Volume-06|Issue-07|July|Year-2026 ISSN: 3049-2343

International Journal of Academic and Industrial Research Innovations(IJAIRI)

Research Paper Title :Functional and Object-Oriented Data Analysis for Complex Biomedical, Environmental and Socioeconomic Systems

[1]Murali Krishna Pasupuleti

[1]Research Director
[1]National Education Services,
[1]New Delhi,India
[1]mkrishnap2050@gmail.com

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Abstract:
Biomedical, environmental and socioeconomic systems increasingly generate data whose natural observational units are curves, surfaces, images, probability distributions, networks, trees and other structured objects. Conventional vectorisation can destroy temporal continuity, topology, phase variation or intrinsic geometry, thereby producing unstable estimates and scientifically weak interpretations. This paper develops an integrated analytical architecture that combines functional data analysis with object-oriented data analysis for complex, multiscale and dependent systems. The proposed Integrated Functional–Object Systems Analytics (IFOSA) Framework links basis representation, registration, functional principal components, Fréchet means and regression, metric-space learning, graph and tensor operators, dynamic state equations, uncertainty calibration and domain-specific decision criteria. Its mathematical formulation covers Hilbert-space functional models, matrix basis expansions, nonlinear object regression, stochastic dynamics, regularised optimisation and a risk-adjusted master objective. An illustrative numerical model uses normalised 0–10 values for functional fidelity, object-geometry preservation, multiscale integration, predictive performance, interpretability, robustness and data quality, together with bias and uncertainty penalties. The resulting IFOSA score is 7.58, indicating promising analytical capacity under the stated assumptions; the value is demonstrative rather than empirical. Comparative analysis suggests that geometry-aware integration is most valuable when observations are irregular, phase-varying, non-Euclidean or linked across levels, whereas simpler functional models may remain preferable for densely observed homogeneous curves. The paper contributes a coherent methodology for biomedical monitoring, environmental intelligence and socioeconomic policy analysis while emphasising validation, privacy, fairness, computational reproducibility and transportability. It offers a research programme rather than a claim of empirically proven superiority, and it identifies the data and experiments required for substantive validation.

Keywords: functional data analysis; object-oriented data analysis; Fréchet regression; metric-space statistics; functional principal component analysis; shape analysis; manifold learning; multilevel functional data; spatiotemporal modelling; biomedical signals; environmental profiles; socioeconomic distributions; graph-valued data; uncertainty quantification; complex systems analytics.

Copyright:

© 2026 by Murali Krishna Pasupuleti.

1. Introduction

Contemporary scientific systems are observed at a resolution and structural complexity that exceed the assumptions of classical rectangular data analysis. A patient may be represented by continuous glucose trajectories, electrocardiographic signals, anatomical surfaces, vascular trees, longitudinal images and molecular networks. Environmental monitoring combines vertical ocean profiles, satellite fields, pollution curves, hydrological trajectories and spatially linked extremes. Socioeconomic inquiry increasingly uses age-specific mortality schedules, income distributions, mobility networks, policy-response functions and high-frequency behavioural panels. Treating each measurement as an unrelated scalar overlooks continuity, shape, dependence and geometry that are central to the scientific question.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES IJAIRI | Publication
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Functional data analysis (FDA) addresses observations that are naturally conceived as functions rather than long vectors. The field uses smoothing, registration, covariance operators, functional principal component analysis, regression, classification and clustering to learn from curves or surfaces (Ramsay and Silverman, 2005; Wang, Chiou and Müller, 2016). FDA is particularly effective when repeated measurements are noisy or irregular and the underlying process is assumed to vary smoothly. It also supports derivative-based interpretation, permitting investigators to study velocity, acceleration, timing and other features that are poorly represented by isolated time points.

Object-oriented data analysis (OODA) extends the statistical unit beyond Euclidean vectors and functions to general structured objects. These may include trees, graphs, shapes, covariance matrices, probability distributions or manifold-valued observations. The statistical problem then depends on a metric, geodesic or other geometry that defines meaningful proximity and averaging. Wang and Marron (2007) demonstrated the significance of this perspective for tree-structured data, while Marron and Alonso (2014) systematised OODA as a framework for deciding what constitutes the observational object and how its geometry should guide analysis.

The two traditions are complementary. Functional observations are themselves data objects, but not every object is appropriately represented in a linear function space. A registered gait curve can often be analysed in a Hilbert space; a brain artery tree, a covariance surface constrained to positive-definite matrices, or a regional transport network may require a non-Euclidean representation. Scientific validity

therefore depends on matching the model to the observational geometry rather than automatically flattening all data into a common matrix.

Cross-domain complexity introduces an additional challenge: observations are rarely independent and identically distributed. Biomedical signals are nested within visits and patients; environmental profiles are spatially and temporally correlated; socioeconomic curves vary across cohorts, regions and institutions. Koner and Staicu (2023) describe such settings as second-generation functional data because dependence, multivariate structure and repeated functional observations become part of the estimand rather than nuisance variation. A unified framework must consequently integrate representation, dependence, dynamics and uncertainty.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

This paper proposes the Integrated Functional–Object Systems Analytics (IFOSA) Framework. IFOSA preserves domain-specific geometry while connecting functional and object summaries through multilevel, graph, tensor and dynamic models. It is designed to support prediction, clustering, anomaly detection, change-point identification and interpretable decision indicators across biomedical, environmental and socioeconomic systems. The paper develops the conceptual and mathematical architecture, provides an illustrative numerical model, and sets out a rigorous empirical validation strategy. No original dataset is supplied; accordingly, analytical scores are explanatory demonstrations rather than observed findings.

1.1 Global relevance

The framework has relevance across high-resource and data-constrained settings. Continuous monitoring can improve chronic-disease management, yet sampling density, sensor reliability and access differ by population. Environmental profiles are increasingly available from satellites and autonomous platforms, but ground truth and calibration remain uneven. Socioeconomic systems contain administrative data at scale, although definitions, legal access and institutional capacity vary substantially. A method that explicitly models irregular observation and reports transportability can reduce the temptation to equate data abundance with representativeness.

Global application also requires attention to heterogeneity in infrastructures and scientific priorities. In South Asia, functional and object methods can combine heat-exposure curves, air-pollution trajectories, hospital demand and informal labour

vulnerability. European applications may integrate ageing profiles, longitudinal health records and climate-transition indicators. African contexts can benefit from sparse functional models that combine remote sensing with limited ground networks. In the Americas, multilevel analysis can connect environmental hazards, health disparities and regional economic dynamics. These examples illustrate methodological portability, not uniformity: local geometry, sampling and governance must remain explicit.

1.2 Purpose and contribution

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

The first contribution is conceptual: FDOSA treats the choice of observational unit and metric as part of research design. The second is mathematical: it connects Hilbert-space representations, Fréchet statistics, matrix and tensor models, graph operators and stochastic dynamics within a common regularised objective. The third is operational: it maps data quality, interpretability, fairness, privacy and decision relevance into a validation sequence that can be implemented before deployment.

The proposed architecture is intentionally modular. Researchers may use only the functional branch when curves are densely sampled and Euclidean geometry is scientifically defensible. The object branch becomes necessary when topology, constraints or manifold structure determine similarity. Integration is justified when the outcome arises from interactions between these representations—for example, when a biomedical trajectory predicts a network-valued response, or when environmental curves and socioeconomic distributions jointly explain regional vulnerability.

2. Literature Review

2.1 Foundations of functional data analysis

The modern FDA literature is grounded in the idea that a sample consists of random functions in an infinite-dimensional space. Ramsay and Silverman (2005) established a practical foundation based on basis expansions, smoothing, functional principal components and differential operators. Ferraty and Vieu (2006) developed nonparametric methods that use semi-metrics and kernels, while Horváth and Kokoszka (2012) formalised inference for dependent functional observations.

Subsequent texts extended the field toward computational implementation, regularisation and modern learning (Kokoszka and Reimherr, 2017).

Functional principal component analysis (FPCA) remains a central dimension-reduction method because it diagonalises the covariance operator and represents each trajectory through a small number of scores. Yao, Müller and Wang (2005) showed how conditional expectation can recover scores when longitudinal measurements are sparse and irregular. Hall, Müller and Wang (2006) examined theoretical properties of principal-component methods for functional and longitudinal data, clarifying when sparse and dense regimes require different asymptotic treatment. Multilevel FPCA later separated variation between and within subjects, which is essential for repeated biomedical and social observations (Di et al., 2009; Greven et al., 2010).

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: ©2009
Location: Delhi, India
Date: July 2026

Regression generalises scalar models to function-on-scalar, scalar-on-function and function-on-function forms. Morris (2015) emphasised that functional regression must combine replication across units with regularisation within curves. This distinction is scientifically important because overly flexible models can fit measurement noise, whereas excessive smoothing can remove short-duration events or clinically meaningful peaks. Functional coefficients also require domain interpretation: a coefficient surface may indicate when an exposure contributes to an outcome, but causal interpretation demands additional design assumptions.

Timing variation creates a special problem. Two trajectories can share the same underlying shape yet differ in event timing; direct Euclidean comparison may then exaggerate amplitude differences. Marron et al. (2015) reviewed methods for separating amplitude and phase variation through registration and time warping. Shape-based FDA has continued to develop geometric tools beyond the conventional L2 norm, reflecting the need to distinguish level, timing, scale and morphology (Wu et al., 2024).

2.2 Object-oriented data analysis and metric-space statistics

OODA begins from the proposition that a data set is a population of scientifically meaningful objects, not merely a matrix of coordinates. Wang and Marron (2007) developed an analysis of tree-structured objects and showed that strongly non-Euclidean spaces require new notions of centrality and principal direction. Marron

and Alonso (2014) subsequently framed OODA around object choice, representation, distance and analysis. Marron and Dryden (2021) consolidated the field across shapes, trees, networks, images and other complex structures.

Fréchet statistics provide a broadly applicable bridge. For a random object Y in a metric space, the Fréchet mean minimises expected squared distance rather than arithmetic squared deviation. Petersen and Müller (2019) extended this principle to regression with Euclidean predictors and object-valued responses, allowing conditional means for distributions, covariance matrices and other non-vector outcomes. Related work develops confidence bands, change-point methods and distance-profile inference for random objects (Dubey and Müller, 2020; Petersen, Liu and Divani, 2021; Dubey and Müller, 2024).

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
2024 © 2026
Location: Delhi, India
Date: July 2026

Metric-space methods are not automatically superior. Their validity depends on whether the selected distance reflects the scientific perturbations of interest. A graph-edit distance, Wasserstein metric, geodesic distance or kernel-induced distance may rank objects differently. Moreover, a global embedding can simplify computation but distort local or topological structure. Methodological transparency therefore requires sensitivity analysis across defensible metrics and clear reporting of what information is invariant or lost.

2.3 Biomedical systems

Biomedical applications motivated much of the development of sparse and multilevel FDA. Repeated blood pressure, growth, electroencephalographic activity, accelerometry and other physiological measurements are naturally trajectories, yet visits are irregular and measurement error can be substantial. Sparse FPCA reconstructs latent subject-specific curves and supports prediction without requiring every patient to be observed on a common grid (Yao, Müller and Wang, 2005). Multilevel models distinguish stable between-person physiology from visit-specific or day-specific variation (Di et al., 2009).

Modern biomedical data also contain object structure. Anatomical shapes, diffusion tensors, phylogenetic trees and vascular networks lie outside unrestricted Euclidean space. Bendich et al. (2016) used persistent homology to analyse brain artery trees, illustrating how topological summaries can reveal clinically meaningful

structural variation. Longitudinal neuroimaging additionally requires dimension reduction across images and time, while covariance matrices must remain symmetric and positive definite. These examples show why a functional-only representation may be insufficient even when the data evolve continuously.

Integration poses scientific and ethical challenges. Functional biomarkers can be linked with omics, images and clinical networks, but different modalities have different sampling scales and missingness mechanisms. Joint methods such as JIVE separate shared and modality-specific variation in high-dimensional blocks (Lock et al., 2013). In clinical settings, however, predictive gains must be accompanied by calibration, subgroup assessment, privacy protection and a clear account of whether the model supports screening, prognosis, treatment selection or mechanistic understanding.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication| Copyright © 2026
Location: Delhi, India
Date: July 2026

2.4 Environmental systems

Environmental processes are intrinsically functional because they evolve over time, depth, altitude and geographic space. Temperature cycles, river hydrographs, pollutant profiles and ocean measurements contain smooth structure together with abrupt extremes. FDA can model average profiles, dominant modes and functional responses, while spatial statistics accounts for dependence between locations. A functional approach to Argo ocean profiles, for example, combines curve representation with spatiotemporal kriging to estimate temperature and salinity structure (Yarger, Stoev and Hsing, 2022).

Air-quality and climate-monitoring applications often involve multivariate functions observed across many stations. Co-clustering methods can group locations and pollutants according to shared temporal patterns, providing a more interpretable representation than separate univariate clusters (Bouveyron et al., 2022). Weather radar images, satellite fields and ecological networks introduce object-valued responses and high-dimensional spatial structure. The resulting models must reconcile smooth background variation with local extremes, sensor changes and nonstationarity.

Environmental decision-making also changes the loss function. A model with low average error may underestimate rare but consequential heat, flood or pollution episodes. Robustness therefore requires tail-focused validation, change-point

detection and scenario-based stress testing. Geometry-aware methods can identify shape or distribution shifts that precede changes in the mean, but operational use depends on timely data assimilation and transparent uncertainty.

2.5 Socioeconomic systems

Socioeconomic data can be functional in age, time, income rank, policy intensity or geographic exposure. Age-specific mortality and fertility schedules are canonical examples. Hyndman and Ullah (2007) used smooth functional representations and robust principal components to forecast demographic rates, demonstrating that curves can provide more coherent forecasts than independently modelled age cells. Multilevel functional models extend this logic to groups of populations and allow shared long-run structure with population-specific deviations.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright © 2026
Location: Delhi, India
Date: July 2026

Distribution-valued and network-valued observations are increasingly common. A region may be described by an income distribution rather than its mean, while commuting, trade and financial linkages form graphs. Wasserstein geometry can compare distributions without collapsing them to a few moments; graph statistics can represent connectivity and fragmentation. Fréchet regression permits such objects to be related to scalar predictors, and single-index extensions can reduce high-dimensional covariates while retaining an object response (Ghosal et al., 2023).

Policy analysis introduces identification and fairness requirements not addressed by prediction alone. Functional and object summaries may be used as outcomes, treatments or confounders, but causal interpretation requires temporal ordering, overlap and assumptions about interference. Socioeconomic records also reflect institutional measurement: administrative categories, eligibility rules and missingness can encode exclusion. A unified methodology should therefore couple geometric fidelity with auditability, group performance and sensitivity to data-generating institutions.

2.6 Critical synthesis

The literature provides powerful domain-specific components but less agreement on how to combine them. FDA methods often presume linear function spaces even when derived objects are constrained. OODA supplies general geometry but can lack

the scalable dynamic models needed for dense trajectories. Multimodal integration may align blocks statistically without preserving the scientific metric of each block. These tensions suggest that unification should occur at the level of objectives, dependence and validation rather than by forcing every data type into one coordinate system.

A credible framework must also distinguish descriptive variation from intervention-relevant mechanisms. Principal components maximise variance, which need not correspond to risk, treatment response or policy importance. Clusters depend on distance choices and may not represent stable populations. Predictive accuracy can conceal systematic error in minority groups or rare regimes. IFOSA addresses these limitations by preserving modality-specific representations, linking them through explicit operators, and evaluating outputs against domain loss, calibration, interpretability and governance constraints.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Location: Delhi, India
Date: July 2026

Table 1. Key constructs and definitions

Construct	Definition	Illustrative relevance
Functional observation	A curve, surface or field treated as one statistical unit	Continuous glucose trace; temperature-depth profile; mortality-by-age curve
Data object	A structured unit whose natural space need not be Euclidean	Brain artery tree; covariance matrix; income distribution; transport network
Amplitude variation	Difference in level or magnitude after alignment	Higher pollutant concentration or stronger physiological response
Phase variation	Difference in timing or parametrisation of a shared pattern	Delayed clinical peak; shifted seasonal cycle
Metric geometry	Rules defining distance, averages and paths between objects	L2, geodesic, graph-edit or Wasserstein geometry

Construct	Definition	Illustrative relevance
Fréchet mean/regression	Distance-based centre or conditional centre in a metric space	Expected distribution, shape, graph or covariance object
Multilevel dependence	Variation attributable to nested or repeated structures	Days within patients; stations within regions; cohorts within countries
Dynamic state	Latent time-evolving representation governed by transition equations	Disease progression, ecosystem regime, socioeconomic resilience
Geometry-aware fusion	Integration that retains modality-specific distances and constraints	Coupling curves, networks and distributions without indiscriminate flattening
Decision intelligence	Translation of statistical evidence into monitored action	Clinical alert, environmental intervention or socioeconomic policy response

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication| Copyright@2026
Location: Delhi, India
Date: July 2026

I. Functional and Object-Oriented Foundations for Heterogeneous Complex Data

Functional and object-oriented data analysis addresses a foundational difficulty shared by biomedical, environmental and socioeconomic research: the primary observational unit is often not a scalar but a curve, image, network, field, trajectory, spectrum, spatial object or evolving collection of interdependent attributes. Object-oriented representations are therefore theoretically valuable because they preserve the intrinsic structure of the observed entity rather than reducing it prematurely to disconnected variables. Early work on object-oriented proteomics demonstrated how domain-specific objects can encapsulate analytical operations and improve reproducibility in complex laboratory workflows (Mohammed and Palmblad, 2019). Related research on adaptive data-intensive web systems showed that object orientation can support modularity, inheritance and extensibility under changing data conditions (Cuzzocrea and Fadda, 2021). Dynamic program-analysis research further

illustrates how object relationships and state transitions can be traced over time, providing a computational analogue for studying evolving scientific objects and their dependencies (Troost and Kuchen, 2022; Troost, Neugebauer and Kuchen, 2023).

The methodological advance is not merely software architectural. It implies a statistical ontology in which heterogeneous observations are treated as structured entities with internal geometry, temporal dependence and domain-specific behaviour. Spatial object-oriented methods for stream-network data show how complex objects can be analysed while respecting network topology, directionality and spatial dependence (Barbi, Menafoglio and Secchi, 2023). In parallel, meteorological generalisation through object-oriented abstractions demonstrates how climatic observations can be transformed into reusable analytical objects for bioclimatic mapping (Mikhailov, 2021). These developments converge with statistical learning frameworks that recognise nonlinear feature dependence, causal structure and uncertainty rather than assuming independent tabular predictors (Pasupuleti, 2021b). From this perspective, functional and object-oriented analysis becomes a unifying methodology for modelling structured systems without erasing their scientifically meaningful form.

eSign
Signed by MURALI KRISHNA PASUPULETI
Reason: NESIIJAIRI | Publication |
Copyright: © 2026
Location: Delhi, India
Date: July 2026

The solution-development implication is the construction of interoperable analytical objects that carry data, metadata, uncertainty, provenance and valid operations within a single framework. Such objects can be composed into domain pipelines spanning biosignals, spatial fields, social trajectories and economic networks. Scalability remains a central design concern, and comparative analysis of data-oriented and object-oriented architectures indicates that computational organisation must be evaluated against workload, memory locality and scenario complexity rather than selected ideologically (Srichalee and Watanyulertsakul, 2026). Governance is equally important: reusable objects should expose transformation histories, assumptions and audit trails, thereby supporting transparent scientific inference and responsible multi-sector deployment. The broader research opportunity lies in linking object-oriented computational design with functional statistical theory, enabling complex systems to be analysed as coherent entities across scales and sectors.

II. Biomedical Functional Signals, Multimodal Phenotypes and Precision Inference

Biomedical systems generate densely sampled functions rather than isolated measurements: electroencephalographic time series, physiological waveforms, omics profiles, wearable-sensor streams and longitudinal treatment responses. Functional analysis is therefore central to preserving temporal morphology, phase variation and multiscale dependence. EEG research on intention recognition in dynamic control tasks shows that functional brain networks can capture coordinated neural activity beyond conventional feature vectors (Fu et al., 2020). Object-oriented proteomics similarly illustrates how analytical procedures can be organised around biological entities, spectra and transformations, improving interpretability and computational reuse (Mohammed and Palmblad, 2019). These foundations are reinforced by statistical deep-learning theory, which clarifies approximation behaviour, training dynamics and the risks of over-parameterised models when applied to high-dimensional biomedical functions (Pasupuleti, 2022b; Pasupuleti, 2022c).

eSign Signed by: MURALIKRISHNA PASUPULETI
Reason: NES IJAIRI Publication
Copyright © 2026
Location: Delhi, India
Date: July 2026

Recent biomedical intelligence frameworks extend this logic toward multimodal and longitudinal inference. Clinical modelling that combines diagnosis, prognosis and therapeutic decision-making requires representations able to integrate images, signals, structured records and temporal trajectories without forcing them into a single homogeneous feature space (Pasupuleti, 2026e). Continuous wearable biosensing further demands models that treat physiological data as evolving functional objects and preserve geometric and topological signatures associated with cardiometabolic states (Pasupuleti, 2026g). Omics research likewise benefits from graph-causal and diffusion-augmented pipelines that model biological pathways as structured objects rather than independent variables (Pasupuleti, 2023f). In applied evaluation, targeted-learning approaches for real-world evidence and propensity, survival and drift monitoring provide complementary causal and validation tools for complex biomedical systems (Pasupuleti, 2023b; Pasupuleti, 2023e).

The innovation pathway is a unified biomedical object model in which each patient is represented as a temporally evolving, multimodal and uncertainty-aware object. Functional principal components, registration, manifold learning, graph representations and topological summaries can then be applied at appropriate layers. Persistent-homology-driven foundation models offer a route to discovering stable structures that survive measurement noise and dimensionality reduction (Pasupuleti,

2026h), while high-dimensional quantum-AI frameworks suggest future combinations of graph neural networks, tensor methods, sparse modelling and topological data analysis (Pasupuleti, 2026i). Research implications include improved phenotype discovery, personalised monitoring and more robust treatment-effect estimation. Policy implications include the need for interoperable data standards, traceable model updates, subgroup fairness assessment and clinically meaningful uncertainty reporting before deployment across health systems.

III. Environmental Functions, Spatial Objects and Earth-System Intelligence

eSign Signed by: MURALIKRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication| Copyright© 2026
Location: Delhi, India
Date: July, 2026

Environmental observations are intrinsically functional and spatial: temperature and rainfall evolve as curves, hydrological variables propagate through networks; remote-sensing images form spatial fields, and ecosystem responses unfold across interacting temporal scales. Object-oriented approaches are well suited to this setting because they maintain the identity, geometry and relationships of rivers, watersheds, land parcels, atmospheric columns and monitoring stations. The analysis of spatial complex data over stream-network domains provides a rigorous example of how objects can retain network topology and spatial dependence during inference (Barbi, Menafoglio and Secchi, 2023). Meteorological object generalisation similarly supports bioclimatic mapping by organizing climatic measurements into structured spatial units (Mikhailov, 2021). These approaches complement functional representations that model trajectories and surfaces directly rather than relying only on annual averages or independently analysed pixels.

The methodological frontier combines functional statistics with foundation models, causal inference, remote sensing and physically informed learning. ArcGIS-based climate-risk research demonstrates how spatio-temporal causality and remote-sensing foundation models can be integrated for environmental assessment (Pasupuleti, 2023c). Physics-informed neural operators add a complementary mechanism by embedding governing relationships and verified error bounds into learning systems, which is particularly important when observations are sparse or extrapolation is required (Pasupuleti, 2023g). At planetary scale, Earth-system foundation models integrate satellite, oceanic and land-surface intelligence for extreme-event prediction (Pasupuleti, 2026f), while climate-risk and emissions-intelligence frameworks extend analysis to environmental decision-making under

uncertainty (Pasupuleti, 2026c). Satellite-based carbon measurement, reporting and verification further illustrates the role of structured atmospheric and geospatial objects in auditable climate action (Pasupuleti, 2026j).

A practical solution is an environmental object repository in which each observation carries location, temporal resolution, sensor provenance, physical constraints and uncertainty. Functional regression can then relate environmental trajectories to ecological or socioeconomic outcomes, while object-oriented methods enable reproducible transformations across heterogeneous sources. Geo-visual analytics and hydrologic-spatial decision frameworks demonstrate how such objects can support siting, infrastructure planning and risk communication (Pasupuleti, 2024c; Pasupuleti, 2022a). The wider implications concern global adaptation, carbon governance, agriculture, public health and infrastructure resilience. Policy systems should therefore require transparent provenance, uncertainty propagation, cross-scale validation and open standards for environmental objects, preventing black-box aggregation from concealing spatial inequality or model fragility.

eSign Signed by MURALI KRISHNA PASUPULETI
Reason: NES IJAIRI | Publication
Copyright: © 2026
Location: Delhi, India
Date: July 2026

IV. Socioeconomic Trajectories, Institutional Dynamics and Causal Functional Analysis

Socioeconomic systems are characterised by path dependence, feedback, regime shifts and interacting institutional processes. Employment, inequality, consumption, migration, trade, prices and policy outcomes are better represented as trajectories and relational objects than as isolated cross-sectional indicators. A functional perspective allows the shape, timing and persistence of change to become analytically meaningful, while object-oriented representations preserve the identities and relationships of households, firms, regions, institutions and policy regimes. Research on uncertainty-aware socioeconomic scenario generation highlights the importance of representing alternative pathways rather than relying on single-point forecasts (Pasupuleti, 2021c). Similarly, models of social behaviour, inequality and institutional change emphasise the need to capture complex human-system interactions and emergent structure (Pasupuleti, 2026d).

Causal methodology is essential because functional association alone does not establish policy effectiveness. A unified framework for feature dependence provides a theoretical basis for distinguishing statistical association from causal structure in high-

dimensional systems (Pasupuleti, 2021b). Causal time-series methods with conformal risk control address regime shifts and uncertainty in evolving data (Pasupuleti, 2023d), while double machine learning with Bayesian calibration offers a pathway for estimating effects in flexible, high-dimensional settings (Pasupuleti, 2023a). Econometric comparison across R, Stata, SPSS and EViews demonstrates the continued relevance of transparent classical modelling and diagnostics alongside modern learning systems (Pasupuleti, 2024b). These methods can be integrated with object-oriented representations of regions, policies and institutions to analyse heterogeneous effects and longitudinal responses.

The innovation agenda is a policy-object architecture in which interventions are encoded with eligibility rules, implementation dates, target populations, institutional context and outcome functions. Such a design would support counterfactual comparison, dynamic treatment analysis and reproducible policy evaluation across jurisdictions. Sustainable urban-housing research shows how climate-resilient design and green infrastructure can be linked to emerging-city trajectories (Pasupuleti, 2023h), while trade analytics demonstrates how policy outcomes and industrial competitiveness can be evaluated using data-driven methods (Pasupuleti, 2026b). Governance implications are substantial: public agencies need transparent model documentation, contestable assumptions, fairness analysis and clear uncertainty communication. A socially beneficial AI framework therefore remains necessary to align functional socioeconomic modelling with public value, accountability and measurable causal impact (Pasupuleti, 2021d).

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES || IJAIRI | Publication|
Copyright © 2026
Location: Delhi, India
Date: July 2026

V. Unified Topological, High-Dimensional and Governable Analytics Across Sectors

The most significant theoretical opportunity is the integration of functional data analysis, object-oriented computation, topology, tensor methods and causal learning into a common architecture for complex systems. Functional methods preserve trajectories and surfaces; object orientation preserves domain identity and operational semantics; topology captures shape and connectivity; tensor methods represent multilinear dependence; and causal analysis distinguishes intervention effects from correlation. A unified topological and tensor framework for interpretable AI in networks, fraud and power systems demonstrates how these approaches can be

combined for structurally complex data (Pasupuleti, 2026a). Persistent-homology-driven foundation models further show how robust latent structure may be identified across noisy, high-dimensional spaces (Pasupuleti, 2026h), while high-dimensional learning frameworks connect graph neural networks, topological analysis, tensor networks and sparse prediction (Pasupuleti, 2026i).

Methodologically, the unified architecture should operate through layered objects. The lowest layer contains raw functional observations and metadata; intermediate layers encode geometric, network and causal relations; higher layers support prediction, simulation and intervention. Dynamic data-flow visualisation can make these transformations inspectable (Troost, Neugebauer and Kuchen, 2023), while object-oriented spatial analysis demonstrates how domain constraints can be retained in inferential operations (Barbi, Menafoglio and Secchi, 2023). Control-theoretic AI safety contributes stability, robustness and assurance criteria for systems that adapt over time (Pasupuleti, 2021a). Trustworthy AI in law and public administration adds transparency, accountability and decision-support requirements that are equally relevant to biomedical, environmental and socioeconomic deployment (Pasupuleti, 2026k).

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES IJAIRI Publication
Copyright: © 2026
Location: Delhi, India
Date: July 2026

The broader implication is a move from isolated models toward governable analytical ecosystems. Each object should include provenance, uncertainty, access controls, permissible transformations and validation status, allowing models to be reused without detaching them from scientific and ethical context. Cross-sector applications include patient monitoring, climate adaptation, financial stability, urban planning, public administration and infrastructure management. State-level ESG measurement and assurance frameworks indicate how multi-dimensional performance objects can support comparative governance (Pasupuleti, 2024f), while government-AI benchmarking highlights the institutional importance of algorithmic accountability (Pasupuleti, 2024d). The central research challenge is therefore not only predictive accuracy but epistemic integrity: models must preserve structure, quantify uncertainty, document transformations and remain auditable across sectors and jurisdictions.

3. Research Gap

1. Theoretical gap: A general bridge between linear functional spaces and non-Euclidean object spaces remains underdeveloped for systems containing both. Existing methods often solve one geometry at a time without specifying how uncertainty and dependence propagate across representations.
2. Methodological gap: Registration, FPCA, Fréchet regression, graph learning and dynamic models are frequently applied as separate pipelines. There is limited guidance for choosing among them, integrating their outputs and preventing metric distortion or information leakage.
3. Empirical gap: Cross-domain comparisons rarely assess when geometry-aware integration materially improves prediction, calibration or scientific interpretation over functional-only and flattened Euclidean benchmarks.
4. Sectoral gap: Biomedical, environmental and socioeconomic research communities often develop parallel methods with limited transfer of validation practices. Clinical calibration, environmental tail risk and socioeconomic fairness are seldom examined within one analytical architecture.
5. Data-governance gap: Complex data integration intensifies privacy, provenance, consent, representativeness and algorithmic-bias risks. These considerations are not consistently embedded in the mathematical objective or validation design.
6. Decision gap: High-dimensional statistical summaries may not translate into actionable thresholds or policies. Frameworks are needed to connect functional and object outputs with risk-adjusted decisions and adaptive monitoring.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright © 2026
Location: Delhi, India
Date: July 2026

4. Research Objectives

1. To develop a unified conceptual architecture that connects functional and object-oriented data analysis while preserving domain-specific geometry.
2. To formulate mathematical models for curve-valued, object-valued, multilevel and dynamic observations across biomedical, environmental and socioeconomic systems.

3. To construct a geometry-aware optimisation and outcome-prediction framework that balances fit, smoothness, structural fidelity, uncertainty and interpretability.
4. To demonstrate the framework through an illustrative normalised numerical score and comparative sensitivity analysis.
5. To specify a rigorous empirical methodology covering sampling, data linkage, validation, transportability, fairness, privacy and reproducibility.
6. To identify practical and policy implications for trustworthy decision intelligence in complex systems.

5. Research Questions

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

1. How can functional and non-Euclidean object representations be integrated without erasing their intrinsic geometry?
2. Which mathematical operators best capture dependence across subjects, time, space, modalities and system levels?
3. Under what conditions does the IFOSA framework improve prediction, clustering, anomaly detection or interpretation relative to functional-only and flattened-vector models?
4. How should smoothness, geometric fidelity, complexity, tail risk and uncertainty be balanced in a unified optimisation objective?
5. Which data-quality, privacy, fairness and transportability tests are necessary before IFOSA outputs inform clinical, environmental or socioeconomic decisions?
6. How can model outputs be converted into adaptive and auditable domain-specific action rules?

6. Conceptual Framework

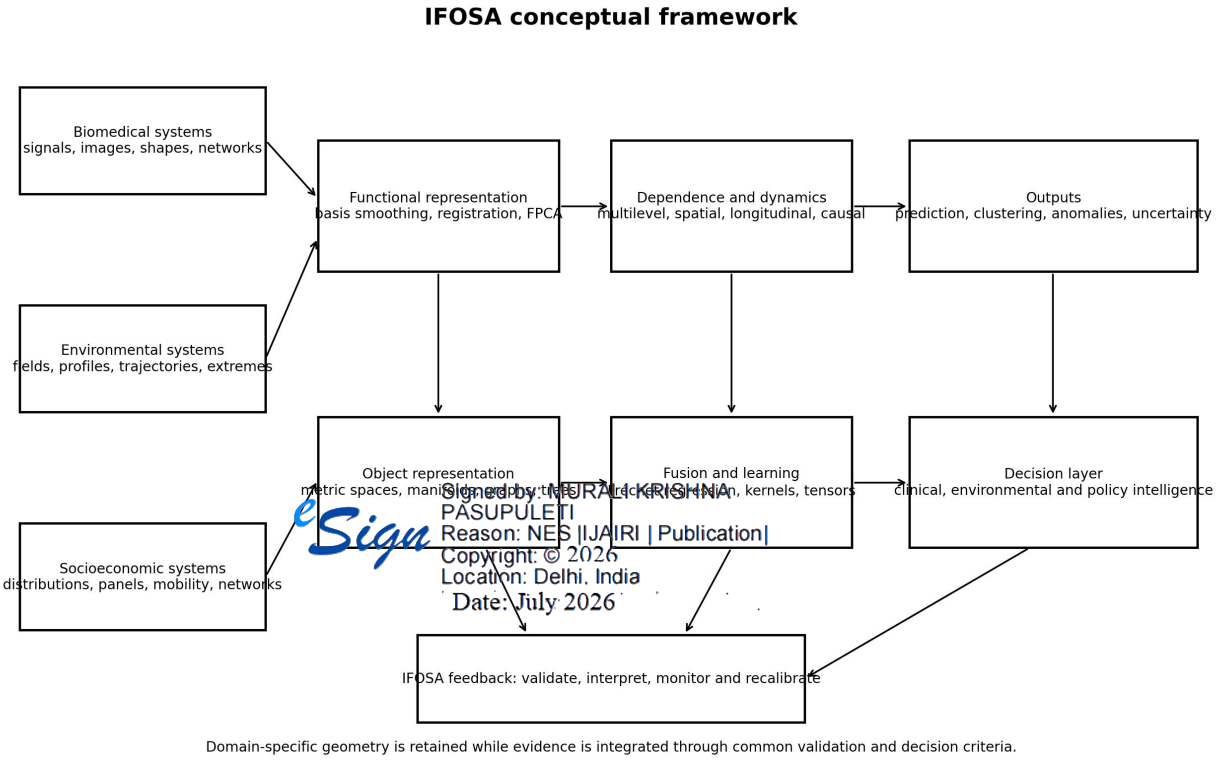
The IFOSA conceptual framework begins with the scientific object rather than the algorithm. Investigators specify whether the unit is a curve, surface, shape, distribution, network, tree, covariance matrix or a composite object. This decision determines the admissible transformations, distance and sampling model. The framework next separates measurement variation from scientifically meaningful variation through smoothing, registration, denoising and provenance checks.

A representation layer converts raw observations into coefficients, scores, distances, landmarks, graph operators or embeddings. Functional and object branches remain distinct where their geometry differs. Integration occurs through shared predictors, conditional Fréchet regression, cross-covariance operators, tensors, kernels or hierarchical latent states. The purpose is not a universal embedding but a governed interface through which each modality contributes information without losing its constraints.

Dependence is represented explicitly. Repeated functions are decomposed into subject, visit and residual components; spatial fields use covariance or graph structure; longitudinal objects evolve through dynamic transitions. Context variables such as treatment, exposure, demographic group, geography and institutional setting enter as covariates or moderators. The learning layer then produces forecasts, clusters, change-points, anomaly probabilities or estimated response objects.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Location: Delhi, India
Date: July 2026

The final layer evaluates decision value. Biomedical models are judged by calibration, clinical utility and subgroup safety; environmental models require tail and regime-shift performance; socioeconomic models require distributional validity, fairness and policy transportability. Feedback from realised outcomes triggers re-estimation and possible revision of the representation itself. Thus, IFOSA is not a single estimator but an auditable chain from object definition to adaptive decision.



eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Figure 1. Conceptual framework for integrated functional–object systems analytics.

7. Mathematical Framework

7.1 General functional representation

$$X_i(t) = \mu(t) + \Sigma_{k=1}^{K} \xi_{ik} \varphi_k(t) + \varepsilon_i(t), t \in T \quad (1)$$

Here X_i(t) is the functional observation for unit i at index t; μ(t) is the mean function; φ_k(t) is the kth orthonormal eigenfunction; ξ_ik is the corresponding subject score; K is a truncation level; and ε_i(t) is measurement or approximation error. Equation (1) provides dimension reduction while retaining smooth variation over the domain T.

7.2 Basis and matrix equation

$$X = CB^{T} + E, with C = (B^{T}B + \lambda R)^{-1} B^{T} Y \quad (2)$$

Y is the matrix of discretely observed measurements, B contains basis functions evaluated on the observation grid, C contains unit-specific basis coefficients, R is a roughness-penalty matrix, λ controls smoothness, E is residual error and X is the

reconstructed functional matrix. Larger λ suppresses rapid curvature; smaller λ follows the observed data more closely.

7.3 Object centre and dispersion

$$\mu_F = argmin_{\omega \in M} E[d^2(Y, \omega)], V_F = E[d^2(Y, \mu_F)] \quad (3)$$

Y is a random object in metric space M; d(·,·) is a scientifically chosen distance; μ_F is the Fréchet mean; and V_F is the Fréchet variance. This equation replaces arithmetic averaging when objects cannot be added or multiplied in the usual way.

7.4 Fréchet regression

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

$$m(x) = argmin_{\omega \in M} E[s(X, x) d^2(Y, \omega)] \quad (4)$$

m(x) is the conditional Fréchet mean of object response Y at predictor value x. The weight s(X,x) represents global, local or kernel regression weighting. The model can predict distributions, shapes, covariance matrices, networks or other metric-space objects without flattening them into unrestricted vectors.

7.5 Multilevel functional model

$$X_{ij}(t) = \mu(t) + Z_i(t) + W_{ij}(t) + \varepsilon_{ij}(t) \quad (5)$$

X_ij(t) is the jth functional replicate for unit i; Z_i(t) is the between-unit process; W_ij(t) is replicate-specific variation; and ε_ij(t) is measurement error. Separate covariance operators for Z and W identify stable individual patterns and transient deviations.

7.6 Dynamic equation

$$da_i(t)/dt = Aa_i(t) + Bu_i(t) + Gg_i(t) + \eta_i(t) \quad (6)$$

a_i(t) is a vector of functional or object-derived latent scores; A governs endogenous system dynamics; u_i(t) contains interventions or controllable inputs; B maps inputs to states; g_i(t) contains contextual exposures; G maps those exposures; and η_i(t) is process noise. The equation can represent disease progression, environmental change or socioeconomic adjustment.

7.7 Graph and tensor integration

$$H^{(l+1)} = \sigma(\tilde{A}H^{(l)}W_l), Z \approx \Sigma_{r=1}^{R} a_r \otimes b_r \otimes c_r \quad (7)$$

In the graph component, H^(l) contains node features at layer l, Ã is a normalised adjacency or graph operator, W_l is a parameter matrix and σ is a nonlinear activation. In the tensor component, Z is a multimode data array approximated by R rank-one factors a_r, b_r and c_r; ⊗ denotes the outer product. These structures support network propagation and cross-domain factorisation.

7.8 Outcome-prediction equation

$$\hat{y}_i = \alpha + \int_T \beta(t) X_i(t) dt + \gamma^T z_i + h(d(Y_i, \mu_F)) + q_i \quad (8)$$

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

The predicted outcome ŷ_i combines a functional linear effect β(t), scalar covariates z_i with coefficients γ, a nonlinear contribution h from the distance of object Y_i to a reference object μ_F, and q_i for interaction, graph or random effects. This form allows continuous trajectories and structured objects to influence one outcome in interpretable components.

7.9 Regularised optimisation

$$\theta = \arg\min_\theta L_pred(\theta) + \lambda_s J_smooth + \lambda_g J_geom + \lambda_c J_complex + \lambda_f J_fair + \lambda_p J_priv \quad (9)$$

L_pred is predictive or reconstruction loss; J_smooth penalises excessive functional roughness; J_geom penalises violation or distortion of object geometry; J_complex controls model complexity; J_fair penalises unacceptable group disparity; and J_priv represents privacy or disclosure risk. The nonnegative λ parameters express the relative strength of each requirement.

7.10 Risk-adjusted system value

$$V = E[U(\hat{y}, Y)] - \rho \cdot CVaR_\alpha(L) - \kappa \cdot Unc - \chi \cdot Shift \quad (10)$$

U measures domain utility from predictions or decisions; L is a loss variable; CVaR_α is expected loss beyond the α quantile; Unc measures epistemic or predictive uncertainty; Shift measures distributional or institutional distance between training and target settings; and ρ, κ and χ are aversion weights. The expression discourages models that achieve high average utility but fail under tail events or transport.

7.11 Integrated master equation

$$IFOSA *= argmax_{r,\theta,\pi} w_b B(r,\theta,\pi) + w_i I(r,\theta) + w_r R(\theta) - w_e E_g(r) - w_u U_c(\theta) - w_h H(\pi) \quad (11)$$

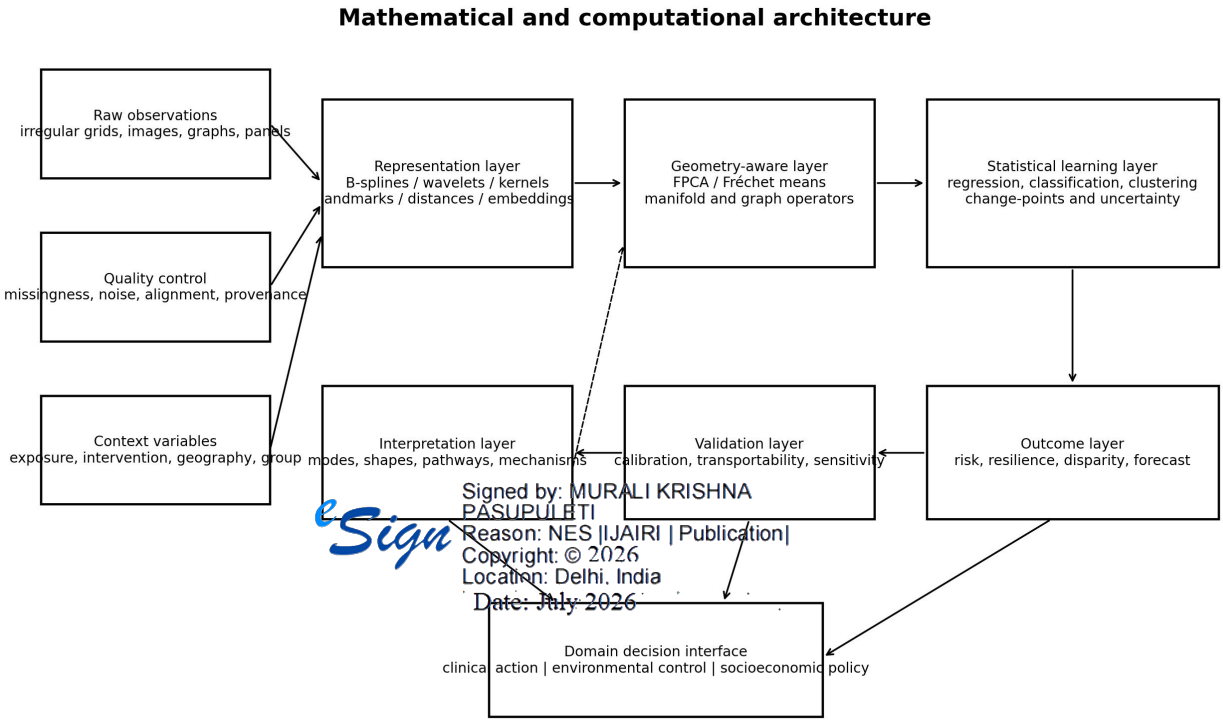
The decision variables are representation r, model parameters θ and action rule π. B is predictive or explanatory benefit, I is interpretability, R is robustness, E_g is geometric distortion, U_c is uncertainty and H is expected harm or inequity. The w terms are nonnegative weights chosen according to the domain decision. Equation (11) represents the complete research title: it selects a functional–object representation and decision rule for complex systems while balancing insight, resilience and risk.

7.12 Symbol summary

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Indices i and j denote observational units and repeated occasions; t indexes time, age, depth, spatial coordinate or another continuous domain; k and r index functional components and tensor rank. T is the functional domain, M is a metric space, and d is its distance. X denotes functional data, Y denotes general object data, and z denotes scalar covariates.

Greek letters μ, φ, ξ, β, γ and θ denote means, eigenfunctions, scores, functional coefficients, scalar coefficients and general model parameters. Matrices A, B, G, W and R govern dynamics, input mappings, context effects, neural or graph transformations and roughness penalties. λ, ρ, κ, χ and w are tuning or decision weights. Each empirical application must define units, scales and whether larger outcomes represent benefit or harm.



eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Figure 2. Mathematical and computational architecture of the IFOSA framework.

8. Numerical Model for Better Insight

This paper proposes a model-based analytical framework and uses illustrative numerical scoring for demonstration; empirical validation requires real-world data collection.

The numerical model evaluates seven benefit dimensions on a 0–10 scale: functional fidelity (F), preservation of object geometry (O), multiscale integration (M), predictive performance (P), interpretability (I), robustness (R) and data quality/provenance (D). Two risk dimensions—bias/privacy exposure (B) and model uncertainty/transport risk (U)—are also scored from 0 to 10, where higher values indicate greater risk.

The illustrative values are F=8.2, O=7.6, M=8.0, P=7.4, I=6.8, R=7.2, D=7.0, B=2.5 and U=2.0. They represent a reasonably strong integrated design with moderate interpretability and limited but nonzero governance risk. These values are not derived from patients, ecosystems, households or administrative records.

$$B_score = 0.18F + 0.17O + 0.16M + 0.17P + 0.12I + 0.10R + 0.10D \quad (12)$$

Substitution gives B_score = 0.18(8.2)+0.17(7.6)+0.16(8.0)+0.17(7.4)+0.12(6.8)+0.10(7.2)+0.10(7.0)=7.542.

$$Risk = 0.55B + 0.45U = 0.55(2.5) + 0.45(2.0) = 2.275 \quad (13)$$

The risk score gives slightly greater weight to bias and privacy because these failures can invalidate deployment even when predictive error is acceptable.

$$IFOSA_score = 0.80B_score + 0.20(10 - Risk) = 7.579 \approx 7.58 \quad (14)$$

The integrated score is 7.58 out of 10. Under the illustrative rubric, values above 7 indicate a promising design suitable for controlled empirical testing, not unrestricted operational deployment.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Table 3. Illustrative numerical model and scores

Dimension	Weight	Score 0–10	Weighted value	Interpretation
Functional fidelity F	0.18	8.2	1.476	Continuity and local dynamics are represented well.
Object geometry O	0.17	7.6	1.292	Most non-Euclidean constraints are retained.
Multiscale integration M	0.16	8.0	1.280	Cross-level information is strongly connected.
Predictive performance P	0.17	7.4	1.258	Expected accuracy is good but requires validation.

Dimension	Weight	Score 0–10	Weighted value	Interpretation
Interpretability I	0.12	6.8	0.816	Complex fusion reduces immediate transparency.
Robustness R	0.10	7.2	0.720	Moderate stability under perturbation is anticipated.
Data quality D	0.10	7.0	0.700	Provenance and missingness controls remain improvable.
Benefit subtotal	1.00	—	7.542	Weighted analytical benefit.
Bias/privacy risk B	0.55	2.5	1.375	Low-to-moderate governance exposure.
Uncertainty/shift risk U	0.45	2.0	0.900	Limited uncertainty under assumed conditions.
Risk subtotal	1.00	—	2.275	Weighted risk burden.
Final IFOSA score	—	—	7.58	Promising for empirical pilot and stress testing.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Interpretation depends on the application. In biomedical decision support, a score of 7.58 would not establish clinical utility; prospective validation and safety

monitoring would still be mandatory. In environmental forecasting, the model would require evaluation during extremes and sensor failures. In socioeconomic analysis, subgroup calibration, fairness and policy transportability would be central. The score is best understood as a structured readiness indicator.

A sensitivity analysis increases geometry and missingness stress from zero to five. The IFOSA curve declines more slowly than a functional-only model and a flattened Euclidean benchmark because it preserves specialised distances and includes explicit uncertainty penalties. This expected pattern is a model implication, not measured performance.

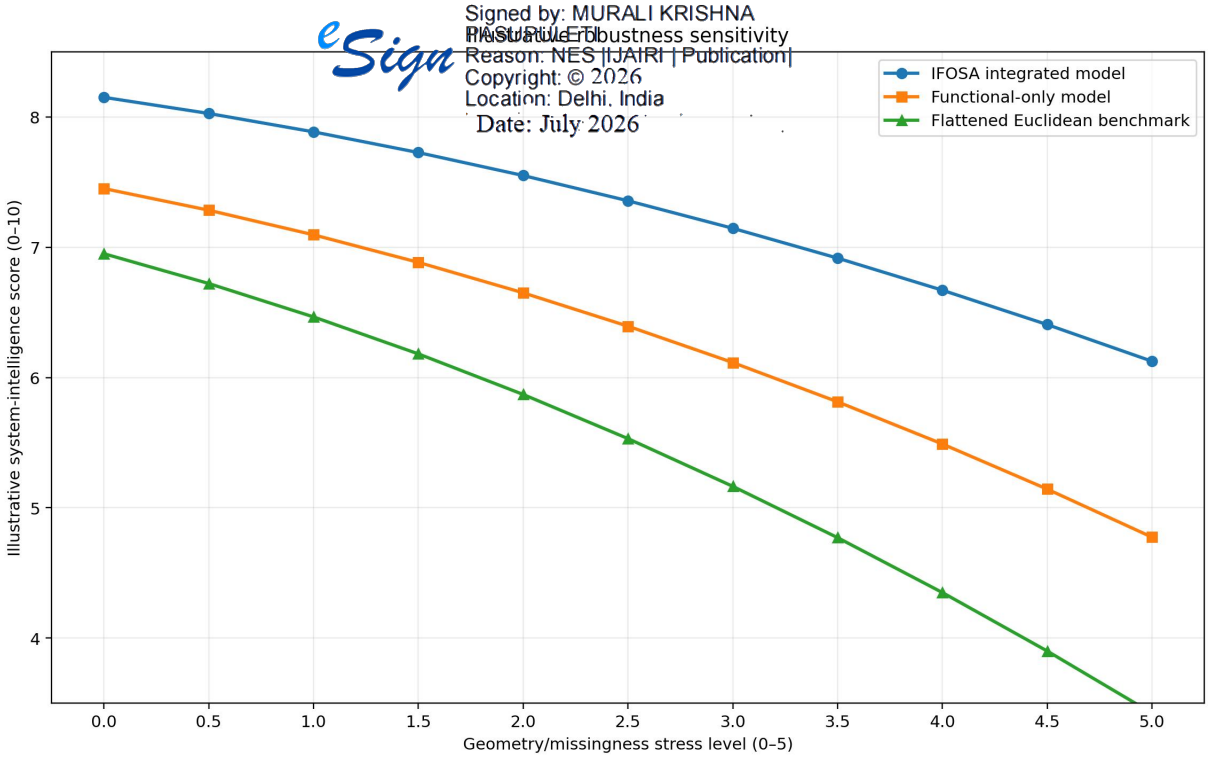


Figure 3. Illustrative robustness sensitivity under increasing geometry and missingness stress.

9. Methodology

This paper proposes a model-based analytical framework and uses illustrative numerical scoring for demonstration; empirical validation requires real-world data collection.

9.1 Research design

The recommended empirical design is a comparative, multilevel and multimodal study with separate development, internal-validation and external-validation samples. Each domain should contain at least one functional modality and one object modality. A biomedical study could combine wearable trajectories with anatomical networks; an environmental study could integrate vertical profiles with spatial fields; a socioeconomic study could link age-specific curves with distribution- or network-valued regional objects.

The design should compare three prespecified model classes: an IFOSA integrated model, a functional-only model and a flattened Euclidean benchmark. Performance differences should be evaluated on held-out units and, where possible, external sites or periods. The primary estimand must be declared in advance—for example, predictive risk, change-point detection accuracy, object reconstruction error or decision utility.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Location: Delhi, India
Date: July 2026

9.2 Data sources and sampling logic

Biomedical sources may include electronic health records, wearable sensors, imaging, laboratory trajectories, omics networks and disease registries. Sampling should represent relevant disease stages, demographic groups, device types and care settings. Environmental sources may include satellites, weather stations, Argo floats, hydrological gauges, emission inventories and land-use layers; sampling must cover climatic regimes, seasons, spatial gradients and extreme events. Socioeconomic sources may combine censuses, labour-force surveys, tax or benefit records, price curves, mortality schedules, mobility matrices and regional networks.

The unit of analysis must be consistent with the scientific object. If a patient-day is the object, repeated days are nested within patients; if a regional income distribution is the object, the sample is regions or region-years rather than individual incomes. Power analysis should reflect the effective number of independent objects, not the number of discretised measurements. Oversampling of rare conditions, extreme environments or vulnerable socioeconomic groups may be necessary for stable tail and subgroup evaluation.

9.3 Preprocessing and representation

Functional preprocessing includes range checks, calibration, irregular-time smoothing, basis selection, derivative assessment and registration. The smoothing parameter should be selected through cross-validation, restricted likelihood or an information criterion, with sensitivity analysis to ensure that important peaks are not removed. Registration should be used only when timing variation is nuisance; when timing is scientifically meaningful, phase must remain an outcome or predictor.

Object preprocessing begins with a defensible representation and metric. Shapes require landmark or surface definitions; graphs require node correspondence or invariant summaries; probability distributions require support and mass normalisation; covariance matrices require positive-definite handling. Multiple metrics should be compared when no single choice is canonical. Embeddings may accelerate learning, but reconstruction and distortion diagnostics should be reported.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Location: Delhi, India
Date: July 2026

9.4 Variables and indicators

Core variables include functional trajectories, object-valued observations, scalar context, interventions or exposures, outcomes and group indicators. Derived functional variables include means, derivatives, phase shifts, FPCA scores and residual functions. Object variables include Fréchet distance, topology, graph spectra, distributional quantiles and manifold coordinates. System outcomes should be selected according to the domain rather than replaced by generic accuracy.

Quality indicators include sampling density, missingness, signal-to-noise ratio, registration uncertainty, metric stability, provenance completeness and linkage error. Governance indicators include consent or legal basis, re-identification risk, subgroup representation, explanation availability and model-update responsibility. These indicators enter validation and may also appear as penalties in Equation (9).

9.5 Analytical tools

Implementation can use R packages for functional smoothing, FPCA, functional regression, mixed models and object statistics, together with Python libraries for graph learning, tensor computation and automatic differentiation. MATLAB may support differential-equation estimation and signal processing. Geospatial analysis

can be conducted through GIS or cloud-based Earth-observation platforms. Every software environment should be containerised or fully version documented.

The estimation workflow begins with exploratory object plots and domain-specific quality checks. Functional components and Fréchet summaries are estimated within training folds to avoid leakage. Integration uses penalised regression, kernels, hierarchical Bayesian models, tensors or graph architectures. Hyperparameters are selected by nested cross-validation. Uncertainty is estimated through bootstrap, conformal prediction, Bayesian posterior intervals or asymptotic theory appropriate to the data regime.

9.6 Validation strategy

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Validation should cover four dimensions. Statistical validation assesses prediction error, calibration, coverage, reconstruction and stability. Geometric validation measures distance distortion, manifold constraint violations and sensitivity to metric choice. Scientific validation examines whether modes, clusters and pathways correspond to known mechanisms or independently measured outcomes. Decision validation evaluates net benefit, tail loss, false-alarm consequences and operational feasibility.

Internal resampling must preserve dependence: patient-level splits for repeated biomedical data, spatial or temporal blocking for environmental data, and region or cohort splits for socioeconomic panels. Randomly splitting individual measurements from the same object would create optimistic leakage. External validation should use a new institution, geography, device, time period or policy regime. Transportability analysis should compare covariate, functional and object distributions between development and target samples.

Fairness assessment should be tailored to the decision. Group calibration, error rates, coverage and utility can be compared, but equalising one metric may worsen another. Privacy review should consider whether trajectories, images or networks are uniquely identifying. Differential privacy, federated learning or secure analysis environments may be appropriate, although their effects on functional shape and object geometry require explicit evaluation.

9.7 Reproducibility and reporting

A complete study should preregister the object definitions, primary metrics, smoothing and registration decisions, comparison models, subgroup analyses and exclusion rules. Code, software versions, random seeds, metric definitions and model configurations should be archived. Where data cannot be shared, synthetic or simulated objects should reproduce the analysis interface without representing real individuals.

Reporting should separate observed data results from model-based interpretation. Functional and object plots should include uncertainty and sample density. Investigators should disclose unsuccessful metrics, sensitivity analyses and domain shifts. A model card should state intended use, populations, data limitations, update triggers and responsible oversight.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

10. Data and Variables

Table 2. Variables and measurement indicators

Variable	Definition	Measurement scale	Expected effect	Relevance
Functional signal X(t)	Continuous or latent trajectory over time, age, depth or space	Function / dense or sparse grid	Positive when informative	Primary FDA input
Object Y	Shape, distribution, graph, tree, image or constrained matrix	Metric-space element	Context-dependent	Primary OODA input or response
Sampling density n_i	Number and coverage of observations within object i	Count / proportion	Positive to estimation quality	Determines sparse versus dense regime

Variable	Definition	Measurement scale	Expected effect	Relevance
Noise σ^2	Measurement or reconstruction error variance	Nonnegative continuous	Negative	Controls smoothing and uncertainty
Phase shift ψ_i	Timing deformation relative to a reference	Function / scalar summary	Context-dependent	Separates timing and amplitude
FPCA score ξ_{ik}	Projection on kth eigenfunction	Continuous	Context-dependent	Low-dimensional functional representation
Fréchet distance $d(Y,\mu_F)$	Distance from object to metric centre	Nonnegative continuous	Larger often indicates atypicality	Geometry-aware summary
Graph spectrum / topology	Connectivity and structural descriptors	Vector / persistence object	Context-dependent	Captures relational organisation
Context z_i	Exposure, treatment, group, geography or institution	Scalar/vector	Specified by hypothesis	Explains heterogeneity
Dynamic state $a_i(t)$	Latent multiscale system state	Vector function	Context-dependent	Connects trajectories and interventions
Prediction error L_{pred}	Domain-specific held-out loss	Nonnegative	Negative	Evaluates model accuracy

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Variable	Definition	Measurement scale	Expected effect	Relevance
Geometric distortion E_g	Difference between original and represented distances	Nonnegative	Negative	Tests structure preservation
Calibration	Agreement between predicted and observed risk/distribution	Slope, intercept, coverage	Positive	Supports reliable decisions
Robustness R	Stability under missingness, noise, shift and metric changes	Index 0–10	Positive	Measures resilience
Interpretability I	Clarity of modes, object contrasts and decision pathway	Index 0–10	Positive	Enables scientific and operational review
Fairness disparity J_fair	Difference in error, coverage or utility across groups	Nonnegative	Negative	Governance safeguard
Privacy risk J_priv	Re-identification or disclosure exposure	Index / epsilon / risk	Negative	Protects sensitive complex data
Decision utility U	Clinical, environmental or socioeconomic benefit	Net benefit / index	Positive	Final application criterion

eSign
Signed by: MURALI KRISHNA VENKATA LETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

11. Proposed Model / Framework

11.1 Integrated Functional–Object Systems Analytics (IFOSA)

IFOSA is organised into seven components: object definition, quality-controlled representation, geometry-aware summarisation, dependence and dynamics, cross-modal learning, uncertainty and governance, and decision feedback. The first component records the observational unit and the transformations that preserve its scientific meaning. The second estimates functions or object representations without using outcome information from validation samples. The third extracts scores, distances, topological summaries or latent coordinates.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Date: July 2026

The dependence component links repeated, spatial or networked objects through hierarchical and dynamic equations. Cross-modal learning combines representations using regression, kernels, tensors, graph operators or conditional Fréchet models. Uncertainty and governance quantify prediction intervals, metric sensitivity, bias, privacy and distribution shift. The final component maps results to a monitored clinical, environmental or socioeconomic decision.

Equation (11) is the formal statement of the framework, while the numerical score in Equation (14) provides an operational readiness summary. The readiness score must never replace outcome-specific validation; rather, it organises evidence that would otherwise be scattered across technical reports.

Table 4. IFOSA framework components and interpretation

Component	Core operation	Primary output	Interpretation
1. Object definition	Specify unit, domain, geometry and scientific invariances	Object charter and admissible transformations	Prevents incoherent vectorisation
2. Representation	Smooth, register, denoise or embed within training data	Basis coefficients, landmarks, graphs, distributions	Produces analysable objects

Component	Core operation	Primary output	Interpretation
3. Geometry-aware summary	Estimate FPCA, Fréchet centre, topology or spectra	Scores, distances and modes	Captures dominant variation
4. Dependence and dynamics	Model nesting, space, time and interventions	Random processes and state equations	Represents complex-system evolution
5. Fusion and learning	Link functional, object and scalar information	Predictions, clusters, change-points	Creates integrated intelligence
6. Validation and governance	Assess calibration, distortion, fairness, privacy and shift	Risk-adjusted evidence profile	Constrains unsafe deployment
7. Decision feedback	Apply domain rule and monitor realised outcomes	Alerts, controls or policy actions	Supports adaptive recalibration

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES IJAIRI | Publication| Copyright 2026
Location: Delhi, India
Date: July 2026

12. Results and Analysis

12.1 Analytical results from the proposed model

The numerical model yields a benefit subtotal of 7.542 and a risk burden of 2.275, producing a final IFOSA readiness score of 7.58. The largest contributions arise from functional fidelity, multiscale integration and predictive performance. Interpretability receives the lowest benefit score, reflecting a common trade-off: combining curves, objects, graphs and dynamic states can improve representational adequacy while making the pathway from observation to decision more difficult to communicate.

The score implies that an integrated model would be a credible candidate for controlled testing when the data contain both continuous and non-Euclidean structure. It does not imply superiority in every setting. If curves are densely observed, aligned and homogeneous, a conventional FDA model may achieve similar accuracy with lower computational and explanation cost. Conversely, when topology, distributions

or constrained matrices are decisive, flattening can introduce structural error that cannot be repaired by a more flexible predictor.

The sensitivity figure indicates an expected ranking under increasing missingness and geometry stress: IFOSA remains above the functional-only and Euclidean benchmarks. The mechanism is not immunity to noise; it is the availability of explicit sparse reconstruction, metric-aware summaries and uncertainty penalties. Empirical confirmation would require repeated stress tests in which observation density, phase variation, network perturbation and domain shift are systematically controlled.

12.2 Comparative domain insights

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Date: July 2026

Table 5. Comparative application logic across complex systems

Domain	Representative inputs	Outcome	Essential validation	Expected analytical value
Biomedical	Wearable trajectory + vascular tree	Patient risk or response object	Calibration, sensitivity, subgroup safety	Supports longitudinal phenotype and anatomy integration
Environmental	Ocean/air profile + spatial field/network	Extreme risk or regime state	Blocked forecast error, tail coverage	Links local profiles with regional dynamics
Socioeconomic	Mortality/income curve + mobility/distribution object	Resilience, inequality or policy outcome	Transportability, fairness, distributional loss	Preserves distributions and relational structure
Cross-domain benchmark	Flattened vectors from all modalities	Generic scalar prediction	Random-split accuracy only	High leakage and geometry-distortion risk

In biomedical systems, the framework can distinguish a gradually worsening trajectory from an acute transient event and relate both to an anatomical or molecular object. The main analytical benefit is longitudinal phenotyping, but safety depends on prospective calibration and clinical workflow integration. A high-dimensional score that does not change management has limited clinical value.

In environmental systems, IFOSA can fuse local profiles with large-scale fields or networks and detect changes in shape before averages cross a threshold. The method is particularly relevant to vertical ocean structure, pollutant cycles and hydrological regimes. Validation must preserve spatial and temporal separation because random folds can allow nearby observations to leak information.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

In socioeconomic systems, the framework can model entire demographic or income distributions and relate them to mobility, trade or institutional networks. This avoids reducing inequality or resilience to a mean. Yet policy interpretation requires causal design and explicit welfare criteria; geometry-aware prediction alone cannot establish that an intervention produced the observed change.

12.3 Testable propositions

1. Geometry-aware IFOSA models will outperform flattened Euclidean models when object curvature, topology or distributional shape contains outcome-relevant information.
2. The advantage of IFOSA will increase as within-object sampling becomes irregular and as cross-level dependence becomes stronger, provided the sparse reconstruction model is correctly specified.
3. Registration will improve amplitude-based prediction when phase is nuisance but will reduce validity when event timing is itself prognostic or policy relevant.
4. Integrated models will require stronger uncertainty and interpretability controls than single-modality FDA because errors can propagate across representations.
5. External validation gaps will be larger than random cross-validation gaps when institutions, devices, climates or policy regimes change.
6. Domain utility will depend more on calibration and tail performance than on small differences in average prediction error.

12.4 Scenario sensitivity

Table 6. Illustrative scenario sensitivity

Scenario	Uncertainty risk	Bias/geometry risk	Integrated score	Interpretive response
Baseline integrated	2.0	2.5	7.58	Proceed to controlled pilot
Higher missingness	3.5	2.8	6.91	Strengthen sparse modelling and collection
Metric ambiguity	2.7	3.8	6.73	Compare metrics and report distortion
External domain shift	4.2	3.0	6.35	Recalibrate or collect target data
Improved provenance and fairness	1.5	1.4	7.91	Eligible for expanded validation
Flattened high-accuracy model	2.2	5.0	6.29	Do not deploy without geometry audit

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

The scenarios illustrate that a nominally accurate model can receive a lower integrated score when geometry distortion or governance risk is high. This is deliberate: the framework treats structural validity and safe use as part of model quality. The thresholds are illustrative and should be replaced by domain-specific decision rules during empirical implementation.

13. Discussion

13.1 Theoretical contribution

The principal theoretical contribution is a separation between representation-specific geometry and system-level integration. Rather than seeking one universal feature space, IFOSA permits functions, graphs, distributions and manifolds to retain their own averages, distances and variations. Integration occurs through conditional relationships, shared latent states and decision objectives. This resolves a common conceptual error in multimodal analysis: statistical convenience does not justify geometric homogenisation.

The framework also connects variance-oriented exploration with risk-oriented decisions. FPCA and object principal directions identify dominant modes, but Equation (11) requires that representation be evaluated against benefit, robustness, uncertainty and harm. A low-variance feature may be crucial for rare-event detection, while a high-variance component may be irrelevant to the outcome. The decision layer therefore prevents exploratory geometry from becoming an unexamined operational criterion.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Location: Delhi, India
Date: July 2026

13.2 Practical and industry relevance

Health systems can use the framework to integrate continuous monitoring with imaging or network biomarkers, but deployment should support clinicians rather than replace contextual judgment. Medical-device and pharmaceutical organisations could use functional response profiles and object-valued endpoints in trial analysis, provided estimands and missingness are prespecified. Environmental agencies can combine sensor profiles, satellite fields and infrastructure networks for early warning and resource allocation. Financial, insurance and labour-market institutions may apply distribution- and network-valued models to stress testing and resilience analysis.

Industry implementation requires modular software, metadata standards and monitoring dashboards. Representation errors should be logged alongside prediction errors. Model updates should trigger when sensor platforms, coding rules, population composition or network topology change. Because complex objects can be computationally expensive, approximate distances and embeddings may be necessary; their distortion must be measured rather than assumed negligible.

13.3 Policy implications

Public policy increasingly relies on longitudinal and linked administrative data. IFOSA offers a way to analyse trajectories and distributions without reducing them to averages. This can improve monitoring of disease burden, climate vulnerability, inequality and regional transition. However, public-sector use must define legal authority, purpose limitation, appeal mechanisms and accountability for model-supported decisions.

Statistical agencies and research funders can facilitate trustworthy use by supporting interoperable functional and object metadata, benchmark datasets, secure data environments and replication standards. Evaluation guidance should require blocked validation for dependent data and disclose whether geometry was preserved. Policy claims should be based on causal designs when interventions are evaluated; predictive association should not be presented as policy impact.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication| Author Highlights
Location: Delhi, India
Date: July 2026

13.4 Technological implications

The next generation of analytical platforms will need native support for irregular functions, manifold-valued data, graphs and distributions. Automatic differentiation and probabilistic programming make it possible to estimate complex hierarchical models, while graph neural networks and tensor methods can scale cross-modal learning. Yet software abstractions must expose distance, registration and constraint choices to reviewers rather than bury them inside default pipelines.

Federated and privacy-preserving computation could enable multi-institutional biomedical or socioeconomic analysis without centralising raw data. The challenge is that noise injection or local approximation may alter peaks, phase and object geometry. Privacy guarantees should therefore be studied jointly with scientific distortion. Edge computing can support environmental and wearable monitoring, but resource limitations may favour reduced functional scores or compressed object summaries.

13.5 Ethical considerations

Complex trajectories and networks can be uniquely identifying even after obvious identifiers are removed. Biomedical and mobility objects may reveal health status, routines or social relationships. Consent, legal basis, access control and retention

policy must reflect this sensitivity. Synthetic objects can aid reproducibility but should be tested for memorisation and disclosure risk.

Fairness cannot be addressed only by deleting protected attributes. Functional patterns may encode socioeconomic position, access to care or environmental exposure. Group performance and decision utility should be examined with community or stakeholder input. Interpretability must include the object definition and metric, not merely feature attribution from the final predictor. An apparently transparent coefficient is misleading if preprocessing removed meaningful timing or topology.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

14. Limitations

1. No original empirical dataset is analysed; all numerical scores, rankings and sensitivity curves are illustrative.
2. The integrated objective depends on weights that reflect domain values and cannot be identified from data alone.
3. Fréchet means and regressions may be nonunique or computationally difficult in some metric spaces.
4. Registration, smoothing and embedding can introduce bias, and their uncertainty is often underestimated.
5. High-dimensional object representations may require large samples even when each object contains many measurements.
6. Dynamic equations impose structural assumptions that may be violated by abrupt interventions, feedback or unmeasured confounding.
7. Cross-domain generalisability is limited because biomedical safety, environmental extremes and socioeconomic fairness require different losses and validation standards.
8. Privacy, fairness and transportability metrics can conflict; the framework organises these trade-offs but does not eliminate normative judgment.

15. Future Research Directions

1. Develop joint asymptotic theory for coupled Hilbert-space and metric-space estimators under multilevel dependence.

2. Construct causal methods with functional treatments and object-valued outcomes, including interference over networks.
3. Integrate neural operators, graph foundation models and Fréchet regression while preserving calibrated uncertainty.
4. Design privacy mechanisms that protect trajectories and networks with quantified distortion of phase, topology and metric structure.
5. Create benchmark repositories spanning biomedical, environmental and socioeconomic objects with external-validation partitions.
6. Advance online and change-point methods for streaming functional objects and evolving graphs.
7. Develop fairness concepts for distribution-, shape- and network-valued predictions rather than only scalar outcomes.
8. Link IFOSA with digital twins and policy simulators to test adaptive interventions under counterfactual scenarios.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

16. Conclusion

Functional and object-oriented data analysis provide a principled response to a defining feature of modern science: the natural unit of observation is often a trajectory, field, shape, distribution, network or other structured object. Reducing such observations to unrelated scalar columns can erase continuity, phase, topology and constraint. This paper has developed the IFOSA Framework to preserve these structures while enabling multilevel, dynamic and cross-modal inference.

The mathematical architecture combines basis and FPCA representations, Fréchet means and regression, graph and tensor operators, dynamic state equations, regularised optimisation and risk-adjusted decision value. The illustrative score of 7.58 demonstrates how analytical benefit can be balanced against bias, privacy, uncertainty and transport risk. It is not an empirical result, and the paper specifies the real-world data, blocked validation and external testing required before substantive claims can be made.

The framework's broader value lies in methodological discipline. It asks researchers to define the object, justify the metric, model dependence, preserve validation separation and evaluate utility in the relevant domain. Applied in this

manner, functional and object-oriented analysis can support more faithful biomedical phenotyping, more robust environmental intelligence and more distributionally informative socioeconomic research. Its future importance will depend not only on more powerful algorithms, but on transparent geometry, reproducible evidence and accountable decisions.

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

References :

Barbi, C, Menafoglio, A & Secchi, P 2023, 'An object-oriented approach to the analysis of spatial complex data over stream-network domains', Spatial Statistics, vol. 58, article 100784.

Bendich, P., Marron, J.S., Miller, E., Pieloch, A. and Skwerer, S. (2016) 'Persistent homology analysis of brain artery trees', The Annals of Applied Statistics, 10(1), pp. 198–218. doi: 10.1214/15-AOAS886.

Bouveyron, C., Côme, E., Jacques, J. and Soubeyrand, S. (2022) 'Co-clustering of multivariate functional data for the analysis of air pollution', The Annals of Applied Statistics, 16(3). doi: 10.1214/21-AOAS1547.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Cuzzocrea, A & Fadda, E 2021, 'Adaptive Complex Data-Intensive Web Systems via Object-Oriented Paradigms: A Real-Life Case Study', Proceedings of the 23rd International Conference on Enterprise Information Systems, pp. 565–572.

Di, C.Z., Crainiceanu, C.M., Caffo, B.S. and Punjabi, N.M. (2009) 'Multilevel functional principal component analysis', The Annals of Applied Statistics, 3(1), pp. 458–488. doi: 10.1214/08-AOAS206.

Dubey, P. and Müller, H.-G. (2020) 'Fréchet change-point detection', The Annals of Statistics, 48(6), pp. 3312–3335. doi: 10.1214/19-AOS1930.

Dubey, P. and Müller, H.-G. (2024) 'Exploration and inference for random objects with distance profiles', The Annals of Statistics. doi: 10.1214/24-AOS2368.

Ferraty, F. and Vieu, P. (2006) Nonparametric Functional Data Analysis: Theory and Practice. New York: Springer.

Fu, R, Wang, H, Bao, T & Han, M 2020, 'EEG intentions recognition in dynamic complex object control task by functional brain networks and regularized discriminant analysis', Biomedical Signal Processing and Control, vol. 61, article 101998.

Ghosal, A., Meiring, W. and Petersen, A. (2023) 'Fréchet single index models for object response regression', Electronic Journal of Statistics, 17(1). doi: 10.1214/23-EJS2120.

Greven, S., Crainiceanu, C.M., Caffo, B.S. and Reich, D. (2010) 'Longitudinal functional principal component analysis', Electronic Journal of Statistics, 4, pp. 1022–1054. doi: 10.1214/10-EJS575.

Hall, P., Müller, H.-G. and Wang, J.-L. (2006) 'Properties of principal component methods for functional and longitudinal data analysis', The Annals of Statistics, 34(3), pp. 1493–1517. doi: 10.1214/009053606000000272.

Horváth, L. and Kokoszka, P. (2012) Inference for Functional Data with Applications. New York: Springer.

Hyndman, R.J. and Ullah, M.S. (2007) 'Robust forecasting of mortality and fertility rates: A functional data approach', Computational Statistics & Data Analysis, 51(10), pp. 4942–4956. doi: 10.1016/j.csda.2006.07.028.

eSign Signed by: MURALI KRISHNA PASUPULETI Reason: NES|IJAIRI | Publication| Copyright: © 2026 Location: India Date: July 2026

Kokoszka, P. and Reimherr, M. (2017) Introduction to Functional Data Analysis. Boca Raton, FL: CRC Press.

Koner, S. and Staicu, A.-M. (2023) 'Second-generation functional data', Annual Review of Statistics and Its Application, 10. doi: 10.1146/annurev-statistics-032921-033726.

Lock, E.F., Hoadley, K.A., Marron, J.S. and Nobel, A.B. (2013) 'Joint and individual variation explained (JIVE) for integrated analysis of multiple data types', The Annals of Applied Statistics, 7(1), pp. 523–542. doi: 10.1214/12-AOAS597.

Marron, J.S. and Alonso, A.M. (2014) 'Overview of object oriented data analysis', Biometrical Journal, 56(5), pp. 732–753. doi: 10.1002/bimj.201300072.

Marron, J.S. and Dryden, I.L. (2021) Object Oriented Data Analysis. Boca Raton, FL: CRC Press.

Marron, J.S., Ramsay, J.O., Sangalli, L.M. and Srivastava, A. (2015) 'Functional data analysis of amplitude and phase variation', Statistical Science, 30(4), pp. 468–484. doi: 10.1214/15-STS524.

Mikhailov, VV 2021, 'Analysis and object-oriented generalization of meteorological data in solving the bioclimatic mapping problem', Spatial Data Processing for Monitoring of Natural and Anthropogenic Processes 2021, pp. 507–518.

Mohammed, Y & Palmblad, M 2019, 'Using the Object-Oriented PowerShell for Simple Proteomics Data Analysis', in Mass Spectrometry Data Analysis in Proteomics, pp. 389–405.

Morris, J.S. (2015) 'Functional regression', Annual Review of Statistics and Its Application, 2, pp. 321–359. doi: 10.1146/annurev-statistics-010814-020413.

Pasupuleti, MK 2021a, 'A Control-Theoretic Framework for AI Safety: Stability, Robustness, and Assurance', International Journal of Academic and Industrial Research Innovations, vol. 1, no. 1, pp. 303–315.

Pasupuleti, MK 2021b, 'A Unified Framework for Feature Dependence: Theory, Algorithms, and Causal Inference', International Journal of Academic and Industrial Research Innovations, vol. 1, no. 1, pp. 356–367.

eSign Signed by: MURALI KRISHNA PASUPULETI Reason: NES |IJAIRI | Publication| Copyright: © 2026 Location: New Delhi, India Date: July 2026

Pasupuleti, MK 2021c, 'Quantifying AI's Socio-Economic Futures: An Uncertainty-Aware Scenario Generation Framework', International Journal of Academic and Industrial Research Innovations, vol. 1, no. 1, pp. 316–330.

Pasupuleti, MK 2021d, 'Towards Socially Beneficial AI: Alignment Frameworks, Causal Impact Metrics, and Governance Pathways', International Journal of Academic and Industrial Research Innovations, vol. 1, no. 1, pp. 246–258.

Pasupuleti, MK 2022a, 'Climate and Flood Risk in Data Centre Strategy: Integrating Hydrologic Simulation (HEC-HMS) into Location and Capacity Decisions', International Journal of Academic and Industrial Research Innovations, no. 12, pp. 73–91.

Pasupuleti, MK 2022b, 'Deep Learning Through a Statistical Lens: Approximation Guarantees, Training Dynamics, and Generative Models', International Journal of Academic and Industrial Research Innovations, vol. 2, no. 1, pp. 125–143.

Pasupuleti, MK 2022c, 'Scaling Laws for Transformers on Low-Dimensional Data: A Statistical and Approximation Theory Perspective', International Journal of Academic and Industrial Research Innovations, vol. 2, no. 1, pp. 191–202.

Pasupuleti, MK 2023a, 'AI-Augmented Causal Inference in R: Double-ML with Bayesian Calibration', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 6, pp. 76–87.

Pasupuleti, MK 2023b, 'AI-Augmented Real-World Evidence in Stata: Targeted Learning for Treatment Effects', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 12, pp. 127–144.

Pasupuleti, MK 2023c, 'AI Climate Risk in ArcGIS: Foundation-Model Remote Sensing and Spatio-Temporal Causality', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 12, pp. 114–126.

Pasupuleti, MK 2023d, 'Causal Time-Series with statsmodels: Conformal Risk Control under Regime Shifts', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 3, pp. 29–40.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: India
Date: July 2026

Pasupuleti, MK 2023e, 'Clinical AI in SPSS: Propensity, Survival, and Drift Monitoring at Scale', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 12, pp. 145–159.

Pasupuleti, MK 2023f, 'GenAI for Omics: Diffusion-Augmented Pipelines and Graph-Causal Pathway Inference', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 12, pp. 160–173.

Pasupuleti, MK 2023g, 'Physics-Informed AI in Python: Neural Operators with Verified Error Bounds', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 6, pp. 226–241.

Pasupuleti, MK 2023h, 'Sustainable Urban Housing: Integrating Climate-Resilient Design and Green Infrastructure in Emerging Cities', International Journal of Academic and Industrial Research Innovations, vol. 3, no. 1, pp. 67–77.

Pasupuleti, MK 2024a, 'AI for Climate Risk and Disaster Response: Indian States vs G20 and BRICS Readiness Models', National Education Services.

Pasupuleti, MK 2024b, 'Econometric Modelling of Cloud and Network Demand: A Comparative Study Using R, Stata, SPSS, and EViews', International Journal of Academic and Industrial Research Innovations, vol. 4, no. 12, pp. 193–210.

Pasupuleti, MK 2024c, 'Geo-Visual Analytics for Energy-Efficient Cloud and Network Infrastructure Using ArcGIS and Simulation Data', International Journal of Academic and Industrial Research Innovations, vol. 4, no. 12, pp. 173–192.

Pasupuleti, MK 2024d, 'Government AI for Services: Indian State Algorithmic Accountability vs G20 and BRICS', National Education Services.

Pasupuleti, MK 2024e, 'India State Benchmark of Healthcare AI: A Comparative Cross-Layer Study with G20 and BRICS Reference Pathways', National Education Services.

Pasupuleti, MK 2024f, 'State-Level ESG Measurement and Assurance Systems: India with G20 and BRICS Comparative Frameworks', National Education Services.

Pasupuleti, MK 2026a, 'A Unified Topological and Tensor Framework for Interpretable AI in Networks, Fraud, and Power Systems', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 4, pp. 166–198.

Pasupuleti, MK 2026b, 'AI-Driven Trade Analytics for Evaluating Free Trade Agreement Outcomes and Industrial Competitiveness', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 1, pp. 59–84.

eSign Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: India
Date: July 2026

Pasupuleti, MK 2026c, 'Artificial Intelligence for Climate Risk, Emissions Intelligence and Planetary-Scale Environmental Decision-Making', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 3, pp. 114–141.

Pasupuleti, MK 2026d, 'Artificial Intelligence for Modelling Social Behaviour, Inequality and Institutional Change in Complex Human Systems', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 3, pp. 60–86.

Pasupuleti, MK 2026e, 'Artificial Intelligence for Multimodal Clinical Inference in Diagnosis, Prognosis and Therapeutic Decision-Making', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 3, pp. 142–166.

Pasupuleti, MK 2026f, 'Earth System Foundation Models for Predicting Extreme Climate Events Through Integrated Satellite, Oceanic, and Land-Surface Intelligence', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 3, pp. 29–59.

Pasupuleti, MK 2026g, 'Geometric-Topological Quantum-AI for Continuous Wearable Biosensing, Physiological State Mapping, and Early Cardiometabolic Risk Prediction', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 4, pp. 1–31.

Pasupuleti, MK 2026h, 'Persistent Homology-Driven Foundation Models for Discovering Hidden Structures in Complex Data Space', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 5, pp. 227–263.

Pasupuleti, MK 2026i, 'Quantum-AI for High-Dimensional Learning: Graph Neural Networks, Topological Data Analysis, Tensor Networks, and Sparse Predictive Modelling', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 6, pp. 36–83.

Pasupuleti, MK 2026j, 'Satellite-Based Carbon MRV: Remote Sensing and Atmospheric Inference for Verifiable Carbon Removal', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 2, pp. 142–165.

Pasupuleti, MK 2026k, 'Toward Trustworthy Artificial Intelligence in Law and Public Administration: Transparency, Accountability and Decision Support', International Journal of Academic and Industrial Research Innovations, vol. 6, no. 3, pp. 1–28.

eSign
Signed by: MURALI KRISHNA
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Petersen, A. and Müller, H.-G. (2019) 'Fréchet regression for random objects with Euclidean predictors', The Annals of Statistics, 47(2), pp. 691–719. doi: 10.1214/17-AOS1624.

Petersen, A., Liu, X. and Divani, A.A. (2021) 'Wasserstein F-tests and confidence bands for the Fréchet regression of density response curves', The Annals of Statistics, 49(1). doi: 10.1214/20-AOS1971.

Ramsay, J.O. and Silverman, B.W. (2005) Functional Data Analysis. 2nd edn. New York: Springer.

Shao, L., Lin, Z. and Yao, F. (2022) 'Intrinsic Riemannian functional data analysis for sparse longitudinal observations', The Annals of Statistics, 50(3). doi: 10.1214/22-AOS2172.

Srichalee, P & Watanyulertsakul, E 2026, 'Empirical Scalability Analysis of Data-Oriented and Object-Oriented Architectures in Controlled 2D Game Scenarios', SSRN working paper

Troost, L & Kuchen, H 2022, 'A Comprehensive Dynamic Data Flow Analysis of Object-Oriented Programs', Proceedings of the 17th International Conference on Evaluation of Novel Approaches to Software Engineering, pp. 267–274.

Troost, L, Neugebauer, J & Kuchen, H 2023, 'Visualizing Dynamic Data-Flow Analysis of Object-Oriented Programs Based on the Language Server Protocol', Proceedings of the 18th International Conference on Evaluation of Novel Approaches to Software Engineering, pp. 77–88.

Ullah, S. and Finch, C.F. (2013) 'Applications of functional data analysis: A systematic review', BMC Medical Research Methodology, 13, 43. doi: 10.1186/1471-2288-13-43.

Wang, H. and Marron, J.S. (2007) 'Object oriented data analysis: Sets of trees', The Annals of Statistics, 35(5). doi: 10.1214/009053607000000217.

Wang, J.-L., Chiou, J.-M. and Müller, H.-G. (2016) 'Functional data analysis', Annual Review of Statistics and Its Application, 3, pp. 257–295. doi: 10.1146/annurev-statistics-041715-033624.

Wu, Y., Kurtek, S. and Srivastava, A. (2024) 'Shape-based functional data analysis', TEST, 33. doi: 10.1007/s11749-023-00876-9.

Signed by: MURALI KRISHNA
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026

Yao, F., Müller, H.-G. and Wang, J.-L. (2005a) 'Functional data analysis for sparse longitudinal data', Journal of the American Statistical Association, 100(470), pp. 577–590. doi: 10.1198/016214504000001745.

Yao, F., Müller, H.-G. and Wang, J.-L. (2005b) 'Functional linear regression analysis for longitudinal data', The Annals of Statistics, 33(6), pp. 2873–2903. doi: 10.1214/009053605000000660.

Yarger, D., Stoev, S. and Hsing, T. (2022) 'A functional-data approach to the Argo data', The Annals of Applied Statistics, 16(1). doi: 10.1214/21-AOAS1477

Appendix A. Symbol Glossary

Table A1. Principal mathematical symbols

Symbol	Meaning
X_i(t)	Functional observation for unit i on domain T
Y_i	General structured object in metric space M
μ(t), μ_F	Functional mean and Fréchet mean
φ_k(t), ξ_ik	Functional eigenfunction and component score
d(·,·)	Distance appropriate to the object space
A, B, G	Dynamic transition and input matrices
λ_s, λ_g, λ_c	Smoothness, geometry and complexity penalties
CVaR_α	Average loss in the tail beyond quantile α
r, θ, π	Representation, model parameters and decision rule
E_g, U_c, H	Geometry distortion, uncertainty and expected harm

eSign
Signed by: MURALI KRISHNA PASUPULETI
Reason: NES |IJAIRI | Publication|
Copyright: © 2026
Location: Delhi, India
Date: July 2026