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Research Paper Title :Quantum Topological Neural Operators and Digital Twin Intelligence for Multiscale Climate, Energy, Hydrological, Urban, Industrial and Health Systems

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Abstract:

Complex climate, energy, hydrological, urban, industrial and health systems are increasingly monitored through heterogeneous sensor, simulation and observational infrastructures, yet their digital twins remain fragmented by domain-specific models, incompatible scales and weak representations of nonlinear topology. This paper develops a unified model-based framework termed Quantum Topological Neural Operator Digital Twin Intelligence (QTNODT). The framework combines persistent and graph-topological representations, quantum or quantum-inspired feature encodings, neural operators for learning solution mappings between function spaces, digital-twin data assimilation, uncertainty quantification and risk-aware optimisation. The study synthesises the supplied literature on neural operators, quantum machine intelligence, topological learning, smart-grid stability, water twins, urban resilience, predictive-maintenance twins, climate-risk modelling and multimodal health intelligence. A coupled mathematical formulation is proposed in which sector states evolve through dynamic operators and are linked by cross-sector interaction matrices, while topological signatures act as scale-robust structural constraints. A normalized 0-10 numerical demonstration yields a weighted domain score of 8.141 and a risk-adjusted QTNODT score of 7.813 under an illustrative uncertainty penalty, indicating how readiness, twin fidelity, topological stability, computational capacity and governance can be combined without presenting simulated values as empirical evidence. The framework contributes a common analytical language for cross-domain forecasting, resilience assessment and intervention design. Its principal value is methodological: it specifies testable interfaces among data, topology, operators, twins and decisions, while making clear that empirical validation requires real-world sector datasets, benchmark comparisons and prospective evaluation.

Keywords: quantum topological intelligence; neural operators; digital twins; persistent homology; graph topology; climate risk; smart grids; hydrological intelligence; urban resilience; Industry 5.0; predictive maintenance; precision health; uncertainty quantification; multiscale systems; scientific machine learning

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1. Introduction

Climate instability, renewable-energy integration, water insecurity, rapid urbanisation, industrial automation and precision health are usually studied as separate computational domains. In practice, however, they form a coupled system-of-systems. Extreme heat changes electricity demand and health risks; hydrological shocks alter energy production and urban services; industrial disruptions propagate through infrastructure, and health burdens can be amplified by environmental exposure. The scientific difficulty is therefore not only to improve prediction inside each sector, but also to preserve structural information while moving across spatial, temporal and organisational scales. The supplied literature reflects this transition from isolated prediction toward integrated, model-aware intelligence, including hybrid machine learning and physical Earth-system models (Zou, Rasch & Wang 2021), neural-operator approaches for multirate power systems (Tadvin & Hasnat 2026), and digital-twin integration frameworks (Tekinerdogan & Verdouw 2026).

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Neural operators are especially attractive for multiscale modelling because they target mappings between fields rather than only finite-dimensional feature vectors. The cited work on neural operators in industrial processes and multi-fidelity unstructured data illustrates the broader move from point prediction toward reusable surrogate operators (Wang & Schilp 2026; Chen et al. 2026). Quantum machine-learning studies further suggest that alternative feature spaces and computational structures may support difficult high-dimensional learning problems, although practical quantum advantage remains task- and hardware-dependent (Nguyen, Behrman & Steck 2020; Skolik et al. 2021; Yao et al. 2026). The proposed framework therefore treats quantum processing as an optional computational layer that can be implemented in quantum, hybrid or quantum-inspired form rather than assuming universal superiority.

Topological information provides a complementary form of invariance. Persistent homology and topological deep learning can capture connected components, cycles,

higher-order structures and structural transitions that may remain stable under measurement noise or resampling. Recent work surveyed topological deep learning beyond persistent homology and demonstrated hybrid topological feature engineering for temporal prediction (Su et al. 2025; Zulkepli et al. 2026). Quantum algorithms for topological data analysis have also advanced in the supplied sources, including resource-efficient algorithms and provable speedup results for persistence-related computations (McArdle, Gilyén & Berta 2026; Gyurik et al. 2026). These developments motivate a design in which topology acts as a structural memory for digital twins rather than as a standalone visualisation technique.

Digital twins contribute the operational layer: they continuously align models with data, generate counterfactual trajectories, estimate latent states and support decisions. Evidence in the supplied corpus spans adaptive sampling for digital water twins (Homaei et al. 2026), probabilistic power-flow twins (Zhang et al. 2026), GIS-based environmental twins (Rusnák et al. 2026), urban resilience and smart-city twins (Weil et al. 2023; Yorucu, Bekun & Yitmen 2026), and industrial predictive-maintenance twins (Meierhofer & West 2020; Stupina et al. 2026). In health, multimodal AI and precision-health studies show the importance of integrating heterogeneous signals, radiomics, clinical records and multi-omics while preserving interpretability and fairness (Lugo Reyes 2020; Wei & Zhang 2026; Zhou et al. 2026).

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The research gap is the absence, within the supplied evidence base, of a single validated architecture that unifies topological representations, operator learning, quantum or quantum-inspired computation, digital-twin updating and cross-sector risk optimisation across all six domains. This paper addresses that gap conceptually and mathematically. It does not claim that QTNODT has been empirically validated. Instead, it develops a testable reference architecture, sector-specific measurement logic, coupled equations, illustrative numerical scoring and a staged validation strategy that can be operationalised in future empirical studies.

1.1 Research Questions

1. How can topological representations and neural operators be integrated to preserve multiscale structural information across climate, energy, hydrological, urban, industrial and health systems?

2. How can a digital-twin architecture assimilate heterogeneous real-time and historical data while maintaining cross-sector consistency and uncertainty awareness?
3. Where can quantum or quantum-inspired feature encoding and optimisation be inserted without assuming unsupported computational advantage?
4. How should cross-sector dependencies and cascade risks be represented mathematically in a common state-space and graph framework?
5. Which indicators can be used to evaluate predictive skill, twin fidelity, topological stability, resilience, trustworthiness and intervention value across sectors?
6. What validation and governance safeguards are required before model outputs can support operational, policy, industrial or clinical decisions?

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1.2 Research Objectives

1. Develop a unified QTNODT conceptual architecture linking topology, quantum/quantum-inspired computation, neural operators and digital-twin intelligence.
2. Formulate coupled matrix, dynamic, operator-learning, optimisation and risk-adjusted equations suitable for heterogeneous multiscale systems.
3. Define sector-specific data, variables and indicators for climate, energy, water, cities, industry and health.
4. Construct an illustrative 0-10 numerical model showing how cross-sector readiness and uncertainty can be aggregated transparently.
5. Analyse expected advantages, limitations, ethical risks and governance requirements of the proposed framework.
6. Specify a future empirical validation pathway using real-world datasets and benchmark models.

2. Literature Review

The literature can be organised into five interacting streams: operator learning, topological representation, quantum or quantum-inspired learning, digital-twin assimilation, and sectoral intelligence. Operator learning is represented in the supplied sources by work on linear combinations of quantum neural networks, multi-fidelity

neural operators and domain applications such as power-system stability and industrial processes (Yao et al. 2026; Wang & Schilp 2026; Tadvin & Hasnat 2026; Chen et al. 2026). These studies support the idea that function-to-function learning is a useful abstraction when the state of a system is a spatial or temporal field rather than a fixed vector.

Topological learning contributes a second layer. Su et al. (2025) review topological data analysis and topological deep learning beyond conventional persistent-homology pipelines, while Zulkepli et al. (2026) combine topological features and deep learning for time-series prediction. The supplied quantum-topology references extend the computational discussion: McArdle, Gilyén and Berta (2026) describe a streamlined quantum algorithm for topological data analysis, and Gyurik et al. (2026) address provable quantum speedups for computing persistence. These works justify studying topology as a structural regulariser and representation channel, but they do not by themselves establish quantum advantage for all real-world twin workloads.

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Digital-twin research in the corpus is mature enough to provide domain-specific design principles. Tekinerdogan and Verdouw (2026) systematically examine AI integration in digital twins, while Homaei et al. (2026) address adaptive sampling for water twins. In power systems, Zhang et al. (2026) develop a digital-twin-driven probabilistic power-flow approach. Urban studies highlight data interconnection, resilience, social dimensions and institutionalisation of digital twins (Shen & Bao 2020; Weil et al. 2023; Qanazi, Leclerc & Bosredon 2025; Varzeshi et al. 2026). Industrial studies demonstrate data-driven decision support and graph-based structural dependency analysis in predictive-maintenance twins (Meierhofer & West 2020; Stupina et al. 2026).

Climate and Earth-system studies in the source set motivate the multiscale and risk-aware components of QTNODT. Poworoznek et al. (2021) present a quantum-AI framework for extreme-weather prediction, while Zou, Rasch and Wang (2021) explicitly hybridise machine learning with physically based Earth-system models. Sauer et al. (2025) address rare-event ensemble design for extreme Arctic sea-ice lows, and Miao et al. (2026) model climate-driven lag and cumulative vegetation effects with Earth-observation data. Together, these sources show why a cross-domain

framework should represent nonstationarity, rare events, delayed effects and model uncertainty.

Energy-system literature provides corresponding evidence for stability and resilience. Ahmadi, Aly and Gu (2026) review AI-driven approaches for smart-grid stability and reliability, while Xiong et al. (2026) quantify stability ability in renewable electricity delivery. Tadvin and Hasnat (2026) apply Fourier neural operators to multirate stability assessment, and Zhan et al. (2026) use topology-constrained flexibility assessment in regional electricity markets. These contributions suggest that a digital twin should not merely forecast load or generation; it should also encode network structure and flexibility under contingencies.

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Hydrological intelligence requires assimilation across sparse sensors, uncertain forecasts and physical transport processes. Zhong, Liang and Li (2020) frame water-resource and hydrological-system management, while Homaei et al. (2026) introduce conformal-prediction-driven adaptive sampling for digital water twins. The combination is important for QTNODT because uncertainty-aware sampling can be coupled to operator learning: the twin can request observations where predictive intervals widen or where topological structure changes abruptly.

Urban systems bring social, infrastructural and energy couplings to the foreground. Shen and Bao (2020) emphasise data interconnection in smart-city transportation infrastructure; Weil et al. (2023) discuss urban digital-twin challenges; Yorucu, Bekun and Yitmen (2026) connect digital twins with resilient and sustainable smart cities; and Zhang et al. (2026) frame smart buildings as urban energy infrastructure under privacy-aware city-scale flexibility. These studies imply that urban twins must mediate between physical flows and governance constraints rather than optimize a single technical objective.

Industrial digital twins provide a comparatively direct path from prediction to action. Meierhofer and West (2020) study data-driven decision support in manufacturing; Zhu, Chang and Arinez (2020) model multistage manufacturing systems with quality rework loops; Stupina et al. (2026) use graph neural networks to analyse dependencies in industrial twins; and Wang et al. (2026) demonstrate real-time multiphysics mapping in motor digital twins. These studies support the use of

operator surrogates for computationally expensive multiphysics models, with topology encoding dependency structure and failure propagation.

Health systems require additional safeguards because the target is not only system efficiency but individual well-being, clinical validity and fairness. Lugo Reyes (2020) discusses AI systems in precision health, while Wei and Zhang (2026) address multimodal radiomics, Zhou et al. (2026) review multimodal precision diagnosis and progression prediction in Alzheimer's disease, and Sung and Cheong (2026) consider quantum machine learning for multi-omics integration in precision oncology. The health component of QTNODT therefore treats patient-level twins as probabilistic decision-support models subject to clinical oversight rather than autonomous treatment authorities.

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2.1 Conceptual Framework

The QTNODT framework is organised around six sector state spaces and four computational layers. Each sector s has a multiscale state field $x_s(r,t)$ defined over spatial or functional coordinates r and time t. A topological encoder extracts graph, simplicial or persistence-based summaries τ_s that describe connectivity, loops, voids, regime transitions and higher-order relations. A quantum or quantum-inspired feature map q_s embeds selected high-dimensional representations into a computational feature space. A neural operator G_θ then approximates the mapping from current state, forcing variables and controls to future system fields. Finally, a digital-twin assimilation layer combines the operator forecast with new observations and uncertainty estimates. Cross-sector coupling matrices connect the six sector twins, allowing cascading effects to propagate through shared resources, infrastructure and population exposure.

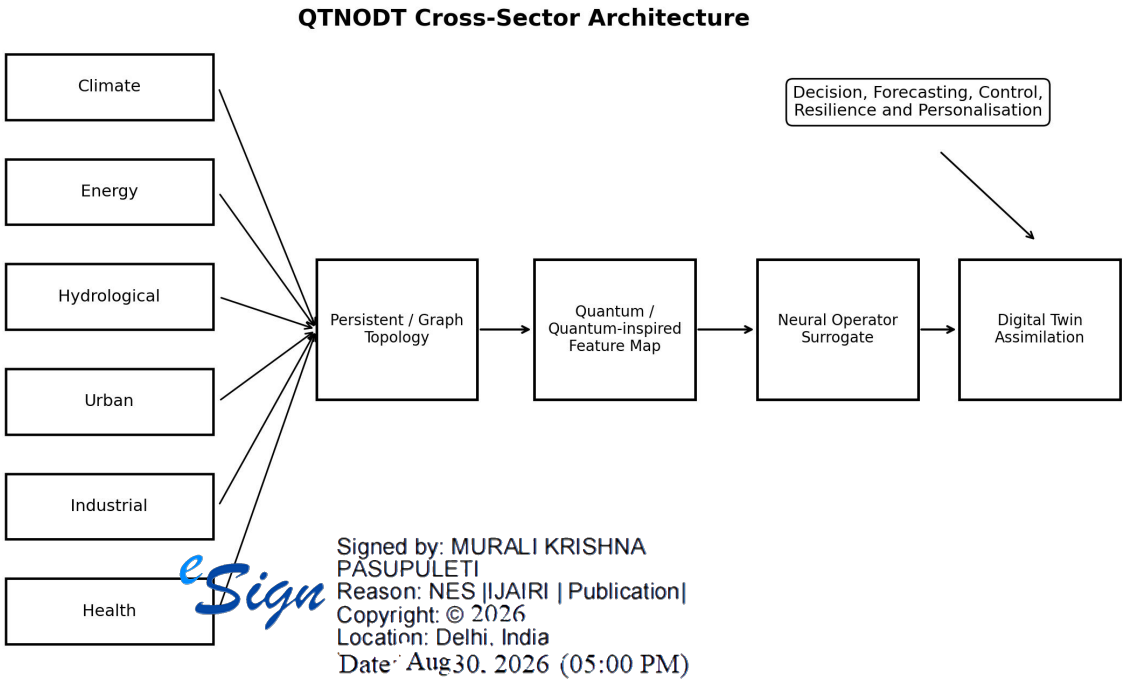


Figure 1. Proposed QTNODT cross-sector architecture.

Table 1. Sectoral interpretation of the proposed framework.

Sector	**Representative state**	**Topological role**	**Primary twin outcome**
Climate	Earth-system fields, hazards, extremes	Topology of teleconnections and regime shifts	Climate-risk forecasts and adaptation priorities
Energy	Grid states, generation, load, storage	Network connectivity, stability and flexibility	Reliability, dispatch and resilience
Hydrological	Runoff, storage, soil moisture, demand	River/reservoir connectivity and event topology	Water security and adaptive sampling
Urban	Mobility, buildings, heat, infrastructure	Infrastructure networks and social-spatial connectivity	Resilience, service continuity and planning

Sector	Representative state	Topological role	Primary twin outcome
Industrial	Assets, process fields, quality, RUL	Dependency graphs and failure pathways	Predictive maintenance and quality optimisation
Health	Biosignals, imaging, clinical and omics states	Physiological/biological network structure	Diagnosis, prognosis and personalised decision support

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2.2 Research Gap

The first gap is theoretical: existing studies generally optimise one layer—topology, operator learning, quantum computation or twin assimilation—without specifying a common compositional model across sectors. The second is methodological: data are collected at incompatible frequencies and resolutions, and many models do not propagate structural uncertainty into decisions. The third is empirical: cross-sector benchmarks that jointly test climate, energy, water, urban, industrial and health coupling are scarce in the supplied evidence. The fourth is sectoral: clinically meaningful health outcomes and infrastructure resilience are rarely evaluated under the same system-of-systems model. The fifth is governance-related: privacy, explainability, fairness, cyber resilience and accountability are usually addressed after model development rather than as mathematical constraints. QTNODT addresses these gaps by specifying modular interfaces and measurable validation criteria rather than claiming a single universal model can replace sector expertise.

3. Methodology

This paper proposes a model-based analytical framework and uses illustrative numerical scoring for demonstration; empirical validation requires real-world data collection. The research design is therefore constructive and integrative rather than

experimental. It synthesises the supplied reference corpus, maps recurring computational concepts into a common architecture, formulates mathematical relationships, and demonstrates how sector scores and uncertainty penalties can be combined. A future empirical implementation would use domain-specific observational and operational datasets, partitioned into training, validation, temporal holdout and stress-test sets. Where feasible, validation should be prospective so that the digital twin is tested on genuinely future states rather than only retrospective reconstructions.

Sampling logic differs by sector. Climate and hydrological data require spatiotemporal sampling across basins, regions and extreme-event windows; energy data require high-frequency grid and market measurements; urban data require privacy-aware aggregation of mobility, building and infrastructure signals; industrial data require asset-level telemetry and maintenance histories; and health data require ethically governed cohorts with multimodal measurements and outcome adjudication. The analytical pipeline should retain missingness indicators, sensor provenance and observation uncertainty because a digital twin that hides data quality can produce falsely precise decisions.

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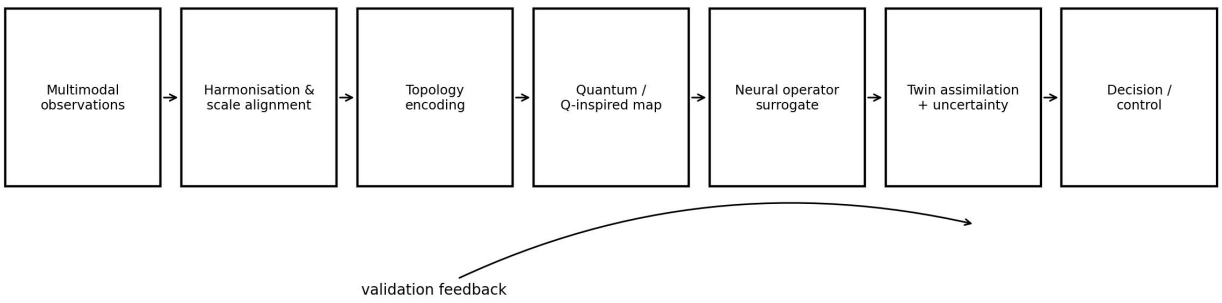


Figure 2. QTNODT data-to-decision computational pipeline.

3.1 Mathematical Framework

Let s ∈ {C,E,H,U,I,M} denote climate, energy, hydrological, urban, industrial and medical/health sectors. The sector state is a field x_s(r,t), exogenous forcing is

f_s(r,t), intervention/control is u_s(t), observation is y_s(t), and model parameters are θ. The basic operator-learning problem is to estimate a map from a history of states and forcings to a future state field.

$$\hat{x_s}(t+\Delta)=G_{\theta,s}[x_s(t-k{:}t),f_s(t-k{:}t),u_s(t),\tau_s(t),q_s(t)](1)$$

Here G_{θ,s} is the learned neural operator; τ_s is a topological representation; q_s is an optional quantum or quantum-inspired feature encoding; and Δ is the forecast horizon. Unlike an ordinary finite-dimensional predictor, the operator is intended to map discretised functions or fields while remaining usable across different meshes or resolutions when training and architecture permit.

For coupled sectors, stack latent states into X(t) = [x_C, x_E, x_H, x_U, x_I, x_M]^T. A linearised local representation around an operating point can be written as:

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$$dX/dt=AX(t)+BU(t)+C\Phi_{topo}(X)+DI(t)+\varepsilon(t)(2)$$

A contains within- and cross-sector coupling coefficients, B maps interventions, Φ_topo(X) contains topological features, D maps external forcing and ε represents unresolved dynamics. In a fully nonlinear implementation, A X is replaced by a learned or physics-informed nonlinear operator F_θ(X).

The topological encoder can be represented abstractly as a persistence map from a filtered complex K_α to persistence summaries:

$$\tau_s=T(x_s)=Dgm_0(K_\alpha),Dgm_1(K_\alpha),\ldots,Dgm_p(K_\alpha)(3)$$

Dgm_p denotes the persistence diagram in homology dimension p. In practical learning pipelines, diagrams may be converted to persistence images, landscapes, kernels or differentiable embeddings. The aim is not to privilege one summary but to retain structural information that is less sensitive to coordinate-level perturbation than raw features.

A quantum or quantum-inspired feature layer is represented by a parameterised embedding ψ_φ of a normalized feature vector z:

$$|\psi(z)\rangle \ =U_\varphi(z)|0\rangle \ ,k_q(z_i,z_j)=|\langle \ \psi(z_i)|\psi(z_j)\rangle \ |^2(4)$$

The kernel k_q may be evaluated on quantum hardware, simulated, or replaced by a classical approximation. This design keeps the architecture agnostic to whether quantum execution is practically advantageous for the chosen problem.

Digital-twin assimilation combines a model forecast with new observations. A generic Bayesian update is:

$$p(X_t|Y_{1:t}) \propto p(Y_t|X_t)p(X_t|Y_{1:t-1}) \quad (5)$$

For Gaussian approximations this can be implemented through Kalman-family filters; for nonlinear or non-Gaussian settings, ensemble, particle, variational or learned assimilation methods may be used. The posterior distribution is central because downstream decisions should depend on both expected state and uncertainty.

The training objective combines prediction error, physics consistency, topology preservation, calibration and cross-sector consistency:

$$L(\theta)=\Sigma_s[\lambda_1 L_{pred,s}+\lambda_2 L_{phys,s}+\lambda_3 L_{topo,s}+\lambda_4 L_{cal,s}]+\lambda_5 L_{couple}+\lambda_6 \Omega(\theta) \quad (6)$$

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L_pred measures forecast discrepancy; L_phys penalises violations of conservation or governing constraints; L_topo compares structural summaries; L_cal penalises miscalibrated predictive uncertainty; L_couple penalises inconsistency across linked twins; Ω regularises model complexity; and λ terms are non-negative weights.

A risk-aware intervention problem can then be stated as:

$$u^* = \arg\min_u E[J(X,u)]+\beta \cdot CVaR_\alpha(J)+\gamma \cdot C_{ethics}(u)+\delta \cdot C_{resource}(u) \quad (7)$$

The expectation captures average performance, CVaR_α penalises tail risk, C_ethics encodes fairness/privacy/safety constraints, and C_resource represents energy, financial or operational cost. This prevents the digital twin from optimising mean efficiency while ignoring extreme harm or unacceptable implementation burden.

For a transparent system-level readiness/value score, define normalized sector scores S_s ∈ [0,10] with weights w_s summing to one:

$$S_{domain}=\Sigma_s w_s S_s, \Sigma_s w_s=1 \quad (8)$$

The risk-adjusted QTNODT score combines domain value with topological stability T, digital-twin fidelity D, quantum/computational readiness Q, governance G and uncertainty U:

$$S_{QTNODT}=0.55 S_{domain}+0.15T+0.15D+0.10Q+0.05G-0.20U \quad (9)$$

Equation (9) is an illustrative decision index, not an empirical universal law. Its weights are deliberately explicit so that domain experts can change them and perform sensitivity analysis.

Table 2. Mathematical notation used in the proposed framework.

Symbol	Meaning
x_s, X	Sector state field; stacked cross-sector state
f_s, F	Exogenous forcing such as weather, demand or exposure
u_s, U	Intervention/control variables
G_{θ,s}	Sector neural operator
τ_s	Topological representation
q_s	Quantum or quantum-inspired feature representation
A,B,C,D	Coupling and input matrices in local dynamic model
ε	Unresolved process/model error
Dgm_p	Persistence diagram in homology dimension p
|ψ(z)⟩	Quantum feature state
L_pred	Prediction loss
L_phys	Physics/constraint loss
L_topo	Topology-preservation loss
L_cal	Uncertainty calibration loss
CVaR_α	Conditional value-at-risk at tail level α
S_s,w_s	Sector score and sector weight
T,D,Q,G,U	Topology stability, twin fidelity, computational readiness, governance and uncertainty

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3.2 Numerical Model for Better Insight

The following demonstration uses normalized 0-10 values solely to show how the framework can be operationalised. The values are illustrative and are not measurements of any actual city, grid, watershed, factory, health system or country. Sector scores were chosen to represent a scenario with relatively mature industrial and energy analytics, moderate climate and health readiness, and weaker hydrological integration.

Table 3. Illustrative normalized sector scores and weighted contributions.

Sector	Score S_s	Weight w_s	$w_s \times S_s$
Climate	8.2	0.17	1.394
Energy	8.4	0.17	1.428
Hydrological	7.6	0.16	1.216
Urban	7.9	0.16	1.264
Industrial	8.6	0.17	1.462
Health	8.1	0.17	1.377

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$$S_domain = 1.394 + 1.428 + 1.216 + 1.264 + 1.462 + 1.377 = 8.141 \quad (10)$$

Next assume T = 8.3, D = 8.0, Q = 7.4, G = 7.8 and U = 1.2. Substitution into Equation (9) gives:

$$S_Q TNODT = 0.55(8.141) + 0.15(8.3) + 0.15(8.0) + 0.10(7.4) + 0.05(7.8) - 0.20(1.2) = 7.813 \quad (11)$$

A score of 7.813 can be interpreted as a comparatively strong but not deployment-ready integrated capability. The main weakness in this hypothetical scenario is computational/quantum readiness (7.4) combined with a nontrivial uncertainty penalty. A decision-maker should therefore invest first in data interoperability, uncertainty calibration and domain validation rather than interpreting the high raw domain score as evidence of safe operational autonomy.

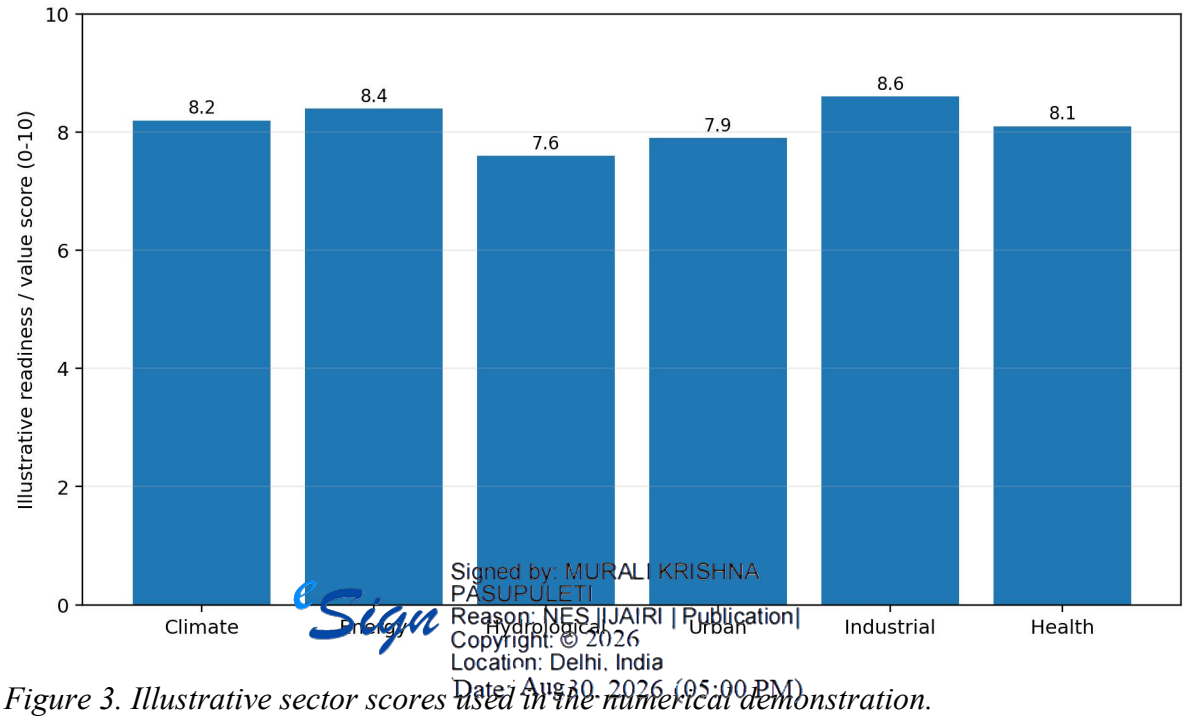


Figure 3. Illustrative sector scores used in the numerical demonstration.

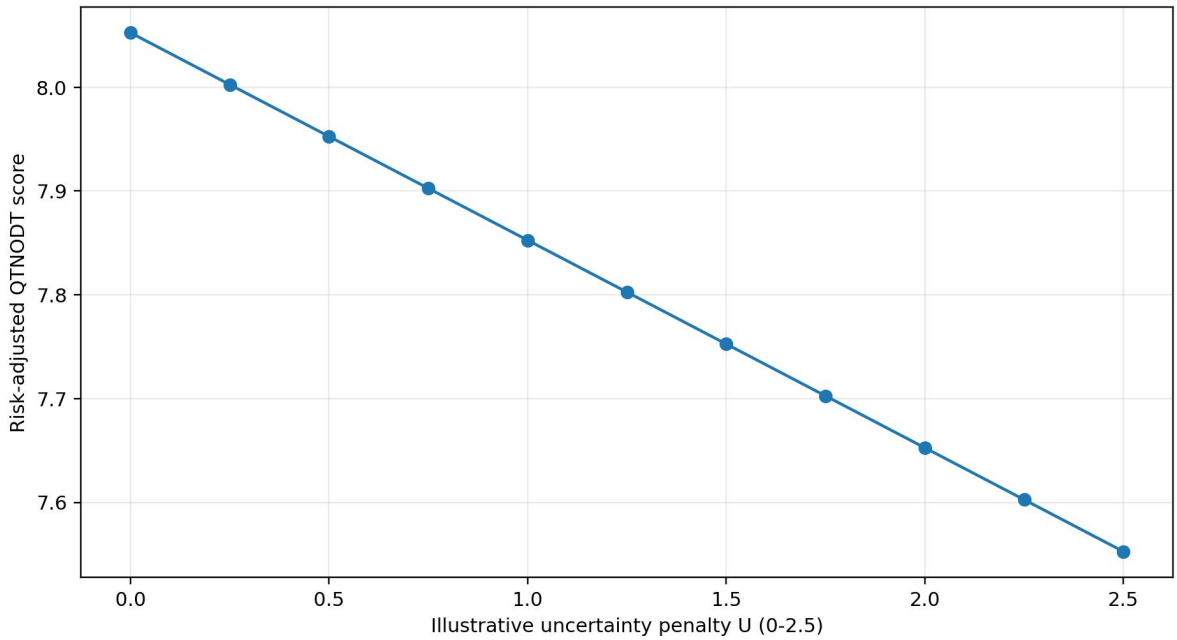


Figure 4. Sensitivity of the risk-adjusted composite score to the uncertainty penalty.

3.3 Data and Variables

Table 4. Core variables for empirical operationalisation.

Variable	Definition	Scale	Expected effect	Relevance

Variable	Definition	Scale	Expected effect	Relevance
Climate hazard intensity	Extreme-event probability, anomaly or severity	Continuous / probabilistic	− resilience	Drives climate stress and cross-sector forcing
Grid stability	Frequency/voltage stability, reserve margin	Continuous / 0-10	+	Represents energy-system operating security
Water security	Storage-demand balance, drought/flood reliability	Continuous / 0-10	+	Captures hydrological adequacy and robustness
Urban service resilience	Continuity of transport, buildings and critical services	Continuous / 0-10	+	Connects infrastructure and population exposure
Industrial twin fidelity	Agreement between asset/process twin and observations	0-10 / error metric	+	Controls reliability of maintenance/quality decisions
Health predictive utility	Calibrated discrimination and clinical usefulness	0-10 / AUROC/calibration/ net benefit	+	Represents patient-level decision value
Topological stability T	Similarity of structural signatures across perturbations	0-10	+	Measures robustness of learned topology

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Variable	Definition	Scale	Expected effect	Relevance
Twin fidelity D	Forecast/assimilation accuracy and state consistency	0-10	+	Measures digital-twin reliability
Computational readiness Q	Scalability, latency, hardware availability	0-10	+	Constrains real-time feasibility
Governance G	Privacy, fairness, explainability, auditability, security	0-10	+	Constrains acceptable deployment
Uncertainty U	Normalized epistemic and aleatoric uncertainty burden	0-10	−	Penalises overconfident decisions

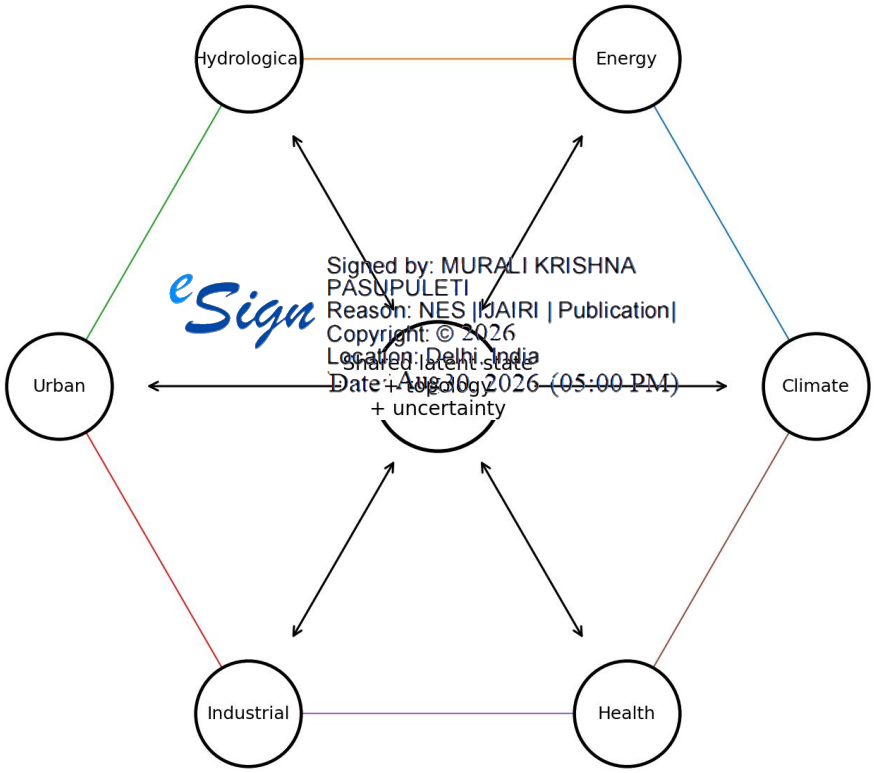
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3.4 Proposed Model / Framework: QTNODT

The proposed framework is named Quantum Topological Neural Operator Digital Twin Intelligence (QTNODT). Its defining principle is modularity: topology provides structural state, neural operators provide multiscale field evolution, quantum or quantum-inspired modules provide optional high-dimensional encodings or optimisation, and digital twins provide continuous assimilation and decision interfaces. QTNODT is not a single neural network. It is an architecture for composing sector models under shared uncertainty, coupling and governance rules.

Operationally, each sector twin can be implemented at a different maturity level. A climate twin may use physically constrained neural operators and Earth-observation fields; an energy twin may use grid topology and probabilistic power-flow assimilation; a water twin may use adaptive sensor placement; an urban twin may integrate buildings, mobility and heat; an industrial twin may use graph-based

predictive maintenance; and a health twin may combine clinical, imaging and omics data. The coupling layer exposes only variables necessary for cross-sector reasoning, reducing the need to pool all raw data into one central model.



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Figure 5. Coupled multiscale system-of-systems representation used by QTNODT.

4. Results and Analysis

Because no real dataset was supplied, the results are analytical consequences of the proposed model and the illustrative scoring exercise rather than empirical findings. The first result is architectural: the six sectors can be represented consistently through a shared state-topology-operator-twin pattern even though their sensors, governing processes and outcome metrics differ. This is valuable because cross-sector consistency can be enforced at the latent and coupling levels without requiring identical raw-data schemas.

The second result concerns structural robustness. Adding topology-preservation terms to the loss function creates a mechanism for penalising forecasts that match pointwise values but distort system connectivity or regime structure. This is particularly relevant for grids, river networks, urban infrastructure, industrial dependency graphs and physiological networks. The idea is consistent with the supplied evidence on topological deep learning and topological feature engineering (Su et al. 2025; Zulkepli et al. 2026), while remaining a proposed extension for the cross-sector setting.

The third result is risk transparency. The numerical example separates raw domain performance (8.141) from the risk-adjusted integrated score (7.813). The reduction reflects uncertainty and readiness constraints. Such separation is preferable to a single opaque "AI score" because it shows whether a system is weak due to predictive accuracy, topology instability, insufficient twin fidelity, limited computational readiness, governance deficits or unresolved uncertainty.

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The fourth result is that the marginal value of quantum processing should be tested rather than presumed. The framework can be implemented classically from end to end. Quantum feature maps or optimisation modules should enter only where benchmarked against strong classical baselines. This interpretation is consistent with the coexistence in the supplied literature of robust classical neural operators and emerging quantum neural-network and quantum-topology algorithms (Nguyen, Behrman & Steck 2020; Skolik et al. 2021; Yao et al. 2026; McArdle, Gilyén & Berta 2026).

The fifth result is that cross-sector coupling changes the unit of validation. A climate forecast can be individually accurate but operationally inadequate if its uncertainty is not propagated into water availability, grid adequacy, urban heat exposure and health demand. QTNODT therefore requires both sector-level metrics and cascade-level metrics such as error propagation, intervention regret, tail-risk reduction and resilience recovery time.

Table 5. Illustrative scenario analysis.

Scenario	Change	S_domain	S_QTNODT	Interpretation
Base	All sector	8.141	7.813	Moderately strong

Scenario	Change	S_domain	S_QTNODT	Interpretation
illustrative case	values as specified			integrated readiness; uncertainty still material
Higher uncertainty	U rises from 1.2 to 2.0	8.141	7.653	Same raw capability, lower decision confidence
Hydrological uplift	Water score rises 7.6→8.5	8.285	7.892	Cross-sector benefit from closing a weak-domain gap
Governance decline	G falls 7.8→6.0	8.141	7.723	Technical performance cannot fully offset governance weakness
No quantum premium	Q treated as generic compute readiness at 7.4	8.141	7.813	Framework remains usable without quantum hardware

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4.1 Discussion

Theoretical contribution. QTNODT combines four ideas that are usually separated: structural topology, operator learning, probabilistic twin updating and cross-sector decision optimisation. The conceptual novelty is not any one component but the interface among them. Topology becomes a persistent structural channel; neural operators become field-evolution engines; the digital twin becomes the assimilation and counterfactual layer; and quantum computation is treated as an optional acceleration or representation module subject to benchmark evidence.

Practical relevance. In climate adaptation, the framework could connect extreme-event forecasts to infrastructure and health consequences. In energy, it could combine

topological grid structure with neural-operator stability surrogates and probabilistic twin updates, consistent with the literature on AI-driven grid stability and digital-twin power flow (Ahmadi, Aly & Gu 2026; Zhang et al. 2026). In water management, conformal adaptive sampling could prioritise sensors when uncertainty widens (Homaei et al. 2026). In cities, the framework could connect building flexibility, mobility, heat and service resilience (Zhang et al. 2026; Varzeshi et al. 2026). In industry, graph dependency models and multiphysics twins could support maintenance and quality interventions (Stupina et al. 2026; Wang et al. 2026). In health, the same architecture could be narrowed to patient-level multimodal inference under clinical governance rather than used for autonomous treatment (Wei & Zhang 2026; Zhou et al. 2026).

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Policy and governance implications. Cross-sector twins can create new systemic risks if data sharing, cyber security, privacy and accountability are not designed into the architecture. Urban and health modules are especially sensitive because individual-level or location-linked data may reveal identity or behaviour. A governance layer should therefore enforce purpose limitation, minimum-necessary data exchange, model-card documentation, drift monitoring, subgroup performance analysis, uncertainty disclosure and human escalation rules. The proposed optimisation objective makes these constraints explicit through C_ethics rather than treating them as narrative afterthoughts.

Technological implications. The literature indicates that operator learning, topological methods, probabilistic twins and multimodal AI are advancing rapidly, but integration cost remains high. A practical implementation should begin with a classical baseline, then add topology if it improves robustness, then test operator learning against conventional surrogates, and only then test quantum or quantum-inspired modules. This staged approach prevents novelty from obscuring benchmark performance and aligns computational ambition with available evidence.

Table 6. Proposed validation matrix for empirical QTNODT studies.

Validation dimension	**Example metric**	**Test design**
Predictive validity	RMSE/MAE, AUROC where	Temporal holdout and

Validation dimension	Example metric	Test design
	relevant, calibration, CRPS	external-site validation
Operator generalisation	Performance across meshes, resolutions, regimes	Resolution transfer and out-of-distribution tests
Topological validity	Persistence stability, structural consistency	Perturbation and bootstrap analysis
Twin fidelity	State-estimation error, forecast skill, assimilation consistency	Replay plus prospective live-data evaluation
Cross-sector resilience	Cascade error, recovery time, tail loss	Multi-hazard stress testing
Fairness and ethics	Subgroup calibration, disparate error, privacy leakage	Audited governance tests
Computational feasibility	Latency, energy use, memory, cost	Classical vs hybrid/quantum benchmark
Decision value	Regret, net benefit, avoided loss	Counterfactual and prospective decision trials

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5. Conclusion

This paper has developed QTNODT, a unified model-based framework for Quantum Topological Neural Operators and Digital Twin Intelligence across climate, energy, hydrological, urban, industrial and health systems. The framework responds to a recurring limitation in contemporary intelligent-system research: powerful methods are often developed in isolation, even though the systems they model are dynamically coupled. QTNODT addresses this by representing each domain through a common sequence of state estimation, topological encoding, optional quantum or

quantum-inspired feature processing, neural-operator forecasting, digital-twin assimilation, uncertainty quantification and risk-aware intervention.

The mathematical formulation provides general operator, matrix, dynamic, Bayesian, topological, optimisation and risk-adjusted equations. The numerical demonstration shows how normalized sector scores can be combined transparently and then reduced by uncertainty rather than presenting simulated performance as empirical proof. The framework is therefore best viewed as a research architecture and validation agenda. Its scientific value will depend on future implementations that compare it with strong classical baselines, test cross-sector generalisation, quantify uncertainty, assess topology preservation, and demonstrate decision benefit under real operational constraints.

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5.1 Limitations

The study has five main limitations. First, no empirical dataset was supplied, so all numerical values are illustrative. Second, the proposed equations simplify complex nonlinear couplings and do not specify a single discretisation or neural-operator architecture. Third, topological summaries can be computationally demanding and may not always improve predictive performance. Fourth, quantum or quantum-inspired modules may add overhead without practical advantage, especially where classical accelerators are strong. Fifth, cross-sector integration creates governance, privacy, cyber-security and accountability challenges that cannot be solved purely by mathematical optimisation. These limitations reinforce the need for staged, domain-specific validation before operational use.

5.2 Future Research Directions

1. Build open benchmark suites that couple at least two sectors, such as climate-energy, water-energy, urban-health or industry-energy, with common stress scenarios.
2. Develop topology-aware neural operators whose loss functions directly constrain persistence diagrams, graph spectra or higher-order structures.

3. Compare classical, quantum-inspired and hardware-executed quantum feature maps on identical operator-learning tasks using latency, accuracy, energy and cost metrics.
4. Integrate conformal prediction, ensemble methods and Bayesian assimilation to produce calibrated cross-sector uncertainty intervals.
5. Create federated or privacy-preserving QTNODT implementations for urban and health settings where raw-data centralisation is inappropriate.
6. Evaluate policy and operational interventions through prospective digital-twin trials, measuring regret, avoided loss, equity effects and resilience recovery time.
7. Study cascade causality and intervention transfer across sectors using graph causal models and counterfactual simulation.
8. Develop standards for audit trails, model updates, digital-twin versioning and human override in high-stakes deployments.

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References

Ahmadi, M, Aly, H & Gu, J 2026, "A comprehensive review of AI-driven approaches for smart grid stability and reliability," Renewable and Sustainable Energy Reviews, vol. 226, p. 116424, accessed <http://dx.doi.org/10.1016/j.rser.2025.116424>.

Chen, Y-T, Luo, X, Xu, W & Shen, H-W 2026, "FLUID: A Neural Operator-Based Framework for Learning Multi-Fidelity of Unstructured Data," IEEE Transactions

on Visualization and Computer Graphics, vol. 32, no. 6, pp. 4731–4741, accessed <http://dx.doi.org/10.1109/tvcg.2026.3694450>.

Gyurik, C, Schmidhuber, A, King, R, Dunjko, V & Hayakawa, R 2026, "Provable Quantum Speedups for Computing Persistence in Topological Data Analysis," PRX Quantum, vol. 7, no. 2, accessed <http://dx.doi.org/10.1103/gvys-hl8h>.

Homaei, M, Tarif, M, Rodriguez, PG, Caro, A & Avila, M 2026, "Conformal prediction-driven adaptive sampling for digital water twins," ICT Express, accessed <http://dx.doi.org/10.1016/j.icte.2026.01.010>.

Lugo Reyes, SO 2020, "Artificial intelligence in precision health: Systems in practice," Artificial Intelligence in Precision Health, pp. 499–519, accessed <http://dx.doi.org/10.1016/b978-0-12-817133-2.00021-5>.

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Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: India
Date: Aug 30, 2026 (05:00 PM)

McArdle, S, Gilyén, A & Berta, M 2026, "A streamlined quantum algorithm for topological data analysis with exponentially fewer qubits," Quantum, vol. 10, p. 2058, accessed <http://dx.doi.org/10.22331/q-2026-04-10-2058>.

Meierhofer, J & West, S 2020, "Data-driven Decision Support by Digital Twins in Manufacturing," 2020 7th Swiss Conference on Data Science (SDS), accessed <http://dx.doi.org/10.1109/sds49233.2020.00019>.

Miao, Z, Li, C, Su, T & Wu, Y 2026, "Global assessment of climate-driven lag and cumulative effects on vegetation using Earth Observation data and multivariable machine learning models," International Journal of Applied Earth Observation and Geoinformation, vol. 152, p. 105403, accessed <http://dx.doi.org/10.1016/j.jag.2026.105403>.

Nguyen, NH, Behrman, EC & Steck, JE 2020, "Quantum learning with noise and decoherence: a robust quantum neural network," Quantum Machine Intelligence, vol. 2, no. 1, accessed <http://dx.doi.org/10.1007/s42484-020-00013-x>.

Poworoznek, E, Thompson, R, Glaudell, A, Jarret, M & Porter, J 2021, A QUANTUM-AI FRAMEWORK FOR EXTREME WEATHER PREDICTION, Office of Scientific and Technical Information (OSTI), accessed <http://dx.doi.org/10.2172/1769650>.

Qanazi, S, Leclerc, E & Bosredon, P 2025, "Integrating Social Dimensions into Urban Digital Twins: A Review and Proposed Framework for Social Digital Twins,"

Smart Cities, vol. 8, no. 1, p. 23, accessed <http://dx.doi.org/10.3390/smartcities8010023>.

Rusnák, M, Tomáš, G, Lukáš, M & Afzali, H 2026, "GIS-Based Digital Twins for Environmental Monitoring and Climate Change," Digital Twin Technology in Geospatial Science: Trends, Applications and Challenges, pp. 115–134, accessed <http://dx.doi.org/10.1007/978-3-032-20311-3_7>.

Sauer, J, Massonnet, F, Zappa, G & Ragone, F 2025, "Ensemble design for seasonal climate predictions: studying extreme Arctic sea ice lows with a rare event algorithm," Earth System Dynamics, vol. 16, no. 3, pp. 683–702, accessed <http://dx.doi.org/10.5194/esd-16-683-2025>.

Shen, Z & Bao, L 2020, "Data Interconnection Framework of Smart City Transportation Infrastructure," Resilience and Sustainable Transportation Systems, pp. 697–704, accessed <http://dx.doi.org/10.1061/9780784482902.082>.

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Reason: NES |IJAIRI | Publication|
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Location: Delhi, India
Date: Aug 30, 2026 (05:00 PM)

Skolik, A, McClean, JR, Mohseni, M, van der Smagt, P & Leib, M 2021, "Layerwise learning for quantum neural networks," Quantum Machine Intelligence, vol. 3, no. 1, accessed <http://dx.doi.org/10.1007/s42484-020-00036-4>.

Stupina, AA, Kukartseva, SV & Stepantsevich, MN 2026, "Application of Graph Neural Networks for Structural Dependency Analysis in Industrial Digital Twins Using the UCI AI4I 2020 Predictive Maintenance Dataset," 2026 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), pp. 1155–1159, accessed <http://dx.doi.org/10.1109/icieam69213.2026.11549674>.

Su, Z, Liu, X, Hamdan, LB, Maroulas, V, Wu, J, Carlsson, G & Wei, G-W 2025, "Topological data analysis and topological deep learning beyond persistent homology: a review," Artificial Intelligence Review, vol. 59, no. 2, accessed <http://dx.doi.org/10.1007/s10462-025-11462-w>.

Sung, J-Y & Cheong, J-H 2026, "Advancing genomics and integration of multi-omics for precision oncology using quantum machine learning," npj Digital Medicine, accessed <http://dx.doi.org/10.1038/s41746-026-02982-y>.

Tadvin, SM & Hasnat, MA 2026, "Fourier Neural Operators for Analyzing Multi-Rate Data in Power System Stability Assessment," 2026 IEEE Texas Power and

Energy Conference (TPEC), pp. 1–6, accessed <http://dx.doi.org/10.1109/tpec67884.2026.11513190>.

Tekinerdogan, B & Verdouw, C 2026, "Modeling artificial intelligence integration in digital twins: a systematic survey," Digital Twins, pp. 9–20, accessed <http://dx.doi.org/10.1016/b978-0-443-45573-5.00001-x>.

Varzeshi, S, Fien, J, Irajifar, L & Kent, A 2026, "From Smart City Pilots to Institutionalised Urban Resilience: The Smart Urban Resilience Framework (SURF)," Smart Cities, vol. 9, no. 5, p. 82, accessed <http://dx.doi.org/10.3390/smartcities9050082>.

Wang, L & Schilp, J 2026, "Neural operators in industrial processes/Neural Operator in industriellen Prozessen," wt Werkstattstechnik online, vol. 116, no. 03, pp. 111–117, accessed <http://dx.doi.org/10.37544/1436-4980-2026-03-15>.

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Location: Delhi, India
Date: Aug 30, 2026 (05:00 PM)

Wang, Y, Cheng, Y, Huang, W, Li, W & Cui, S 2026, "Dynamic electromagnetic-thermal mapping in motor digital twins: A real-time multiphysics framework," Digital Engineering, vol. 8, p. 100082, accessed <http://dx.doi.org/10.1016/j.dte.2025.100082>.

Wei, Y & Zhang, J 2026, "Multimodal radiomics for precision management of colorectal cancer," Discover Oncology, vol. 17, no. 1, accessed <http://dx.doi.org/10.1007/s12672-026-04751-5>.

Weil, C, Birbi, S, Longchamp, R, Golay, F & Alahi, A 2023, Urban Digital Twins: Challenges & Perspectives for Sustainable Smart Cities, accessed <http://dx.doi.org/10.2139/ssrn.4429379>.

Xiong, J, Pei, W, Wang, G, Deng, W & Xiao, H 2026, "Quantitative Analysis Method of Stability Ability for Renewable Electric Energy Delivery System," IET Smart Grid, vol. 9, no. 1, accessed <http://dx.doi.org/10.1049/stg2.70077>.

Yao, H, Liu, X, Jing, M, Li, G & Wang, X 2026, "LCQNN: linear combination of quantum neural networks," Quantum Machine Intelligence, vol. 8, no. 1, accessed <http://dx.doi.org/10.1007/s42484-026-00364-x>.

Yorucu, V, Bekun, FV & Yitmen, I 2026, "Interdisciplinary Studies on Urban Resilience: Urban Digital Twins and Construction 5.0 for Resilient, Sustainable and Smart Cities," Modern Approach of Resilient and Sustainable Smart Cities, pp. 141–155, accessed <http://dx.doi.org/10.1007/978-3-032-05715-0_9>.

Zhan, B, Shan, Z, Zhang, X, Wang, K, Yan, R, Qiu, S, Fan, Z & Lin, Q 2026, "Topology-Constrained Flexibility Assessment of Adjustable Resources in the Regional Electricity Spot Market," Energies, vol. 19, no. 11, p. 2501, accessed <http://dx.doi.org/10.3390/en19112501>.

Zhang, P, Huang, S, Nematbakhsh, E & Wang, Y 2026, "Smart buildings as urban energy infrastructure: A scalable, privacy-aware framework for city-scale flexibility and resilience," Sustainable Cities and Society, vol. 143, p. 107370, accessed <http://dx.doi.org/10.1016/j.scs.2026.107370>.

Zhang, P, Jiang, J, Huang, Y, Tang, H, Chen, Y & Shen, L 2026, "Digital Twin-Driven Dynamic Probabilistic Power Flow in Distribution Networks via Semi-Invariant Method," Digital Twins and Applications, vol. 3, no. 1, accessed <http://dx.doi.org/10.1049/dgt2.70038>.

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Zhong, H, Liang, Z & Li, C 2020, "Managing Water Resources and Hydrological Systems," Managing Water Resources and Hydrological Systems, pp. 185–194, accessed <http://dx.doi.org/10.1201/9781003045045-22>.

Zhou, W, Wang, Y, Wu, Y, Li, X, Liu, H, Wang, H, Zhang, Z & Huang, H 2026, "AI-driven multimodal precision diagnosis and progression prediction of Alzheimer's disease: Data fusion mechanisms, clinical applications, and research trends (2017–2024)," DIGITAL HEALTH, vol. 12, accessed <http://dx.doi.org/10.1177/20552076251412649>.

Zou, Y, Rasch, P & Wang, H 2021, Hybridizing Machine Learning and Physically-based Earth System Models to Improve Prediction of Multivariate Extreme Events (AI Exploration of Wildland Fire Prediction), Office of Scientific and Technical Information (OSTI), accessed <http://dx.doi.org/10.2172/1769718>.

Zulkepli, NFS, Kasihmuddin, MSM & Gobithaasan, RU 2026, "Topological feature engineering and persistent homology hybrid deep learning model for time-series prediction," Complex & Intelligent Systems, vol. 12, no. 8, accessed <http://dx.doi.org/10.1007/s40747-026-02315-2>.