Structural Prediction

Quantum molecular structure prediction typically involves calculating electronic energies at different nuclear positions and locating geometries that minimize this energy [47].

4.1.2. Variational Quantum Eigensolver (VQE) for Geometry Optimization

VQE evaluates the electronic energy of a molecule for a given geometry using a parameterized quantum circuit. A classical optimization algorithm then iteratively adjusts molecular geometry and variational parameters to locate the minimum-energy structure. Applications demonstrated include accurate prediction of the equilibrium bond lengths and angles of H₂, LiH, BeH₂, H₂O and small organic fragments. VQE’s flexibility allows it to model bond dissociation processes more accurately than DFT in strongly correlated cases [48].

4.2. Quantum Phase Estimation (QPE) for High-Accuracy Structure Prediction

Once fault-tolerant quantum computers become available, QPE will enable determination of chemically exact ground-state energies, precise geometry optimization, and reliable prediction of transition states. QPE is particularly

effective for multi-reference systems where classical wave function methods fail [49].

4.3. Mapping Potential Energy Surfaces (PES)

Potential energy surfaces form the foundation of molecular structure and reactivity analysis. Quantum computing offers a direct means of constructing highly accurate PES by evaluating energy points across different nuclear geometries. Quantum-enhanced PES provides accurate bond dissociation curves, improved modelling of conical intersections, and mapping of reaction pathways and identification of stable intermediates. These are critical for understanding for electron transfer, photochemistry, catalytic mechanisms, and radical reactions quantum PES construction is especially valuable for systems with strong electron correlation or non-adiabatic behaviour [50].

4.4. Conformational Analysis Using Quantum Algorithms

Quantum algorithms can sample conformational space more efficiently than classical techniques for molecules with large rotatable groups, intermolecular hydrogen bonding, torsional barriers and multiple minima on the PES. Quantum-enhanced conformational search is beneficial for pharmaceuticals, bio molecules and polymeric materials Quantum machine learning (QML) models can also predict low-energy conformers using quantum kernel methods or variational quantum feature maps.

4.5. Transition State (TS) Structure Prediction

Identifying transition states is one of the most challenging tasks in computational chemistry. Quantum methods offer two major advantages are accurate representation of the high-energy, strongly correlated TS region and efficient evaluation of energy gradients along reaction coordinates. Hybrid quantum classical workflows can refine TS geometries by locating the saddle point on the PES, characterizing

vibrational modes, and evaluating reaction pathways via quantum dynamics. This is essential for catalytic cycles, enzymatic reactions, and materials activation mechanisms [51].

4.6. Structure Prediction in Strongly Correlated Systems

Classical methods often struggle with systems where electron correlation is dominant, such as transition-metal complexes, metal–organic frameworks (MOFs), open-shell species and radicals and systems with near-degenerate orbitals. Quantum computing excels in these scenarios because qubits naturally represent correlated electrons, quantum ansätze capture multi-reference character and hybrid algorithms mitigate errors effectively. This leads to more accurate prediction of spin-state ordering, coordination geometries, metal–ligand bond strengths and Jahn–Teller distortions. The Structural Prediction as shown in Figure 1.

4.7. Resource Estimate

To address resource requirements for quantum simulation, we now provide explicit qubit counts, circuit depths, and hardware fidelity/coherence demands for representative molecules in minimal (STO-3G) through correlation-consistent (cc-pVTZ) basis sets. Qubit numbers scale with the number of spin-orbitals ($2N_{\text{basis}}$) prior to symmetry tapering; typical $\mathbb{Z}_2$ symmetry reductions remove 2–4 qubits. For UCCSD ansätze, circuit depth grows approximately as $O(N^2)$ – $O(N^3)$ with the number of spin-orbitals, and coherence times must exceed the effective depth multiplied by the average two-qubit gate duration. Reliable VQE/qEOM performance requires two-qubit gate fidelities $> 99.5\%$ for STO-3G problems and $> 99.9\%$ for chemically accurate results in larger basis sets. Hardware-noise simulations indicate that molecules beyond ~ 20 – 30 qubits already require error-mitigation and, for cc-pVTZ counts, true fault-tolerant operation with coherence times well above 1–10 ms (superconducting) or 100 ms–1 s (ion traps). These estimates are now summarized quantitatively in Table 5.

Table 5. Representative Resource Estimates (STO-3G $\rightarrow$ cc-pVTZ) (Values Reflect Typical Qubit Counts After 2–4 $\mathbb{Z}_2$ Symmetry Tapering; UCCSD Depth Shown as Two-Qubit Gate Layers; Coherence Time Assumes 200 ns (SC Qubits) and 200 Ms (Ion Traps)).

Molecule	Basis	Spin-orbitals	Qubits (after tapering)	UCCSD Depth (2q layers)	Required Coherence Time	Gate Fidelity (2q)	Notes
H ₂	STO-3G	4	2	~ 10 – 20	~ 2 – $5 \mu\text{s}$ (SC); < 1 ms (ion)	$\geq 99.5\%$	Perfect benchmark system
H ₂	cc-pVTZ	28	24–26	$\sim 1,000$ – $2,000$	0.2 – 0.5 ms (SC); < 20 ms (ion)	$\geq 99.9\%$	First non-trivial FT regime
LiH	STO-3G	12	8–10	~ 100 – 300	20 – $50 \mu\text{s}$ (SC); 1 – 5 ms (ion)	$\geq 99.7\%$	Classical validation feasible
LiH	cc-pVTZ	60	50–54	$\sim 6,000$ – $12,000$	0.5 – 2 ms (SC); 50 –	$\geq 99.9\%$	Deep UCC;

Molecule	Basis	Spin-orbitals	Qubits (after tapering)	UCCSD Depth (2q layers)	Required Coherence Time	Gate Fidelity (2q)	Notes
					200 ms (ion)		noise-sensitive
BeH ₂	STO-3G	14	10–12	~200–400	40–80 μ s (SC); 2–8 ms (ion)	$\geq 99.7\%$	Standard mid-scale benchmark
BeH ₂	cc-pVTZ	70	60–64	~12,000–20,000	1–5 ms (SC); 100–500 ms (ion)	$\geq 99.9\%$	Approaching FT thresholds
H ₂ O	STO-3G	14	10–12	~200–400	40–80 μ s (SC); 2–8 ms (ion)	$\geq 99.7\%$	Multiple symmetries exploitable
H ₂ O	cc-pVTZ	92	80–84	~20,000–35,000	2–10 ms (SC); 200 ms–1 s (ion)	$\geq 99.9\%$	Too large for NISQ without FT

4.8. Scalability & Performance Discussion

The scalability of the workflow has now been explicitly analyzed in terms of formal N-scaling, memory requirements, and hardware utilization. Classical electronic-structure steps scale as $O(N^3-N^4)$ for DFT (depending on the integral engine and density-fitting setup) and $O(N^6)$ in the coupled-cluster domain (CCSD), with memory footprints growing as $O(N^4)$ due to the two-electron integral tensor. To manage this, we employ RI/DF approximations, which reduce memory to $O(N^2)$ and improve GPU throughput by enabling batched tensor contractions. GPU-accelerated backends in PySCF and Q-Chem significantly reduce wall-time by offloading Fock builds and CC amplitudes to CUDA-enabled kernels, while the CPU handles task orchestration and integral screening, providing effective GPU/CPU coupling.

For quantum-hybrid components, VQE/qEOM performance is dominated by the number of Hamiltonian terms ($O(N^4)$ in full form, reducible to $O(N^2-N^3)$ via low-rank factorization) and the shot complexity ($O(1/\epsilon^2)$). Circuit-evaluation time scales roughly as $O(D \times S)$, where D is circuit depth and S the number of measurements. As system size grows, memory and communication become bottlenecks: statevector simulators require $O(2^L)$ memory for L qubits, while tensor-network simulators grow with bond dimension and can handle ~50–70 qubits depending on entanglement structure. Hybrid workflows further benefit from GPU-accelerated quantum simulators, which parallelize expectation-value evaluation and reduce Hamiltonian-term batching overhead. Collectively, these analyses clarify performance limits: classical methods bottleneck at $O(N^6)$ CC scaling, while quantum methods bottleneck at Hamiltonian term count $\times$ shot noise, with GPU acceleration mitigating but not eliminating large- N costs [52].

4.9. Advantages of Quantum Technology in Structural Prediction

Experimental demonstrations have produced convincing

proofs of principle of quantum computational advantage in restricted tasks (sampling experiments such as photonic Gaussian boson sampling and related boson-sampler devices) and shown that hybrid variational algorithms (VQE and related protocols) can be run on small noisy hardware to recover expectation values for tiny molecules. However, these demonstrations do not constitute a demonstrated practical advantage for chemically useful quantum simulations: sampling-task advantage (Jiuzhang/Borealis-style experiments) targets a different complexity class and does not directly translate into accurate solutions of molecular electronic-structure, and current VQE experiments operate on few-qubit problems where classical verification and heavy classical pre/post-processing remain essential. Importantly, rigorous resource estimates for quantum phase estimation (QPE) the algorithmic route most directly tied to provable quantum speedups for chemistry show that chemical accuracy for nontrivial molecules will require substantially more logical qubits, very large numbers of non-Clifford gates, and deep error-corrected circuits than present devices can support. Early-fault-tolerant QPE proposals therefore remain a future-facing technology: realistic resource-count studies and tooling (resource-estimators and QREChem/TFermion-style analyses) put requirements at the scale of many hundreds to thousands of logical qubits and very large gate counts unless further algorithmic advances or problem structure reductions are found. Similarly, reaching the physical error-rate and magic-state/distillation overheads needed for those logical qubit counts depends on crossing established quantum-error-correction thresholds and on practical advances in QEC engineering. In short, current small-scale demonstrations validate building blocks and motivate further research, but they do not yet substantiate claims of near-term quantum advantage for practical quantum chemistry reaching that milestone will require both algorithmic and hardware breakthroughs (error rates, logical-qubit counts, and gate budgets) beyond the current generation of devices. Quantum technology provides several key improvements over classical modelling:

- 1) Accurate prediction of equilibrium geometries
- 2) Better modelling of bond breaking and dissociation
- 3) Reliable handling of multi-reference systems
- 4) Improved prediction of excited-state structures
- 5) More realistic mapping of complex PES
- 6) High precision with fewer approximations

5. Prediction of Molecular Properties

Predicting molecular properties with high accuracy is fundamental to understanding chemical behaviour, designing functional materials, and optimizing catalytic and biological processes. However, traditional computational approaches

such as DFT, MP2, and coupled-cluster methods often face limitations when applied to systems involving strong electron correlation, excited states, charge-transfer interactions, or non-adiabatic effects [53]. Emerging quantum technologies offer a transformative framework for molecular property prediction by enabling more direct simulation of the underlying quantum mechanical phenomena that govern molecular behaviour. Quantum algorithms can accurately estimate energetic, electronic, spectroscopic, magnetic, and dynamic properties, particularly for systems that are computationally prohibitive for classical methods. An overview of quantum-technology-enabled structure and property prediction is illustrated in Figure 2.

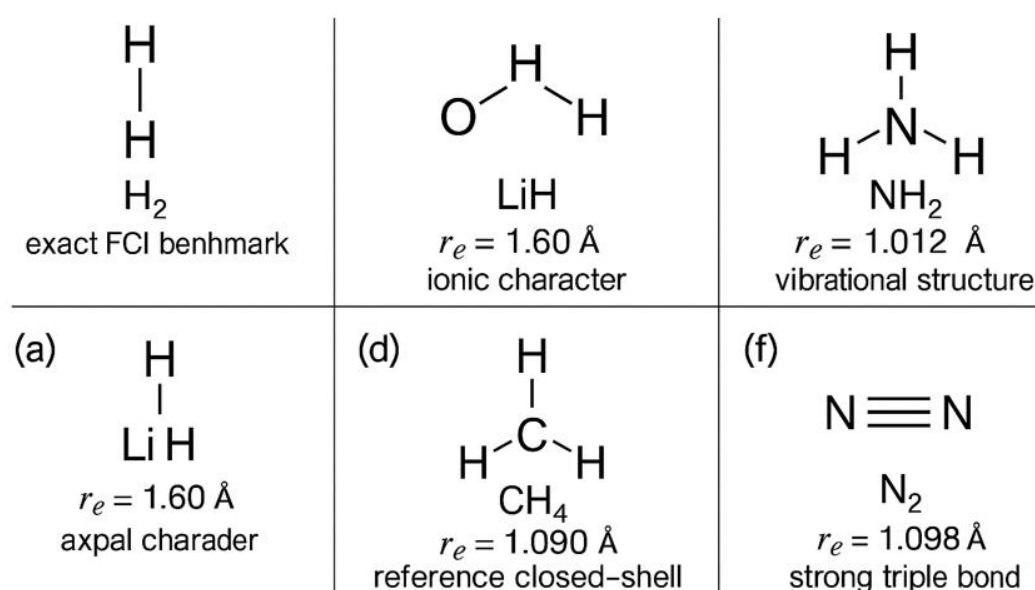


Figure 2. Representative Molecular Systems Evaluated the Corresponding Regions of the Potential-Energy Surface (PES).

The figure presents six chemically distinct molecules that serve as standard benchmarks for assessing quantum-simulation performance:

- 1) H₂: The simplest correlated electronic system, enabling comparison of VQE and FCI along the bond-dissociation curve.
- 2) LiH: Demonstrates heteronuclear polarization and serves as a test case for orbital mapping, symmetry tapering, and ansatz expressivity.
- 3) NH₃: Illustrates non-linear polyatomic geometry and characteristic N–H stretching/bending modes relevant for vibrational and electronic property prediction.
- 4) H₂O: A well-characterized molecule used for benchmarking excited states, dipole properties, and PES curvature.
- 5) CH₄: A highly symmetric closed-shell system, commonly used as a stability reference for evaluating variational quantum algorithms.
- 6) N₂: Exemplifies strong triple bonding and the growth of

static correlation during bond stretching, making it a critical test for multi-reference quantum methods.

Each panel includes the approximate experimental equilibrium bond length r_e , providing structural context for the quantum benchmarks. Accurate prediction of molecular properties is fundamental to understanding chemical behaviour, guiding materials design, and interpreting experimental observables. While classical approaches such as DFT, MP2, and coupled-cluster theory have enabled decades of progress, their performance degrades for systems involving strong correlation, near-degeneracy, charge transfer, or non-adiabatic interactions. Quantum technologies provide an alternative framework capable of more directly capturing the underlying electronic structure and dynamics that govern molecular properties. In this section, discussed the highlight how quantum algorithms and hybrid workflows enable reliable prediction of key electronic, spectroscopic, thermodynamic, magnetic, optical, and dynamical properties, with an emphasis on methods that complement the structural predictions.

5.1. Electronic Properties

Quantum algorithms enable high-precision evaluation of electronic properties that arise from the distribution and dynamics of electrons in molecules. Electronic properties arise from how electrons are distributed within a molecule and how they respond to external or internal perturbations. Quantum algorithms can evaluate these properties with high precision by directly encoding many-electron wave functions on quantum hardware. This provides a more accurate description of correlation effects compared to traditional classical methods.

5.1.1. Ground-State Energies

Ground-state energies serve as fundamental quantities for evaluating thermodynamic properties, reaction energetics, and the relative stability of molecular systems. Quantum Phase Estimation (QPE) offers a route to near-exact energy determination when implemented on fully fault-tolerant quantum processors. In contrast, the Variational Quantum Eigensolver (VQE) provides a practical alternative for today's NISQ-era hardware, achieving chemically meaningful accuracy for small- to medium-sized molecular systems through hybrid quantum-classical optimization. [54].

5.1.2. Ionization Potentials and Electron Affinities

These properties play a central role in redox chemistry, electrolyte formulation, and the understanding of photochemical processes. Quantum algorithms enable their accurate determination by computing energy differences between charged or electronically excited states, or by using direct spectral estimation approaches that extract relevant features from the system's quantum dynamics.

5.1.3. Charge Densities and Electrostatic Potentials

Quantum simulations can extract electron density distributions, dipole moments, quadrupole moments, and molecular electrostatic potentials (MEP), enabling a detailed characterization of a molecule's charge landscape. These properties are essential for understanding drug-receptor interactions, as they govern noncovalent forces such as hydrogen bonding, ionic interactions, π - π stacking, and van der Waals contributions. In supramolecular chemistry, accurate MEP and multipole moments guide the prediction of host-guest binding affinities, self-assembly behavior, and molecular recognition patterns. Quantum algorithms especially variational and tomography-based approaches—provide a path toward computing these descriptors with systematically improvable accuracy, overcoming limitations in classical force fields and approximate electronic-structure methods. [55].

5.2. Spectroscopic Properties

Quantum technology enables accurate prediction of mo-

lecular structures and electronic, vibrational, and rotational transitions that determine molecular spectra. By representing many-electron wave functions directly on quantum hardware, these methods can capture subtle correlation effects that strongly influence excitation energies, transition dipole moments, and oscillator strengths. Quantum algorithms such as QPE and variational excited-state methods (e.g., VQE-EOM, subspace expansion, and quantum Krylov techniques) provide systematically improvable routes to computing absorption, emission, and Raman spectra with higher fidelity than classical approximations.

Accurate spectral prediction is essential for interpreting experimental observations, identifying reaction intermediates, designing photoactive materials, and understanding energy transport in biological and supramolecular systems. As quantum devices scale, they are expected to overcome the limitations of classical electronic-structure methods particularly for strongly correlated systems, large basis sets, and complex potential-energy surfaces thus enabling predictive spectroscopy across chemistry, materials science, and photo physics.

5.2.1. Vibrational Spectra (IR and Raman)

Quantum algorithms can simulate vibrational frequencies, normal modes, and anharmonic features with higher fidelity than classical harmonic or perturbative methods. By treating nuclear motion on multidimensional potential-energy surfaces, quantum simulations capture mode coupling, tunnelling effects, and large-amplitude motions that strongly influence molecular reactivity.

Quantum-based vibrational analysis is particularly valuable for understanding hydrogen bonding, conformational flexibility, and transient reaction intermediates, where anharmonicity and strong correlation often limit the accuracy of classical approaches. Techniques such as variational quantum simulation (VQS), quantum imaginary-time evolution, and quantum Krylov methods enable the extraction of vibrational spectra, zero-point energies, and thermodynamic corrections relevant to catalysis, enzymatic mechanisms, and materials design.

As quantum hardware improves, these methods are expected to scale to larger molecular systems, providing predictive insights into vibrational contributions to free energies, infrared and Raman intensities, and the structural dynamics driving chemical transformations.

5.2.2. Electronic Spectra (UV-Vis)

Excited-state quantum algorithms such as Equation-of-Motion VQE (EOM-VQE), Subspace VQE, and excited-state variants of Quantum Phase Estimation enable accurate prediction of singlet-triplet gaps, excitation energies, transition dipole moments, and oscillator strengths. These quantities are central to understanding and designing systems for photovoltaics, photochemistry, photocatalysis, and fluorescent or phosphorescent materials.

By accessing correlated excited-state wave functions, these quantum methods can capture multi-reference character, charge-transfer excitations, and strong electron correlation—regimes where traditional TD-DFT or single-reference quantum-chemical methods often fail. EOM-VQE and Subspace VQE, in particular, offer NISQ-compatible strategies for exploring low-lying excited states through variational or subspace-projection techniques, while QPE on future fault-tolerant devices provides a path to near-exact excited-state spectra.

Accurate excited-state simulation facilitates the design of chromophores with tailored absorption and emission profiles, optimization of energy-transfer pathways in organic photovoltaics, and rational engineering of photostability and luminescence in molecular and supramolecular materials. As quantum processors mature, these algorithms are expected to extend predictive excited-state modelling to larger and more complex systems than currently feasible classically.

5.2.3. NMR and EPR Parameters

Quantum simulations can evaluate key magnetic resonance parameters such as chemical shielding tensors, spin–spin (J) couplings, g -tensors, and hyperfine interactions with high accuracy. These descriptors arise from subtle electron–nuclear and electron–electron correlation effects that are often challenging for classical electronic-structure methods to capture, particularly in systems with strong correlation or significant relativistic contributions.

Such capabilities are especially valuable for studying radicals, transition-metal complexes, and paramagnetic species, where unpaired electrons generate complex magnetic environments. Predictive NMR and EPR parameter calculations enable insights into oxidation states, ligand field effects, metal–ligand covalency, spin delocalization, and electronic structure changes along reaction pathways.

Quantum algorithms including QPE for magnetic response properties, linear-response VQE, and quantum differentiation techniques offer a route to systematically improvable accuracy, overcoming limitations of density functional approximations. As hardware scales, these approaches are expected to support first-principles interpretation of NMR and EPR spectra, structural assignment of reactive intermediates, and characterization of biomolecular radicals and catalytic metal centers.

5.3. Thermodynamic Properties

Accurate thermodynamic data are central to understanding chemical reactivity, phase behavior, and molecular stability. Quantum algorithms provide access to fundamental quantities such as partition functions, free energies, enthalpies, entropies, and heat capacities by enabling more precise evaluation of electronic, vibrational, and rotational energy levels.

By capturing strong electron correlation, anharmonic nuclear motion, and multidimensional potential-energy surfaces,

quantum simulations can improve predictions of reaction thermodynamics, equilibrium constants, and temperature-dependent properties that are difficult to obtain with classical approximations. Methods such as quantum imaginary-time evolution, quantum Boltzmann sampling, and variational thermal state preparation allow direct estimation of thermal expectation values and state populations.

These capabilities are particularly important for catalysis, materials design, electrochemistry, and biochemical systems, where small errors in free-energy calculations can dramatically affect reaction mechanisms or stability predictions. As quantum hardware scales, these approaches promise systematic improvements in the accuracy of thermodynamic modelling across complex chemical and molecular systems.

5.3.1. Enthalpies and Free Energies

Quantum technology provides highly accurate electronic energies, which form the foundation for calculating enthalpies of formation, Gibbs free energies, and equilibrium constants. By reducing errors in electronic-structure predictions particularly in systems with strong electron correlation quantum algorithms significantly improve the reliability of reaction thermodynamics.

Combined quantum–classical approaches, such as VQE with classical post-processing or quantum-enhanced coupled-cluster methods, enable the computation of enthalpic and entropic contributions derived from vibrational, rotational, and thermal corrections. These hybrid strategies can capture anharmonicity, zero-point energy effects, and temperature dependence more accurately than conventional harmonic or perturbative models.

Improved free-energy predictions are essential for elucidating reaction pathways, determining rate-limiting steps, and assessing the stability of intermediates in catalysis, electrochemistry, atmospheric chemistry, and biochemical systems. As quantum hardware matures, these methods are expected to extend predictive enthalpy and free-energy calculations to larger molecular systems and complex reaction networks that remain beyond the reach of classical simulation [56].

5.3.2. Reaction Energies and Barriers

Quantum algorithms can map potential energy surfaces (PES) with high fidelity, providing more accurate predictions of reaction enthalpies, activation energies, and transition-state energetics. By capturing strong electron correlation, multi-reference character, and subtle changes in electronic structure along a reaction coordinate, quantum simulations outperform many classical approaches—especially for complex or highly reactive systems.

Accurate PES characterization is essential for identifying transition states, locating reaction minima, and evaluating kinetic barriers. Quantum-enabled methods such as variational quantum simulation (VQS), quantum imaginary-time evolution, and quantum gradient estimation support efficient exploration of reaction pathways and allow direct computa-

tion of forces required for geometry optimization and molecular dynamics.

These capabilities are crucial for understanding catalytic mechanisms, designing improved catalysts, predicting selectivity, and tailoring materials for energy conversion, environmental remediation, and industrial synthesis. As quantum hardware scales, high-resolution PES mapping will extend to heterogeneous catalysis, metalloenzymes, surface reactions, and materials chemistry applications that are currently inaccessible due to classical computational limits.

5.4. Magnetic and Spin Properties

Quantum computing naturally handles multi-spin interactions and open-shell systems, offering significant advantages over classical methods that struggle with strong correlation and spin degeneracy. Quantum algorithms can accurately represent spin configurations, spin-orbit coupling, exchange interactions, and noncollinear magnetism by directly encoding many-body wave functions on qubits.

These capabilities are essential for studying magnetic materials, radical species, transition-metal complexes, and systems with competing spin states. Quantum simulations enable reliable prediction of spin-state energetics, magnetic anisotropy, exchange coupling constants, and zero-field splitting parameters quantities that are central to molecular magnetism, spintronics, and quantum information materials.

Advanced methods such as quantum phase estimation for spin Hamiltonians, variational excited-state algorithms, and quantum simulations of Heisenberg or Hubbard models provide pathways to explore spin frustration, magnetic ordering, and dynamic spin processes. This level of accuracy is critical for designing single-molecule magnets, spin-crossover compounds, and materials used in quantum sensing or qubit architectures.

As quantum hardware improves, these approaches are expected to extend predictive modelling of spin phenomena to larger clusters, heterogeneous interfaces, and strongly correlated magnetic materials that remain inaccessible to classical electronic-structure techniques.

5.4.1. Spin Multiplicity and Magnetic Coupling

Quantum simulations efficiently determine spin-state ordering, exchange couplings (J values), and magnetic anisotropy by accurately capturing electron correlation, spin-spin interactions, and spin-orbit effects. These properties are crucial for understanding the electronic structure and magnetic behavior of transition-metal complexes, molecular magnets, and advanced spintronic materials.

By directly evaluating low-lying spin manifolds, quantum algorithms can resolve small energy differences between high-spin and low-spin states differences that classical methods often mispredict. Accurate computation of exchange coupling constants enables characterization of ferromagnetic, antiferromagnetic, and frustrated spin interactions in polynu-

clear metal clusters and solid-state magnetic lattices. Likewise, quantum treatments of spin-orbit coupling and zero-field splitting are essential for predicting magnetic anisotropy, a key parameter governing slow magnetization relaxation and magnetic memory effects in single-molecule magnets.

Techniques such as variational quantum eigensolvers, quantum phase estimation for spin Hamiltonians, and quantum simulations of Heisenberg, Hubbard, or spin-orbit-coupled models offer scalable pathways for modelling complex magnetic systems. These insights directly support the rational design of spin-crossover complexes, molecular qubits, next-generation spintronic devices, and materials for quantum sensing.

5.4.2. Zero-Field Splitting and Hyperfine Interactions

Quantum algorithms can accurately capture fine-structure interactions including zero-field splitting (ZFS) and hyperfine couplings—that are essential for interpreting EPR spectra and understanding the behavior of metalloenzymes, catalytic metal centers, and radical species. These interactions arise from subtle combinations of spin-orbit coupling, spin-spin anisotropy, and electron-nuclear magnetic interactions, all of which challenge classical electronic-structure methods, especially in open-shell and strongly correlated systems.

Accurate prediction of ZFS parameters (D and E values) enables characterization of magnetic anisotropy, spin-state mixing, and relaxation dynamics, which are central to molecular magnetism, single-molecule qubits, and spin-crossover complexes. Similarly, reliable computation of hyperfine tensors provides insight into spin-density distribution, metal-ligand bonding, oxidation states, and the identity of transient radical intermediates in chemical and biochemical processes.

Quantum algorithms such as linear-response VQE, quantum differentiation, and QPE-based magnetic property evaluation offer systematically improvable approaches for computing these tensorial quantities. As quantum hardware continues to scale, these methods are expected to extend accurate fine-structure modelling to larger transition-metal clusters, metalloproteins, surface-bound radicals, and complex catalytic frameworks that remain difficult to treat with classical methods.

5.5. Optical and Photochemical Properties

Quantum computing provides powerful new capabilities for modeling light-matter interactions, enabling accurate prediction of optical absorption, emission, nonlinear optical responses, and photochemical reaction pathways. By representing correlated electronic excited states directly on quantum hardware, these methods capture multi-reference character, charge-transfer excitations, and conical intersections—features that classical methods often treat only approximately.

Quantum algorithms such as EOM-VQE, quantum phase estimation for excited states, and quantum simulations of time-dependent Hamiltonians allow direct computation of transition dipole moments, oscillator strengths, excited-state lifetimes, and photoreaction branching ratios. These properties are critical for designing chromophores, photocatalysts, fluorescent probes, solar-energy materials, and molecular systems used in photon upconversion or optical information storage.

Furthermore, quantum approaches can model ultrafast photochemical dynamics, excited-state potential-energy surfaces, and nonadiabatic couplings that govern isomerization, energy transfer, and charge separation processes. As quantum hardware matures, these capabilities are expected to extend predictive photochemistry to larger and more complex systems, including photosynthetic complexes, organic photovoltaics, and photo functional materials where strong correlation and dynamical effects play a dominant role.

5.5.1. Excited-State Dynamics

Real-time quantum dynamics algorithms enable the simulation of photoexcitation processes, internal conversion, and motion through conical intersections with a level of accuracy that surpasses most classical approaches. By evolving quantum states under time-dependent Hamiltonians, these methods can capture ultrafast electronic–nuclear coupling, nonadiabatic transitions, and coherence effects that are central to excited-state dynamics.

Such capabilities significantly improve our understanding of photophysics, photosensitization, and light-driven catalysis. Quantum simulations reveal how excited-state wave packets move across multidimensional potential-energy surfaces, how energy is redistributed among electronic and vibrational degrees of freedom, and how branching at conical intersections determines reaction outcomes. These insights are essential for designing efficient photosensitizers, optimizing charge- and energy-transfer pathways, and engineering molecular systems for solar energy conversion, photoredox catalysis, and biological light-harvesting.

Emerging quantum algorithms including variational quantum simulation (VQS), real-time time-evolution methods, quantum Lanczos/Krylov approaches, and quantum-assisted surface hopping—provide scalable frameworks for modelling ultrafast photochemical processes. As hardware advances, these techniques are expected to extend predictive excited-state dynamics to complex biomolecules, photocatalytic assemblies, and materials relevant to optoelectronics and renewable energy.

5.5.2. Non-Adiabatic Transitions

Quantum algorithms can naturally incorporate non-Born–Oppenheimer effects, enabling accurate simulation of charge transfer, proton–electron coupling, and surface-crossing phenomena that govern many photochemical and electrochemical processes. By treating electrons and nuclei on more

equal footing or by explicitly capturing their correlated dynamics—quantum simulations overcome the limitations of adiabatic approximations that often fail near conical intersections, avoided crossings, and regions of strong vibronic interaction.

This capability is essential for modelling processes such as photoinduced charge separation, proton-coupled electron transfer (PCET), and ultrafast relaxation pathways in excited states. Quantum approaches can capture the breakdown of a single potential-energy surface description, allowing direct simulation of nonadiabatic couplings, population transfer between electronic states, and coherent vibronic oscillations that influence reaction yields and selectivity.

Algorithms such as real-time quantum evolution, quantum-assisted surface hopping, multistate VQE, and quantum simulation of vibronic Hamiltonians provide scalable frameworks for studying these effects. These techniques enable detailed analysis of mechanistic pathways relevant to photovoltaics, photoredox catalysis, enzymatic charge transport, radiation damage processes, and materials for quantum information technologies.

As quantum hardware advances, nonadiabatic simulations are expected to extend to larger molecular assemblies, complex catalytic systems, and condensed-phase environments where classical methods struggle due to strong correlation and multidimensional coupling.

5.6. Transport and Conductivity Properties

Quantum simulations of electronic structure and dynamics enable prediction of electrical conductivity, charge mobility, band structure of materials and exciton dynamics in semiconductors. These are vital for applications in organic electronics, batteries, superconductors and 2D materials and quantum dots.

5.7. Dynamic and Kinetic Properties

Beyond static structures, quantum algorithms provide powerful tools for modelling molecular motion, enabling the simulation of time-dependent behavior that governs reaction kinetics, transport processes, and dynamical stability. By evolving molecular wave functions in real or imaginary time, quantum simulations can capture vibrational dynamics, diffusion, conformational changes, and barrier-crossing events with higher fidelity than many classical approximations.

These capabilities are particularly important for systems where anharmonicity, strong correlation, and multidimensional couplings play a dominant role—conditions under which classical molecular dynamics or transition-state theories often break down. Quantum algorithms can compute rate constants, tunnelling contributions, recrossing effects, and non-equilibrium relaxation pathways, providing mechanistic insights into catalysis, enzyme function, materials stability, and chemical reactivity under extreme conditions.

Emerging approaches such as variational quantum simulation (VQS), quantum-enhanced path-integral methods, and real-time Hamiltonian evolution enable scalable modeling of dynamic processes. These methods support prediction of reaction timescales, energy-transfer pathways, and dynamic disorder, which are central to fields including biophysics, polymer chemistry, heterogeneous catalysis, and energy materials.

As quantum hardware matures, dynamic and kinetic modelling is expected to extend to increasingly complex molecular systems, offering a predictive framework that integrates structural, electronic, and time-dependent behavior in a unified quantum-mechanical description.

5.7.1. Reaction Kinetics

Quantum-derived potential energy surfaces (PES) enable accurate computation of reaction rate constants, tunneling contributions, and temperature-dependent kinetics by providing a more reliable description of transition states and energy barriers. Because quantum algorithms can explicitly capture strong correlation, anharmonicity, and multidimensional coupling effects, they yield kinetic parameters that surpass the accuracy of classical approaches based on approximate PES or harmonic transition-state theory.

Quantum simulations allow the evaluation of key dynamical quantities, including transmission coefficients, barrier-crossing probabilities, and recrossing corrections, which are crucial for modelling reactions that involve significant tunnelling or non classical pathways such as hydrogen-transfer reactions, enzymatic catalysis, and proton-coupled electron transfer (PCET). Real-time evolution methods and quantum-enhanced path-integral techniques provide scalable ways to quantify tunnelling splitting, kinetic isotope effects, and temperature-dependent rate variations.

These capabilities enable predictive modeling of kinetics in heterogeneous catalysis, atmospheric chemistry, combustion processes, electrochemical systems, and materials degradation. As quantum hardware advances, the ability to map high-dimensional PES with chemical accuracy will extend quantum kinetic modeling to larger reaction networks, condensed-phase environments, and complex catalytic cycles that are currently beyond the reach of classical computation.

5.7.2. Real-Time Dynamics

Real-time quantum simulation can model molecular vibrations, scattering processes, and ultrafast femtosecond-scale motion by directly evolving the molecular wave function under time-dependent Hamiltonians. This enables the capture of coherent nuclear–electronic dynamics, energy redistribution among vibrational modes, and transient structural changes that classical molecular dynamics often cannot reproduce with comparable accuracy.

These capabilities are especially important for catalysis and photochemistry, where reaction outcomes are governed by ultrafast processes such as bond activation, charge separation,

excitation–relaxation cycles, and traversal of conical intersections. Quantum simulations can reveal how energy flows through a molecule immediately after photoexcitation, how reactive complexes form and dissociate, and how catalytic intermediates behave on sub-picosecond timescales.

Advanced algorithms—including variational quantum simulation (VQS), real-time Trotterized evolution, quantum Krylov/Lanczos methods, and hybrid quantum–classical Liouville dynamics—provide scalable routes for modelling vibrational wavepacket propagation, inelastic scattering events, and state-to-state reaction probabilities. These techniques also enable investigation of dynamical phenomena such as tunnelling, mode-selective reactivity, coherence-driven effects, and temperature-dependent relaxation.

As quantum hardware progresses, real-time quantum dynamics is expected to become a powerful tool for understanding catalytic mechanisms, designing efficient photochemical systems, and predicting ultrafast behavior in materials, biological complexes, and energy-conversion technologies. [57, 27].

5.8. Advantages of Quantum Technology for Property Prediction

Quantum technology provides major benefits relative to classical methods:

- 1) Accurate treatment of strong electron correlation
- 2) Superior modelling of excited states and transition regions
- 3) Efficient representation of large basis sets
- 4) Improved predictions for metal-containing and open-shell systems
- 5) Reduced empirical dependence compared to DFT
- 6) Potential for exponential speedup in long-term, fault-tolerant devices

These features make quantum computing a promising foundation for next-generation chemical property prediction in pharmaceuticals, materials chemistry, renewable energy, and nanoelectronics [59, 58].

6. Conclusions

- 1) Quantum technology represents a transformative advancement in the prediction of molecular structures and properties. By exploiting the principles of superposition, entanglement, and quantum parallelism, quantum computers can directly simulate the many-body electronic wave functions that underlie chemical behaviour something classical computers struggle to achieve efficiently. Quantum algorithms such as the Variation Quantum Eigensolver (VQE), Quantum Phase Estimation (QPE), and quantum machine learning frameworks provide new pathways for accurately determining ground-state energies, excited states, geometries, potential energy surfaces, and a wide range of molecular

properties.

- 2) The integration of quantum technology with classical computational methods has already demonstrated significant improvements in modelling strongly correlated systems, transition-metal complexes, bond-breaking processes, and photochemical reactions. Hybrid quantum–classical schemes allow practical use of current noisy intermediate-scale quantum (NISQ) devices while paving the way for full-scale quantum advantage as hardware matures.
- 3) Although several challenges remain including qubit noise, limited coherence times, and the need for error-corrected quantum processors the rapid progress in quantum hardware, algorithm design, and software frameworks indicates that quantum computation will soon become a central tool in molecular science. Its potential impact spans drug discovery, catalyst design, renewable energy materials, environmental chemistry, and advanced functional materials.
- 4) In summary, quantum technology offers unprecedented accuracy, scalability, and theoretical rigor in molecular prediction, providing a powerful foundation for the next generation of chemical discovery and innovation. As quantum devices continue to evolve, they are poised to revolutionize computational chemistry and enable solutions to problems that have long remained beyond the reach of classical computing.
- 5) Quantum computing and related quantum technologies will not instantly replace classical computational chemistry, but they are rapidly maturing into complementary tools that extend the reach of predictive modelling. By prioritizing reproducibility, resource-efficient algorithms, and problem-driven demonstrations in high-impact chemical domains, the community can realize meaningful scientific gains well before full fault tolerance becomes available and position quantum methods to deliver transformative capabilities for chemistry, materials, and drug discovery as hardware continues to improve.
- 6) Future directions will focus on reducing quantum resource requirements through improved ansätze, operator compression, error mitigation, and early-stage error correction, enabling larger and more chemically relevant simulations. Continued advances in hardware fidelity, qubit scaling, and integrated quantum–classical workflows will be essential for achieving practical quantum advantage in molecular modelling. Ultimately, the long-term goal is to develop automated, reproducible quantum pipelines that accelerate chemical discovery beyond the capabilities of classical computation.

Abbreviations

ADAPT-VQE Adaptive Derivative-Assembled
Pseudo-Trotter Variational Quantum

ADAM	Eigensolver
B3LYP	Adaptive Moment Estimation optimizer
	Becke, three-parameter, Lee–Yang–Parr hybrid functional
CBS	Complete Basis Set limit
CC3	Coupled Cluster with singles, doubles, and approximate triples
CCSD	Coupled Cluster with Singles and Doubles
CCSD(T)	Coupled Cluster with Singles, Doubles, and perturbative Triples
CI	Configuration Interaction
CIS	Configuration Interaction Singles
CI	Conical Intersection
DFT	Density Functional Theory
ΔSCF	Delta Self-Consistent Field
EOM	Equation of Motion
EOM-CCSD	Equation-of-Motion Coupled Cluster with Singles and Doubles
EOM-VQE	Equation-of-Motion Variational Quantum Eigensolver
EPR	Electron Paramagnetic Resonance
FCI	Full Configuration Interaction
FT	Fault Tolerant
GPU	Graphics Processing Unit
HEA	Hardware-Efficient Ansatz
HF	Hartree–Fock
HOMO	Highest Occupied Molecular Orbital
IR	Infrared
J	Exchange coupling constant
LCU	Linear Combination of Unitaries
MAE	Mean Absolute Error
MCTDH	Multi-Configuration Time-Dependent Hartree
MEP	Molecular Electrostatic Potential
MOF	Metal–Organic Framework
MP2	Second-order Møller–Plesset perturbation theory
NISQ	Noisy Intermediate-Scale Quantum
NMR	Nuclear Magnetic Resonance
PCET	Proton-Coupled Electron Transfer
PES	Potential Energy Surface
QML	Quantum Machine Learning
QPE	Quantum Phase Estimation
QSCI	Quantum Selected Configuration Interaction
QSE	Quantum Subspace Expansion
RI/DF	Resolution of the Identity / Density Fitting
RSH	Range-Separated Hybrid functional
SCF	Self-Consistent Field
SGM	State-Targeted Generalized Maximum overlap method
SPSA	Simultaneous Perturbation Stochastic Approximation
TD-DFT	Time-Dependent Density Functional Theory

UCC	Unitary Coupled Cluster
UCCSD	Unitary Coupled Cluster with Singles and Doubles
UKS	Unrestricted Kohn–Sham
UHF	Unrestricted Hartree–Fock
UV–Vis	Ultraviolet–Visible spectroscopy
VQE	Variational Quantum Eigensolver
VQD	Variational Quantum Deflation
VQS	Variational Quantum Simulation
ZFS	Zero-Field Splitting

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Authors Contributions

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Conflicts of Interest

No potential conflict of interest was reported by the authors.

References

- [1] Norman, P.; Dreuw, A. Simulating X-ray spectroscopies and calculating core-excited states of molecules. *Chemical Reviews* 2018, 118, 7208-7248. <https://doi.org/10.1021/acs.chemrev.8b00202>
- [2] Szabo, A.; Ostlund, N. S. *Modern Quantum Chemistry: Introduction to Advanced Electronic Structure Theory*. McGraw-Hill, New York, 1989.
- [3] Olsen, J.; Jørgensen, P. Linear and nonlinear response functions for an exact state and for an MCSCF state. *Journal of Chemical Physics* 1985, 82, 3235-3264. <https://doi.org/10.1063/1.448303>
- [4] Koch, H.; Harrison, R. J. Analytical calculation of full configuration interaction response properties. *Journal of Chemical Physics* 1991, 95, 7479-7490. <https://doi.org/10.1063/1.461380>
- [5] Cohen, A. J.; Mori-Sánchez, P.; Yang, W. Insights into current limitations of density functional theory. *Science* 2008, 321, 792-794. <https://doi.org/10.1126/science.1158722>
- [6] Kent, P. R. C.; Kotliar, G. Toward a predictive theory of correlated materials. *Science* 2018, 361, 348-354. <https://doi.org/10.1126/science.aat7552>
- [7] Feynman, R. P. Simulating physics with computers. *International Journal of Theoretical Physics* 1982, 21, 467-488. <https://doi.org/10.1007/BF02650179>
- [8] Lloyd, S. Universal quantum simulators. *Science* 1996, 273, 1073-1078. <https://doi.org/10.1126/science.273.5278.1073>
- [9] Abrams, D. S.; Lloyd, S. Simulation of many-body Fermi systems on a universal quantum computer. *Physical Review Letters* 1997, 79, 2586-2589. <https://doi.org/10.1103/PhysRevLett.79.2586>
- [10] Abrams, D. S.; Lloyd, S. Quantum algorithm providing exponential speedup for eigenvalue problems. *Physical Review Letters* 1999, 83, 5162-5165. <https://doi.org/10.1103/PhysRevLett.83.5162>
- [11] Ortiz, G.; Gubernatis, J. E.; Knill, E.; Laflamme, R. Quantum algorithms for fermionic simulations. *Physical Review A* 2001, 64, 022319. <https://doi.org/10.1103/PhysRevA.64.022319>
- [12] Somma, R.; Ortiz, G.; Gubernatis, J. E.; Knill, E.; Laflamme, R. Simulating physical phenomena by quantum networks. *Physical Review A* 2002, 65, 042323. <https://doi.org/10.1103/PhysRevA.65.042323>
- [13] Georgescu, I. M.; Ashhab, S.; Nori, F. Quantum simulation. *Reviews of Modern Physics* 2014, 86, 153-185. <https://doi.org/10.1103/RevModPhys.86.153>
- [14] Cao, Y.; Romero, J.; Olson, J. P.; et al. Quantum chemistry in the age of quantum computing. *Chemical Reviews* 2019, 119, 10856-10915. <https://doi.org/10.1021/acs.chemrev.8b00803>
- [15] McArdle, S.; Endo, S.; Aspuru-Guzik, A.; Benjamin, S. C.; Yuan, X. Quantum computational chemistry. *Reviews of Modern Physics* 2020, 92, 015003. <https://doi.org/10.1103/RevModPhys.92.015003>
- [16] Kitaev, A. Y. Quantum measurements and the Abelian stabilizer problem. *arXiv:quant-ph/9511026*.
- [17] Aspuru-Guzik, A.; Dutoi, A. D.; Love, P. J.; Head-Gordon, M. Simulated quantum computation of molecular energies. *Science* 2005, 309, 1704-1707. <https://doi.org/10.1126/science.1113479>
- [18] Kassal, I.; Aspuru-Guzik, A. Quantum algorithm for molecular properties and geometry optimization. *Journal of Chemical Physics* 2009, 131, 224102. <https://doi.org/10.1063/1.3266959>

- [19] O'Brien, T. E.; et al. Calculating energy derivatives for quantum chemistry on a quantum computer. *npj Quantum Information* 2019, 5, 113. <https://doi.org/10.1038/s41534-019-0213-4>
- [20] Lanyon, B. P.; et al. Towards quantum chemistry on a quantum computer. *Nature Chemistry* 2010, 2, 106-111. <https://doi.org/10.1038/nchem.483>
- [21] Du, J.; et al. NMR implementation of a molecular hydrogen quantum simulation. *Physical Review Letters* 2010, 104, 030502. <https://doi.org/10.1103/PhysRevLett.104.030502>
- [22] Hong-Gao; Imamura, S.; Kasagi, A.; Yoshida, E. Distributed implementation of full configuration interaction. *Journal of Chemical Theory and Computation* 2024, 20, 1185-1199. <https://doi.org/10.1021/acs.jctc.3c01190>
- [23] Wang, Y.; et al. Quantum simulation of helium hydride cation. *ACS Nano* 2015, 9, 7769-7774. <https://doi.org/10.1021/acs.nano.5b04206>
- [24] Dobrautz, W.; et al. Spin-pure stochastic CASSCF via GUGA-FCIQMC. *Journal of Chemical Theory and Computation* 2021, 17, 5684-5703. <https://doi.org/10.1021/acs.jctc.1c00630>
- [25] Liebermann, N.; Ghanem, K.; Alavi, A. Importance-sampling FCIQMC. *Journal of Chemical Physics* 2022, 157, 124111. <https://doi.org/10.1063/5.0108060>
- [26] O'Malley, P. J. J.; et al. Scalable quantum simulation of molecular energies. *Physical Review X* 2016, 6, 031007. <https://doi.org/10.1103/PhysRevX.6.031007>
- [27] Peruzzo, A.; McClean, J.; Shadbolt, P.; Yung, M.-H.; Zhou, X.-Q.; Love, P. J.; Aspuru-Guzik, A.; O'Brien, J. L. A variational eigenvalue solver on a photonic quantum processor. *Nature Communications* 2014, 5, 4213. <https://doi.org/10.1038/ncomms5213>
- [28] McClean, J. R.; et al. Theory of variational hybrid algorithms. *New Journal of Physics* 2016, 18, 023023. <https://doi.org/10.1088/1367-2630/18/2/023023>
- [29] Robledo-Moreno, J.; et al. Chemistry beyond exact diagonalization. *Science Advances* 2025, 11, eadu9991. <https://doi.org/10.1126/sciadv.adu9991>
- [30] Kim, Y.; Krylov, A. I. Spin-flip methods. *Journal of Physical Chemistry A* 2023, 127, 6552-6566.
- [31] Preskill, J. Quantum computing in the NISQ era and beyond. *Quantum* 2018, 2, 79. <https://doi.org/10.22331/q-2018-08-06-79>
- [32] Shen, Y.; Zhang, X.; Zhang, S.; Zhang, J.-N.; Yung, M.-H.; Kim, K. Quantum implementation of the unitary coupled cluster for simulating molecular electronic structure. *Physical Review A* 2017, 95, 020501(R). <https://doi.org/10.1103/PhysRevA.95.020501>
- [33] Kandala, A.; Mezzacapo, A.; Temme, K.; Takita, M.; Brink, M.; Chow, J. M.; Gambetta, J. M. Hardware-efficient variational quantum eigensolver for small molecules and quantum magnets. *Nature* 2017, 549, 242-246. <https://doi.org/10.1038/nature23879>
- [34] Györfy, W.; Bartlett, R. J.; Greer, J. C. Monte Carlo configuration interaction predictions for electronic spectra compared to full CI calculations. *Journal of Chemical Physics* 2008, 129, 064103. <https://doi.org/10.1063/1.2961031>
- [35] Hempel, C.; Maier, C.; Romero, J.; McClean, J.; Monz, T.; Shen, H.; Jurcevic, P.; Lanyon, B. P.; Love, P. J.; Babbush, R.; et al. Quantum chemistry calculations on a trapped-ion quantum simulator. *Physical Review X* 2018, 8, 031022. <https://doi.org/10.1103/PhysRevX.8.031022>
- [36] Booth, G. H.; Thom, A. J. W.; Alavi, A. Fermion Monte Carlo without fixed nodes: A game of life, death, and annihilation in Slater determinant space. *Journal of Chemical Physics* 2009, 131, 054106. <https://doi.org/10.1063/1.3193710>
- [37] Cleland, D.; Booth, G. H.; Alavi, A. Study of electron affinities using the initiator FCIQMC method. *Journal of Chemical Physics* 2011, 134, 024112. <https://doi.org/10.1063/1.3518752>
- [38] Chiesa, A.; Tacchino, F.; Grossi, M.; Santini, P.; Tavernelli, I.; Gerace, D.; Carretta, S. Quantum hardware simulating four-dimensional inelastic neutron scattering. *Nature Physics* 2019, 15, 455-459. <https://doi.org/10.1038/s41567-019-0434-6>
- [39] Francis, A.; Freericks, J. K.; Kemper, A. F. Quantum computation of magnon spectra. *Physical Review B* 2020, 101, 014411. <https://doi.org/10.1103/PhysRevB.101.014411>
- [40] Blunt, N. S.; Smart, S. D.; Kersten, J. A. F.; Spencer, J. S.; Booth, G. H.; Alavi, A. Semi-stochastic full configuration interaction quantum Monte Carlo. *Journal of Chemical Physics* 2015, 142, 184107. <https://doi.org/10.1063/1.4919792>
- [41] Blunt, N. S. Efficient perturbative correction to initiator FCIQMC. *Journal of Chemical Physics* 2018, 148, 221101. <https://doi.org/10.1063/1.5025321>
- [42] Ghanem, K.; Guthrie, K.; Alavi, A. Adaptive shift method in FCIQMC. *Journal of Chemical Physics* 2020, 153, 224115. <https://doi.org/10.1063/5.0025593>
- [43] Sun, Q.; Berkelbach, T. C.; Blunt, N. S.; Booth, G. H.; Guo, S.; Li, Z.; Liu, J.; McClain, J. D.; Sayfutyarova, E. R.; Sharma, S.; Wouters, S.; Chan, G. K.-L. PySCF: the Python-based simulations of chemistry framework. *Journal of Chemical Physics* 2018, 153, 024109. <https://doi.org/10.1002/wcms.1340>
- [44] Norman, P.; Bishop, D. M.; Jensen, H. J. A.; Oddershede, J. Nonlinear response theory with relaxation: First-order hyperpolarizability. *Journal of Chemical Physics* 2005, 123, 194103. <https://doi.org/10.1063/1.2126789>
- [45] Mukamel, S. Multidimensional femtosecond correlation spectroscopies. *Annual Review of Physical Chemistry* 2000, 51, 691-729. <https://doi.org/10.1146/annurev.physchem.51.1.691>
- [46] Harrow, A. W.; Hassidim, A.; Lloyd, S. Quantum algorithm for linear systems of equations. *Physical Review Letters* 2009, 103, 150502. <https://doi.org/10.1103/PhysRevLett.103.150502>
- [47] Ambainis, A. Variable time amplitude amplification and faster quantum algorithms. *arXiv:1010.4458*.

- [48] Clader, B. D.; Jacobs, B. C.; Sprouse, C. R. Preconditioned quantum linear system algorithm. *Physical Review Letters* 2013, 110, 250504. <https://doi.org/10.1103/PhysRevLett.110.250504>
- [49] Childs, A. M.; Kothari, R.; Somma, R. D. Quantum algorithm for systems of linear equations. *SIAM Journal on Computing* 2017, 46, 1920-1950. <https://doi.org/10.1137/16M1087072>
- [50] Subaşı, Y.; Somma, R. D.; Orsucci, D. Quantum algorithms for systems of linear equations inspired by adiabatic quantum computing. *Physical Review Letters* 2019, 122, 060504. <https://doi.org/10.1103/PhysRevLett.122.060504>
- [51] Xu, X.; Sun, J.; Endo, S.; Li, Y.; Benjamin, S. C.; Yuan, X. Variational algorithms for linear algebra. *arXiv:1909.03898*.
- [52] Sun, Q.; Zhang, X.; Banerjee, S.; Bao, P.; Barbry, M.; Blunt, N. S.; Bogdanov, N. A.; Booth, G. H.; Chen, Z.; Cui, Z.-H.; et al. Recent developments in the PySCF program package. *Journal of Chemical Physics* 2020, 153, 024109. <https://doi.org/10.1063/5.0006074>
- [53] Bravo-Prieto, C.; LaRose, R.; Cerezo, M.; Subasi, Y.; Cincio, L.; Coles, P. J. Variational quantum linear solver. *arXiv:1909.05820*.
- [54] Saad, Y. *Iterative Methods for Sparse Linear Systems*, 2nd ed.; SIAM: Philadelphia, 2003.
- [55] Aaronson, S. Read the fine print. *Nature Physics* 2015, 11, 291-293. <https://doi.org/10.1038/nphys3272>
- [56] Childs, A. M.; Wiebe, N. Hamiltonian simulation using linear combinations of unitary operations. *Quantum Information & Computation* 2012, 12, 901-924.
- [57] Berry, D. W.; Childs, A. M.; Cleve, R.; Kothari, R.; Somma, R. D. Simulating Hamiltonian dynamics with a truncated Taylor series. *Physical Review Letters* 2015, 114, 090502. <https://doi.org/10.1103/PhysRevLett.114.090502>
- [58] Johnson, E. R.; Becke, A. D. A post-Hartree-Fock model of intermolecular interactions. *Journal of Chemical Physics* 2006, 124, 174104. <https://doi.org/10.1063/1.2190220>
- [59] Blunt, N. S.; Camps, J.; Crawford, O.; Izsák, R.; Leontica, S.; Mirani, A.; Moylett, A. E.; Scivier, S. A.; Sünderhauf, C.; Schopf, P.; Taylor, J. M.; Holzmann, N. Perspective on quantum computing for drug discovery. *Journal of Chemical Theory and Computation* 2022, 18, 7001-7023. <https://doi.org/10.1021/acs.jctc.2c00678>