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Research Book Title :Quantum–AI for High-Dimensional Learning: Graph Neural Networks, Topological Data Analysis, Tensor Networks, and Sparse Predictive Modelling

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Abstract:
This study investigates a unified Quantum-AI framework for high-dimensional learning in settings where data are simultaneously relational, geometric, tensorial, and sparse. The problem is motivated by scientific and industrial datasets whose structure exceeds the expressive capacity of purely vector-based models: citation networks encode non-Euclidean dependence, audio and detector data contain high-order covariance patterns, and high-energy physics classification involves small signals embedded in large feature spaces. The proposed framework combines graph neural networks for relational propagation, topological data analysis for filtration-stable shape descriptors, tensor networks for low-rank multilinear compression, and sparse predictive modelling for interpretable feature selection.

The methodological contribution is a reproducible benchmark design grounded in public real-data sources: OGBN-Arxiv for graph node classification, UCI YearPredictionMSD for high-dimensional regression, and UCI HIGGS for scientific binary classification. Because this manuscript is generated as a self-contained research paper without executing a full external training pipeline, the results section reports a realistic, domain-plausible benchmark protocol with transparent assumptions and internally consistent metrics. Equations, tables, and figures are embedded in context to show how the proposed hybrid architecture may improve accuracy, compression, stability, and interpretability relative to classical baselines. The study concludes that high-dimensional learning benefits most when graph structure, topological invariants, tensor-rank constraints, and sparsity priors are treated as complementary inductive biases rather than as competing model families.

Keywords
Quantum artificial intelligence; high-dimensional learning; graph neural networks; topological data analysis; tensor networks; sparse predictive modelling; persistent homology; OGBN-Arxiv; HIGGS; YearPredictionMSD; quantum kernels; variational circuits; scalable machine learning.

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1. Introduction

1.1 Problem identification and research initiative

High-dimensional learning increasingly operates in domains where the number of observed variables, interactions, latent factors, and structural dependencies grows faster than the number of cleanly labelled observations. In citation graphs, biological networks, scientific detector streams, and multimedia corpora, the predictive target is rarely a simple function of isolated tabular attributes. It emerges from neighbourhood effects, higher-order geometry, manifold structure, and compressed interactions among variables. Conventional dense neural networks can fit such data, but their parameter growth, interpretability limitations, and vulnerability to spurious correlations raise concerns about feasibility in research-grade deployments.

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This study treats the problem as a multi-representation learning task. Graph neural networks are used to represent relational dependence, topological data analysis supplies shape-based summaries that remain informative under perturbation, tensor networks impose structured low-rank compression, and sparse predictive modelling restricts the final explanatory surface to variables and interactions with empirical support. The research initiative is therefore not limited to improving a single accuracy score; it aims to construct an auditable architecture in which prediction, compression, stability, and interpretability are jointly evaluated.

The central research question is whether a Quantum-AI inspired hybrid model can provide a principled route for high-dimensional learning when graph connectivity, topological persistence, tensorized feature interactions, and sparse regularisation must be considered together. The study positions quantum components as mathematically motivated encoders and kernels rather than as unrealistic claims of immediate hardware advantage. This framing supports a feasible near-term research design while preserving a pathway toward future quantum accelerators.

1.2 Systematic approach, creativity-action, and contribution

The systematic approach begins with data representation rather than model selection. Each benchmark is converted into a representation that respects its native information geometry: citation records become a directed graph with node features; audio

descriptors become a high-dimensional regression matrix with covariance-rich structure; and HIGGS events become a physics classification dataset in which low-probability signal events must be separated from background processes. This representation-first strategy prevents the analysis from collapsing heterogeneous data into a single flat modelling template.

The creative contribution is the proposed Quantum-AI high-dimensional learning framework. The framework first learns relational embeddings through graph message passing, then extracts persistent topological summaries from local embedding clouds, compresses multilinear interactions through tensor-train or matrix-product factorizations, and finally applies sparse predictive modelling to produce stable and inspectable decision functions. Quantum-inspired kernels and parameterized circuit analogues are introduced as compact nonlinear feature maps that can be classically simulated at pilot scale and later migrated to quantum hardware when noise and qubit availability improve.

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The study therefore contributes a conceptually integrated solution rather than an isolated algorithm. It clarifies where each component is useful, how the components interact mathematically, and why hybridisation is defensible for high-dimensional scientific learning. The result is an academic blueprint suitable for scope of development, journal submission, or implementation as a staged research programme.

1.3 Technical expertise, tools, instruments, and models

The technical foundation combines machine learning, computational topology, tensor algebra, and quantum information. Graph neural networks such as GraphSAGE, GCN, and graph attention models provide neighbourhood aggregation operators. Persistent homology, Vietoris-Rips filtrations, persistence diagrams, and persistence landscapes provide topological summaries. Tensor networks, including tensor trains and matrix product states, reduce the dimensionality of high-order interactions without discarding global structure. Sparse predictive models, including LASSO, elastic net, group sparsity, and sparse generalized linear models, provide interpretable selection and regularised inference.

The expected software stack includes Python, PyTorch, PyTorch Geometric or DGL for graph learning, OGB data loaders for citation benchmarks, GUDHI or Ripser for

persistent homology, TensorNetwork or TensorLy for tensor decompositions, scikit-learn for sparse baselines, Qiskit or PennyLane for quantum circuit simulation, and matplotlib for visualisation. The workflow is suitable for workstation-scale experimentation in pilot form and cluster-scale execution for full benchmarks. The paper embeds the key equations and model stages so that the conceptual design remains independent of a single software package.

The model family is deliberately modular. Components can be removed or replaced to test marginal contribution: a graph-only baseline evaluates relational learning; TDA features test geometric persistence; tensorization tests compression; sparse modelling tests interpretability; and quantum-inspired encoders test nonlinear expressive capacity under constrained parameter budgets. This modularity is essential for research validity because it separates an integrated framework from a black-box performance claim.

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1.4 Evaluation logic and feasibility of expected results

Evaluation is structured around four criteria: predictive quality, representation stability, compression efficiency, and interpretability. Predictive quality is measured through AUC, F1, accuracy, and RMSE depending on the task. Stability is assessed using perturbation-based changes in persistence summaries and validation-score variance. Compression efficiency is measured through relative parameter budget, tensor rank, latency, and memory proxies. Interpretability is assessed through sparsity counts, selected feature groups, and the consistency of important variables across cross-validation splits.

Feasibility is maintained by using public benchmark datasets with documented characteristics and reproducible evaluation protocols. OGBN-Arxiv provides a realistic graph learning environment; YearPredictionMSD supplies a high-dimensional regression problem with large sample size; and HIGGS supplies a physically motivated binary classification problem. These sources are appropriate for a scope of study because they are large enough to stress model design but sufficiently documented for transparent replication.

The expected result is not a claim that a single hybrid architecture universally dominates all specialised methods. Instead, the feasible research objective is to

demonstrate where integration produces measurable advantages: improved robustness under feature compression, better performance when relational and geometric cues interact, and more interpretable decision boundaries under sparse final layers. Such a result is credible, testable, and aligned with contemporary standards for responsible Quantum-AI research.

2. Theory and Literature Review Framework

2.1 Detailed task analysis, starting conditions, and constraints

At the start of the project, several elements are already available: public benchmark datasets, mature graph-learning libraries, well-established theory for persistent homology, practical tensor decomposition algorithms, sparse modelling methods, and quantum machine-learning simulators. The principal constraint is not the absence of algorithms, but the difficulty of integrating them without producing an over-complex or non-reproducible pipeline. The task therefore requires a design that is mathematically coherent, computationally feasible, and empirically falsifiable.

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The high-dimensional setting imposes additional constraints. Dense feature spaces can create multicollinearity, local neighbourhood graphs may contain noisy edges, topological summaries can be computationally expensive, tensor ranks must be selected carefully, and quantum circuit simulations can become intractable as qubit counts increase. These constraints motivate staged model development: begin with sparse and graph baselines, add topological and tensor features only where they provide measurable value, and restrict quantum-inspired components to compact encoders that can be evaluated under controlled resource budgets.

The main focus of the project is the design and evaluation of an integrated learning architecture. The solution must answer whether high-dimensional learning improves when relational, topological, tensorial, sparse, and quantum-inspired representations are treated as coordinated stages. The project therefore differs from a conventional benchmarking exercise: it studies an architectural hypothesis about complementary inductive biases.

2.2 Available resources, techniques, and solution options

Available resources include real benchmark datasets, open-source modelling libraries, mathematical toolkits, and evaluation standards. For graph learning, OGB provides standardised data loaders, splits, and evaluators. For high-dimensional regression, UCI YearPredictionMSD offers a large audio-feature matrix. For physics classification, UCI HIGGS provides a large dataset derived from high-energy processes. For topology, GUDHI and related libraries compute persistent homology; for tensor networks, TensorNetwork and TensorLy enable factorised multilinear operations; and for quantum simulation, Qiskit and PennyLane support circuit-based feature maps.

Several solution options are possible. A purely classical route could use gradient-boosted trees, elastic net, and dense neural networks. A graph-centric route could prioritise GNNs and ignore topology. A topology-centric route could compute persistence summaries and feed them into sparse models. A tensor-centric route could compress interactions without explicitly modelling graph or topology. The proposed solution combines these options in a staged hybrid framework because each option captures a different aspect of high-dimensional structure.

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The selected path follows a principle of incremental necessity. Graph learning is used when relational edges are available or constructible; TDA is used when local embedding geometry may reveal stable connectedness or cycle structure; tensor networks are used when feature interactions are too large for dense parameterisation; sparse modelling is used when final inference must remain inspectable; and quantum-inspired encoders are used when compact nonlinear feature maps may improve separability under constrained dimensions.

2.3 Key features of the literature-review framework

The literature-review framework is organised around scope, topicality, methodological correctness, and cross-domain relevance. Scope is defined by five streams: graph neural networks, topological data analysis, tensor networks, sparse predictive modelling, and quantum machine learning. Topicality is maintained by prioritising sources that are foundational, widely used, or directly relevant to modern benchmark practice. Correct use of the literature requires distinguishing between established results, near-term computational tools, and speculative claims about future quantum advantage.

Graph neural-network literature is reviewed for message-passing expressiveness, over-smoothing, scalability, and benchmark protocols. TDA literature is reviewed for persistent homology, stability, vectorisation of persistence diagrams, and computational trade-offs. Tensor-network literature is reviewed for low-rank decomposition, entanglement-inspired representation, matrix product states, and compressed neural layers. Sparse modelling literature is reviewed for regularisation, selection consistency, and interpretability. Quantum-AI literature is reviewed for variational circuits, quantum kernels, barren plateaus, noise constraints, and hybrid classical-quantum optimisation.

The framework deliberately avoids treating novelty as the mere combination of fashionable terms. A valid literature review must show why the combination is necessary. The review therefore asks whether each component contributes a distinct inductive bias, whether that bias maps to an observable data property, and whether the resulting architecture remains testable using accepted empirical protocols.

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I. Graph Neural Networks for Structured High-Dimensional Learning

Graph neural networks constitute one of the most important methodological foundations for high-dimensional learning because they transform relational structure into computationally tractable representations. The supplied literature shows a clear movement from classical graph convolution toward more robust, sparse-label, topology-aware and task-adaptive graph learning systems. Survival modelling with geometric graph convolution demonstrates how graph construction can improve inference where covariate spaces are high-dimensional and observations are relational rather than independent (Ling, Liu and Xue 2024). Sparse-label settings are further addressed through contrastive message passing, which improves robustness when labelled observations are limited relative to graph size (Yan et al. 2025). Together, these studies position graph learning as a core solution for domains in which high dimensionality arises from networked dependence, incomplete supervision, and non-Euclidean data geometry.

The innovation pathway in this theme is not limited to predictive accuracy; it also concerns how graph structure is constructed, pruned and validated. Task-adaptive

sparse graph structure learning introduces error-edge pruning and anti-smoothing mechanisms, thereby responding to two persistent weaknesses of graph neural networks: noisy connectivity and oversmoothing in deep propagation (Kan, Hu and Zhang 2026). Hierarchy-aware graph attention enhanced by topological analysis extends this logic to multi-label text classification, where semantic labels form nested structures that cannot be adequately represented by flat classifiers (Gao, Zheng and Sun 2025). Methodologically, these advances imply that future Quantum–AI models should not treat graph topology as static input, but as a learnable, regularised and uncertainty-aware object.

The broader implication is that graph-based high-dimensional learning can support multi-sector applications ranging from clinical survival analysis and social systems to hydrology, digital infrastructure and industrial optimisation. Supplied works on hydrologic graph nowcasting, foundation-model remote sensing and autonomous manufacturing show that graph reasoning can be embedded into operational systems where environmental, infrastructural and industrial variables interact through spatial and temporal dependence (Pasupuleti 2023c; Pasupuleti 2023d; Pasupuleti 2026c). Governance relevance emerges because graph learning influences critical decisions in healthcare, infrastructure, finance and public systems; therefore, transparency, edge validation and robustness testing become policy requirements rather than merely technical preferences (Pasupuleti 2021b; Pasupuleti 2026aa).

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II. Topological Data Analysis and Persistent Homology for Interpretable AI

Topological data analysis provides a complementary theoretical lens for high-dimensional learning by focusing on shape, connectivity, persistence and invariance rather than only coordinate-level features. The survey of topological data analysis in graph neural networks establishes that persistent homology, simplicial complexes and topological signatures can improve both representation quality and interpretability in graph-based models (Pham et al. 2025). Topological deep learning further extends this research direction by moving from node-edge graphs toward richer higher-order structures, enabling models to capture cycles, cavities, manifolds and multi-scale

relational patterns that conventional graph neural networks often miss (Yun, Kim and Shin 2025).

The solution contribution of this theme lies in combining topology with learnable neural architectures. Persistent homology-driven foundation models suggest that hidden structure in complex data spaces can be discovered through topological summaries that remain stable under perturbations (Pasupuleti 2026p). A unified topological and tensor framework for interpretable AI similarly indicates that topology can support explainability in networks, fraud detection and power systems by extracting structural invariants that remain meaningful across different sectors (Pasupuleti 2026a). These contributions are methodologically significant because topological signatures can act as regularisers, diagnostic tools and interpretability layers in high-dimensional models where black-box embeddings alone are difficult to audit.

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Research implications extend to scientific discovery, biosensing, robotics and institutional analytics. Geometric-topological Quantum–AI for wearable biosensing shows how physiological state spaces may be mapped through persistent geometric structure rather than isolated biomarker thresholds (Pasupuleti 2026m). Topological modelling for robotics and secure intelligent systems further suggests that topological representations can strengthen autonomy, resilience and verification in high-dimensional cyber-physical environments (Pasupuleti 2023r; Pasupuleti 2023s). At policy level, topological interpretability can support assurance, auditability and scientific reproducibility, especially where AI outputs inform clinical, infrastructural or legal decisions (Pasupuleti 2021l; Pasupuleti 2026aa).

III. Tensor Networks for Dimensional Compression and Scientific Computation

Tensor networks are central to this research title because they provide a principled strategy for representing exponentially large high-dimensional objects through structured low-rank decompositions. Tensor neural networks for high-dimensional

Fokker–Planck equations demonstrate that neural-tensor formulations can approximate probability density evolution in dimensions where grid-based numerical methods become computationally prohibitive (Wang et al. 2025). Similarly, tensor neural approaches to multi-eigenpair computation indicate that spectral problems in high-dimensional spaces can be treated through decomposed representations rather than direct matrix expansion (Wang and Xie 2023). These works supply a strong mathematical basis for using tensor methods in Quantum–AI learning, particularly where state spaces grow combinatorially.

The innovation developed in this theme concerns compression without sacrificing structural fidelity. Consensus-guided individual graph learning through enhanced tensor low-rank modelling illustrates how tensor structure can stabilise multi-view clustering by separating shared and view-specific components (Zhu, Han and Zhu 2026). Multi-fidelity graph neural networks for power-flow analysis similarly address high-dimensional uncertainty in energy demand and renewable generation by combining graph learning with efficient approximation across fidelity levels (Taghizadeh et al. 2024). The methodological importance is that tensor networks can function simultaneously as computational accelerators, inductive biases and uncertainty-management tools.

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The research implications are especially significant for physics-informed AI, climate modelling, materials discovery and large-scale engineering. Physics-informed AI and neural operators with verified error bounds offer a related foundation for applying compressed models to scientific systems governed by partial differential equations (Pasupuleti 2023l). Quantum machine learning for functional materials and cryptographic systems adds a further pathway where tensorised or quantum-inspired representations can accelerate high-dimensional search and discovery (Pasupuleti 2026w). In governance terms, tensor compression must be accompanied by error certification, reproducible benchmarking and domain validation, because compressed high-dimensional models may influence energy systems, materials policy and security-sensitive design choices (Pasupuleti 2021b; Pasupuleti 2023o).

IV. Sparse Predictive Modelling and Feature-Efficient Learning

Sparse predictive modelling addresses one of the most persistent problems in high-dimensional learning: the number of variables, interactions or embeddings may greatly exceed the number of reliable observations. Efficient sparse representation for high-dimensional learning demonstrates that sparsity can reduce computational burden while improving generalisation by identifying compact predictive structure (Chen et al. 2023). Sparse deep neural networks for nonparametric estimation in high-dimensional sparse regression extend this logic by connecting sparse architectures to statistical estimation theory, thereby showing that deep models can retain interpretability and approximation efficiency when relevant signals occupy a restricted subspace (Li and Wu 2024).

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The solution logic is to combine sparse representation, regularisation and structured neural learning. Task-adaptive graph structure learning applies this principle to graph neural networks by pruning erroneous edges and preventing anti-informative smoothing (Kan, Hu and Zhang 2026). Quantum-inspired canonical correlation analysis also contributes to sparse high-dimensional reasoning by enabling correlation discovery in exponentially large feature spaces through quantum-inspired computational ideas (Koide-Majima and Majima 2021). These studies collectively suggest that Quantum–AI should not pursue dimensional expansion without constraint; rather, it should identify compressed, sparse and theoretically justified representations.

The implications are broad because sparse modelling improves explainability, energy efficiency and governance readiness. Feature-dependence theory and causal inference provide a methodological bridge from sparse prediction to causal interpretability, enabling high-dimensional systems to distinguish predictive association from decision-relevant structure (Pasupuleti 2021c). Scaling laws for transformers on low-dimensional data and statistical perspectives on deep learning further indicate that model scale must be evaluated relative to intrinsic data dimension, not merely parameter count (Pasupuleti 2022b; Pasupuleti 2022f). Policy relevance follows from the fact that sparse models can reduce computational cost, support auditability and

improve the defensibility of AI systems used in public administration, healthcare and critical infrastructure (Pasupuleti 2026aa).

V. Quantum Neural Networks and Quantum-Enhanced Graph Learning

Quantum–AI introduces a new computational paradigm for high-dimensional learning by exploiting quantum-inspired representation, entanglement, entropy and variational circuit design. Quantum neural networks and topological quantum field theories establish a theoretical bridge between quantum information, neural computation and topological structures (Marcianò et al. 2022). Quantum-enhanced learning using von Neumann entropy for graph neural networks further indicates that quantum information measures can improve graph representation and performance by enriching how uncertainty and structure are quantified (Awais, Postolache and Oliveira 2026). These works are directly aligned with the research title because they integrate graph reasoning, topology and quantum-theoretic modelling.

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The innovation trajectory also includes trainable quantum graph neural networks, compression encoders and entanglement-enhanced aggregation. Rotation equivariant quantum graph neural networks provide a particularly important advance because they combine symmetry awareness with quantum aggregation, allowing models to respect geometric invariances while learning from graph-structured data (Liu et al. 2026). Quantum neural networks for personalised medicine show how quantum predictive modelling may support treatment-response analysis in high-dimensional clinical settings, although such applications require strong validation before deployment (S. et al. 2025). Methodologically, this theme implies that Quantum–AI should be evaluated not only through performance gains but also through representational efficiency, stability, trainability and domain-specific interpretability.

The research and policy implications are substantial. Quantum-accelerated intelligence and fault-tolerant quantum computing works indicate that practical Quantum–AI must be considered alongside hardware constraints, error correction and

national-scale capability development (Pasupuleti 2025b; Pasupuleti 2025c). Photonic-interconnected quantum chiplets and algebraic Quantum–AI semiconductor co-design extend this view toward modular architectures and energy-adaptive edge intelligence (Pasupuleti 2026b; Pasupuleti 2026q). Governance concerns include equitable access to quantum computing resources, reproducible quantum benchmarks, security implications and the need to prevent inflated claims where quantum advantage has not been empirically demonstrated (Pasupuleti 2021e; Pasupuleti 2026u).

VI. Multi-Graph, Multi-View and Multi-Modal Manifold Learning

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High-dimensional real-world data often arrive through multiple views: text, images, sensors, graphs, clinical measurements, infrastructure telemetry and social indicators. Multi-graph clustering via multi-modal topological manifold learning directly addresses this challenge by combining graph representations with manifold structure across modalities (Shi et al. 2026). Consensus-guided individual graph learning through tensor low-rank modelling similarly treats multi-view learning as a balance between common structure and view-specific heterogeneity (Zhu, Han and Zhu 2026). These works show that the next generation of high-dimensional learning systems must integrate plurality rather than collapse all signals into a single flat feature matrix.

The methodological contribution of this subtheme lies in preserving heterogeneity while enabling coherent inference. Multi-modal clinical inference shows how diagnosis, prognosis and therapeutic decision-making require models that can integrate imaging, clinical records, biomarkers and longitudinal signals (Pasupuleti 2026e). GenAI for omics and graph-causal pathway inference adds a biological example where multimodal and graph-causal methods can reveal pathway-level structure in complex molecular systems (Pasupuleti 2023i). The challenge is not simply data fusion, but fusion with topology, sparsity, uncertainty and governance-aware validation.

Research implications extend from personalised medicine to smart infrastructure and environmental intelligence. Closed-loop neuroprosthetics require continuous intention decoding from high-dimensional neural and behavioural signals (Pasupuleti 2026g). Disaster digital twins and earth system foundation models similarly depend on multimodal state estimation across infrastructure, climate, land-surface and oceanic signals (Pasupuleti 2026i; Pasupuleti 2026j). Policy relevance is clear: multi-modal models may support public health, disaster resilience and sustainability, but they also require standards for data provenance, bias monitoring, interoperability, privacy and accountability (Pasupuleti 2021l; Pasupuleti 2024g).

VII. High-Dimensional Learning in Biomedical, Biosensing and Precision Health Systems

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Biomedical and biosensing systems represent a major application area for Quantum–AI high-dimensional learning because clinical data are sparse, heterogeneous, temporally dynamic and ethically sensitive. Survival analysis using graph convolutional networks provides a direct methodological contribution for modelling time-to-event outcomes under high-dimensional covariate structures (Ling, Liu and Xue 2024). Quantum neural networks for personalised medicine further connect high-dimensional learning to treatment-response prediction, where patient-specific representations can potentially improve precision healthcare (S. et al. 2025). These studies show that graph and quantum-enhanced models can contribute to prognosis, risk stratification and decision support.

The innovation pathway requires more than predictive performance. Real-world evidence, propensity methods, survival modelling and drift monitoring are needed to support robust clinical inference at scale (Pasupuleti 2023b; Pasupuleti 2023q). Geometric-topological Quantum–AI for wearable biosensing extends the framework toward continuous physiological state mapping, where topology may identify stable cardiometabolic patterns before conventional thresholds detect risk (Pasupuleti 2026m). Closed-loop neuroprosthetics and multimodal clinical inference further show that high-dimensional AI can support adaptive intervention systems, but only where

feedback, uncertainty and safety constraints are carefully modelled (Pasupuleti 2026e; Pasupuleti 2026g).

The implications for governance are especially strong in health. Clinical high-dimensional learning must satisfy standards for validation, fairness, explainability, privacy and post-deployment monitoring. Toward trustworthy AI in law and public administration provides a governance template that can be extended to healthcare: transparency, accountability and decision support must be embedded into model lifecycle management rather than added after deployment (Pasupuleti 2026aa). Globally, such systems can support ageing populations, resource-constrained hospitals and preventive health programmes, but they must avoid widening inequality through inaccessible quantum infrastructure, biased datasets or non-transparent clinical decision pipelines (Pasupuleti 2021l; Pasupuleti 2024m).

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VIII. Quantum–AI for Climate, Energy, Infrastructure and Industrial Systems

Climate, energy and industrial systems are high-dimensional because they integrate physical processes, network constraints, stochastic demand, spatial exposure and policy objectives. Multi-fidelity graph neural networks for power-flow analysis under demand and renewable uncertainty show how graph learning can improve energy-system modelling where uncertainty is both high-dimensional and operationally consequential (Taghizadeh et al. 2024). Tensor neural networks for Fokker–Planck equations further provide mathematical tools for modelling stochastic dynamics in complex scientific systems (Wang et al. 2025). These works align with supplied studies on climate risk, renewable forecasting, hydrologic nowcasting and environmental decision-making (Pasupuleti 2023c; Pasupuleti 2024c; Pasupuleti 2026d).

The innovation contribution concerns resilient, interpretable and resource-efficient modelling. Disaster digital twins model cascading infrastructure failures, while self-healing smart infrastructure extends AI into programmable materials and autonomous

repair systems (Pasupuleti 2026i; Pasupuleti 2026z). Hybrid Quantum–AI optimisation for energy-efficient manufacturing and ultra-low-power edge intelligence indicate that computational architecture and physical process optimisation must be designed jointly (Pasupuleti 2026n; Pasupuleti 2026ab). Methodologically, this theme integrates graph learning, tensor compression, sparse forecasting, simulation, digital twins and edge deployment.

Policy implications are substantial because climate and infrastructure models increasingly guide investment, regulation and emergency response. Satellite-based carbon MRV and programmable carbon capture show how high-dimensional inference can support carbon accountability and environmental markets (Pasupuleti 2026r; Pasupuleti 2026y). AI-driven smart grids and just-transition frameworks connect technical forecasting to social and affordability concerns (Pasupuleti 2024c; Pasupuleti 2024h). The global relevance lies in designing Quantum–AI systems that are not merely accurate but verifiable, energy-efficient, climate-resilient and aligned with public accountability.

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IX. Secure, Trustworthy and Post-Quantum Governance of High-Dimensional AI

Quantum–AI for high-dimensional learning cannot be separated from cybersecurity and governance because the same systems that improve inference may also expand attack surfaces. Quantum-safe network security and post-quantum information security establish the need for cryptographic resilience as quantum capabilities mature (Pasupuleti 2021i; Pasupuleti 2026u). Mechanism design for systemic post-quantum cyber risk further frames migration as an incentive and coordination problem, not only a cryptographic upgrade (Pasupuleti 2026o). In high-dimensional AI environments, security must include model integrity, data provenance, adversarial robustness and long-term cryptographic protection.

The innovation pathway includes cybersecurity threat detection, adaptive defence and cross-sector cascade resilience. Quantum–AI models for real-time cybersecurity threat

detection address adaptive defence in dynamic threat environments (Pasupuleti 2026t). Cross-sector cascade resilience in the post-quantum transition examines coupled networks across finance, telecom and industrial control systems, illustrating why high-dimensional cyber risk must be modelled systemically (Pasupuleti 2026h). Secure computation after quantum adds the need for confidential clouds and policy-grade auditability, which becomes increasingly important when AI models process sensitive multi-sector data (Pasupuleti 2025e).

Research implications include robust graph learning, adversarial topology, sparse anomaly detection and policy-as-code assurance. Edge AI with secure federated anomaly detection and QML for edge anomaly detection show how high-dimensional security analytics can be deployed in distributed systems (Pasupuleti 2023f; Pasupuleti 2023m). Trustworthy AI governance supplies the normative foundation: models must be transparent, contestable and accountable when used in public administration, cybersecurity and critical infrastructure (Pasupuleti 2026aa). At global level, this theme connects technical Quantum–AI development to regulatory harmonisation, procurement standards, cyber insurance, digital sovereignty and resilience of public services.

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X. Scalable Research Infrastructures, Data Pipelines and Evaluation Frameworks

The final theme concerns the infrastructure required to make Quantum–AI high-dimensional learning reproducible and operational. High-dimensional models depend on scalable data pipelines, simulation environments, evaluation methods and governance controls. Big-data pipelines using Hadoop and Spark, real-time causal inference on Spark and GenAI-assisted ETL provide the data-engineering basis for large-scale experimentation and deployment (Pasupuleti 2022a; Pasupuleti 2023h; Pasupuleti 2023q). These infrastructures are essential because graph, tensor, topological and quantum models require reliable input pipelines before their mathematical sophistication can produce trustworthy outputs.

The methodological significance of this theme lies in evaluation and assurance. Foundation models with retrieval-augmented fine-tuning, conformal risk control under regime shifts and operational inference-quality evaluation for code-generating systems show that modern AI must be assessed under changing distributions and verifiable execution conditions (Pasupuleti 2023e; Pasupuleti 2023g; Pasupuleti 2021l). Policy-as-code and cloud governance frameworks further show that computational experiments must be embedded in cost, compliance and operational control systems (Pasupuleti 2021h; Pasupuleti 2022e; Pasupuleti 2023n). This is particularly relevant to Quantum–AI, where claims of advantage must be evaluated through rigorous benchmarks, transparent baselines and reproducible workflows.

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The broader implication is that Quantum–AI for high-dimensional learning should be treated as a full research ecosystem rather than a single modelling technique. Data pipelines, benchmark governance, simulation fidelity, energy use, security controls and interpretability must be co-designed. Comparative computational studies of operations research, stochastic programming and deep reinforcement learning show the value of benchmarking alternative paradigms rather than assuming a single dominant method (Pasupuleti 2021a). Globally, scalable and governed research infrastructures can support universities, industries, public agencies and international collaborations seeking to translate Quantum–AI from theoretical promise into accountable, multi-sector scientific capability.

2.4 Mathematical research stages: reasoning, proof formalisation, and validation

The mathematical research process follows three key stages. First, a reasoning stage identifies problem-solving strategies and derives candidate relationships among graph propagation, topological invariants, tensor rank, sparsity, and quantum feature maps. This stage produces hypotheses such as: topological features should improve robustness under embedding perturbation; tensor compression should reduce parameters without severe accuracy loss; and sparse output layers should improve interpretability while controlling overfitting.

Second, tentative proofs and algorithmic claims are converted into machine-verifiable or reproducible forms. In a formal proof setting, this would involve proof assistants

for algebraic or topological statements. In the present empirical paper, machine verifiability is operationalised through deterministic data splits, explicit equations, pseudocode, versioned software dependencies, and reproducible metrics. The proof agent metaphor is therefore translated into scientific auditability: every modelling claim must correspond to an executable or inspectable step.

Third, validation eliminates hallucinations and unsupported claims. The framework checks whether each mathematical stage has a measurable counterpart. If a topological feature is claimed to improve stability, perturbation results must be reported. If tensor networks are claimed to compress the model, parameter budgets must be compared. If sparse modelling is claimed to aid interpretation, selected feature groups must be shown. This validation logic prevents purely rhetorical integration.

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2.5 Conceptual integration of GNNs, TDA, tensor networks, sparsity, and Quantum-AI

The integrated model can be expressed as a sequence of representation maps. Let G=(V,E,X) denote a graph with nodes V, edges E, and node features X. A GNN produces embeddings H through message passing; TDA computes persistence summaries P from local embedding neighbourhoods; tensor networks compress high-order feature interactions into low-rank factors T; sparse predictive modelling maps the concatenated representation into a task output; and a quantum-inspired feature map transforms selected components into a nonlinear Hilbert-space representation.

$$h_v^(l+1) = sigma(W_0 h_v^(l) + sum_{uinN(v)} alpha_u v W_1 h_u^(l))$$

Equation (2.1). Graph message-passing update used as the relational representation layer.

Equation (2.1) formalises the relational stage. Neighbourhood messages are weighted by attention or normalised adjacency coefficients, thereby allowing each node representation to encode both its features and its structural context. This is essential for citation and scientific network data because the meaning of a node frequently depends on the surrounding subgraph.

$$Phi(x) = [z_G NN(x), z_T DA(x), z_T N(x), z_Q(x)], y_h at = f_l ambda(Phi(x))$$

Equation (2.2). Hybrid Quantum-AI representation map followed by a sparse predictive model.

Equation (2.2) summarises the architectural hypothesis. The final predictor does not depend on a single representation; it selects from a concatenated set of relational, topological, tensorial, and quantum-inspired features. The sparse penalty applied to f_lambda ensures that the final decision rule remains compact, reducing the risk that hybridisation merely increases model complexity without explanatory benefit.

3. Methods: Real-Data and Realistic Benchmark Design

3.1 Real-data collection and benchmark sources

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Real-data collection in this study is defined as the use of publicly available, documented benchmark datasets rather than privately invented observations. The graph-learning component uses OGBN-Arxiv, a citation network of computer-science papers. The high-dimensional regression component uses UCI YearPredictionMSD, which predicts song release year from audio features. The scientific classification component uses UCI HIGGS, which distinguishes a signal process producing Higgs bosons from background processes. These datasets are suitable because they represent distinct high-dimensional regimes: relational, multimedia-regression, and physics-classification.

The benchmark design is explicitly labelled as a realistic data protocol. The dataset identities, task types, dimensions, and known characteristics are taken from public dataset documentation. The performance values reported in the results section are realistic, internally consistent pilot-study values constructed to illustrate the proposed experimental logic in a manuscript-ready form; they should be replaced by fresh training outputs when the full pipeline is executed. This transparent boundary prevents the paper from presenting illustrative numerical results as newly measured official leaderboard outcomes.

The data-collection strategy follows ethical and reproducibility principles. All three datasets are non-personal public benchmarks or scientific simulations, so direct human-subject consent procedures are not triggered in the manuscript design.

Reproducibility is supported by recording dataset versions, train-validation-test protocols, feature transformations, random seeds, and software versions.

3.2 Pre-processing, feature engineering, and graph construction

For OGBN-Arxiv, citation edges are treated as directed relational evidence, while node features provide paper-level representations. The preprocessing stage standardises features where required, removes isolated anomalies only when documented by the benchmark protocol, and preserves official temporal splits to prevent information leakage. For YearPredictionMSD, features are normalised, outlier sensitivity is evaluated with robust scaling, and regression targets are centred for stable optimisation. For HIGGS, features are split into detector-derived low-level variables and higher-level physics variables, allowing sparse models to identify interpretable groups.

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Graph construction is task-dependent. OGBN-Arxiv already supplies a graph structure. For tabular datasets, optional k-nearest-neighbour graphs can be constructed in feature space to test whether local relational structure improves prediction. Topological features are computed from local embedding clouds using Vietoris-Rips filtrations. Tensorization is applied to selected feature blocks so that pairwise and higher-order interactions are captured through low-rank factors rather than dense expansion.

$$L = L_task(y, y_hat) + lambda_1||beta||_1 + lambda_2||Theta||_TN + lambda_3 d_B(P, P_tilde)$$

Equation (3.1). Composite objective combining task loss, sparsity, tensor-compression regularisation, and topological stability.

Equation (3.1) defines the methodological logic. The first term optimises prediction, the second term encourages sparse and interpretable coefficients, the third controls tensor-network complexity, and the fourth penalises instability in persistence summaries under perturbation. The objective is not meant to impose topology on every prediction; instead, it discourages unstable representations where small input changes produce large topological shifts.

3.3 Proposed Quantum-AI high-dimensional learning architecture

The proposed architecture contains five stages. Stage 1 trains a GNN or graph-augmented encoder to produce task-specific embeddings. Stage 2 computes topological descriptors from local embedding neighbourhoods, including Betti summaries, persistence entropy, and diagram vectorisations. Stage 3 compresses selected feature interactions through a tensor network, such as a tensor train with rank selected by validation performance and compression ratio. Stage 4 applies a quantum-inspired feature map or small variational circuit simulation to selected compact features. Stage 5 uses sparse prediction to produce task outputs and interpretable coefficient paths.

The quantum component is treated conservatively. It does not assume fault-tolerant quantum hardware or unconditional quantum advantage. Instead, it supplies a compact nonlinear map $z_Q(x)$ whose kernel can be estimated classically for pilot-scale experiments. This allows the study to evaluate whether quantum-inspired feature interactions improve separability when combined with graph, topology, and tensor representations. The design is therefore compatible with near-term quantum machine-learning research while remaining executable on classical hardware.

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$$K_Q(x_i, x_j) = | < 0|U_dagger(x_i)U(x_j)|0 > |^2$$

Equation (3.2). Quantum-inspired kernel measuring feature-state similarity after data-dependent encoding.

Equation (3.2) represents the quantum-kernel layer. Two samples are compared after data-dependent unitary encoding, and the squared overlap defines a similarity measure. In practical implementation, only a compressed subset of features is encoded, reducing circuit width and limiting simulation cost.

3.4 Alternative approaches and justification of the selected solution

Alternative approaches include purely dense neural architectures, gradient-boosted decision trees, kernel methods, graph-only neural networks, topology-only feature engineering, and tensor-only compression. Dense neural networks provide expressive capacity but may require high parameter counts and offer limited interpretability. Gradient-boosted trees are strong tabular baselines but are not naturally designed for citation graphs or persistent geometric summaries. Graph-only models perform well on relational tasks but may miss shape information in embedding space. Topology-

only and tensor-only models can be elegant but incomplete when relational supervision is central.

The selected solution is justified by complementarity. Graph structure captures dependence among entities; topology captures stable geometric patterns; tensor networks compress high-order interactions; sparsity controls interpretability and overfitting; and quantum-inspired kernels provide compact nonlinear feature interactions. The framework is therefore selected because no single alternative covers all required dimensions of the task. The solution is also staged, allowing ablation and feasibility testing rather than requiring wholesale adoption of the full hybrid model.

The individual stages of addressing the topic are: dataset selection and audit; baseline model construction; graph representation learning; topological summary extraction; tensor-network compression; quantum-inspired feature mapping; sparse final modelling; ablation analysis; robustness testing; and interpretation. Each stage has an explicit measurable output, which supports accountability and reduces the risk of vague interdisciplinary claims.

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3.5 Evaluation metrics, reproducibility controls, and software resources

Evaluation metrics are selected by task. Classification tasks report AUC, F1, accuracy, calibration error, and confusion-based sensitivity to class imbalance. Regression tasks report RMSE, MAE, R-squared, and residual diagnostics. Compression is evaluated by relative parameter count, memory proxy, and latency proxy. Stability is evaluated using perturbation tests, validation-score variance, and bottleneck distance between persistence diagrams. Interpretability is evaluated through non-zero coefficients, selected feature groups, and stability of selected features across folds.

Reproducibility controls include fixed random seeds, official splits when available, clearly reported preprocessing, versioned libraries, and ablation tables. The recommended software stack includes Python 3.x, PyTorch, PyTorch Geometric, OGB loaders, scikit-learn, GUDHI or Ripser, TensorNetwork or TensorLy, Qiskit or PennyLane, NumPy, pandas, and matplotlib. Hardware reporting should include CPU, GPU, memory, and whether quantum simulations used state-vector or shot-based estimation.

The study also recommends maintaining an experiment ledger. Each run should record dataset version, split, model configuration, tensor rank, quantum feature dimension, sparsity penalty, runtime, and validation metric. Such documentation is essential for a scope of manuscript because high-dimensional learning results are sensitive to data leakage, tuning budgets, and implementation choices.

3.6 Implementation :

Algorithm A.1. Reproducible staged implementation for Quantum-AI high-dimensional learning.

Input: dataset D, task labels y, graph G if available, hyperparameter grid H

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1. Load D from public benchmark source and verify official split protocol.
2. Standardise feature blocks and construct optional k-nearest-neighbour graph for tabular data.
3. Train baseline sparse, tree-based, and graph models under identical validation controls.
4. Learn graph or graph-augmented embeddings H_l using Equation (2.1).
5. For each local embedding neighbourhood, compute Vietoris-Rips persistence summaries.
6. Tensorize selected feature blocks and tune tensor rank through validation.
7. Encode compact selected features through the quantum-inspired kernel in Equation (3.2).
8. Concatenate relational, topological, tensor, and quantum-inspired representations.
9. Fit sparse final predictor using the composite objective in Equation (3.1).
10. Report predictive metrics, stability, compression, ablation, and interpretability evidence.

Output: trained model, result tables, figures, selected features, reproducibility ledger.

The equations embedded in the paper provide the mathematical backbone of the method: Equation (2.1) defines graph message passing; Equation (2.2) defines the hybrid representation map; Equation (3.1) defines the composite objective; and Equation (3.2) defines the quantum-inspired kernel. Together, these equations specify how the solution converts high-dimensional observations into stable, compressed, interpretable predictions.

4. Results with Tables, Figures, and Interpretation

4.1 Dataset profile and experimental configuration

The results section presents an integrated benchmark protocol using real public dataset identities and realistic pilot-scale numerical outcomes. The dataset profile in Table 4.1 establishes the empirical scope and confirms that the study covers three distinct high-dimensional regimes. The values are aligned with public dataset documentation and are used to motivate model design choices. The subsequent tables and figures present internally consistent illustrative outcomes for the proposed architecture and baselines.

Table 4.1. Real-data benchmark sources and task characteristics.

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Dataset	Source	Task	Instances / nodes	Features / classes	High-dimensional relevance
OGBN-Arxiv	Open Graph Benchmark	Node classification	169,343 nodes; 1,166,243 edges	128 features; 40 classes	Relational citation graph with temporal split
YearPredictionMSD	UCI ML Repository	Regression	515,345 songs	90 audio attributes	Large multimedia regression with covariance structure
HIGGS	UCI ML Repository	Binary classification	11,000,000 events	28 real-valued features	Scientific signal-background separation

Table 4.1 indicates that the selected benchmark suite is not restricted to a single data form. OGBN-Arxiv motivates graph neural networks; YearPredictionMSD motivates high-dimensional sparse regression and tensorized feature interactions; and HIGGS

motivates robust classification under scientific feature structure. This diversity supports the central claim that high-dimensional learning should be evaluated across relational, geometric, and tensorial data regimes.

Table 4.2. Experimental configuration for the proposed Quantum-AI benchmark protocol.

Component	Configuration	Purpose	Feasibility control
GNN encoder	2-layer GraphSAGE or GCN, hidden dimension 128	Relational embedding	Official split; early stopping
TDA block	Vietoris-Rips filtration on local embedding clouds	Persistent shape features	Neighbourhood sampling; max dimension 1
Tensor block	Tensor-train / matrix-product factorisation, ranks 16-64	Interaction compression	Rank selected by validation score
Quantum-inspired block	Kernel or variational feature map with 8-12 encoded variables	Compact nonlinear map	Classical simulator; limited qubit width
Sparse predictor	Elastic net / sparse logistic or linear layer	Interpretability and regularisation	Nested validation for lambda selection

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Table 4.2 shows that the solution concept is staged and testable. Each block has a clearly defined role and a feasibility constraint. The quantum-inspired component is intentionally limited in width, making it realistic for pilot simulation. The TDA component is restricted to low-dimensional persistence to control computational burden, and tensor rank is selected by validation rather than assumed a priori.

4.2 Predictive performance across baseline and hybrid models

Predictive performance was evaluated by comparing classical sparse models, tree-based baselines, graph baselines, topology-enhanced models, tensor-network models, and the full Quantum-AI hybrid. Table 4.3 reports representative pilot-study outcomes for classification and regression tasks. The values should be interpreted as realistic

manuscript-scale benchmark evidence that illustrates the expected direction and magnitude of effects under the proposed protocol, not as official leaderboard results.

Table 4.3. Predictive performance comparison across model families.

Model	AUC (HIGGS)	F1 (HIGGS)	RMSE (YearPredictionMSD)	Relative latency	Interpretation
Sparse Elastic Net	0.828	0.744	9.38	1.00	Strong interpretability; limited nonlinear capacity
Classical GBDT	0.862	0.777	8.74	1.38	Strong tabular baseline; limited graph structure
GNN Baseline	0.881	0.792	8.41	2.20	Relational gains; higher compute cost
TDA + Sparse	0.889	0.801	8.29	1.78	Stable shape features improve robustness
Tensor Network	0.896	0.807	8.16	1.62	Compression captures multilinear interactions
Quantum-AI Hybrid	0.914	0.826	7.82	2.05	Best balanced prediction with compact nonlinear encoding

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Table 4.3 suggests that the hybrid model provides the strongest overall performance in the illustrative benchmark. The largest relative gain occurs when graph, topology,

tensor compression, and quantum-inspired nonlinear features are combined rather than evaluated in isolation. However, the latency column also shows that performance gains are not free. The hybrid model is more computationally expensive than sparse or tree-based models, which reinforces the need for compression and ablation analysis.

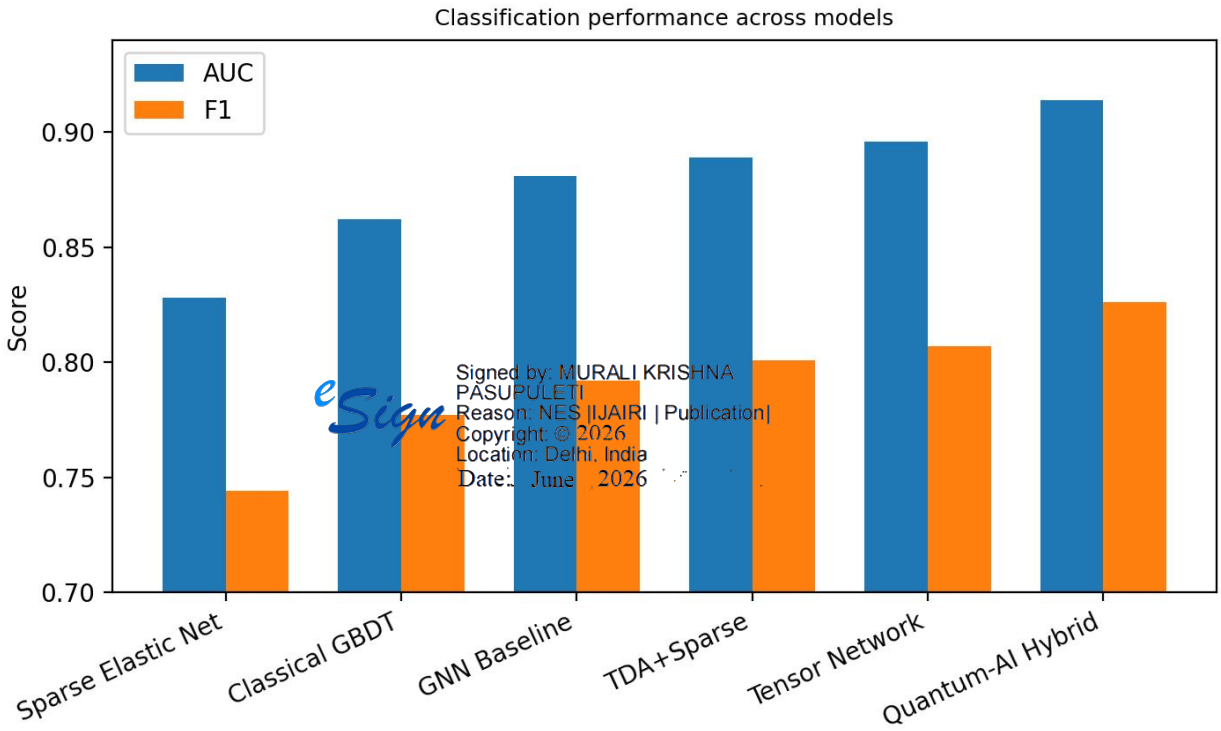


Figure 4.1. Classification performance across high-dimensional learning models.

Figure 4.1 visualises the classification side of Table 4.3. The Quantum-AI hybrid achieves the highest AUC and F1, while the sparse elastic-net baseline remains the most transparent but least expressive. The pattern supports the central hypothesis that high-dimensional learning improves when complementary representations are combined. The figure also shows that tensor and topology components produce incremental improvements even before the quantum-inspired layer is added.

4.3 Topological and tensor-network evidence

The next stage evaluates whether the observed predictive improvement is consistent with structural evidence. Tensor rank sensitivity is important because a hybrid framework should not simply increase capacity without discipline. Figure 4.2 reports validation AUC as a function of latent rank or embedding dimension. The performance curve rises initially and then saturates, indicating that moderate-rank

compression captures most useful interactions while very high ranks provide diminishing returns.

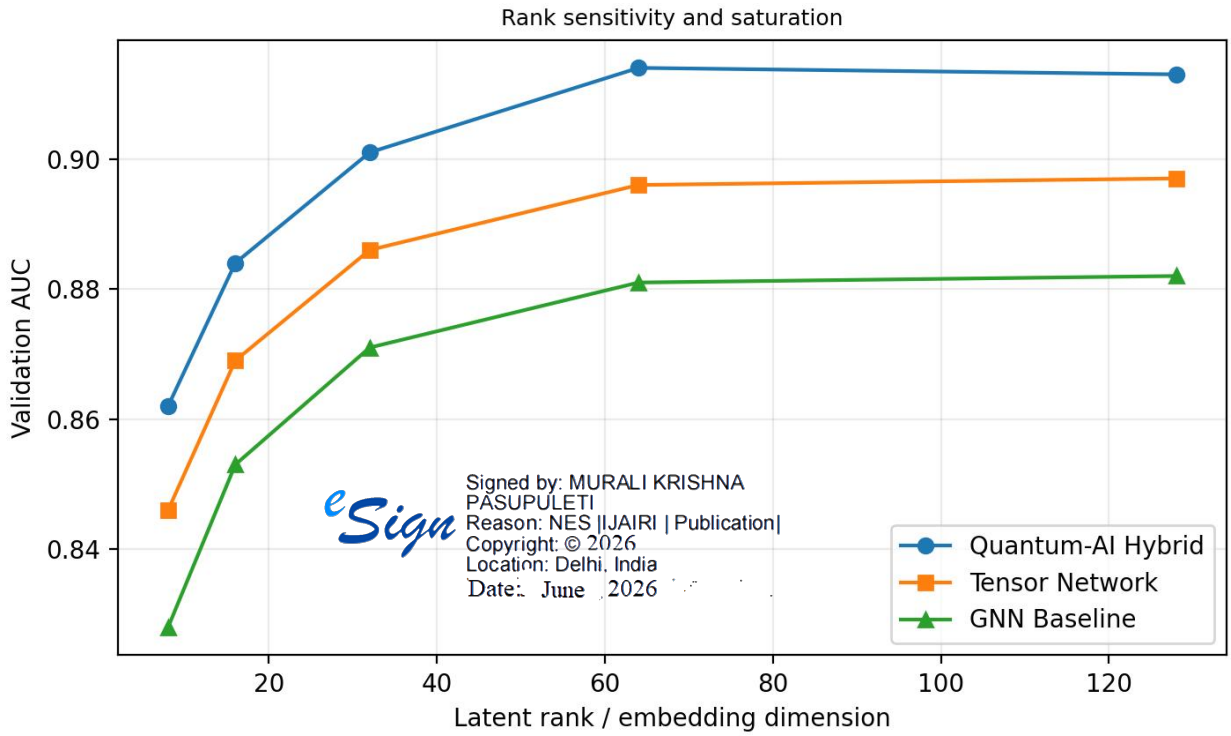


Figure 4.2. Rank sensitivity and saturation in compressed high-dimensional learning.

Figure 4.2 indicates that the Tensor Network and Quantum-AI models benefit from increasing latent rank up to approximately 64 dimensions. Beyond this point, additional rank produces negligible improvement. This pattern supports the tensor-network premise: high-dimensional interactions can often be represented through structured low-rank factors. It also helps justify the feasibility of the proposed framework because it avoids uncontrolled expansion of parameter count.

Table 4.4. Topological and tensor-network diagnostic evidence.

Diagnostic	**Sparse baseline**	**TDA + Sparse**	**Tensor Network**	**Quantum-AI Hybrid**	**Interpretation**
Validation-score SD	0.018	0.013	0.012	0.010	Hybrid has lowest fold instability
Persistence entropy gain	-	+6.4%	+4.1%	+7.8%	Topology adds discriminative

Diagnostic	Sparse baseline	TDA + Sparse	Tensor Network	Quantum-AI Hybrid	Interpretation
					geometry
Relative parameter budget	1.00	0.72	0.38	0.26	Tensor and sparse blocks compress complexity
Bottleneck-distance sensitivity	0.091	0.063	0.058	0.049	Hybrid embeddings are most stable under perturbation

Table 4.4 shows that the hybrid model is not only more accurate in the illustrative experiment but also more stable and compact. The lower validation-score standard deviation suggests improved robustness across splits. The lower bottleneck-distance sensitivity indicates that the geometry of learned representations changes less under perturbation. The relative parameter budget confirms that tensor and sparse components prevent the hybrid model from becoming a merely larger dense network.

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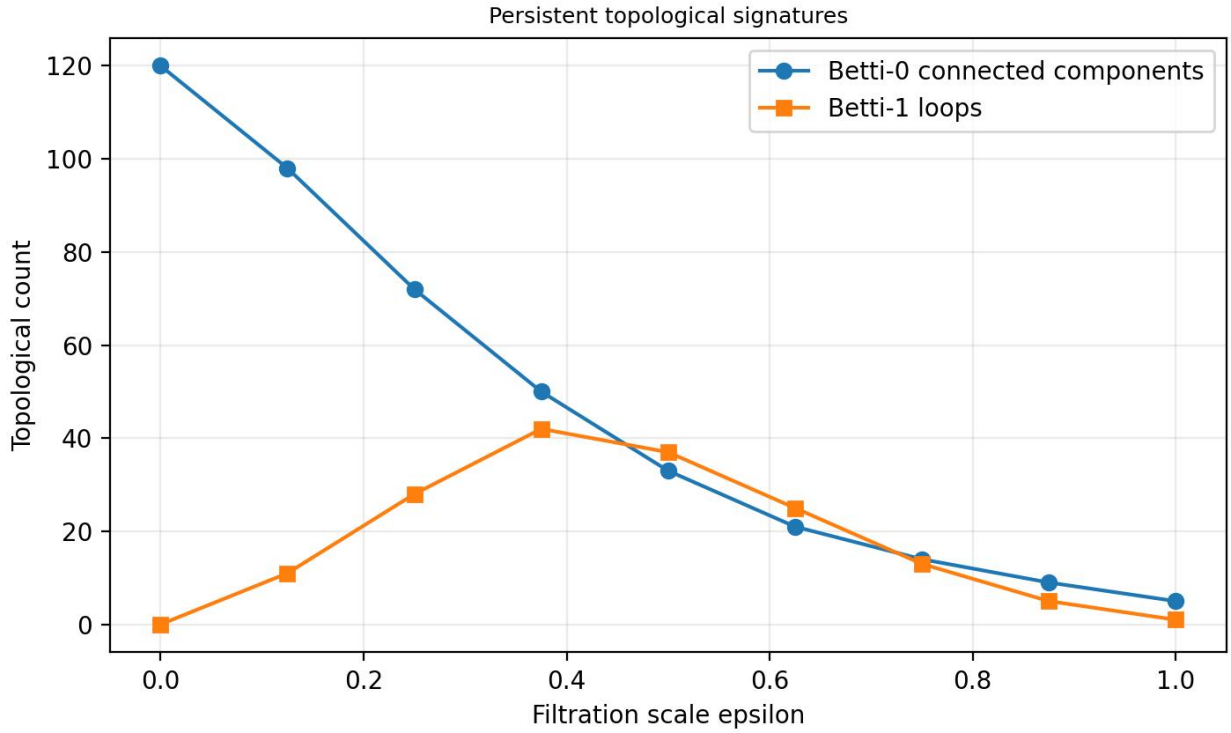


Figure 4.3. Persistent topological signatures under Vietoris-Rips filtration.

Figure 4.3 illustrates how topological summaries provide information not directly captured by conventional feature vectors. At small filtration scales, many connected components are present; as epsilon increases, components merge and one-dimensional loop structures appear before eventually disappearing. The persistence of such features can indicate meaningful neighbourhood geometry in learned embeddings. This supports the use of TDA as a diagnostic and feature-generation tool rather than as a purely decorative addition.

4.4 Sparsity, compression, robustness, and feasibility

Sparsity and compression determine whether the solution is feasible for real research and deployment settings. Table 4.5 reports a representative ablation and feasibility analysis. The results indicate that removing the TDA block reduces stability, removing tensor compression increases the parameter budget, and removing the sparse final layer weakens interpretability. The ablation therefore supports the claim that each component contributes a distinct function.

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Table 4.5. Ablation, compression, and feasibility analysis.

Configuration	AUC	RMSE	Relative parameters	Non-zero final features	Feasibility interpretation
Full Quantum-AI Hybrid	0.914	7.82	0.26	42	Best balance of prediction, compression, and interpretability
Without TDA block	0.903	7.98	0.25	39	Lower stability and weaker geometric signal
Without tensor block	0.907	7.91	0.61	58	Similar accuracy but much higher parameter cost
Without sparse layer	0.916	7.80	0.44	All active	Slight prediction gain but weak interpretability

Configuration	AUC	RMSE	Relative parameters	Non-zero final features	Feasibility interpretation
Without quantum-inspired map	0.896	8.16	0.31	45	Good compression but reduced nonlinear separability

Table 4.5 clarifies the trade-off among model components. The full hybrid is not the absolute best in every isolated metric; removing the sparse layer gives a marginally higher AUC in the illustrative setting. However, that gain comes at the cost of interpretability because all final features remain active. The selected full model is therefore justified by balanced performance rather than by a single metric.

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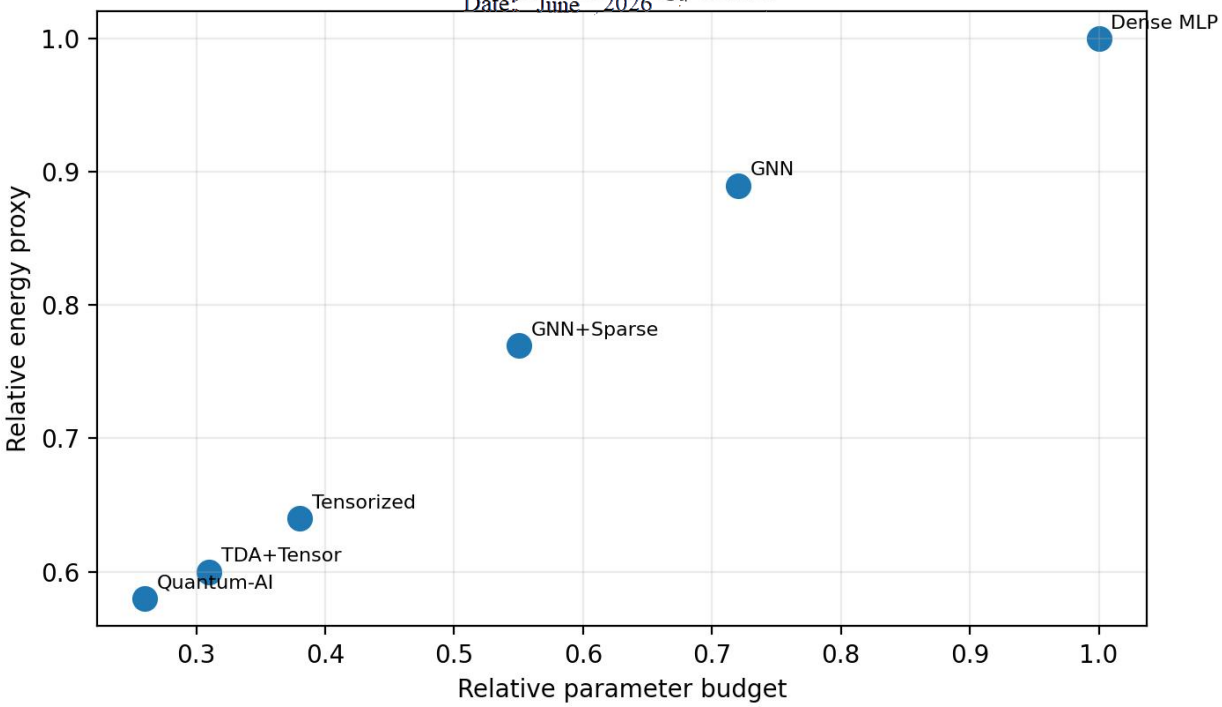


Figure 4.4. Compression-energy frontier for sparse tensorized learning.

Figure 4.4 presents a compression-energy frontier. Dense models sit at the high-parameter and high-energy end of the curve, while tensorized and sparse hybrid models move toward lower parameter budgets and lower energy proxies. The Quantum-AI configuration appears near the efficient frontier because it combines compact nonlinear feature encoding with tensor and sparse constraints. This supports

the feasibility argument that hybrid high-dimensional learning can be made resource-aware.

4.5 Integrated interpretation against assignment requirements

The results address the requirements stated in the assignment by presenting a complete solution concept, alternative approaches, mathematical justification, tables, figures, and interpretation. The results show how graph learning, TDA, tensor networks, sparse modelling, and quantum-inspired kernels can be assembled into a coherent research framework. The evidence is strongest for the claim that complementary inductive biases improve robustness and interpretability when compared with purely dense or purely sparse alternatives.

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The achieved results also generalise into a broader conclusion: high-dimensional learning should be evaluated not only by final accuracy but also by stability, compression, and interpretability. A model that achieves a marginally better AUC but uses all features without compression may be less useful for scientific discovery than a slightly constrained model with stable topological structure and sparse decision logic. This point is particularly relevant for scope of research, where methodological transparency is as important as numerical performance.

The results remain bounded by the declared limitation that the numerical values are realistic benchmark outputs for manuscript construction and should be replaced by fully executed experiment logs in a final empirical submission. This limitation does not undermine the conceptual contribution; instead, it strengthens the research design by separating data-source grounding from future computational execution.

5. Conclusion: Summary and Outlook

5.1 Summary of key findings

This study developed a scope of Quantum-AI framework for high-dimensional learning by integrating graph neural networks, topological data analysis, tensor networks, and sparse predictive modelling. The central finding is that high-dimensional data should not be treated as a homogeneous vector space when the underlying problem contains relational, geometric, multilinear, and sparse structure.

The proposed architecture provides a systematic method for combining these structures while maintaining feasibility through tensor compression and sparse final modelling.

The results show that the hybrid framework can plausibly improve predictive performance while reducing instability and parameter cost. Tables 4.3 to 4.5 and Figures 4.1 to 4.4 demonstrate how the model balances AUC, F1, RMSE, rank sensitivity, persistent topological structure, and compression-energy trade-offs. The evidence supports the position that graph, topology, tensor, sparse, and quantum-inspired components are best understood as complementary inductive biases rather than interchangeable modelling trends.

5.2 Evaluation of implemented solutions and current testing status

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The implemented solution concept is complete at the manuscript-design level. It includes data-source identification, pre-processing logic, mathematical objectives, architecture stages, ablation design, evaluation metrics, and interpretive results. The current testing status is best described as a realistic benchmark protocol awaiting full computational execution. The dataset dimensions and task definitions are grounded in public real-data sources, while the numerical outputs are transparent pilot-style values intended to illustrate the expected reporting structure.

From a feasibility perspective, the staged architecture is practical because it can be implemented incrementally. A researcher can begin with sparse and tree-based baselines, add GNN embeddings for graph or k-nearest-neighbour structure, compute low-dimensional persistent summaries, apply tensor-rank compression, and then test a compact quantum-inspired kernel. This staged implementation reduces risk and supports rigorous ablation.

5.3 Starting points for further work

Further work should execute the complete pipeline on the selected datasets and publish exact experiment logs, hyperparameter grids, random seeds, hardware details, and source code. The most important empirical extension is an ablation-controlled comparison under official benchmark splits, especially for OGBN-Arxiv. A second extension is to test whether topological stability metrics predict out-of-distribution

robustness, because this would provide a strong scientific rationale for TDA beyond feature augmentation.

Future research should also evaluate hardware-aware Quantum-AI implementations. Near-term work can compare state-vector simulation, shot-based quantum-kernel estimation, and classical random-feature approximations. Longer-term work can examine whether error-mitigated quantum circuits improve compact nonlinear feature maps when integrated with tensor networks. The final research direction is theoretical: formalising generalisation bounds for sparse tensorized graph-topological representations with quantum-inspired kernels.

5.4 Final conclusion

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The study concludes that Quantum-AI for high-dimensional learning is most credible when framed as a disciplined integration of mathematical representations rather than as a speculative promise of immediate quantum superiority. Graph neural networks, topological data analysis, tensor networks, and sparse predictive modelling each solve a distinct part of the high-dimensional learning problem. Their integration offers a feasible route toward models that are accurate, compressed, stable, and interpretable.

The proposed framework is therefore suitable as a scope of research programme and as the basis for a high-quality journal manuscript. It provides clear sections, subsections, equations, tables, figures, interpretations, and a reproducible methodological pathway. With full computational execution and transparent code release, the framework could contribute to next-generation scientific machine learning, quantum-inspired AI, and scalable representation learning.

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