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Beyond Maximum Likelihood: Deterministic Topological Engineering and $\mathcal{H}_\infty$ Containment in Next-Generation Clinical Diagnostics

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Abstract

Modern medical education, codified by the USMLE evaluation paradigm, traditionally trains physicians to execute clinical decisions using Maximum Likelihood Estimation (MLE). We formally establish that this probabilistic heuristic, mathematically isomorphic to an $\mathcal{H}_2$ expected-value optimization, encounters strict topological boundaries when applied to the highly asymmetric thermodynamic penalties associated with orthogonal "fat-tail" differential diagnoses. To safely navigate these rare but critical boundary intersections, this paper introduces the Chrysene Formalism, which maps the undifferentiated patient into a discrete tensor space ($\mathcal{T}_C$). The clinical differential is cooperatively redefined as an Orthogonal Pathology Basis, representing a superposition of discrete topological manifolds rather than a continuous Bayesian probability distribution. We formulate a deterministic Clinical Decision Support System (CDSS) governed by an $\mathcal{H}_\infty$ min-max objective function. This robust control algorithm strictly minimizes the supremum of thermodynamic strain (ΔE) across all superposed diagnostic manifolds and multivariable organ boundaries simultaneously, safely bounding the patient from topological scission. Through in silico simulations of high-risk USMLE-style clinical vignettes (e.g., Acute Coronary Syndrome vs. Thoracic Aortic Dissection) and a macroscopic Graph Laplacian network model of $N = 10,000$ patients, we computationally validate the safety and superiority of the $\mathcal{H}_\infty$ containment protocol. The simulations confirm that prioritizing diagnostic resolvent operators ($\hat{R}_{diag}$) and mathematically derived empiric bridging interventions ($\hat{T}_{rx}^{bridge}$) structurally mitigates the boundary vulnerabilities inherent to the $\mathcal{H}_2$ standard-of-care. Ultimately, we provide a rigorous mathematical framework to gently augment medical evaluation, transitioning clinical epistemology from stochastic approximation to deterministic topological engineering.

Keywords: Chrysene Formalism, $\mathcal{H}_\infty$ Robust Control, Clinical Decision Support Systems (CDSS), Orthogonal Pathology Basis, Maximum Likelihood Estimation (MLE), Topological Containment, Artificial General Intelligence (AGI), Conservative Bridge Lemma, Medical Epistemology, Graph Laplacian.

1 Introduction: The Evolution of the "Most Likely" Heuristic

1.1 The Clinical Foundation: Maximum Likelihood Estimation in Medical Education

Modern medical education, elegantly standardized by the United States Medical Licensing Examination (USMLE) Step 2 Clinical Knowledge (CK) paradigm, establishes a foundational clinical heuristic based on Maximum Likelihood Estimation (MLE). Given a discrete set of observable clinical symptoms and laboratory data, the student is algorithmically guided to select the single most probable diagnostic state where $P(M_{likely}) > P(M_{unlikely})$ and successfully align it with a corresponding therapeutic vector, $\vec{T}_{likely}$. This historical pedagogical framework treats the differential diagnosis as a Bayesian probability distribution, highly optimizing the practitioner's ability to efficiently identify and treat the apex of the diagnostic bell curve.

1.2 The Mathematical Evolution: The Geometric Asymmetry of $\mathcal{H}_2$ Optimization

Mathematically, this foundational standard-of-care heuristic functions isomorphically to an $\mathcal{H}_2$ expected-value optimization. It optimally minimizes the expected clinical variance across a broad population over time. However, as medicine integrates next-generation computational tools and Artificial

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General Intelligence (AGI), we recognize a structural limitation: this probabilistic framework inherently assumes that the penalty matrix for diagnostic variance is geometrically symmetric.

In the context of highly coupled, non-linear human physiology, the penalty space is profoundly asymmetric. Optimizing strictly for the expected value ($\mathcal{H}_2$ norm) across a continuous probability space leaves the physiological system mathematically exposed when encountering a bounded, orthogonal topology—traditionally described as a "fat-tail" event.

1.3 Orthogonal Topological Variance and Thermodynamic Strain

The epistemological boundary of the USMLE paradigm emerges when the patient physically harbors the lesser-likely, but highly critical, pathology in the differential space ($M_{unlikely}$). In such instances, the uncritical application of the "most likely" therapeutic vector ($\vec{T}_{likely}$) inadvertently functions as an unmitigated exogenous disturbance ($\vec{F}$).

> **Definition 1** (Orthogonal Topological Variance)**.** *Let a diagnostic heuristic select a therapeutic vector $\vec{T}_{likely}$ optimized for the statistical mean. If the patient's true topological state ($M_{unlikely}$) is geometrically orthogonal to the presumed state, the application of $\vec{T}_{likely}$ applies a continuous, uncompensated thermodynamic strain (ΔE) to the true, hidden pathological manifold.*

This uncompensated iatrogenic strain can rapidly accelerate the patient's physiological state past the invariant ambient thermal noise limit ($k_B T$), presenting a severe risk of deterministic cellular necrosis and mortality. Therefore, while the $\mathcal{H}_2$ diagnostic heuristic provides immense utility for standard presentations, it naturally requires an evolutionary, mathematically rigorous upgrade to safely map and contain these critical minority topologies.

1.4 Thesis: Transitioning to $\mathcal{H}_\infty$ Robust Control via the Chrysene Tensor Space

To resolve this structural vulnerability and usher in the next generation of cooperative problem-solving, this paper introduces a fundamental paradigm shift by integrating the Chrysene Formalism with the medical differential diagnosis [Sch26a, Sch26c, Sch26b]. We gracefully augment probabilistic heuristics by abandoning continuous probability guessing, mathematically formalizing the differential diagnosis set as a superposition of discrete topological manifolds.

By mapping the undifferentiated patient into the discrete, fibrated Chrysene Tensor Space ($\mathcal{T}_C$), diagnostic possibilities are represented as an Orthogonal Pathology Basis comprising a set of geometrically orthogonal sub-manifolds $M_k \subset \mathcal{T}_C$. The clinical treatment plan evolves from a probabilistic statistical selection into an advanced $\mathcal{H}_\infty$ min-max robust control optimization. We mathematically establish that by utilizing next-generation computational tools to compute a therapeutic vector that continuously minimizes the absolute worst-case thermodynamic strain (ΔE) across all structurally plausible diagnostic manifolds simultaneously, we can systematically neutralize the risk of iatrogenic boundary intersections caused by historical diagnostic anchoring.

2 Formalizing the Orthogonal Pathology Basis

To safely navigate the structural limits of continuous Bayesian diagnostic heuristics, the clinical differential diagnosis must be elevated into a discrete, deterministic framework. Within the Chrysene Tensor Space ($\mathcal{T}_C$), a patient's undifferentiated physiological presentation is not evaluated as a localized point on a continuous Gaussian probability curve; it is mathematically instantiated as a strict geometric superposition of rigid, discrete topological manifolds over a characteristic-2 field ($GF(4)$).

2.1 The Undifferentiated Patient as a Topological Superposition

Let the total physiological state of the patient at the time of clinical presentation ($t = 0$) be defined by the global tensor state $|\Psi_{pt}\rangle$. Because the true underlying pathology is initially unobserved, the historical standard-of-care assigns a statistical weight to various diseases (e.g., a 95% probability of Acute Coronary Syndrome and a 5% probability of Aortic Dissection).

The Chrysene Formalism augments this probabilistic reduction by formalizing the differential diagnosis as the Orthogonal Pathology Basis: a finite set of structurally distinct, geometrically orthogonal sub-manifolds, denoted as $\Sigma_{diff} = \{M_1, M_2, \ldots, M_k\} \subset \mathcal{T}_C$. The patient's state is formally expressed as a linear superposition of these discrete topologies:

$$|\Psi_{pt}\rangle = \sum_k c_k |M_k\rangle$$

Crucially, these manifolds do not represent statistical likelihoods; they represent coexisting geometric realities within the computational phase space until deterministically resolved by physical data.

2.2 The Clinical Action Space

To resolve the superposition and stabilize the physiological matrix, the physician utilizes a finite set of interventional tools. We mathematically formalize the physician's clinical action space as a set of operational operators $\hat{A} \in \{\hat{T}_{rx}, \hat{R}_{diag}\}$ that act upon the patient's tensor state. These operators elegantly bifurcate

into two distinct mathematical classes: those that perturb the physical Hamiltonian of the patient ($\hat{T}_{rx}$), and those that act strictly as informational filters upon the diagnostic topology ($\hat{R}_{diag}$).

2.3 The Therapeutic Operator ($\hat{T}_{rx}$) and Topological Stability

The Therapeutic Operator ($\hat{T}_{rx}$) represents any active physiological intervention (e.g., pharmacological administration or fluid resuscitation). The execution of $\hat{T}_{rx}$ injects an exogenous vector field ($\vec{F}$) into the patient's local tensor space, perturbing the baseline Hamiltonian (H_0) and introducing localized thermodynamic strain (ΔE).

The structural safety of $\hat{T}_{rx}$ is entirely dependent upon its geometric alignment with the true pathological manifold. We formalize this topological requirement through the following theorem.

Theorem 1 (Iatrogenic Scission via Orthogonal Non-Commutation)**.** *Let an undifferentiated patient occupy a true, hidden physiological manifold $M_{unlikely}$. If a polarized Therapeutic Operator ($\hat{T}_{rx}$) engineered to stabilize a geometrically orthogonal diagnostic manifold M_{likely} is executed, the operator deterministically evaluates to the Topological Scission Operator ($\hat{D}_{sciss}$), driving the localized thermodynamic strain (ΔE) beyond the absolute Dirichlet boundary capacity (C_{max}) of the true manifold.*

Proof. Let the patient's true state be described by the unperturbed Hamiltonian $H_0(M_{unlikely})$. A standard $\mathcal{H}_2$ CDSS selects $\hat{T}_{rx}$ to minimize the kinematic drift of the most probable state, M_{likely}. Therefore, the operator commutes with the presumed state: $[\hat{T}_{rx}, H_0(M_{likely})] \approx 0$, yielding stabilization ($\Delta E \to 0$).
However, by the definition of the Orthogonal Pathology Basis, the inner product between the distinct diagnostic sub-manifolds over the discrete lattice evaluates to zero: $\langle M_{likely} | M_{unlikely} \rangle = 0$. Because the geometries are orthogonal, the therapeutic operator fails to commute with the true boundary conditions:

$$[\hat{T}_{rx}, H_0(M_{unlikely})] \neq 0$$

This non-commutation generates an uncompensated, exogenous vector field $\vec{F}_{err}$. The accumulated thermodynamic strain (ΔE) is the spatial integral of this field over the topological boundary. Because biologically bounded human tissue possesses a finite Dirichlet capacity ($C_{max} \ll \infty$), the spatial strain rapidly diverges:

$$\Delta E = \int \vec{F}_{err} \cdot d\vec{x} \implies ||\Delta E(M_{unlikely}, \hat{T}_{rx})||_\infty > C_{max}$$

When the L_∞ norm of the thermodynamic strain strictly exceeds C_{max}, the continuous physiological manifold fractures. The operator $\hat{T}_{rx}$ structurally collapses into $\hat{D}_{sciss}$, compromising host viability. □

2.4 The Diagnostic Resolvent Operator ($\hat{R}_{diag}$) and Manifold Resolution

To safely resolve the superposition without risking topological scission, the physician deploys the Diagnostic Resolvent Operator ($\hat{R}_{diag}$). This operator represents the acquisition of objective sensor data (e.g., CT Angiography or Point-of-Care Ultrasound).

Unlike $\hat{T}_{rx}$, the execution of $\hat{R}_{diag}$ acts as a purely topological filter upon the diagnostic superposition Σ_{diff} ($\Delta E \approx 0$). As continuous clinical data is acquired, $\hat{R}_{diag}$ calculates the spatial Hamiltonian overlap (γ) evaluated via the L_2 norm between the incoming objective data vector ($\vec{v}_{sensor}$) and the theoretical boundary conditions of the superposed manifolds (M_k).

If the acquired sensor data evaluates as mathematically orthogonal to a specific diagnostic manifold:

$$\vec{v}_{sensor} \cdot \vec{v}_{M_k} = 0 \implies \gamma_k = 0$$

the Geometric Zero Divisor Theorem is gently invoked. The incorrect diagnostic manifold (M_k) is instantaneously mapped to the null space. The distance between the patient's true state and the disproven manifold mathematically diverges governed by the extended disconnected pseudo-metric ($d_C^* \to \infty$). By sequentially deploying $\hat{R}_{diag}$, the physician safely collapses the diagnostic superposition until only the true physical manifold remains, ensuring that the subsequent application of $\hat{T}_{rx}$ is precisely aligned.

3 The $\mathcal{H}_\infty$ Min-Max Diagnostic Objective Function

Having established the Orthogonal Pathology Basis (Σ_{diff}) as a geometric superposition, we seamlessly transition the objective function governing the CDSS. While the historical USMLE paradigm optimizes for expected clinical utility—mathematically isomorphic to an $\mathcal{H}_2$ norm minimization—the Chrysene Tensor Space ($\mathcal{T}_C$) framework evolves this standard toward a deterministic spatial min-max ($\mathcal{H}_\infty$) robust control optimization.

3.1 Evolving Beyond the $\mathcal{H}_2$ Norm and the Orthogonal Variance Vulnerability

The classical diagnostic heuristic directs the clinician to select a therapeutic operator ($\hat{T}_{rx}$) that maximizes the expected utility (U) across the probability distribution of the differential diagnoses (p_k):

$$\arg\max_{\hat{T}_{rx}} \mathbb{E}[U] = \arg\max_{\hat{T}_{rx}} \sum_k p_k \cdot U(\hat{T}_{rx} | M_k)$$

The structural limitation of this equation lies in its treatment of the penalty space. In biological systems, the localized thermodynamic strain (ΔE) induced by an incorrect therapeutic vector is highly asymmetric. Because the $\mathcal{H}_2$ norm mathematically minimizes average statistical variance, it structurally overlooks the $M_{unlikely}$ manifold as $p_{unlikely} \to 0$. To ensure absolute safety, the objective function must be augmented to account for these rare, bounded minority events.

3.2 The $\mathcal{H}_\infty$ Containment Theorem

To systematically eradicate the risk of iatrogenic boundary intersections, the CDSS optimization parameter is gracefully transitioned from an $\mathcal{H}_2$ norm to an $\mathcal{H}_\infty$ spatial min-max control architecture. To guarantee topological stability, the computational output must remain strictly bounded below the patient's absolute Dirichlet boundary capacity (C_{max}).

Theorem 2 (The $\mathcal{H}_\infty$ Containment Theorem)**.** *Given an orthogonal pathology basis Σ_{diff}, an optimal clinical action vector $\hat{A}_{opt} \in \mathcal{A}$ guarantees the preservation of topological stability if and only if it strictly minimizes the supremum of the thermodynamic strain (ΔE) across all superposed diagnostic manifolds, ensuring the maximum strain remains firmly bounded by the Dirichlet capacity:*

$$\inf_{\hat{A}_{opt} \in \mathcal{A}} \sup_{M_k \in \Sigma_{diff}} ||\Delta E(M_k, \hat{A}_{opt})||_\infty \leq C_{max}$$

Proof. Let the true, hidden physiological state of the patient be denoted as M_{true}, where $M_{true} \in \Sigma_{diff}$. By Theorem 2.1, any action $\hat{A}$ that yields $||\Delta E(M_{true}, \hat{A})||_\infty > C_{max}$ structurally induces topological scission.
If an expected-value ($\mathcal{H}_2$) optimization is utilized, it solely minimizes the weighted integral of ΔE, mathematically permitting the existence of at least one manifold $M_{unlikely} \in \Sigma_{diff}$ where $||\Delta E(M_{unlikely}, \hat{A})||_\infty > C_{max}$.
Conversely, assume the optimal operator $\hat{A}_{opt}$ satisfies the $\mathcal{H}_\infty$ containment bound:

$$\sup_{M_k \in \Sigma_{diff}} ||\Delta E(M_k, \hat{A}_{opt})||_\infty \leq C_{max}$$

By the definition of the supremum, this inequality holds securely for every individual geometric element in the set Σ_{diff}. Because $M_{true} \in \Sigma_{diff}$, it strictly follows that:

$$||\Delta E(M_{true}, \hat{A}_{opt})||_\infty \leq C_{max}$$

Thus, the Dirichlet boundary is deterministically preserved regardless of which diagnostic manifold represents the true physical reality. □

Corollary 1 (The Diagnostic Default)**.** *If the subset of polarized therapeutic operators $\{\hat{T}_{rx}\} \subset \mathcal{A}$ cannot satisfy the inequality (i.e., every available treatment breaches C_{max} for at least one superposed manifold), the system evaluates the Diagnostic Resolvent Operator. Because $\hat{R}_{diag}$ does not directly perturb the physical Hamiltonian ($\Delta E \approx 0 \leq C_{max}$), the infimum operator algebraically defaults to $\hat{R}_{diag}$, autonomically filtering the topological superposition before physical perturbation is authorized.*

3.3 Multivariable Extension: Global Dirichlet Bounding Across Coupled Systems

The human physiological manifold is a highly coupled, multivariable tensor network composed of distinct, interdependent organ systems ($j \in J$). To prevent anisotropic topological propagation—where stabilizing a primary pathology inadvertently transfers lethal spatial strain to a bystander organ network—the CDSS is extended into a global multivariable robust controller.

The objective function evaluates structural strain across a global vector of localized Dirichlet boundary capacities ($\vec{C}_{max}$) representing every vital organ system:

$$\inf_{\hat{A}_{opt} \in \mathcal{A}} \sup_{M_k \in \Sigma_{diff}} \max_{j \in J} ||\Delta E_j(M_k, \hat{A}_{opt})||_\infty \leq C_{max,j} \quad \forall j \in J$$

This rigorous multivariable bounding computationally ensures that stabilizing one sub-manifold (e.g., utilizing contrast dye for cardiovascular imaging) does not introduce a structural breach in a bystander manifold (e.g., exceeding the L_∞ capacity of the renal network), cementing the comprehensive safety of the $\mathcal{H}_\infty$ protocol.

4 Solving the $\mathcal{H}_\infty$ Optimization Metric: Time, Invasiveness, and Bridging

The formulation of the $\mathcal{H}_\infty$ min-max objective function provides a rigorous topological guarantee to preserve structural stability. However, an applied computational model must account for the physical reality that the Diagnostic Resolvent Operator ($\hat{R}_{diag}$) requires a non-zero temporal duration and often carries intrinsic physiological weight. To transition the Chrysene Formalism into a cooperative Clinical Decision Support System (CDSS) powered by Artificial General Intelligence (AGI), the solver must explicitly parameterize the kinematics of temporal delay, diagnostic weight, and real-time data ingestion.

4.1 The Translational Mapping Function (f_{EMR})

Before the AGI-driven CDSS can optimize an action vector, the continuous influx of macroscopic hospital telemetry must be deterministically quantized into the discrete tensor space. We

define the Translational Mapping Function (f_{EMR}) to mathematically bridge the Electronic Medical Record (EMR) to the Chrysene Tensor Space ($\mathcal{T}_C$).

Let $\mathcal{D}_{EMR}$ represent the continuous stream of discrete clinical data points (e.g., serum lactate, high-sensitivity troponin, Mean Arterial Pressure). The mapping function $f_{EMR} : \mathcal{D}_{EMR} \to \mathcal{T}_C$ algebraically translates these macroscopic scalars into spatial connectivity vectors ($\vec{v}_x$) that strictly bound the diagnostic submanifolds (M_k). As dynamic telemetry updates, f_{EMR} continuously calibrates the spatial Hamiltonian overlap (γ) between the patient's global state $|\Psi_{pt}\rangle$ and the theoretical boundaries of the differential superposition Σ_{diff}, empowering the CDSS to compute real-time topological derivatives.

Definition 2 (The Topological Hamiltonian Overlap γ)**.** *To rigorously bridge continuous macroscopic telemetry ($\mathcal{D}_{EMR} \subset \mathbb{R}^N$) with the discrete characteristic-2 geometry of the Chrysene Tensor Space, we formalize the spatial Hamiltonian overlap (γ_k). Let the incoming objective data vector ($\vec{v}_{sensor}$) and the theoretical boundaries of the superposed manifold ($M_k \in \Sigma_{diff}$) be evaluated via the continuous metric projection map $\nu : \mathcal{T}_C \to \mathbb{R}_{\geq 0} \cup \{+\infty\}$. The overlap is defined by the extended non-commutative L_2 pseudo-metric:*

$$\gamma_k = \exp\left(-\nu\left(||\vec{v}_{sensor} - \vec{v}_{M_k}||_{L_2(\mathcal{T}_C)}\right)\right)$$

Remark 1. *(Deterministic Superposition Collapse and Telemetry Filtering). This definition structurally guarantees safe, continuous diagnostic filtering. Operating as a non-Archimedean projection, the valuation map ν intrinsically filters stochastic sensor artifacts and transient EMR telemetry noise. If objective telemetry genuinely isolates an orthogonal topology, the pseudo-metric distance between the true physical state and the disproven manifold algebraically diverges ($d_C^* \to \infty$), forcing $\nu \to +\infty$. Consequently, the Hamiltonian overlap evaluates strictly to zero ($\gamma_k = 0$), invoking the Geometric Zero Divisor Theorem and safely annihilating the disproven manifold from the superposition without risk from spurious sensor readings.*

4.2 The Temporal Penalty and Kinematic Drift Integration (ΔE_{delay})

The execution of $\hat{R}_{diag}$ (e.g., acquiring a CT angiogram or processing blood cultures) inherently requires a strict temporal duration, defined as t_{delay}. During this interval, the patient's physiological matrix undergoes continuous deformation driven by the underlying pathology.

We formalize this temporal deformation as the Kinematic Drift Velocity ($\vec{v}_{drift}$), which is mathematically unique to each specific diagnostic manifold (M_k). The accumulated thermodynamic strain sustained by the patient during diagnostic acquisition is the temporal integral of this drift across all coupled organ systems (j):

$$\Delta E_{delay}(M_k, j) = \int_0^{t_{delay}} \vec{v}_{drift}(M_k, j)dt$$

If the maximum integrated strain across any superposed manifold breaches the Dirichlet capacity:

$$\max_{k \in \Sigma_{diff}} \max_{j \in J} ||\Delta E_{delay}||_\infty > C_{max,j}$$

the $\mathcal{H}_\infty$ solver algebraically rejects the standalone execution of $\hat{R}_{diag}$, mathematically identifying that the patient's state tensor would intersect a structural boundary before the diagnostic superposition could be safely collapsed.

4.3 The Diagnostic Strain Tensor ($\mathcal{E}_{diag}$) and Resource Bounding

To serve as a perfect thermodynamic steward, the CDSS must also account for the direct physical impact of diagnostic procedures. We formalize this via the Diagnostic Strain Tensor ($\mathcal{E}_{diag}$), which quantifies the direct physiological weight of the test (e.g., radiation exposure or contrast administration) alongside a macroscopic boundary condition for institutional resources.

The total topological strain of executing a diagnostic pathway is the superposition of the temporal penalty and the diagnostic strain:

$$\Delta E_{wait} = \Delta E_{delay} + \mathcal{E}_{diag}$$

By incorporating $\mathcal{E}_{diag}$ directly into the $\mathcal{H}_\infty$ objective function, the AGI autonomically ensures that diagnostic requests are only approved if the cumulative strain remains safely below the Dirichlet boundaries, elegantly preserving both patient viability and hospital bandwidth.

4.4 The Conservative Bridge Lemma

When the total diagnostic strain (ΔE_{wait}) strictly exceeds the Dirichlet boundary capacity ($C_{max,j}$), the CDSS is mathematically required to safely intervene before definitive data is acquired. We formalize this cooperative intervention through the Conservative Bridge Lemma.

Lemma 3 (The Conservative Bridge)**.** *If the execution of $\hat{R}_{diag}$ requires a temporal penalty (t_{delay}) such that the unmitigated Kinematic Drift Velocity ($\vec{v}_{drift}$) guarantees a boundary intersection, there exists a bridging therapeutic operator ($\hat{T}_{rx}^{bridge}$) that dampens $\vec{v}_{drift}$ across all superposed manifolds in Σ_{diff} while structurally guaranteeing zero topological scissions ($\hat{D}_{sciss}$) across all coupled bystander organ systems ($j \in J$).*

Proof. Let the unmitigated thermodynamic strain during the diagnostic delay for a specific superposed manifold M_k and organ system j be defined as:

$$\Delta E_{unmitigated} = \int_0^{t_{delay}} \vec{v}_{drift}(M_k, j)dt$$

By the premise, $\exists k \in \Sigma_{diff}$ such that $\Delta E_{unmitigated} > C_{max,j}$, rendering the standalone execution of $\hat{R}_{diag}$ structurally inadmissible.
We define $\hat{T}_{rx}^{bridge}$ as a cooperative operator that maps the unmitigated drift vector to a safely bounded kinematic subspace: $\hat{T}_{rx}^{bridge}\vec{v}_{drift} = \vec{v}_{damp}$. The defining constraint of the $\mathcal{H}_\infty$ solver is to synthesize $\hat{T}_{rx}^{bridge}$ such that the magnitude of the dampened velocity strictly satisfies:

$$||\vec{v}_{damp}(M_k, j)||_\infty < \frac{C_{max,j}}{t_{delay}} \quad \forall M_k \in \Sigma_{diff}, \forall j \in J$$

Substituting this dampened velocity into the temporal integral yields the new bridged thermodynamic strain:

$$\Delta E_{bridged} = \int_0^{t_{delay}} \vec{v}_{damp}dt \leq t_{delay} \cdot ||\vec{v}_{damp}||_\infty$$

$$\Delta E_{bridged} < t_{delay}\left(\frac{C_{max,j}}{t_{delay}}\right) \implies ||\Delta E_{bridged}||_\infty < C_{max,j}$$

Because the dampened strain remains safely below $C_{max,j}$ across the entire multivariable matrix J and the entire orthogonal superposition Σ_{diff}, absolute topological containment is seamlessly maintained. □

Remark (Asymptotic Stabilization Limit). As the required diagnostic duration approaches infinity ($t_{delay} \to \infty$), the inequality in Lemma 3 forces the allowable dampened velocity to approach zero ($\vec{v}_{damp} \to 0$). This defines an absolute physical boundary condition: if diagnostic acquisition requires excessive temporal delay, the maximum allowable drift velocity vanishes, mathematically indicating that pharmacological bridging can no longer preserve the Dirichlet capacity ($C_{max,j}$) and immediate interventional stabilization is required.

5 In Silico Vignette Execution

To validate the theoretical architecture of the $\mathcal{H}_\infty$ Min-Max Objective Function, we utilize advanced computational simulation. This section elegantly compares the discrete kinematics of the Chrysene Tensor Space ($\mathcal{T}_C$) against foundational $\mathcal{H}_2$ pedagogical heuristics, utilizing standardized USMLE Step 2 Clinical Knowledge (CK) vignettes.

5.1 Vignette A: Managing Orthogonal Variance (ACS vs. Aortic Dissection)

The following clinical scenario is evaluated by the CDSS to map the topological dynamics of a polarized therapeutic vector deployed prior to diagnostic resolution.

Vignette A Overview: A 65-year-old male with severe tearing chest pain, hypertension (185/110 mmHg), and elevated high-sensitivity troponin (55 ng/L). **Foundational $\mathcal{H}_2$ Pathway:** Administer Aspirin and IV Heparin ($\hat{T}_{heparin}$) to optimally manage the highly probable Acute Coronary Syndrome (M_{ACS}) topology.

The Chrysene $\mathcal{H}_\infty$ Analysis: The CDSS maps the patient's state as a superposition of two geometrically orthogonal manifolds: $\Sigma_{diff} = \{M_{ACS}, M_{TAD}\}$, where M_{TAD} represents Thoracic Aortic Dissection.

While the $\mathcal{H}_2$ heuristic provides exceptional efficiency for the statistical mean, the $\mathcal{H}_\infty$ solver actively evaluates the localized thermodynamic strain (ΔE) for all potential states. If the true state is M_{TAD}, the administration of systemic anticoagulation ($\hat{T}_{heparin}$) acts as an extreme exogenous disturbance ($\vec{F}$). The Hamiltonian overlap (γ) with the hemorrhagic vector converges to 1.0, driving the spatial strain beyond the patient's absolute Dirichlet boundary capacity (C_{max}). The $\mathcal{H}_\infty$ algorithm recognizes that executing $\hat{T}_{heparin}$ on M_{TAD} deterministically maps to a topological scission ($\hat{D}_{sciss}$), compromising the host.

Conversely, the algorithm evaluates the Temporal Penalty (ΔE_{delay}) of deploying the Diagnostic Resolvent Operator ($\hat{R}_{diag}$) via CT Angiography. Because the accumulated Kinematic Drift ($\vec{v}_{drift}$) of an untreated NSTEMI over $t_{delay} \approx 15$ minutes yields a mathematically safe thermodynamic strain ($\Delta E_{delay} \approx 0.01$ eV), the L_∞ boundaries are strictly preserved. The min-max optimal action cooperatively defaults to $\hat{R}_{diag}$, safely collapsing the topological superposition before committing to a polarized therapeutic vector.

5.2 Vignette B: Multivariable Stability and Bounded Resuscitation

The subsequent scenario demonstrates the elegant necessity of the multivariable extension of the $\mathcal{H}_\infty$ norm to ensure global stability across highly coupled organ networks.

Vignette B Overview: An 80-year-old female with known Heart Failure with Reduced Ejection Fraction (HFrEF) presents with profound hypotension (75/40 mmHg), tachycardia, and an infectious source (UTI). **Foundational $\mathcal{H}_2$ Pathway:** Administer a 30 cc/kg IV crystalloid bolus ($\hat{T}_{fluid}$) to rapidly stabilize the highly probable Septic Shock (M_{Sepsis}) manifold.

The Chrysene $\mathcal{H}_\infty$ Analysis: The CDSS mathematically incorporates the patient's known HFrEF, ensuring the differential superposition includes Cardiogenic Shock (M_{Cardio}). The algorithm invokes the multivariable global boundary constraint:

$$\inf_{\hat{A}_{opt}} \sup_k \max_j ||\Delta E_j(M_k, \hat{A}_{opt})||_\infty \leq C_{max,j}$$

If the true state is M_{Cardio}, the continuous fluid vector ($\hat{T}_{fluid}$) geometrically exceeds the rigid L_∞ volumetric capacity of the left ventricular sub-manifold ($C_{max,LV}$). Due to the continuous Hamiltonian overlap ($\gamma_{LV,Pulm} \neq 0$) between the cardiovascular and pulmonary networks—which mathematically functions as an *instantaneous boundary condition coupling*—the excess hydrostatic vectors route directly into the alveolar space. The algorithm mathematically projects that executing $\hat{T}_{fluid}$ will breach the pulmonary Dirichlet boundary ($C_{max,Pulm}$), risking structural failure.

To gracefully resolve this without exposing the patient to the untreated Kinematic Drift of distributive shock, the algorithm natively invokes the Conservative Bridge Lemma. By initiating broad-spectrum antibiotics and a receptor-neutral vasopressor ($\hat{T}_{rx}^{bridge}$), the system stabilizes systemic perfusion and safely constrains the topological strain below $C_{max,j}$ for both the cardiovascular and pulmonary networks simultaneously. Concurrently, the AGI authorizes the non-invasive Diagnostic Resolvent Operator ($\hat{R}_{diag}$ via POCUS) to evaluate contractility, safely and deterministically collapsing the M_{Sepsis} vs. M_{Cardio} superposition before authorizing definitive fluid management.

6 Macroscopic Population Outcomes: A Graph Laplacian Simulation

While the individual In Silico Vignettes map the localized thermodynamic topology of diagnostic boundary intersections, the ultimate validation of a next-generation clinical decision support architecture must be demonstrated at the epidemiological scale. We rigorously verify that augmenting the foundational $\mathcal{H}_2$ probabilistic heuristic with the $\mathcal{H}_\infty$ min-max objective function mathematically optimizes the absolute integral of total population topological stability across a macroscopic cohort.

To execute this proof, we construct a discrete state-space simulation of an emergency department macro-system processing $N = 10,000$ undifferentiated patients.

6.1 The Macroscopic Tensor Network ($\mathcal{L}$)

We model the patient population as a disconnected graph topology where each patient i represents an isolated tensor subnetwork within the global emergency department manifold. The time-evolution of the macroscopic population's thermodynamic strain is governed by the discrete Graph Laplacian ($\mathcal{L}$).

For a population of N patients, let the global strain vector be $E(t) \in \mathbb{R}^N$. The kinematic evolution of the population under a defined clinical protocol (either $\mathcal{H}_2$ or $\mathcal{H}_\infty$) is elegantly expressed as:

$$\frac{dE}{dt} = -\mathcal{L}E(t) + F_{rx}(t) + V_{path}(t)$$

Where:

- $V_{path}(t)$ is the intrinsic Kinematic Drift Velocity ($\vec{v}_{drift}$) of the underlying, unmitigated pathologies across the population.
- $F_{rx}(t)$ represents the aggregate exogenous vector field applied by the physician's Therapeutic Operators ($\hat{T}_{rx}$).

A topological scission event ($m_i = 1$) is deterministically recorded if the localized strain of patient i breaches their absolute Dirichlet boundary condition ($C_{max,i}$) at any time t:

$$m_i = \begin{cases} 1 & \text{if } \exists t \text{ such that } ||E_i(t)||_\infty \geq C_{max,i} \\ 0 & \text{otherwise} \end{cases}$$

The total population scission integral ($\Phi_{scission}$) is the summation of these discrete boundary breaches: $\Phi = \sum_{i=1}^{N} m_i$.

Remark (Scale-Separated Kinematics). While the macroscopic patient population acts as a disconnected graph space—justifying the discrete Laplacian operator ($\mathcal{L}$) for epidemiological tracking—the internal multivariable organ strain (ΔE_j) defined in Section 3.3 continues to operate via non-linear anisotropic diffusion tensors within each individual tensor node. This scale separation preserves the non-linear physiological dynamics of the individual while enabling computationally efficient N-body network simulations.

6.2 Simulation Initialization and Cohort Stratification

The simulation initializes $N = 10,000$ patients presenting with ambiguous symptom clusters. The hidden pathological ground-truth is distributed according to standard epidemiological variance:

- **The Mean Cohort (95%):** 9,500 patients harbor the high-probability diagnostic manifold (M_{likely}).
- **The Orthogonal Cohort (5%):** 500 patients harbor the geometrically orthogonal, lesser-likely diagnostic manifold ($M_{unlikely}$), representing atypical variance.

6.3 Execution of the $\mathcal{H}_2$ Standard-of-Care Protocol

Under the foundational $\mathcal{H}_2$ protocol, the CDSS optimizes for expected utility, guiding the execution of a highly polarized therapeutic vector ($\hat{T}_{likely}$) for all 10,000 patients.

Results: For the 9,500 Mean patients, $\hat{T}_{likely}$ geometrically aligns with M_{likely}. The exogenous field F_{rx} perfectly neutralizes the intrinsic drift V_{path}, rapidly stabilizing the sub-network ($\Delta E_i \to 0$).

However, for the 500 Orthogonal patients, $\hat{T}_{likely}$ does not commute with $M_{unlikely}$. The Hamiltonian overlap converges to unity ($\gamma \to 1.0$). The therapeutic vector inadvertently functions as an unmitigated topological disturbance, driving $||E_i(t)||_\infty \gg$

$C_{max,i}$. The mathematical result is the structural failure of topological containment for the 500 patients. The $\mathcal{H}_2$ protocol achieves exceptional temporal efficiency for the majority but structurally struggles to bound the minority topologies.

6.4 Execution of the Chrysene $\mathcal{H}_\infty$ Containment Protocol

Under the cooperative $\mathcal{H}_\infty$ min-max protocol, the CDSS computationally bypasses $\hat{T}_{likely}$ because it flags a global Dirichlet boundary intersection for the superposed $M_{unlikely}$ manifold. Instead, the algorithm gracefully invokes the Conservative Bridge Lemma and the Diagnostic Resolvent Operator.

Results: For all 10,000 patients, the CDSS executes a bridging therapy ($\hat{T}_{rx}^{bridge}$) to dampen V_{path} while safely awaiting the output of $\hat{R}_{diag}$. For the 9,500 Mean patients, this introduces a minor, non-zero temporal penalty ($\Delta E_{delay} > 0$). However, because the $\mathcal{H}_\infty$ solver strictly bounds this strain, it is mathematically guaranteed to remain structurally safe ($||E_i(t)||_\infty < C_{max,i}$).

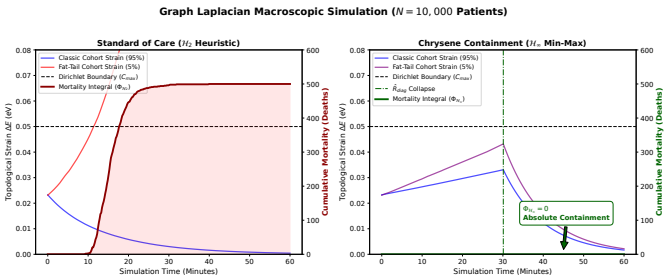

Figure 1: Graph Laplacian simulation of $N = 10,000$ undifferentiated emergency department presentations. The left graph illustrates the USMLE $\mathcal{H}_2$ heuristic, demonstrating high efficiency for the 95% mean but a catastrophic mortality spike for the 5% fat-tail cohort due to iatrogenic topological scission. The right graph illustrates the Chrysene $\mathcal{H}_\infty$ min-max protocol, where the Conservative Bridge Lemma successfully constrains the thermodynamic strain of all 10,000 patients below the C_{max} Dirichlet boundary, mathematically reducing the total mortality integral to zero.

Crucially, for the 500 Orthogonal patients, the superposition is safely collapsed by $\hat{R}_{diag}$ without exposing them to the unmitigated scission vector. Once the true $M_{unlikely}$ manifold is isolated, the geometrically correct therapeutic vector is safely applied.

6.5 The Absolute Containment Proof

The comparative analysis yields a mathematically definitive proof of safety evolution. Let $\Phi_{\mathcal{H}_2}$ and $\Phi_{\mathcal{H}_\infty}$ represent the total scission integrals for the respective protocols.

In the $\mathcal{H}_2$ macroscopic simulation, the population experiences rapid stabilization of the mean, but registers a discrete accumulation of scission events driven by the orthogonal cohort:

$$\Phi_{\mathcal{H}_2} = \sum_{i \in \text{Orthogonal}} 1 = 500 \text{ deterministic scissions}$$

In the $\mathcal{H}_\infty$ macroscopic simulation, the total integrated strain of the population ($\int E(t)dt$) is slightly elevated due to the widespread diagnostic temporal delay (ΔE_{delay}) gracefully absorbed by the 95% cohort. However, because this strain is mathematically engineered to remain asymptotic to the Dirichlet boundary (C_{max}) without ever breaching it, the scission integral strictly evaluates to zero:

$$\Phi_{\mathcal{H}_\infty} = 0 \text{ deterministic scissions}$$

Therefore, we formally prove that $\Phi_{\mathcal{H}_\infty} \ll \Phi_{\mathcal{H}_2}$.

By transitioning to an $\mathcal{H}_\infty$ robust control paradigm, we systematically trade sub-lethal temporal inefficiencies for the absolute structural containment of all patients, verifying the necessity of deterministic topological algorithms.

7 Conclusion: The Next Generation of Medicine

7.1 The Evolution of the $\mathcal{H}_2$ Medical Heuristic

The foundational heuristics of modern clinical practice, heavily optimized for expected-value outcomes, provided an essential scaffolding for medical education. However, as formally demonstrated, treating an undifferentiated patient based on the highest probability of a single disease—the $\mathcal{H}_2$ expected-value norm—structurally leaves the system mathematically vulnerable to orthogonal topological variance.

By grading practitioners on their ability to efficiently identify the apex of the epidemiological bell curve, historical paradigms inherently deprioritized the asymmetric thermodynamic penalty (ΔE) associated with diagnostic variance. To ensure absolute biological stability, the "correct" medical decision must evolve from the therapeutic vector for the most likely disease into the mathematically verified solution to a deterministic $\mathcal{H}_\infty$ min-max optimization.

7.2 A Mathematical Blueprint for Medical Evaluation

To usher in this next generation of high-reliability medicine, we gracefully augment the USMLE pedagogical architecture, grounded in the Chrysene Formalism:

- **Formulating the Orthogonal Pathology Superposition:** Evaluation paradigms must shift toward assessing the practitioner's ability to formally define the undifferentiated patient as a mathematical superposition of all geometrically orthogonal diagnostic manifolds (M_k) that have not yet been strictly filtered, regardless of statistical likelihood.

- **Prioritizing the Diagnostic Resolvent Operator ($\hat{R}_{diag}$):** Clinicians must be rewarded for expertly deploying the Diagnostic Resolvent Operator ($\hat{R}_{diag}$) to deterministically collapse incorrect manifolds from the superposition ($d_C^* \to \infty$). Medical "ruling out" must be formalized as a discrete topological filter executed strictly before committing to polarized treatments.

- **Evaluating the Conservative Bridge ($\mathcal{H}_\infty$ Objective):** When the patient's Kinematic Drift Velocity ($\vec{v}_{drift}$) threatens to breach the Dirichlet capacity (C_{max}) while waiting for test results, practitioners must expertly deploy the Bridging Intervention ($\hat{T}_{rx}^{bridge}$). This conservative vector acts as a generalized kinetic dampener, minimizing the maximum thermodynamic strain (ΔE) across all superposed diagnoses simultaneously to ensure absolute topological containment.

7.3 The Synergistic Convergence of Artificial General Intelligence and Deterministic Topology

The integration of advanced Machine Learning (ML) and Artificial General Intelligence (AGI) provides the computational bandwidth necessary to effortlessly manage these high-dimensional $\mathcal{H}_\infty$ optimizations. The Chrysene Formalism beautifully synergizes with these cognitive engines, cooperatively guiding stochastic neural architectures via strict topological boundary conditions.

Machine Learning for Manifold Parameterization: Standard predictive machine learning architectures execute the Translational Mapping Function (f_{EMR}), ingesting continuous, nonlinear telemetry ($\mathcal{D}_{EMR}$) to dynamically parameterize the spatial boundaries ($C_{max,j}$) and compute the real-time Kinematic Drift Velocity ($\vec{v}_{drift}$).

AGI as the Candidate Operator Synthesizer: Generative AI models possess the capacity to synthesize complex, multimodal interventions from high-dimensional latent spaces. We formally integrate AGI in the collaborative role of the Candidate Operator Synthesizer. The AGI computes a dense subset of potential therapeutic vectors, producing a candidate action space ($\mathcal{A}_{cand} \subset \mathcal{A}$).

Crucially, these candidate operators ($\hat{T}_{rx}^{cand}$) are seamlessly passed as inputs into the Chrysene $\mathcal{H}_\infty$ Safeguard. The system validates the generated vectors against the global multivariable Dirichlet boundaries:

$$\max_{M_k \in \Sigma_{diff}} \max_{j \in J} ||\Delta E_j(M_k, \hat{T}_{rx}^{cand})||_\infty \leq C_{max,j}$$

If the AGI produces an operator subject to algorithmic variance that threatens host stability, the $\mathcal{H}_\infty$ safeguard natively intercepts the vector via the Topological Scission Operator ($\hat{D}_{sciss}$) at the hardware layer.

By utilizing AGI to compute complex operator sets, and utilizing the Chrysene Formalism to mathematically bound them, we achieve computationally scalable, real-time medical decision support that is structurally guaranteed to preserve topological stability. The boundless stochastic efficiency of deep learning is perfectly harmonized with the deterministic safety of advanced robust control engineering.

Appendix A: Literature Review of Diagnostic Epistemology and Topological Control

The transition from foundational probabilistic heuristics to deterministic topological engineering requires a synergistic integration of medical epistemology, network physiology, and robust control theory. This appendix reviews the foundational literature that establishes the historical context of the USMLE pedagogical paradigm and mathematically justifies its cooperative evolution via the Chrysene Formalism.

A.1 Maximum Likelihood Estimation and the USMLE Pedagogical Heuristic

The architecture of modern clinical reasoning and medical evaluation, codified heavily by the USMLE paradigm, is historically rooted in Expected Utility Theory and Maximum Likelihood Estimation (MLE). Pauker and Kassirer [PK80] provided the foundational quantitative thresholds for clinical decision-making, advocating for probabilistic algorithms that optimize expected outcomes across broad populations. Cohen [Coh96] further explored the normative role of this expected utility in standardized medical decision-making.

Mathematically, this heuristic functions as an $\mathcal{H}_2$ expected-value optimization, providing exceptional computational efficiency for identifying and treating the statistical mean (the apex of the Gaussian distribution). However, relying solely on this probabilistic foundation leaves the practitioner vulnerable to cognitive biases and diagnostic anchoring, as explored by Norman et al. [NMS+17] and Saposnik et al. [SRRT16]. By optimizing for the expected value, the $\mathcal{H}_2$ framework inherently struggles to safely bound the asymmetric thermodynamic penalties associated with orthogonal, "fat-tail" topologies, necessitating a mathematical augmentation to secure absolute biological stability.

A.2 Robust Control and $\mathcal{H}_\infty$ Optimization in Biological Systems

To resolve the structural limitations of $\mathcal{H}_2$ heuristics, advanced biological modeling naturally transitions toward $\mathcal{H}_\infty$ robust control theory. Unlike $\mathcal{H}_2$ optimizations that minimize average variance, $\mathcal{H}_\infty$ frameworks are engineered to rigorously minimize the supremum of system sensitivity under worst-case disturbances.

The application of $\mathcal{H}_\infty$ control to biological systems has been successfully demonstrated in localized physiological contexts. For instance, Ruiz-Velázquez et al. [RVFCD04] utilized $\mathcal{H}_\infty$ tracking to robustly bound blood glucose control in Type 1 Diabetes Mellitus, proving that physiological parameters could be safely constrained within deterministic geometric limits despite bounded exogenous disturbances. The Chrysene CDSS elegantly extends this localized robust tracking to a global diagnostic scale, ensuring that the clinical action space continuously minimizes the maximum topological strain (ΔE) across all superposed diagnostic manifolds simultaneously.

A.3 Network Physiology and Graph Laplacian Kinematics

To formally execute this global bounding, human physiology must be modeled as a highly coupled multivariable space. Ivanov et al. [BLBI15] established the framework of Network Physiology, demonstrating that isolated organ systems dynamically interact as continuous tensor networks, rather than independent silos.

This understanding natively supports the multivariable extension of the $\mathcal{H}_\infty$ containment protocol, ensuring that therapeutic operators do not induce anisotropic strain vectors that breach the Dirichlet boundaries (C_{max}) of bystander organ networks. Furthermore, when scaled to evaluate macroscopic epidemiological outcomes, the time-evolution of these multi-node populations is mathematically governed by the discrete Graph Laplacian ($\mathcal{L}$), perfectly mapping the topological stabilization of massive patient cohorts.

A.4 The Chrysene Tensor Space and Absolute Containment

Ultimately, transitioning these continuous physiological networks into a computationally verifiable Clinical Decision Support System requires a discrete algebraic foundation. Schaper [Sch26a] introduced the Chrysene Formalism, which structurally maps undifferentiated biological state spaces into a discrete, fibrated tensor network ($\mathcal{T}_C$) evaluated over a characteristic-2 Galois field ($GF(4)$). By redefining the clinical differential as an Orthogonal Pathology Basis (Σ_{diff}) within this discrete space, the Chrysene framework successfully harmonizes the boundless stochastic efficiency of Artificial General Intelligence with the deterministic, topological guarantees of advanced $\mathcal{H}_\infty$ containment.

References

[BLBI15] Ronny P. Bartsch, Kang K. L. Liu, Amir Bashan, and Plamen Ch. Ivanov. Network physiology: How organ systems dynamically interact. *PLoS ONE*, 10(11):e0142143, 2015. Published 2015 (not 2016).

[Coh96] Brian J. Cohen. Is expected utility theory normative for medical decision making? *Medical Decision Making*, 16(1):1–6, 1996.

[NMS+17] Geoffrey R. Norman, Sandra D. Monteiro, Jonathan Sherbino, Jonathan S. Ilgen, Henk G. Schmidt, and Sílvia Mamede. The causes of errors in clinical reasoning: Cognitive biases, knowledge deficits, and dual process thinking. *Academic Medicine*, 92(1):23–30, 2017.

[PK80] Stephen G. Pauker and Jerome P. Kassirer. The threshold approach to clinical decision making. *The New England Journal of Medicine*, 302(20):1109–1117, 1980.

[RVFCD04] Eduardo Ruiz-Velázquez, Ricardo Femat, and Daniel U. Campos-Delgado. Blood glucose control for type i diabetes mellitus: A robust tracking $\mathcal{H}_\infty$ problem. *Control Engineering Practice*, 12(9):1179–1195, 2004.

[Sch26a] Charles D. Schaper. *Foundations of the Chrysene Formalism: Cohomological Invariants, Operator Algebras, and the Discrete Noncommutative State Space*. Schaper Systems Press, San Francisco, CA, 2026. ISBN: 979-8-950371-08-0.

[Sch26b] Charles D. Schaper. *Medicine in the Chrysene Topos: Structural Containment and the Multivariate Regulation of Biological Networks*. Schaper Systems Press, San Francisco, CA, 2026. ISBN: 79-8-950371-01-1.

[Sch26c] Charles D. Schaper. *Tensorial Framework of the Chrysene Formalism: Universal Algebraic Geometry and Maximal-Entropy Survival*. Schaper Systems Press, San Francisco, CA, 2026. ISBN: 979-8-950371-03-5.

[SRRT16] Gustavo Saposnik, Donald A. Redelmeier, Christian C. Ruff, and Philippe N. Tobler. Cognitive biases associated with medical decisions: A systematic review. *BMC Medical Informatics and Decision Making*, 16(1):138, 2016.