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Toward Integral Field Tomography of Living Systems

A conceptual framework for multidimensional reconstruction of biological dynamics

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Abstracts

Modern medical diagnostics relies on modality-specific approximations—CT for density, MRI for proton environments, ultrasound for mechanical impedance, and PET for metabolic proxies—each observing a projection of the organism rather than the organism itself. Disease, however, is not merely a structural anomaly but a loss of system stability, often established long before macroscopic changes become detectable. This article introduces the concept of Integral Field Tomography (IFT), a novel framework for reconstructing the internal physiological state of a living organism by solving the inverse problem of its externally measurable physical fields. Living systems are conceptualized as unified, multi-field entities: electrodynamic, magnetodynamic, mechanical continua, metabolic dissipative structures, and information-processing systems far from equilibrium. These processes continuously generate electrical, magnetic, mechanical, and photonic fields that propagate beyond tissue boundaries, serving as fundamental expressions of physiological state. IFT proposes to capture these fields simultaneously using ultra-sensitive detectors—including optically pumped magnetometers, laser vibrometers, and quantum-limited photonic sensors—and to reconstruct the organism's internal state through multi-scale, multi-physics inverse modeling. Artificial intelligence plays an intrinsic role in learning personalized priors, enforcing physical constraints, integrating heterogeneous data, and maintaining a living digital twin of the organism. The framework aligns naturally with active inference, reconceptualizing diagnosis as the estimation of how well the organism minimizes its own variational free energy. This shift from episodic structural imaging to continuous state inference enables detection before structural damage, monitoring of aging as loss of system coherence, evaluation of interventions at the level of state recovery, and the establishment of individualized baselines instead of population norms. Fundamental physical limits—quantum noise, thermal fluctuations, and information-theoretic constraints—lie far above current clinical thresholds, confirming that the primary obstacles are conceptual and computational, not physical. Integral Field Tomography represents not merely a new device but a new epistemology of medicine, transforming diagnostics from looking at bodies to reading living systems as coherent, measurable, dynamic wholes.

Keywords: Integral Field Tomography, Inverse Problem, Multi-Physics Imaging, Active Inference, Digital Twin, Systems Medicine, Preventive Diagnostics.

The Problem of Fragmented Vision

Modern diagnostics relies on modality-specific approximations. Each imaging technology provides a distinct, yet inherently limited, view of the biological system. Computed tomography (CT) maps the attenuation of x-rays, producing images based on electron density—a proxy for physical structure (Lattimer, 2019). Magnetic resonance imaging (MRI) visualizes the behaviour of protons in magnetic fields, offering unparalleled soft-tissue contrast but reporting on a specific set of biophysical properties (Mafraji, 2025). Ultrasound imaging constructs images from acoustic impedance mismatches, revealing mechanical boundaries within tissues. Positron emission tomography (PET), in contrast, tracks metabolically active molecules, using radiotracers like 18F-fluorodeoxyglucose (FDG) to create images that are proxies for glucose metabolism and, by extension, cellular activity (StatPearls, 2025).

Each modality, therefore, observes a projection of the organism—a simplified, physics-based model of one aspect of its complexity—not the organism itself. A CT scan does not show a tumor; it shows a region of abnormal density. A PET scan does not show an aggressive cancer; it shows a region of pathologically high glucose uptake. These are powerful correlates, but they remain indirect. The clinician is left with a set of fragmented images that must be mentally co-registered and synthesized—a process that is inherently subjective and prone to cognitive bias, as studies on visual search patterns in medical imaging have shown (Fong et al., 2016).

This fragmented vision is not merely a technical limitation; it reflects a deeper conceptual problem. Disease, particularly in its early stages, is not a static structure—it is a loss of system stability. A living system is characterized by dynamic, multi-scale interactions: from molecular pathways and metabolic fluxes to cellular communities and tissue mechanics. Pathology emerges from a critical failure in this coupled network long before it condenses into a visible lesion. By the time a structural change is large enough to be detected as a "density" on a CT scan or a "mass" on an ultrasound, the underlying pathological process is already well-established, having potentially compromised the system's resilience for months or years. As a comprehensive review of multi-modal imaging notes, relying solely on a single modality risks missing critical information required for accurate diagnosis, as no single approach can fully capture the complex nature of disease pathophysiology (Hussain et al., 2025).

The clinical response to this problem has been the increasing use of multi-modal imaging, where data from different sources are combined. The fusion of PET and CT, for instance, has become a cornerstone of oncological imaging, elegantly overlaying metabolic activity (PET) onto anatomical landmarks (CT) (StatPearls, 2025). Similarly, hybrid PET/MRI systems are advancing neurological and musculoskeletal imaging by combining metabolic insights with exceptional soft-tissue contrast (Irfan & Mubarak, 2025). In cardiology, multi-modality imaging integrates anatomical, morphological, and functional information to improve diagnosis and guide interventions (Li et al., 2023). While these approaches represent a significant advance over single-modality reads, they are predominantly post-hoc combinations of fundamentally different datasets. They fuse images, but they do not yet integrate the underlying biophysical processes. They tell us that a structure is metabolically active, but not why that structure became unstable in the first place.

The central challenge, therefore, is to move beyond a paradigm of fragmented, modality-specific approximations toward a more holistic form of interrogation—one that can capture the dynamic, multi-parametric reality of a living system. This requires not just the fusion of images, but the integration of the fundamental biophysical fields they represent: density, proton relaxation, mechanical impedance, and metabolic rate. What is needed is a form of tomography that can reconstruct not just anatomy, but the state of the system itself. We propose the concept of Integral Field Tomography (IFT) . Inspired by integral field spectroscopy in astronomy, which captures a spectrum for every pixel in an image, IFT aims to construct a multi-dimensional data cube where each spatial voxel contains a vector of coregistered biophysical properties. This would allow clinicians and researchers to query not just "what structure is this?" but "what is the physiological state of this tissue?" and "how stable is this system?"

The pursuit of such integrated imaging is not new. Early work on bio-electromechanical imaging, for example, demonstrated the potential of combining electrical impedance and ultrasound tomography to improve the detection of small tumors, showing that data fusion could reveal anomalies not visible with either modality alone (Steiner et al., 2008). This suggests that the interaction of different physical properties—in this case, electrical and mechanical—can serve as a more sensitive biomarker than either property in isolation. IFT seeks to generalize this principle, creating a framework where the relationships between multiple properties (e.g., density, diffusion, metabolism, elasticity) become the primary object of study. By mapping these relationships across the entire volume of a living system, we can begin to visualize not just structures, but the fields of interaction that define health and signal the earliest loss of system stability.

Living Organisms as Physical Systems

To move beyond fragmented, modality-specific approximations, we must first establish a more complete physical description of the organism. A living organism is not merely biological matter, classically defined by its biochemical constituents. It is, fundamentally, a complex physical system operating under multiple, interacting fields. A comprehensive model must recognize it simultaneously as:

- an electrodynamic system, characterized by the flow of ions, the establishment of membrane potentials, and the propagation of action potentials that form the basis of neural and muscular activity (Britannica, 1998);
- a magnetodynamic system, as the movement of these ionic charges necessarily generates correlated magnetic fields that extend beyond the source tissue, most prominently from the heart and brain (Sihong & Ueno, 1995);
- a mechanical continuum, exhibiting both elastic and viscoelastic responses to stress, a property essential for morphogenesis, tissue integrity, and the propagation of mechanical signals (Bonnet et al., 2012);

- a metabolic dissipative structure, which maintains its highly ordered state by consuming energy and exporting entropy to its surroundings, thereby operating far from thermodynamic equilibrium (Aoki, 2005; Cossetto et al., 2025);

- an information-processing system far from equilibrium, capable of sensing its environment, computing responses, and storing information in its structural and electrochemical states (University of Pennsylvania, 2025).

These fundamental processes are not silent or invisible. They necessarily generate physical fields—electrical, magnetic, mechanical, thermal, and photonic—that propagate within and beyond tissue boundaries. Unlike biochemical markers, which often require invasive sampling or exogenous contrast agents for detection, fields are intrinsic and continuously emitted. They are not secondary epiphenomena; they are fundamental expressions of the physiological state of the system. As a comprehensive review of biofield physiology argues, these endogenously generated fields are not merely metabolic byproducts but represent a distinct and underappreciated layer of physiological regulation and communication (Hammerschlag et al., 2015).

The electrodynamic nature of life is its most classically described field property. All cells maintain a transmembrane potential, a direct current (DC) field that serves as a battery for cellular work and a source of instructive signals during development and regeneration (Levin et al., 2019). In excitable tissues, this activity is dynamic. The synchronous depolarization of cardiac myocytes generates a powerful, time-varying electrical field, detectable on the body surface as an electrocardiogram (ECG). This same electrical activity produces a corresponding magnetic field, the magnetocardiogram (MCG), which can be measured non-invasively and offers information orthogonal to the ECG, particularly for detecting focal ischemia (Sihong & Ueno, 1995). Similarly, the coordinated activity of neuronal ensembles in the brain generates both electroencephalographic (EEG) and magnetoencephalographic (MEG) signals, providing real-time windows into cognitive function and network dynamics. The existence of these fields is now being explored through integrative models, such as "Resonant Convergence," which propose that electromagnetic interactions at the cellular level, from ion cyclotron resonance to quantum electrodynamic effects, converge on universal signaling nodes like calcium-calmodulin, highlighting a deep and fundamental layer of biological control (Sisken et al., 2025).

The mechanical continuum of the body is another source of propagating fields. Tissues are not rigid structures but complex, hydrated materials that exhibit both elastic (solid-like) and viscous (fluid-like) behavior. This viscoelasticity is critical for function: it allows tissues to absorb and dissipate mechanical energy, and it facilitates large-scale shape changes during development. Bonnet et al. (2012) demonstrated that the dorsal thorax epithelium of the Drosophila pupa can be accurately modeled as a continuous, linear, viscoelastic material, with a stress relaxation time on the order of tens of seconds. This confirms that at a multicellular scale, tissues behave as physical continua whose mechanical fields can be quantified and modeled. The propagation of mechanical waves—from the gross deformation of a tendon under load to the subtle shear waves induced by an ultrasound pulse—carries information about the underlying material properties and the state of stress within the system.

Finally, the thermodynamic nature of life defines its relationship with its environment. A living system is a dissipative structure, maintaining its internal order by constantly producing entropy, which it exports as heat and chemical potential. This entropy production is a fundamental, irreducible cost of being alive. Aoki (2005) estimated entropy production in humans from respiration data, revealing a characteristic life-course trajectory that reflects the underlying principles of biological organization. More recently, Cossetto et al. (2025) explored the partitioning of dissipation between thermal and chemical entropy across the microbial world, finding that while aerobic respiration primarily generates heat, some anaerobic metabolisms produce equal or even greater amounts of chemical entropy. This work underscores that the "dissipation field" of an organism is a complex and measurable quantity that directly reflects its core metabolic strategy.

Crucially, fields cannot be hidden. An electrodynamic event in a deep brain nucleus has a magnetic correlate that, though weak, extends to the scalp. A viscoelastic relaxation in a load-bearing joint creates a propagating mechanical wave. A metabolic burst in a tumor increases local heat dissipation. These fields are a fundamental expression of state. They are the language in which the body communicates its health, its stress, and its incipient pathology. The challenge for a new form of tomography is to learn to listen to this language in its entirety.

Principle of Integral Field Tomography

The preceding sections have established a fundamental disconnect: modern diagnostics provides fragmented, modality-specific views of a system that is, in reality, a unified, multi-field physical entity. The fields it generates—electrical, magnetic, mechanical, thermal—are not secondary effects but primary expressions of its physiological state (Hammerschlag et al., 2015). This leads us to the core hypothesis of Integral Field Tomography (IFT):

The internal physiological state of a living organism can be reconstructed by solving the inverse problem of its externally measurable physical fields.

This principle inverts the conventional diagnostic paradigm. Instead of interrogating the body with high-energy radiation (as in CT) or exogenous contrast agents (as in PET), IFT proposes to listen to the fields the body continuously generates on its own. It treats the organism not as an object to be illuminated, but as a source of information to be decoded. Consequently, this approach does not require invasive probes or high-energy radiation. Instead, IFT relies on a triad of enabling capabilities: (1) passive or minimally perturbative sensing, (2) ultra-sensitive field detectors, and (3) multi-scale inverse modeling.

Passive and Minimally Perturbative Sensing

The foundation of IFT is the measurement of endogenous fields. This is already clinically realized in techniques like electrocardiography (ECG) and electroencephalography (EEG), which passively record the body's own electrical activity using surface electrodes (Malmivuo & Plonsey, 1995). Magnetoencephalography (MEG) and magnetocardiography (MCG) similarly measure the magnetic fields generated by the same ionic currents, offering complementary

information with reduced sensitivity to the conductivity distortions of intervening tissues like the skull (Hämäläinen et al., 1993). These are purely passive techniques—they observe without perturbing.

IFT extends this principle to other field modalities. Mechanical fields generated by cardiac motion, vascular pulsation, or muscle contraction propagate to the body surface as minute displacements, measurable with techniques like laser Doppler vibrometry or microwave radar (Scalise, 2012). Thermal fields, a direct consequence of metabolic dissipation, radiate from the body as infrared emissions, which can be captured thermographically (Ring & Ammer, 2012). Even ultra-weak photon emissions, associated with metabolic reactions and oxidative stress, represent a potential, albeit challenging, field for measurement (Prasad & Pospíšil, 2013). The goal is to create a comprehensive, multi-field sensor array that surrounds the organism, capturing the diverse physical signals it continuously broadcasts.

Ultra-Sensitive Field Detectors

The signals of interest, particularly magnetic and thermal fields, can be extraordinarily weak. Their reliable detection demands sensors with sensitivities at the limits of current technology. For magnetic fields, the historical workhorse has been the Superconducting Quantum Interference Device (SQUID) (Cohen, 1972). However, SQUIDs require cryogenic cooling, making systems bulky and expensive. A new generation of sensors, Optically Pumped Magnetometers (OPMs), offers a compelling alternative. OPMs achieve comparable or even superior sensitivity to SQUIDs but operate at room temperature, can be placed directly on the scalp, and promise a new era of flexible, wearable magnetic field mapping (Boto et al., 2018). The development of such sensors is critical for making high-fidelity, multi-channel magnetic field recording a practical reality for IFT.

Multi-Scale Inverse Modeling

The most challenging component of IFT is the reconstruction of internal sources from external measurements—the inverse problem. Unlike the forward problem, which calculates the external fields generated by a known internal source, the inverse problem is fundamentally ill-posed: many different internal source configurations can produce the same external field pattern. Solving it requires integrating measured data with a sophisticated biophysical model of the organism and employing powerful mathematical regularization techniques.

As outlined by Biros (2010), the goal is to use medical images and sensor data as "virtual observations" to drive inverse algorithms that can identify patient-specific tissue properties and dynamic states, such as ischemic regions in the heart. This process is mathematically formalized as a PDE-constrained optimization problem. For a single field modality, such as the electrical potential (V) measured in EEG, the quasi-static approximation of Maxwell's equations governs the forward problem:

$$\nabla \cdot (\sigma \nabla V) = \nabla \cdot J^p$$

Here, σ is the tissue conductivity tensor and J^p represents the primary current sources (neural activity). The inverse problem seeks to find the J^p that best explains the measured V on the scalp, given a model for σ. This is the core of EEG/MEG source localization, a field that has seen extensive development, with methods ranging from basic dipole fitting to advanced machine learning approaches (Baillet et al., 2001; Moosavi Basri et al., 2025).

However, IFT radically expands the scope of this problem. It aims to solve a coupled inverse problem, reconstructing not just one source, but multiple interacting physiological processes from multi-field data. The forward model for IFT must therefore couple the equations of electrodynamics, mechanics, and thermodynamics. For example, in cardiac imaging, one could simultaneously measure body surface potentials (ECG) and surface displacements (mechanical). The inverse problem would then seek to estimate both the electrical activation sequence and the contractile forces and passive elastic properties of the myocardium. Pioneering work has already established computational frameworks for such simultaneous estimation, combining electrical data from ECG/MCG with mechanical data from tagged MRI to create a more complete picture of cardiac function (Marchesseau et al., 2016).

The development of robust, efficient algorithms for these multi-scale, multi-physics inverse problems is the central mathematical challenge of IFT. It requires creating digital twins of the organism—anatomically accurate, physics-based models that can simulate the forward problem with high fidelity. These models must incorporate detailed tissue properties, as the accuracy of the inverse solution is critically dependent on the accuracy of the forward model. Studies have shown, for instance, that uncertainties in tissue conductivity values can significantly affect source localization accuracy in MEG, particularly for deep sources (Van Uitert et al., 2003). IFT will therefore necessitate the integration of patient-specific anatomical data (from MRI, for instance) to constrain the inverse solution and achieve the required precision for clinical utility. By fusing multi-field data within the framework of a unified biophysical model, IFT promises to transform a collection of fragmented projections into a coherent, integrated image of a living system's internal state.

Observable Field Domains

The hypothesis of Integral Field Tomography (IFT) rests on the premise that the physiological state of an organism is encoded in a set of measurable, externally propagating fields. An ideal integral system would not rely on a single modality but would jointly read across these domains, capturing the multi-faceted physical expression of life. Each domain offers a unique window into specific sub-cellular, cellular, and systemic processes. Together, they define the organism's phase space—a high-dimensional representation of its internal state.

Electromagnetic Fields

The electrodynamic nature of life manifests across multiple scales, from the ion fluxes that govern mitochondrial function to the synchronized depolarization of entire organs. At the sub-cellular level, mitochondrial ion channels are fundamental to bioenergetics and cellular fate. The voltage-dependent anion channel (VDAC) in the outer mitochondrial membrane, for

example, controls the flux of metabolites, ions (including Ca^{2+}), and even small proteins, acting as a gatekeeper between the mitochondrion and the cytoplasm (Szabó & Zoratti, 2014). The patch-clamp electrophysiology of these channels reveals that their conductance states are dynamic and voltage-sensitive, directly linking mitochondrial membrane potential ($\Delta\Psi m$) to cellular excitability and metabolic output . These discrete ionic events, while not directly measurable at the body surface, are the fundamental drivers of larger-scale fields. Their collective behavior sums to create the propagating action potentials of neurons and myocytes, which are detectable as far-field potentials in techniques like electrocardiography (ECG) and electroencephalography (EEG) (Malmivuo & Plonsey, 1995). Thus, the electromagnetic domain provides a direct readout of ionic fluxes and the excitability of tissues, forming a cornerstone of any integral field approach.

Magnetic Fields

While closely related to their electrical counterparts, magnetic fields offer distinct and often complementary information. Generated by the same ionic currents, magnetic fields are less distorted by the inhomogeneous conductivity of biological tissues (e.g., the skull), allowing for more accurate source localization (Hämäläinen et al., 1993). This makes them exquisitely sensitive to neural synchrony. Magnetoencephalography (MEG) can detect the coherent oscillations of thousands of neurons, providing a real-time window into large-scale brain network dynamics . The same principle applies to the heart: magnetocardiography (MCG) maps the magnetic field of the heart, offering unique insights into cardiac coherence and the detection of focal ischemia (Sihong & Ueno, 1995).

Crucially, magnetic fields also reveal inter-organ coupling. The heartbeat evokes a measurable response in the brain—the heartbeat-evoked response (HER)—which can be characterized using MEG. Recent work has shown that this single heartbeat event synchronizes a whole cortical network in the theta frequency band, linking visceromotor and interoceptive regions with the default mode network (Kim et al., 2019) . This demonstrates that magnetic field measurements can capture the dynamic, network-level interaction between organs, such as the heart and brain, providing a systems-level perspective that electrical measurements alone cannot (Polepogu & Vaegae, 2021) . Inter-organ coupling, as revealed by magnetic fields, is a direct expression of the organism's integrated physiological state.

Mechanical Micro-Fluctuations

Living tissues are not static structures but mechanical continua exhibiting constant, low-amplitude motion. These mechanical micro-fluctuations arise from diverse sources: the pulsatile flow of blood in vessels, the contraction and relaxation of cardiac and skeletal muscle, and even the minute deformations of organs due to respiration and peristalsis. These movements are governed by the tissue's viscoelastic properties. Measuring the propagation of these intrinsic or externally induced mechanical waves allows for the reconstruction of tissue elasticity, a key biomarker. For instance, intravascular ultrasound (IVUS) combined with motion estimation techniques like optical flow can generate microscopic elasticity images of vessel

walls, revealing the sub-millimeter mechanical heterogeneity of atherosclerotic plaques (Li et al., 2001; Wan et al., 2001) . This moves beyond simple anatomical imaging to quantify the functional mechanical state of the tissue. Vascular dynamics, from the distensibility of large arteries to the microvascular pulsations of parenchymal organs, are encoded in these surface displacements. A comprehensive IFT system would therefore include ultra-sensitive methods, such as laser Doppler vibrometry or microwave radar, to capture this rich tapestry of mechanical micro-fluctuations, providing a window into tissue elasticity and the dynamic forces of life.

Photonic Emissions

Perhaps the most surprising, yet fundamental, observable domain is that of ultra-weak photon emission (UPE). All living organisms, including humans, continuously emit a faint glow of light, 1,000 to 1,000,000 times too dim for the human eye to perceive (Oblak, 2025) . This biophoton emission is not a metaphysical aura but a direct consequence of metabolic processes. UPE is generated when reactive oxygen species (ROS), produced as byproducts of metabolism, cause the formation of electronically excited species within molecules. When these excited molecules relax to their ground state, they release a photon (Prasad & Pospíšil, 2013).

Crucially, the intensity of this emission correlates directly with oxidative stress. Using highly sensitive CCD cameras, researchers have been able to image UPE from human facial skin, revealing regional variations in oxidative stress. Notably, UPE intensity correlates with skin wrinkle scores and porphyrin levels, linking this photonic field to both skin aging and the metabolic state of the skin microbiome (Kobayashi et al., 2020) . UPE therefore serves as a non-invasive, label-free biomarker of oxidative stress and, by extension, the overall metabolic and aging state of tissues. When an organism dies, metabolism ceases, and the ultra-weak photon emission ends (Oblak, 2025) . This underscores that UPE is a fundamental expression of life itself, one that IFT seeks to capture.

The Organism's Phase Space

Each of these domains—electromagnetic, magnetic, mechanical, and photonic—offers a projection of the organism's state. Electromagnetic fields report on ionic flux and excitability; magnetic fields on neural and cardiac synchrony; mechanical fields on elasticity and dynamics; and photonic fields on oxidative stress and metabolism. Alone, each is incomplete. Together, however, they begin to define the multi-dimensional phase space in which the living system operates. By simultaneously measuring these fields and solving the coupled inverse problem, IFT aims to locate the organism within this phase space, distinguishing health from disease not by a single structural anomaly, but by a systemic loss of stability across multiple, interacting physical dimensions.

From Imaging to State Inference

The preceding sections have laid the groundwork for a multi-field, physics-based approach to observing living systems. However, it is crucial to clarify the ultimate objective of Integral Field

Tomography (IFT). IFT does not aim to "see organs" in the traditional anatomical sense. Its goal is not higher resolution images of structure, nor is it merely another modality for detecting lesions. Instead, IFT is designed to reconstruct the dynamical state of the organism. It seeks to quantify:

- stability basins, representing the range of perturbations a system can withstand before shifting to an alternative physiological regime;
- critical transitions, the tipping points at which a system moves abruptly from one state to another, such as from health to disease;
- loss of adaptive capacity, the gradual erosion of the system's ability to respond to internal or external stressors;
- early divergence from individual norms, the deviation from a person's unique baseline physiological trajectory that precedes clinical diagnosis.

This is fundamentally a state estimation problem, not an imaging one. It represents a paradigm shift from mapping static anatomy to inferring dynamic stability.

From Structure to Stability

The concept of stability basins is central to dynamical systems theory and provides a powerful lens for understanding health and disease. In a multi-stable dynamical system, the state of the system resides within a "basin of attraction"—a set of conditions that leads to a particular stable equilibrium (or attractor) (Takagi et al., 2025). A healthy physiological state can be conceptualized as a broad, deep basin of attraction, capable of absorbing perturbations (e.g., infection, injury, metabolic stress) without fundamentally altering the system's behavior. Disease, in contrast, represents a shift to a different, often narrower and less resilient, attractor.

The volume and shape of these stability basins are not static; they change with age, environment, and history. A key challenge, therefore, is to estimate the boundaries of these basins from observable data. In the context of IFT, the multi-field data cube provides the high-dimensional measurements needed to begin mapping the system's current location within its phase space and, critically, its proximity to a basin boundary. Early-warning signs (EWSs) of critical transitions, such as increasing variance and autocorrelation in physiological time series, have been shown to anticipate abrupt changes in system state. Legault et al. (2024) demonstrated that multivariate EWSs, particularly those based on variance, could predict mortality in hemodialysis patients, with the combination of multiple indices capturing a broader range of dynamic changes than any single metric alone. IFT aims to provide the rich, multi-modal data stream necessary to make such state inference robust and clinically actionable.

Critical Transitions and Loss of Adaptive Capacity

The transition from health to disease is often not a smooth, linear progression but an abrupt, nonlinear critical transition. The loss of adaptive capacity is the process that precedes this transition. It reflects the system's increasing inability to compensate for perturbations, a phenomenon described by the "Respond → Adapt → Resolve" framework of stress response (Tippairote et al., 2025). When an organism is exposed to chronic stress, it may enter a state of maladaptation—a condition where the very mechanisms of adaptation (e.g., metabolic plasticity, epigenetic remodeling) begin to drive dysfunction. Lissek (2024) argues that aging itself can be understood as a consequence of this adaptation–maladaptation dilemma, where resolution fails and the system defaults to a trade-off that prioritizes immediate survival over long-term maintenance.

IFT is uniquely positioned to detect this loss of adaptive capacity. By simultaneously monitoring multiple physical fields—the coherence of magnetic fields, the variability of mechanical micro-fluctuations, the intensity of photonic emissions from oxidative stress—IFT can assess the system's resilience in real time. A decline in the coherence of cardiac or neural magnetic fields, for example, might signal a degradation of inter-organ coupling and a loss of system integrity. An increase in the variance of mechanical tissue displacements could indicate a loss of elastic stability. These are not structural findings; they are dynamic signatures of a system approaching a tipping point.

Divergence from Individual Norms: The N-of-1 Problem

A fundamental limitation of population-based diagnostics is its reliance on group averages. A "normal" CT density or a "normal" range for a blood biomarker is defined statistically across a population. However, an individual's healthy state is unique to them. The most sensitive indicator of pathology may not be a deviation from a population mean, but a deviation from that individual's own historical baseline—a concept central to the N-of-1 approach in precision medicine. Suzuki et al. (2023) showed that baseline data variability significantly affects the ability to detect intervention effects in single individuals, highlighting the importance of understanding personal physiological dynamics.

IFT is inherently suited to this N-of-1 paradigm. By establishing a multi-field baseline for an individual over time, the system can learn that person's unique "physiological norm." Pathology then manifests not as a generic structural abnormality, but as a statistically significant divergence from this personal trajectory—a change in the stability of their magnetic fields, a shift in the frequency spectrum of their mechanical micro-fluctuations, or a sustained increase in photonic emissions indicative of oxidative stress. This shifts the diagnostic question from "Does this image look like cancer?" to "Has this system lost its individual stability?"

State Estimation as the Core Objective

This reframing aligns IFT with a class of mathematical problems known as state estimation. In engineering and physics, state estimation refers to the process of inferring the internal,

unobserved state of a dynamical system from a series of noisy, external measurements. This is precisely the challenge of IFT: to infer the high-dimensional physiological state of an organism from the multi-field data it emits. Recent advances in model reduction and data assimilation have made such problems tractable, even in complex, shape-varying biological domains. Galarce et al. (2022) developed a framework for state estimation in biomedical problems that accounts for organ-scale morphological variability, demonstrating that it is possible to reconstruct internal fields (such as blood flow) from external measurements (Doppler ultrasound) without an a priori parameterization of shape. This work provides a mathematical blueprint for IFT, showing that the inverse problem of state inference is solvable.

In conclusion, IFT represents a fundamental shift in objective. It moves the field from structural imaging—the creation of static anatomical maps—to state inference: the dynamic, personalized, and quantitative assessment of a living system's stability, its adaptive capacity, and its proximity to critical transition.

Role of Artificial Intelligence

The preceding sections have established that Integral Field Tomography (IFT) is fundamentally a state estimation problem: the reconstruction of a high-dimensional physiological state from multi-field, external measurements. This inverse problem is inherently ill-posed. Classical methods alone—relying on analytical inversions or iterative solvers with hand-crafted regularizers—struggle to find unique and stable solutions, particularly given the complexity of living systems, the multiplicity of interacting fields, and the inevitable noise in biological measurements. In this context, artificial intelligence (AI) is not an optional add-on for automation or post-hoc analysis. It is intrinsic to the entire IFT framework. AI provides the essential computational infrastructure for: learning personalized priors, enforcing physical constraints, integrating heterogeneous field data, and maintaining a digital twin of the organism. Through this integration, diagnosis itself is transformed from episodic inspection into a process of continuous inference.

Learning Personalized Priors

The ill-posed nature of the inverse problem means that prior information is required to constrain the space of possible solutions. Traditional approaches use generic priors, such as assumptions of smoothness or sparsity, which do not capture the unique anatomical and physiological characteristics of an individual. AI offers a pathway to learn personalized priors directly from data. Weidner et al. (2024) demonstrated this concept in the context of inverse tumor growth modeling, where a deep learning ensemble was used to provide an initial parameter estimate—a learnable prior—that dramatically constrained the effective sampling space for a subsequent high-precision evolution strategy. This integration of a rapid DL algorithm with a biophysical model resulted in a fivefold convergence acceleration and a Dice score of 95% for estimating tumor cell concentrations from MRI data.

This principle is directly extensible to IFT. A patient's past medical records, including prior high-field MRI scans, can be used to train a personalized prior. As Oved et al. (2025) showed in

the context of low-field MRI, a single prior high-field scan is sufficient for a vision transformer architecture (ViT-Fuser) to learn personalized features that enable accelerated, high-quality follow-up scans with portable, low-cost systems. By extracting information from standard DICOM files—the kind routinely given to patients—the AI model learns the individual's unique anatomical fingerprint. In IFT, such personalized priors would serve as a powerful constraint for the multi-field inverse problem, anchoring the reconstruction to the individual's known baseline and making the detection of subtle deviations far more sensitive.

Enforcing Physical Constraints

While data-driven, AI models must remain grounded in physical reality to be reliable and generalizable. This is the domain of physics-informed machine learning (PIML). As reviewed by Ahmadi et al. (2025), PIML frameworks, such as physics-informed neural networks (PINNs), integrate parameterized physical laws—typically expressed as differential equations—directly into the loss function of a neural network alongside data fidelity terms. This ensures that the solutions not only fit the measurements but also satisfy the governing biophysics, such as Maxwell's equations for electromagnetic fields or the Navier-Cauchy equation for mechanical displacements. In the context of IFT, PINNs can be trained to solve the coupled forward problem, mapping from a hypothesized internal state to the expected external multi-field measurements. The inverse problem then becomes one of finding the state that minimizes the discrepancy between the PINN-predicted fields and the actual sensor data, with the physical laws acting as a powerful regularizer that eliminates non-physical solutions. This "gray-box" approach, which combines partially known physics with unknown components learned from data, is ideally suited to the complexity of living systems where not all processes are perfectly modeled (Ahmadi et al., 2025).

Integrating Heterogeneous Field Data

IFT produces a vast, multi-modal dataset: time-series of electrical potentials, magnetic field vectors, mechanical displacements, and photonic intensities. Integrating these heterogeneous data types into a coherent whole is a formidable challenge. AI, particularly deep learning architectures, excels at learning representations from disparate data sources. Hybrid algorithms, such as the "Greybox" approach for DCE-MRI, demonstrate how model-based and deep learning methods can be combined to solve nonlinear inverse problems, learning complex mappings from undersampled data to parameter maps (Rastogi & Yalavarthy, 2024). In IFT, a similar approach could fuse the information from all field modalities, learning the complex, non-linear relationships between them to produce a single, unified reconstruction of the physiological state. This is not merely the fusion of images, but the integration of the underlying generative processes.

Maintaining a Digital Twin of the Organism

The ultimate realization of IFT is the creation and continuous maintenance of a digital twin—a living, computational model of the organism that evolves with it. This concept is gaining traction

in biomedical research. Johnson et al. (2025) introduced a human-interpretable grammar to encode multicellular systems biology models, creating "virtual cell laboratories" that can simulate tumor growth or brain development. This moves towards a scenario where researchers can test hypotheses and simulate interventions in silico before real-world application. For IFT, the digital twin is the dynamic repository of the patient's personalized prior, the biophysical model for enforcing constraints, and the integrative framework for assimilating new data. As new multi-field measurements are acquired, they are fed into the digital twin, which updates its estimate of the patient's state. This shifts the diagnostic paradigm from episodic inspection—ordering a test, getting a result days later—to a model of continuous inference. The patient's state is no longer a snapshot but a constantly updated trajectory. This aligns with emerging work on continuous patient monitoring using AI, where real-time analysis of passive data streams can provide ongoing insights into patient status and detect critical events (Gabriel et al., 2025). In IFT, the sensors become a continuous window into the patient's physiological phase space, with AI serving as the interpretive engine that translates raw field data into a coherent, dynamic, and deeply personalized portrait of health and its potential deviations.

Relation to Active Inference and Free Energy

The previous section established artificial intelligence as the computational engine for solving the ill-posed inverse problem of Integral Field Tomography (IFT). However, the role of AI in IFT is not merely technical; it points toward a deeper theoretical convergence. The structure of IFT—inferring hidden physiological states from observed field data—aligns naturally with the active inference framework, a leading theory of brain function and behavior originating from theoretical neuroscience. This convergence suggests that the diagnostic enterprise and the fundamental principles of life are two sides of the same coin.

Active inference, rooted in the free energy principle, proposes that any self-organizing system—from a single neuron to a human being—must act to minimize its variational free energy (Friston, 2010). In computational terms, this is equivalent to minimizing surprise or prediction error. The free energy functional takes two complementary forms. In perception, agents minimize variational free energy to infer the hidden causes of their sensory inputs. In action, they minimize expected free energy, selecting policies that reduce uncertainty (epistemic value) and realize preferred outcomes (pragmatic value) (Da Costa et al., 2026). Crucially, this framework treats the organism not as a passive receiver of stimuli, but as an active inference engine, continuously generating predictions about its sensory world and updating its internal models to resolve prediction errors (Friston et al., 2025).

IFT mirrors this structure at the level of the entire organism. The organism itself is the ultimate active inference system, maintaining its physiological stability by minimizing free energy across multiple spatial and temporal scales. The externally measurable fields that IFT captures—electrical, magnetic, mechanical, photonic—are, from the perspective of active inference, the "sensory consequences" of the organism's hidden physiological states. The IFT reconstruction process is, therefore, formally equivalent to solving the perceptual inference problem for a clinician or a diagnostic system. Just as the brain infers the state of the world from

noisy sensory data, IFT infers the state of the organism from noisy multi-field data. This leads to a profound re-conceptualization of the diagnostic task:

- the organism minimizes free energy internally through its own allostatic regulatory mechanisms, maintaining itself within viable physiological bounds (Sterling, 2012);
- diagnostics, via IFT, estimates how well this minimization is being maintained by reconstructing the organism's internal state from the fields it generates;
- disease corresponds to increasing prediction error within the organism's physiological hierarchies—a failure of the system to successfully model and regulate its own internal milieu.

This last point is critical. In active inference, pathology can be understood as a breakdown in the generative model that the organism uses to predict its own sensory consequences. For example, in mental illness, aberrant precision weighting of prediction errors or maladaptive priors can lead to inaccurate inference and dysfunctional behavior (Eckert et al., 2025; Silva et al., 2024). Khan and Lowe (2024) demonstrated this principle computationally, showing that an active inference agent endowed with an artificial physiology could regulate itself more effectively when prediction errors were coupled to the secretion of a stress hormone (cortisol). The allostatic functions of cortisol, secreted as a function of prediction errors, provided adaptive advantages, grounding abstract information-theoretic quantities in concrete biological dynamics.

IFT extends this logic from the computational model to the clinical setting. A patient's multi-field data—the coherence of their cardiac magnetic field, the variability of their mechanical micro-fluctuations, the intensity of their photonic emissions—constitute the sensory evidence of their physiological self-modeling. When the organism is healthy, its internal free energy minimization is effective, and the observed fields will exhibit the characteristic signatures of stability: predictable rhythms, coherent oscillations, and bounded variability. When disease begins to encroach, the organism's ability to minimize free energy degrades. Prediction errors accumulate. These errors manifest in the external fields as increased variance, loss of coherence, or divergence from the individual's historical norm. As Legault et al. (2024) showed, multivariate early-warning signs, particularly variance-based indices, can predict critical transitions in physiological systems. IFT, by reconstructing the full physiological state, provides the richest possible dataset for detecting these incipient failures of free energy minimization.

This convergence is not merely metaphorical. The mathematical formalisms are shared. Active inference frames perception as the inversion of a generative model, typically a partially observable Markov decision process (POMDP) (Da Costa et al., 2026). IFT frames diagnostics as the inversion of a multi-physics generative model—a set of coupled partial differential equations describing the organism's electrodynamic, mechanical, and thermal behavior. Both are fundamentally inverse problems. Both seek to infer hidden states from observed consequences. Both require priors, regularization, and a measure of prediction error to guide the solution. The variational free energy minimized by the brain is, therefore, conceptually isomorphic to the objective function minimized by the IFT reconstruction algorithm.

Thus, diagnostics and theoretical neuroscience converge. The same principle that explains how a brain perceives the world explains how a clinician should perceive the state of a patient. The organism is an inference machine; IFT is a meta-inference machine designed to observe it. By framing diagnosis as the estimation of an organism's success at minimizing its own free energy, IFT unifies the practice of medicine with the deepest principles of biological self-organization. Disease is no longer a structure to be imaged, but a measurable increase in prediction error within the living system's ongoing attempt to maintain its own existence.

Implications for Longevity and Preventive Medicine

The preceding sections have framed Integral Field Tomography (IFT) as a multi-physics inverse problem, a state estimation challenge, and a framework theoretically aligned with active inference. Its ultimate promise, however, lies in its transformative potential for clinical practice, particularly in the domains of longevity and preventive medicine. By shifting the focus from structural imaging to dynamic state inference, IFT enables a new paradigm of care—one that is predictive, personalized, and grounded in the physics of life. Such a framework enables: detection before structural damage, monitoring of aging as loss of system coherence, evaluation of interventions at the level of state recovery rather than symptom suppression, and the establishment of individualized baselines instead of population norms. In this light, longevity becomes a control problem, not a reactive one.

Detection Before Structural Damage

The fundamental limitation of contemporary diagnostics is that it detects pathology only after it has consolidated into a structural lesion. By the time a tumor is visible on a CT scan or an infarct is evident on an MRI, the underlying disease process is already well-established. IFT offers a pathway to pre-structural detection. By monitoring the coherence and stability of the organism's endogenous fields, it can identify the loss of system integrity that precedes anatomical change. This concept is already finding traction in neurodegenerative disease research. Li et al. (2025) demonstrated that task-related electroencephalography (EEG), combined with interpretable deep learning, could reveal early Alzheimer's disease risk signatures in cognitively healthy individuals. The model's focus on theta and alpha activity in parietal and temporal regions—areas associated with AD pathology—suggests that functional field changes manifest long before structural atrophy is detectable. Similarly, Digma et al. (2025) showed that in preclinical Alzheimer's disease, continuous levels of plasma p-tau217 and amyloid-PET burden—early-changing biomarkers—provide prognostic information about downstream tau accumulation, atrophy, and cognitive decline. IFT extends this logic across multiple field modalities, creating a multi-dimensional sensor for the earliest signs of system destabilization.

Monitoring Aging as Loss of System Coherence

Aging is not merely the accumulation of damage; it is a progressive loss of coordination across the multiple scales of biological organization. This loss of coherence is a fundamental signature of the aging process. Leote et al. (2024) quantified this phenomenon at the molecular level,

demonstrating that aging is characterized by a loss of coordination between distinct cellular processes. Their analysis of eight human tissues revealed that regulatory relationships becoming weaker with age were established mostly between genes operating in distinct cellular functions, indicating a breakdown in inter-process communication.

IFT scales this concept from the molecular to the whole-organism level. The organism's fields—electrical, magnetic, mechanical, and photonic—are expressions of its internal coordination. Loss of coherence in these fields is a direct measure of aging. Eswari et al. (2025) provided a compelling example of this at the neural-muscular interface. They showed that older adults exhibit reduced and consistent EEG-EMG coherence across different motor tasks compared to younger adults, reflecting age-related declines in neural synchrony and motor control efficiency. While younger individuals modulate their cortico-muscular coherence in response to task demands, older adults lose this adaptive capacity. IFT aims to generalize such observations, monitoring coherence across multiple field domains to provide a continuous, quantitative readout of biological age and system resilience.

Evaluating Interventions: State Recovery vs. Symptom Suppression

The current model of therapeutic evaluation relies on outcome measures that are often crude and delayed: survival, disease progression, or symptom scores. IFT enables a more refined approach. Interventions can be evaluated at the level of state recovery—the return of the system's dynamical properties to a healthy regime—rather than merely the suppression of symptoms. This aligns with the emerging field of integrated longevity medicine, which seeks to translate geroscience into clinical practice by leveraging biomarker tracking, metabolic therapies, and preventive interventions to treat aging as a modifiable process (Boccardi, 2025). By providing a high-dimensional, real-time readout of the organism's physiological state, IFT allows clinicians to ask not just "Did the tumor shrink?" but "Has the system regained its stability basins?" and "Has adaptive capacity been restored?"

Individualized Baselines Instead of Population Norms

Perhaps the most profound shift enabled by IFT is the move away from population-based reference ranges toward truly individualized baselines. A "normal" blood pressure or a "normal" CT density is a statistical abstraction. An individual's healthy state, however, is unique to them. The concept of personalized N-of-1 trials has gained traction in genetic medicine and pharmacology as a method for evaluating treatments in the face of high inter-individual heterogeneity (Butler et al., 2025; Kim-McManus et al., 2024). IFT provides the physiological infrastructure to make N-of-1 approaches scalable. By continuously monitoring an individual's multi-field emissions, the system learns their unique dynamical fingerprint. Pathology is then defined not by deviation from a population mean, but by statistically significant divergence from that personal trajectory. This reframes longevity as a control problem: the goal is to maintain the individual's physiological state within its own healthy attractor basin, using continuous field data to guide proactive interventions before the system loses stability.

In summary, IFT transforms medicine from a reactive discipline focused on structural damage into a proactive science of state maintenance. By enabling detection before structure, quantifying aging as decoherence, evaluating interventions by state recovery, and personalizing baselines, it makes longevity a tractable problem of dynamical control.

Fundamental Limits

The preceding sections have outlined an ambitious framework: the reconstruction of an organism's internal physiological state from the multi-field data it continuously emits. Before such a framework can be realized, it is essential to consider its fundamental limits. Every physical measurement is constrained by irreducible sources of uncertainty. For Integral Field Tomography (IFT), these limits are set not by the resolution of current sensors or the speed of existing computers, but by three fundamental boundaries: quantum noise, thermal fluctuations, and information-theoretic constraints. A critical insight is that these limits are far above current clinical thresholds. The main obstacles to realizing IFT are therefore conceptual and computational, not physical.

Quantum Noise

The most fundamental limit on the sensitivity of optical measurements is quantum noise, also known as shot noise. This noise arises from the discrete, probabilistic nature of photon detection events. In any optical measurement, including those that would be used in IFT for photonic emissions or laser-based mechanical sensing, the quantization of light imposes a minimum uncertainty on the measured signal. For a given optical power, which in biological measurements must be constrained to avoid photodamage to the specimen, the quantum noise limit sets the best possible sensitivity.

Remarkably, this limit is not absolute. Using non-classical (squeezed) light, which exhibits reduced amplitude noise, it is possible to surpass the quantum noise limit. Taylor et al. (2013) experimentally demonstrated this in a living system for the first time, performing microrheology within Saccharomyces cerevisiae yeast cells. By tracking naturally occurring lipid granules with squeezed light, they achieved sensitivity 2.4 dB beyond the quantum noise limit, allowing the viscoelastic properties of the cytoplasm to be determined with a 64% higher measurement rate than possible classically. This establishes a crucial precedent: the fundamental quantum limit can be overcome in biological contexts, and the true physical floor for IFT sensitivity is even lower than the standard quantum limit.

Furthermore, advances in single-molecule biosensing have achieved quantum-noise-limited performance with optical intensities four orders of magnitude lower than previous state-of-the-art systems, enabling detection of nanoparticles as small as 3.5 nm (Mauranyapin et al., 2017). This demonstrates that the sensitivity required for detecting the ultra-weak photonic and mechanical fields emitted by living systems is already within reach of current quantum-limited technologies.

Thermal Fluctuations

A second fundamental limit arises from thermodynamics. Any system in thermal equilibrium exhibits spontaneous fluctuations. A well-known example is Johnson-Nyquist noise, the voltage fluctuations across a resistor. In the context of temperature measurement, which is relevant to IFT's thermal field domain, these fluctuations impose a fundamental resolution limit. Day et al. (1997) demonstrated that the low-frequency temperature noise density of a thermometer connected to a reservoir is fundamentally constrained by the thermal resistance of the link and the temperature itself, given by $\sqrt{(4Rk_B T^2)}$, where R is the thermal resistance, k_B is Boltzmann's constant, and T is the temperature. This implies that for a given thermal environment, there is an irreducible floor to the precision with which temperature fluctuations can be resolved.

In the context of IFT, thermal fluctuations in the organism and its environment will set a lower bound on the detectability of subtle metabolic signals. However, current clinical thermography operates many orders of magnitude above this fundamental limit, leaving vast room for improvement. The thermal noise floor for a typical biological measurement at body temperature (310 K) is on the order of microkelvin fluctuations for microscopic volumes, far below the millikelvin sensitivity required for detecting metabolic hotspots associated with inflammation or early neoplasia.

Information-Theoretic Constraints

Beyond the physics of individual measurements, information theory imposes constraints on the inverse problem itself. The reconstruction of an internal state from external measurements is a classic inverse problem, and the amount of recoverable information is fundamentally limited. De Micheli and Viano (2009) analyzed inverse optical imaging as a communication channel problem, showing that the maximum number of distinguishable messages that can be conveyed from the image back to the object is related to Kolmogorov's ε-capacity. In the limit of vanishing noise ε, this capacity scales as $M_\varepsilon \sim 2S \log(1/\varepsilon)$, where S is the Shannon number. This establishes that the information recoverable about an object from its image is finite and determined by the properties of the imaging system and the noise level.

This principle extends directly to IFT. The inverse problem of reconstructing the physiological state from multi-field data is band-limited and ill-posed, meaning that not all degrees of freedom of the internal state can be independently recovered. The Shannon number represents the maximum number of independent parameters that can be reconstructed from the data. Recent work in small-angle X-ray scattering (SAXS) has shown that the ill-conditioning of such inverse transforms is directly related to the Shannon number, and that exploiting oversampling allows direct inversion provided the recovered information does not exceed this fundamental limit (Rambo & Tainer, 2025). For IFT, this means that the dimensionality of the reconstructable physiological state is bounded, but this bound is determined by the quality and quantity of the sensor data, not by any fundamental physical principle that prevents us from reaching clinically relevant resolutions.

Conceptual, Not Physical, Obstacles

The critical realization is that these fundamental limits—quantum, thermal, and informational—lie far below the sensitivities required for clinically meaningful diagnostics. Current clinical imaging operates many orders of magnitude above the quantum noise limit (Mauranyapin et al., 2017). The thermal fluctuation limits on temperature measurement are similarly far below the resolution of current infrared thermography. And the information-theoretic bounds on inverse problems, while fundamental, still permit reconstruction of high-dimensional physiological states from multi-field data, as demonstrated by recent advances in model reduction and state estimation (Galarce et al., 2022).

Therefore, the main obstacles to realizing IFT are not physical impossibilities. They are conceptual and computational: developing the coupled multi-physics forward models, solving the ill-posed inverse problem with personalized priors, integrating heterogeneous data streams, and building the ultra-sensitive, multi-channel sensor arrays required. These are engineering and scientific challenges, not violations of the laws of physics. The fundamental limits are far enough away that there is ample room to build a transformative diagnostic paradigm before they are approached.

Conclusion — A Shift of Paradigm

Throughout this article, we have traversed the conceptual landscape of a new approach to medical diagnostics. We began with the problem of fragmented vision—the recognition that current modalities offer only projections of the organism, not the organism itself. We then explored the physical nature of living systems as generators of multiple, interacting fields: electromagnetic, magnetic, mechanical, and photonic. From this foundation, we articulated the core hypothesis of Integral Field Tomography (IFT): that the internal physiological state of a living organism can be reconstructed by solving the inverse problem of its externally measurable physical fields. We examined the observable field domains, the shift from imaging to state inference, the intrinsic role of artificial intelligence, the convergence with active inference, the implications for longevity and preventive medicine, and the fundamental physical limits that constrain, but do not preclude, this vision.

As we conclude, a unifying theme emerges. Medical diagnostics must evolve from looking at bodies to reading living systems. Integral Field Tomography represents not a device, but a new epistemology of medicine, where the organism is understood as a coherent, measurable, dynamic whole.

The Limitations of the Anatomical Gaze

Modern medicine, for all its technological sophistication, remains largely rooted in what might be termed the "anatomical gaze"—a focus on structure as the primary arbiter of disease. This paradigm, which reached its apotheosis with the development of CT and MRI, has delivered undeniable benefits. Yet it is fundamentally limited. As Vainio (2025) argues in a sweeping philosophical analysis of 20th-century medicine, the very success of technological diagnostics

has paradoxically distanced us from a holistic understanding of the patient. The body is increasingly viewed as a collection of images and data points, losing its integrity as a lived, biological whole.

This fragmentation is not merely philosophical; it has practical consequences. By the time a structural change is large enough to be detected, the underlying pathological process is already established. Disease, as we have argued, is not a structure—it is a loss of system stability. The anatomical gaze, fixated on static form, is blind to the dynamical processes that precede and produce structural change. What is needed is a fundamental reorientation: from the static to the dynamic, from the structural to the systemic, from the image to the state.

The Organism as a Coherent, Measurable Whole

IFT offers this reorientation. It is predicated on a view of the organism as a coherent whole—a system whose integrity is expressed through the correlations and couplings between its multiple physical fields. The electrical field of the heart is not independent of its mechanical motion; the magnetic field of the brain is not independent of its metabolic state; the photonic emissions of tissues are not independent of their oxidative stress. These fields are not separate signals to be analyzed in isolation. They are facets of a single, unified reality: the living system in action.

The challenge, and the opportunity, of IFT is to capture this coherence. By simultaneously measuring multiple fields and solving the coupled inverse problem, IFT aims to reconstruct not just a map of sources, but a portrait of the system's internal coordination. This aligns with emerging trends in personalized and predictive medicine, which increasingly recognize that health is a property of the whole system, not the absence of local lesions (Boccardi, 2025). As Leote et al. (2024) demonstrated at the molecular level, aging itself is characterized by a loss of coordination between basic cellular processes. IFT scales this insight to the whole organism, offering a way to quantify the coherence—or loss thereof—that defines health and disease.

A New Epistemology of Medicine

To speak of IFT as a new epistemology is to claim that it changes not just what we measure, but how we know. In the current paradigm, diagnosis is episodic and reactive: a patient presents with symptoms, an image is acquired, a lesion is identified, and a treatment is prescribed. Knowledge is localized and static. In the IFT paradigm, diagnosis becomes continuous and proactive. The patient's state is inferred in real time from the fields they continuously emit. Knowledge is distributed and dynamic.

This epistemological shift has profound implications. It transforms the patient from a passive subject of imaging into an active source of information. It transforms the clinician from an interpreter of static images into a reader of dynamical systems. It transforms the concept of disease from a localized abnormality into a systemic loss of stability. And it transforms the goal of intervention from lesion removal or symptom suppression to the restoration of system coherence and adaptive capacity.

The Path Forward

The realization of IFT will require sustained, interdisciplinary effort. The forward models must be developed and validated. The inverse problems must be solved with robust, efficient algorithms. The sensor technologies must achieve the required sensitivity and scalability. The artificial intelligence must learn personalized priors and integrate heterogeneous data streams. And the clinical community must embrace a new way of thinking about diagnosis and health.

Yet the fundamental limits, as we have shown, are not prohibitive. Quantum noise, thermal fluctuations, and information-theoretic constraints lie far below clinically relevant thresholds (Taylor et al., 2013; Mauranyapin et al., 2017; Rambo & Tainer, 2025). The obstacles are conceptual and computational—they are challenges to be overcome, not barriers that cannot be crossed.

In conclusion, Integral Field Tomography represents not merely a technological advance, but a shift of paradigm. It offers a vision of medicine that is holistic, dynamic, and deeply grounded in the physics of life. It invites us to stop looking at bodies and start reading living systems. The organism, in all its complexity, is a coherent, measurable, dynamic whole. It is time we learned to listen.

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