

Article

Deterministic Systems Intelligence: Admissible-State Operators for Feasibility-First Inference in Sequential Systems

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and or methodology.

- DSI formalises feasibility as a pre-inferential systems layer through a set-valued admissible-state operator conditioned by structural clocks, regimes, structural memory and explicit constraints.
- The framework is positioned as complementary to viability, reachability, state-space, control and time-series traditions, while extending their feasibility logic to partially formalised operational and socio-technical sequential systems.

What are the main findings and/or the implications of the main findings?

- A worked sequential-system example shows that the same observed emission can support different feasible futures when clock, regime or history conditions differ, so inferential eligibility cannot be determined from the emission alone.
- DSI is empirically assessable through agreement in admissibility construction, infeasible-output rates, regime-transition detection and comparative performance of otherwise identical pipelines with and without an admissibility gate.

Abstract

Sequential systems are commonly analysed with probabilistic, state-space, dynamical and learning-based methods, yet these approaches may define state spaces broader than the states that an active system can actually reach under structural constraints, regimes and accumulated history. This creates a systems-representation problem: inference can remain technically valid while operating over infeasible states or transitions. Deterministic Systems Intelligence (DSI) is developed as a systems-science framework for addressing that problem by operationalising admissibility as an explicit pre-inferential systems layer. DSI distinguishes conceivable from admissible state spaces and defines a set-valued admissible-state operator constructed from clock, regime, memory and constraint predicates. Six scoped methodological propositions specify implications for feasibility, masking, regime transition, memory, optimisation and admissibility-consistent explanation. The framework is positioned relative to cybernetics, viability and reachability theory, state-space modelling, nonlinear dynamics, time-series analysis and machine learning, with explicit boundaries on what DSI inherits and what it adds. A fully specified sequential-system example demonstrates how identical observed emissions can yield different admissible futures under different clocks, regimes and histories, while comparative evaluation criteria are defined for admissibility construction and inferential withholding. DSI is proposed as a complementary admissibility layer that makes representational feasibility explicit before downstream estimation, prediction, optimisation or release governance.



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Keywords: Deterministic Systems Intelligence; admissible-state operators; systems science; sequential systems; feasibility-first modelling; structural constraints

1. Introduction

Sequential data analysis is central to contemporary science, management and decision support. Forecasting, monitoring, anomaly detection, state inference, early warning, control and planning all depend on time-indexed observations whose present and future behaviour are conditioned by prior states, interventions and constraints. Established probabilistic, econometric, state-space, dynamical and learning-based methods provide indispensable ways of representing temporal dependence, uncertainty, latent structure, structural breaks and distributional change [1–3].

A cybernetic and systems-theoretical perspective adds a further emphasis: systems do not merely emit data; they regulate, observe, decide, adapt and remain constrained by their organisation. Classical cybernetics and management cybernetics treated communication, control, regulation and organisational viability as coupled systems problems [4–6]. General systems theory, system dynamics and systems thinking traditions likewise reinforced the view that organised complexity should be studied through feedback, constraint, structure, adaptation and behaviour over time [7–10].

Deterministic Systems Intelligence (DSI) is formulated as a systems-science framework for sequential inference. It distinguishes between a conceivable state space—the set of states expressible under a modelling language—and an admissible state space—the subset reachable under active structural constraints. The central problem is representational: whether the state space over which probabilistic, dynamical or learning-based inference operates is feasible for the active system. The framework specifies the representational objects, admissible-state operator, structural propositions and release logic used to determine whether downstream inference should proceed, be bounded, monitored, reversed or withheld.

The framing is complementary rather than oppositional. Where uncertainty is intrinsic, structural information is unavailable or the aim is calibrated prediction under partial knowledge, probabilistic and learning-based approaches remain necessary. DSI adds a prior representational question: has the model distinguished states that are feasible from states that are merely conceivable?

This distinction matters because many sequential systems are constrained before uncertainty is quantified. Physical systems obey conservation laws and reachability constraints. Controlled systems operate under permitted transitions. Institutional and operational systems are shaped by clocks, regimes, capacities and prior commitments. Computational systems may be deterministic while producing output streams that pass tests of irregularity or randomness under limited observation. In such settings, an observed sequence may appear irregular not because all conceivable states are sampled from a stable probability law, but because only a constrained subset is reachable and that subset is only partially observed.

The methodological contribution is an admissibility layer for systems inference. Before downstream prediction, optimisation or decision support, the analyst asks whether the active system state and its candidate transitions are feasible under the relevant clocks, regimes, structural memory and stable constraints. Figure 1 summarises this ordering. The admissible-state operator does not replace statistical modelling; it conditions downstream inference on the feasible state set.

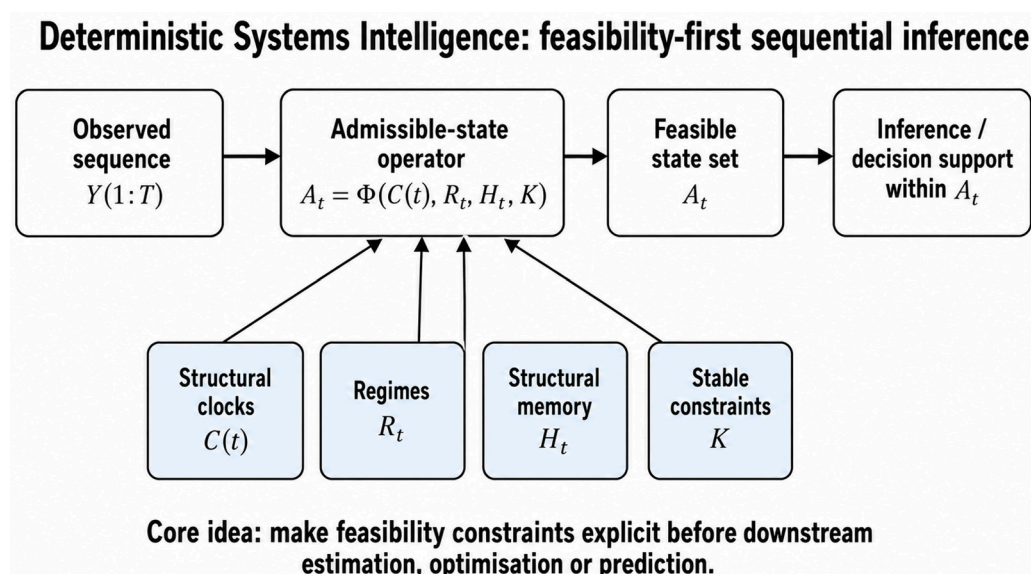


Figure 1. Feasibility-first systems inference in Deterministic Systems Intelligence. The admissible-state operator constrains downstream inference by structural clocks, regimes and memory before probabilistic, learning-based or decision-support tools are applied.

The motivation also reflects a long-standing lesson from nonlinear dynamics and computation: irregular observation does not uniquely identify stochastic generation. Deterministic dynamics can be difficult to forecast from finite observations, and deterministic systems may appear irregular when the state is only partially observed [11–13]. Computational accounts of randomness likewise show that deterministic procedures can produce sequences that are difficult to distinguish from random sequences under broad classes of tests [14–16].

DSI extends this lesson from irregular dynamics to constrained sequential admissibility. A system can appear irregular not only because it is sensitive to initial conditions, but because feasible trajectories are gated by structural clocks, conditioned by regimes and restricted by structural memory. The implication is epistemic: irregular observation alone does not establish that feasibility constraints are irrelevant, and stochasticity may remain part of the system representation.

Elements of this general logic have been operationalised in four peer-reviewed studies. A regime-conditioned admissible-state operator was used in national electricity-demand inference to classify states for release or HOLD under comparable prior support [17]. A clinical-AI perspective applied feasibility-first reasoning to release, monitoring, rollback and withholding in high-consequence care pathways [18]. A cross-domain study examined admissible-state reasoning and pooling artefacts across public operational and physical systems [19]. An AI-ethics study extended admissible-state reasoning to AI-mediated institutional action, distinguishing computational output from ethically warranted action under conditions of authority, accountability, implementation capacity and remedy [20]. These studies document prior applications of components of the framework and are not treated as independent validation; comparative evaluation by other investigators and against established methods remains necessary.

The framework makes five methodological contributions. First, it distinguishes conceivable and admissible state spaces as separate objects of systems representation. Second, it specifies a feasibility-first ordering for sequential inference. Third, it defines the admissible-state operator as a set-valued intersection of explicit admissibility predicates and states minimal properties that follow from that construction. Fourth, it states six scoped methodological propositions concerning feasibility, masking, regime transition, memory,

optimisation and admissibility-consistent explanation, with operational implications that can be evaluated in domain studies. Fifth, it locates DSI relative to established systems science, cybernetic, viability, reachability, control, time-series and learning traditions, and sets out conditions under which the framework can be tested or rejected. The contribution is not the origination of feasible-state reasoning; it is the organisation of clocks, regimes, structural memory, admissibility construction and inferential release or withholding into a portable pre-inferential architecture for constrained sequential systems.

DSI does not introduce a new forecasting algorithm, optimisation method or machine-learning architecture, and its scientific claims do not depend on proprietary implementation details. It develops a systems methodology for constrained sequential inference whose contribution can be evaluated through conceptual coherence, formal clarity, compatibility with established systems traditions and empirical performance when instantiated in specific domains.

2. Systems Formulation and Formal Vocabulary

Let the time index be denoted by

$$t \in T$$

Let observable emissions and the possibly latent system state be denoted by

$$Y_t \text{ and } X_t,$$

respectively. Let X denote the state space definable under a modelling language. The admissible subset at time t is

$$A_t \subseteq X.$$

The distinction between X and A_t is the central representational distinction. X records what the modelling language can express; A_t records what the active system can reach under its current organisation. DSI is concerned with the relation between these two spaces and with the consequences of allowing downstream inference to operate over states or transitions that are not feasible.

A sequential system is any system whose observations are indexed in time and whose present or future behaviour depends in a nontrivial way on prior states, prior observations, prior decisions or prior constraints. This includes conventional time series, state-space systems, controlled systems, discrete-event systems, dynamical systems and operational systems [21,22]. DSI is concerned not only with the statistical properties of Y_t , but with the structural constraints governing the evolution of the process that produces, conditions or restricts Y_t .

A state X_t is a representation of the system's internal configuration at time t . A modelling language may define a broad state space X , containing all states that can be represented in principle. DSI distinguishes this from the admissible state space A_t , the subset of X that the system can actually occupy at time t under its constraints. This distinction is routine in reachability and viability reasoning, but is often implicit in statistical modelling [23–25]. Figure 2 illustrates the difference between outcome-space and admissible-state interpretations.

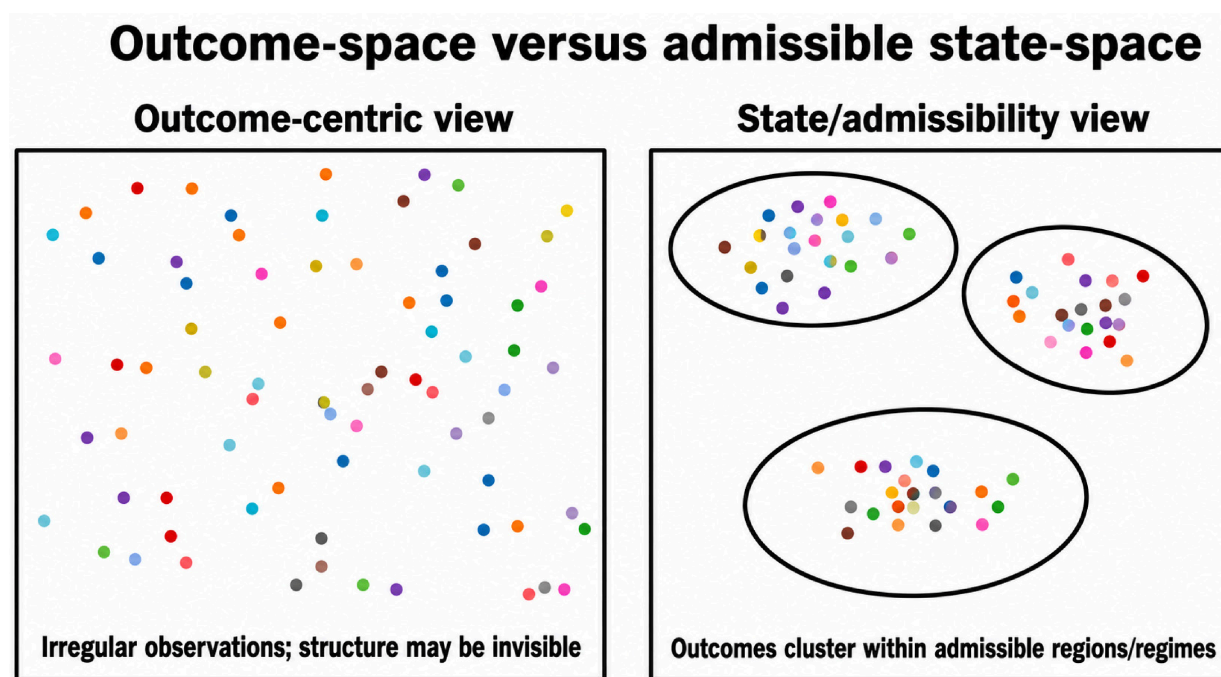


Figure 2. Outcome-space versus admissible state-space. An outcome-centric view may present irregular observations as dispersed points. A state/admissibility view interprets observations as projections from constrained admissible regions.

A sequential system is deterministic if, conditional on its current state and explicit inputs, its next state is fixed by an update rule:

$$X_{t+1} = F(X_t, U_t).$$

Determinism in this sense does not imply practical predictability. Sensitivity to initial conditions, incomplete state observation, measurement noise and many-to-one observation maps may make deterministic systems difficult to forecast.

A system exhibits masked determinism when state evolution is deterministic or tightly constrained, but the observable emission process appears irregular because the analyst observes only a projection, aggregation or distorted surface of the underlying state evolution. Formally, emissions may be represented as

$$Y_t = G(X_t)$$

or

$$Y_t = G(X_t, \epsilon_t),$$

where G is an observation or emission map and ϵ_t denotes observational disturbance rather than necessarily generative stochasticity.

A structural clock is a rule-governed temporal mechanism that enables, disables, gates or conditions classes of state transitions. A clock may be periodic, quasi-periodic, event-triggered, threshold-dependent or piecewise-defined. Structural clocks are common in timed automata, discrete-event systems, controlled processes and institutional systems [22,26]. Their importance for DSI is that they can produce discontinuities in feasible futures without requiring a stochastic explanation.

A regime is a configuration of constraints under which admissibility has stable structural form. A regime transition occurs when the constraint configuration changes so that the admissible set A_t , the update rule or both are redefined. Regime-switching and structural-break models often treat such changes statistically [27,28]. DSI treats them structurally: a regime change is a reconfiguration of feasibility.

Structural memory is the persistence of prior trajectories as constraints on future feasibility. It includes path dependence, lock-in, hysteresis-like effects, sunk commitments, irreversible transitions and history-conditioned reachability [29–31]. Structural memory is broader than autocorrelation. Two systems may have identical present emissions but different feasible futures because they arrived at the present through different histories.

Structural memory can be represented computationally in more than one way. For example, an accumulated memory variable may evolve as $H_{t+1} = \lambda H_t + q(X_t, U_t)$, with $0 \leq \lambda \leq 1$ and q representing a state- or action-dependent increment. A memory gate can then be written $k_H(x) = 1[H_t \leq h^*]$ for transitions that become inadmissible above a prespecified burden or commitment threshold h^* . In systems with irreversible transitions, the same idea may be represented instead by a history-dependent set of forbidden transitions. These are domain-specific constructions of H_t , not a universal memory equation.

The admissible-state operator is represented compactly as

$$A_t = \Phi(C(t), R_t, H_t, K),$$

where $C(t)$ denotes clock conditions, R_t the active regime, H_t structural memory and K a collection of stable or currently active constraints. To make Φ operational rather than merely notational, let $K = \{k_1, \dots, k_m\}$ denote admissibility predicates, with each hard predicate $k_j(x; C(t), R_t, H_t) \in \{0, 1\}$. For a candidate state $x \in X$, $k_j = 1$ means that x satisfies constraint j under the current clock, regime and history. The admissible-state operator is then defined as

$$\Phi(C(t), R_t, H_t, K) = A_t = \{x \in X: k_j(x; C(t), R_t, H_t) = 1 \text{ for all } j = 1, \dots, m\}.$$

Equivalently, if $A_{j,t} = \{x \in X: k_j(x; C(t), R_t, H_t) = 1\}$, then $A_t = \bigcap_j A_{j,t}$. This construction permits exact admissibility when constraints are known and deterministic, and bounded or competing admissibility sets when one or more constraints are uncertain. Uncertain constraints should not be silently converted into hard exclusions; they can be represented as alternative predicate sets or confidence-bounded admissibility envelopes and carried forward to downstream inference.

Four minimal design properties are intended to hold for this construction rather than being presented as universal theorems. First, constraint monotonicity: adding a valid hard constraint cannot enlarge A_t , because intersecting the current admissible set with an additional predicate set can only preserve or reduce membership. Second, conditional reproducibility: fixed X , $C(t)$, R_t , H_t and K yield the same A_t under the same predicate definitions, because the operator is evaluated from the same declared inputs and predicates. Third, regime and history sensitivity: a change in R_t or H_t may alter A_t even when the current emission is unchanged, because both variables enter the admissibility predicates and can therefore change which states satisfy them. Fourth, modular updating: when the predicate factorisation is known, a change in one clock, regime, memory or constraint component requires recomputation only of the affected predicate sets before the intersection is updated. These are design properties of the stated construction; they do not imply uniqueness of the analyst's constraint specification, and disagreement over K remains an empirical and methodological issue addressed in Section 7.

The framework proposes that probabilistic or learning-based inference should be conditioned on feasibility whenever relevant constraints can be specified. Probability assignment is then made over the admissible set rather than over states already excluded by the system structure. Figure 3 shows how masking can distort observation without changing the underlying feasible set.

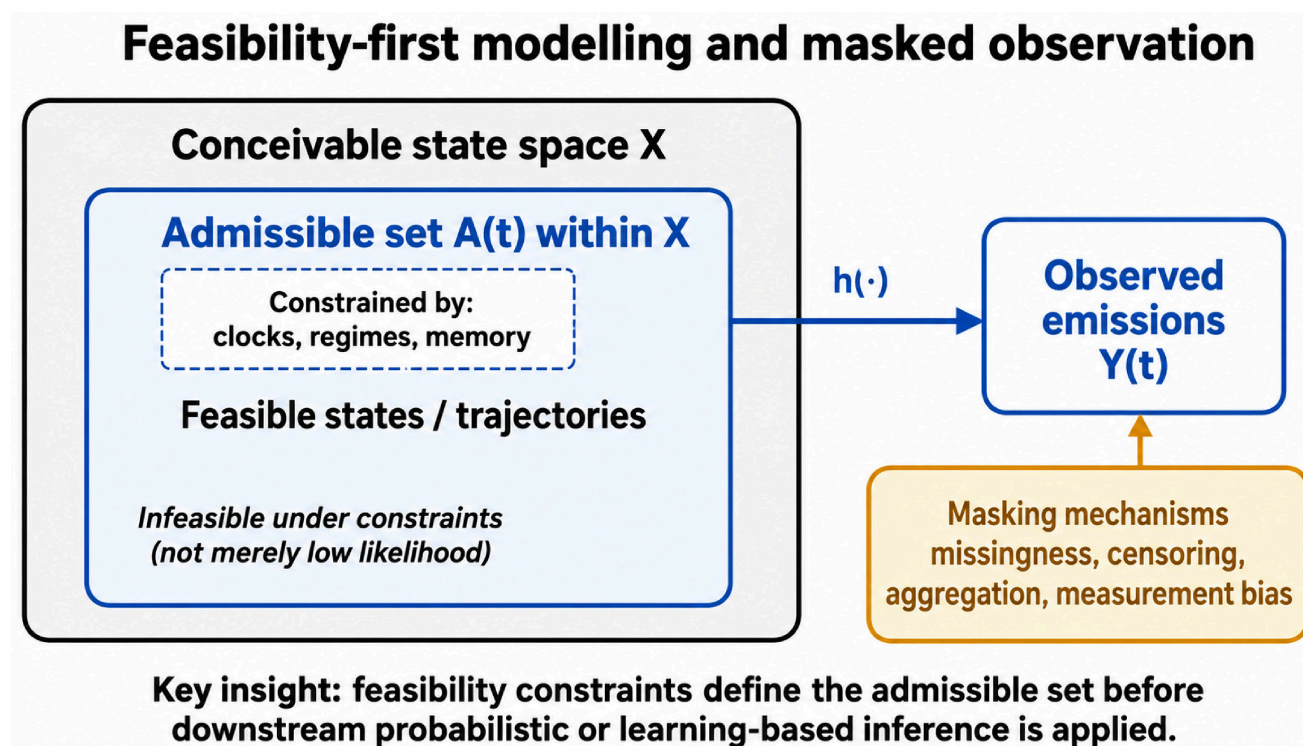


Figure 3. Feasibility-first modelling and masked observation. Structural constraints define an admissible set of feasible states or trajectories within the broader conceivable state space, while masking mechanisms distort observation rather than feasibility.

Table 1 summarises the core DSI primitives and their operational interpretation.

Table 1. Core DSI primitives and operational interpretation.

DSI Primitive	Operational Interpretation
Sequential system	A time-indexed process in which present behaviour depends on prior states, observations, decisions or constraints.
Conceivable state space X	All states definable under a modelling language, including states the system may never reach.
Admissible state space A_t	Time- and history-conditioned subset of X feasible under clocks, regimes, memory and constraints.
Structural clock	Rule-governed temporal gate that enables, disables or conditions classes of transitions.
Regime	Constraint configuration under which admissibility has stable structural form.
Regime transition	Change in constraint configuration that redefines admissibility.
Structural memory	History-conditioned reachability: prior trajectories restrict future feasibility beyond present observables.
Masked determinism	Deterministic or constrained state evolution producing irregular emissions under partial observation or aggregation.
Admissibility-consistency	Model-validity requirement that implied futures respect feasible states and transitions.

3. Structural Propositions

This section states six scoped methodological propositions. They are not universal axioms for all sequential analysis and are not presented as exhaustive proofs. They apply

when sequential dependence, partial observability and constraint-conditioned feasibility are materially present, particularly when model outputs enter consequential inference or decision pathways. Each proposition states a representational requirement and an operational implication that can be examined in a domain-specific instantiation. Throughout, the central distinction is between the conceivable state space X and the admissible state space A_t . Figure 4 summarises the implied workflow.

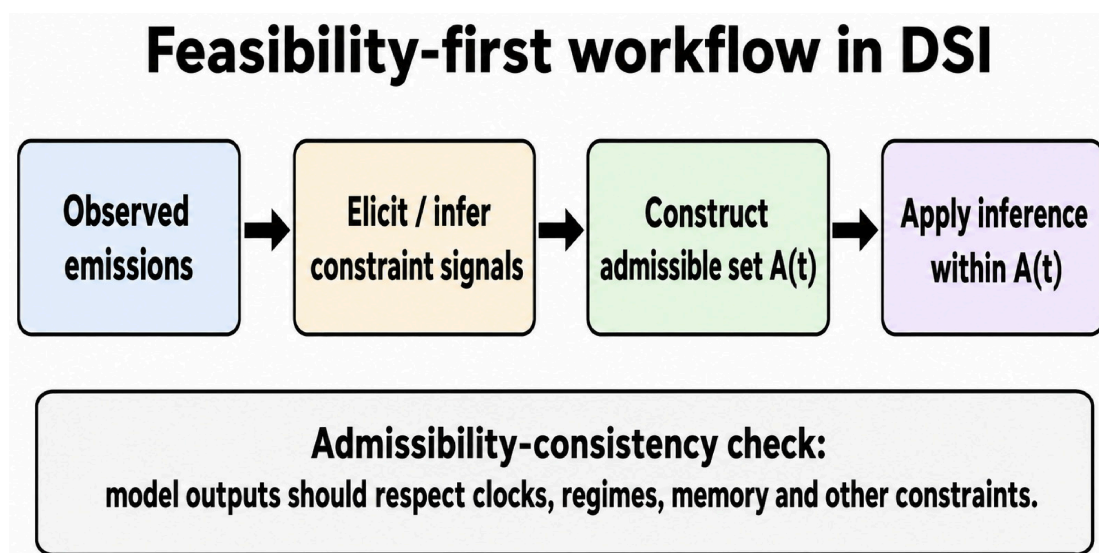


Figure 4. Feasibility-first workflow in DSI. Constraint elicitation and admissibility construction precede downstream probabilistic, statistical or learning-based inference.

Proposition 1. *Feasibility precedes probabilistic assignment. For a sequential system with admissible state space A_t , probabilistic statements about future states or emissions are representationally valid only relative to the admissible set. Assigning positive probability to states known to be outside A_t indicates misspecification of the possibility space. Once feasibility has been specified, uncertainty within that set may be represented probabilistically.*

Operational implication/test: if an inference pipeline assigns positive support to a state independently established as structurally infeasible under the active constraints, the pipeline is admissibility-inconsistent even if its aggregate predictive calibration is acceptable.

Proposition 2. *Irregular emissions can be induced by masking. A deterministic or constrained sequential system may generate emissions that are statistically compatible with stochastic processes when the emission map is partially observable, many-to-one, aggregated, noisy or otherwise masking. Observations are not the same as states. If the observation map hides the structure of state evolution, the resulting sequence can appear irregular even when state evolution is constrained.*

Operational implication/test: where two latent or system states map to similar emissions, admissibility should be assessed against the state/constraint representation rather than inferred from emission irregularity alone; failure is indicated if the framework treats masking as proof of stochastic generation.

Proposition 3. *Regime transitions redefine admissibility. If the admissible set depends on a regime variable, then regime transitions change reachable futures by redefining admissibility. Historical frequency may not approximate future feasibility after a regime transition. Generalisation across time therefore requires generalisation across admissibility regimes.*

Operational implication/test: a documented change in the active constraint configuration should produce a corresponding change in A_t when it affects feasible transitions, even if the marginal emission distribution has not yet changed detectably.

Proposition 4. *Structural memory conditions feasible futures. Structural memory exists when prior trajectories restrict future feasibility beyond what is captured by contemporaneous observables. Path dependence is not merely narrative history; it is a constraint mechanism. Two systems can look similar at a time point but differ in feasible futures because of different accumulated histories.*

Operational implication/test: two cases with the same contemporaneous observables but different histories should be allowed to produce different admissible futures when a prespecified memory variable or forbidden-transition rule differs.

Proposition 5. *Optimisation cannot recover infeasible states. No optimisation or learning procedure can make a structurally infeasible state feasible, regardless of model capacity. If the model's hypothesis space is misaligned with the system's feasible state space, learning may improve fit while retaining the wrong representation. This is a representational error, not merely an estimation error.*

Operational implication/test: improving fit, capacity or optimisation objective value should not be counted as correction of a structural error if model-supported states continue to violate independently specified feasibility constraints.

Proposition 6. *Explanation requires admissibility-consistency. A model can be predictively adequate in a limited window yet fail as an explanation if it treats infeasible states or transitions as plausible futures. Predictive success does not uniquely identify structure. In high-stakes settings, this criterion is especially important because infeasible recommendations may carry operational, ethical, financial or safety costs.*

Operational implication/test: explanatory adequacy requires that model-implied transitions remain admissible under the active clock, regime, memory and constraint specification; predictive accuracy alone is insufficient evidence of structural consistency.

Taken together, the propositions define an admissibility discipline for sequential systems. The discipline asks whether an inference pipeline has identified, approximated or bounded the feasible state set before applying likelihood, optimisation, prediction, classification or control. The admissible set may be uncertain or only partially recoverable. In that case, the framework requires the uncertainty about feasibility to remain explicit rather than disappear inside residual error, distributional uncertainty or model misspecification.

4. Position Within Systems Science and Analytic Traditions

DSI complements cybernetics, general systems theory, operations research, control, time-series modelling, machine learning and viability theory. Its narrower contribution is to organise a representational question shared across systems science and these analytic traditions: whether a sequential inference process operates over states and transitions that the active system can actually reach. Table 2 summarises the relationship between DSI and selected neighbouring traditions.

Table 2. Relationship between DSI and neighbouring systems and analytic traditions: inheritance, added organisation and claim boundaries.

Tradition	What DSI Inherits	Established Formal Strength	What DSI Adds/ Organises	Boundary of DSI Claim
Cybernetics/management cybernetics	Feedback, regulation, organisational constraint and viable variety	System regulation, communication and organisational viability	Makes inferential eligibility explicit as a feasibility question before release or downstream modelling	Does not replace cybernetic models of feedback or organisational control
State-space modelling	Separation of latent state evolution from observed emissions	Filtering, smoothing and probabilistic latent-state estimation	Requires the represented latent state space to be checked against feasible evolution before inference within it	Does not provide a new filter or estimator
Control, reachability and viability theory	Feasible trajectories, invariant/viable sets and constraint-aware evolution	Rigorous construction of reachable, controllable and viable sets for formally specified systems	Extends feasibility-first ordering to partially formalised, history-dependent, institutional and operational sequential systems and links it to inferential release/withholding	Does not claim to supersede formal reachability or viability analysis where those methods are directly applicable
Timed automata/discrete-event systems	Clock-conditioned transitions and event-gated state evolution	Formal timing constraints and transition systems	Uses structural clocks as one component of a broader admissibility operator that also includes regime and memory	Does not introduce a new automata formalism
Time-series/regime-switching analysis	Temporal dependence, uncertainty, structural breaks and regime variation	Statistical estimation, forecasting and change-point/regime detection	Distinguishes statistical distributional change from structural reconfiguration of feasible states	A statistical break and a DSI regime change need not imply one another
Machine learning	Flexible learned mappings and representation learning	Prediction/classification under observed training distributions	Adds an external or jointly specified admissibility gate for query-state support, structural constraints and withholding	Does not claim superior predictive accuracy or a new learning architecture
DSI	Admissible state space under clocks, regimes, memory and constraints	Set-valued predicate construction at the framework level; domain-specific exact or approximate instantiation	Integrates feasibility representation with inferential eligibility and operational release, restriction, monitoring, rollback or HOLD	Its value must be shown comparatively; admissibility construction may be uncertain and domain dependent

The affinity with cybernetics is direct. Cybernetics addresses communication, control, feedback and regulation, while management cybernetics extends these concerns to organisational viability [5,6]. DSI adds an explicit feasibility question: observed variety should be interpreted in relation to the variety that remains available under constraint. In Ashby's

terms, the issue is not only what variety is observed, but what variety the system can still realise under its current organisation [5].

The framework also resonates with second-order cybernetics because the analyst participates in defining the state space under study. A model does not simply mirror a pre-given system; it selects distinctions, constructs variables and determines which futures are represented as possible. Admissibility therefore depends partly on the modelling boundary and on how the observer constructs the possibility space [32,33].

Time-series analysis provides mature methods for describing dependence, forecasting future values, estimating uncertainty and identifying structural breaks [1,21,34]. Econometric methods also formalise volatility and parameter instability, including ARCH/GARCH and structural-break frameworks [27,35,36]. DSI complements these methods by asking whether the modelled state space respects feasibility constraints.

A statistical structural break and a DSI regime transition are therefore related but non-equivalent events. A statistical break denotes a detectable change in the distribution, parameters or dependence structure of observed data. A DSI regime transition denotes a change in the constraint configuration that changes feasible states or transitions. Neither necessarily implies the other. For example, a new operating rule may immediately forbid a transition at a specified clock time while the observed outcome distribution remains temporarily unchanged; this is a DSI regime transition without an immediately detectable statistical break. Conversely, a demand shock can shift an observed distribution while leaving the governing transition constraints unchanged. Statistical change-point methods can therefore supply evidence about regime change, but they do not by themselves define it in DSI.

State-space models already distinguish latent state from observation, making them close allies of DSI [2,37,38]. However, a state-space model can still define a latent state space more broadly than the system can reach. DSI adds an admissibility layer upstream of filtering or smoothing: latent states should not only be estimated; they should be constrained by feasible evolution.

Dynamical systems theory shows that deterministic systems may be difficult or impossible to forecast precisely in practice. DSI accepts this insight. Its emphasis differs: irregular emissions may arise not only from sensitivity to initial conditions, but also from constraint-conditioned admissibility and masking. The framework therefore extends the interpretive space between determinism and practical unpredictability.

Algorithmic and computational accounts of randomness show that deterministic processes can generate sequences that pass statistical tests or resist compression [14,16,39]. DSI draws a cautious epistemic lesson: emission-level irregularity does not settle the ontological status of the generator. It may reflect stochastic generation, deterministic complexity, masking or constrained admissibility under partial observability.

Control theory, reachability analysis and viability theory already treat feasibility as a first-class object [23–25], and DSI does not claim priority for that idea. DSI inherits the same logical ordering: feasible evolution is constrained before optimisation or probabilistic reasoning proceeds within the resulting set. Its proposed contribution is organisational and methodological portability: clocks, regime, structural memory and heterogeneous constraints are combined as an explicit admissibility layer that can be used when the system is only partly formalised and when constraints are operational, institutional, historical or difficult to parameterise in a conventional control model. Where a mature reachability or viability formulation fully specifies the problem, DSI should be viewed as compatible framing rather than a replacement.

Machine-learning approaches provide flexible prediction, classification and representation learning, often without an explicit representation of system constraints [40]. They are

also vulnerable to dataset shift, distribution shift and regime change [41–43]. Deep-learning approaches to time series have expanded the modelling repertoire, but high capacity does not by itself resolve mismatch between training conditions and active feasible states [44–46]. DSI interprets part of this vulnerability as admissibility mismatch: the learned mapping may have been trained under one feasible state regime and applied under another.

The practical implication is that high-capacity models may require constraint-aware checks when outputs are used beyond the regime represented in training data. If the active admissible set has changed, the learned mapping may require restriction, recalibration, review or non-release. This recommendation is consistent with broader calls for interpretability and auditability in high-stakes modelling [47,48], but DSI locates the problem specifically at the level of feasible state representation.

5. Methodological Implications for Systems Inference and Governance

DSI adds admissibility-consistency to the vocabulary of model validity. A model is admissibility-consistent when its implied states and transitions remain within the feasible set defined by the active system constraints. This criterion complements predictive validation rather than replacing it. A model may therefore be evaluated both by how accurately it predicts and by whether it represents futures the system can actually reach.

This yields a three-part distinction among errors. Estimation error concerns inaccurate parameter estimates. Approximation error concerns insufficient flexibility in the model class. Structural error concerns mismatch between the model-implied feasible state space and the system's actual feasible state space. Structural error may persist despite more data or a more flexible algorithm because the underlying problem is representational rather than statistical.

This distinction is consistent with the broader modelling lesson that a model may be useful while remaining structurally limited [49–51]. It is also consistent with the no-free-lunch insight that optimisation performance depends on problem structure and assumptions [52]. DSI makes those assumptions explicit at the level of feasibility.

For a model to generalise across time, its representation must remain valid across relevant changes in feasibility. If the admissible set changes, historical accuracy may no longer imply representational adequacy. Under DSI, regime change is not only a statistical challenge; it is a change in the feasible set over which inference is being made.

DSI also treats non-occurrence as potentially informative. If a system never enters certain states, or repeatedly avoids certain transitions, this may signal feasibility constraints rather than low probability alone. Explanation should therefore include not only why observed events occurred, but why certain conceivable events did not occur.

The governance implication is most relevant when model outputs enter consequential decisions. An analytic pipeline may require more than a point estimate or probability interval; it may require an explicit release condition. Depending on the application, the available states may include Release, Restricted Interpretation, Active Monitoring, Rollback or HOLD. These are not universal labels that every domain must adopt. They illustrate how admissibility can be translated into operational decisions about whether inference should proceed, be bounded, be watched, be reversed or be withheld.

Admissibility should not be conflated with desirability or utility. A state may be structurally admissible yet clinically, economically, ethically or operationally undesirable. DSI therefore addresses whether an inference or candidate action is supportable under the represented system constraints; selection among admissible actions requires domain-specific risk assessment, decision analysis, value judgements and governance criteria. Likewise, RELEASE, RESTRICTED INTERPRETATION, ACTIVE MONITORING, ROLLBACK and HOLD are illustrative operational states rather than a universal decision-theoretic solution.

DSI functions as a pre-inferential framework rather than a forecasting algorithm: it identifies, approximates or bounds the admissible state space before established inferential tools are applied. The empirical question is whether making that layer explicit improves representation, decision quality, auditability or failure detection in comparison with otherwise similar pipelines that omit it.

6. Illustrative Socio-Technical Operationalisation

The admissibility formulation is designed for socio-technical systems in which technical outputs enter human, organisational or institutional decision pathways. The examples illustrate how operator-level admissibility can be translated into practice without reproducing the detailed methods, data or outcomes of domain-specific studies. They are schematic applications rather than empirical validations.

In a socio-technical instantiation, the admissible set is shaped not only by the technical state of a system but also by the authority to act, the active institutional or operational regime, prior commitments, monitoring capacity and the consequences of action or non-action. The same analytic output may therefore support different practical states under different configurations. Operationalisation requires the analyst to identify the current emission or model output, declare the relevant clocks, regime and structural memory, construct or bound the admissible set, and then assign the narrowest defensible release condition for the stated decision.

6.1. Worked Example: Clock-, Regime- and Memory-Conditioned Admissibility

Consider a minimal sequential service system with four states $X = \{B, E, I, R\}$: baseline (B), elevated condition (E), intervention-active (I) and recovery (R). The stable transition constraint K permits $B \rightarrow \{B, E\}$, $E \rightarrow \{E, I\}$, $I \rightarrow \{I, R\}$ and $R \rightarrow \{R, B\}$. Let the structural clock $C_t \in \{\text{open}, \text{closed}\}$ indicate whether routine intervention is operationally available. Let the regime $R_t \in \{\text{normal}, \text{contingency}\}$; under contingency, an emergency pathway can permit $E \rightarrow I$ even when the routine clock is closed. Let structural memory $H_t \in \{0, 1\}$ indicate whether an intervention occurred in the immediately preceding interval; under the normal regime, $H_t = 1$ blocks a repeated transition to I.

For a current state E, define three predicates: $k_K(x)$, which enforces the stable transition graph; $k_{C,R}(x)$, which permits I only when $C_t = \text{open}$ or $R_t = \text{contingency}$; and $k_{H,R}(x)$, which permits I only when $H_t = 0$ or $R_t = \text{contingency}$. The admissible set is $A_t = \{x \in X: k_K(x)k_{C,R}(x)k_{H,R}(x) = 1\}$. This fully specified instantiation of Φ yields the same A_t for the same predicate definitions and inputs.

$$A_t = \{x \in X: k_K(x) = 1 \wedge k_{C,R}(x) = 1 \wedge k_{H,R}(x) = 1\}.$$

Assume that the observed emission Y_t is a binary alert that equals 1 in both E and I. The emission alone therefore does not distinguish an elevated condition from an intervention-active state. Four cases, summarised in Table 3, illustrate why admissibility depends on more than Y_t .

An unconstrained probabilistic model fitted only to the observed alert history could assign positive probability to I in all four cases because Y_t is identical. The DSI gate does not claim that the probability model is statistically invalid; it changes the possibility space supplied to that model. Cases B and D exclude I because the transition is infeasible under the active clock or memory condition, whereas Case C restores I after a regime change. The example also shows that a regime transition can alter admissibility without requiring an immediately observable distributional break, and that structural memory can alter feasible futures without changing the current emission.

Table 3. Worked instantiation of the admissible-state operator for a four-state sequential service system.

Case	C_t	R_t	H_t	A_t from Current E	Inferential/Operational Consequence
A	open	normal	0	{E, I}	Routine $E \rightarrow I$ is feasible; downstream inference may proceed within {E, I}.
B	closed	normal	0	{E}	I is structurally excluded despite the same alert; intervention inference should be withheld or restricted.
C	closed	contingency	0	{E, I}	Regime change re-opens $E \rightarrow I$ even though the clock is closed.
D	open	normal	1	{E}	Recent intervention history blocks repetition; the same current alert supports a different feasible future.

6.2. Cross-Domain Socio-Technical Illustrations

Three schematic examples are shown in Table 4. In health-system decision support, an alert may be technically available but should be released only if the patient-care stage, recent interventions, data quality and responsible clinical review pathway make the inference admissible. In public infrastructure analytics, a forecast or anomaly signal may require restriction when the active demand, maintenance or contingency regime is poorly represented by the historical reference. In institutional decision support, a prioritisation or risk output may warrant review or HOLD when policy conditions, case history, decision authority or remedial capacity have changed [20]. In each case, the DSI contribution is not the domain outcome model itself; it is the explicit representation of whether the current claim is sufficiently supported for release into a consequential socio-technical action pathway.

Table 4. Minimal socio-technical illustrations of admissibility from analytic output to practice and outcome.

Socio-Technical Setting	Analytic Output	Active Admissibility Conditions	DSI Question	Illustrative Operational Outcome
Health-system decision support	Clinical alert, risk estimate or monitoring signal	Care stage; recent intervention; data quality; clinician authority; monitoring capacity	Is the current claim supported for this patient state and intended clinical use?	RELEASE for review; RESTRICT to a bounded use; MONITOR; ROLLBACK; or HOLD
Public infrastructure analytics	Demand forecast, anomaly signal or operational recommendation	Demand cycle; maintenance state; contingency regime; historical comparability; available response	Does the active operating regime remain represented by the support used for inference?	Release routine use; restrict to supported subsystems or periods; recalibrate; or HOLD
Institutional decision support	Prioritisation score, eligibility signal or risk classification	Policy cycle; case history; resource constraint; decision authority; appeal/review pathway	Is the inference admissible under the current institutional regime and accountable action pathway?	Release; bounded interpretation; monitored decision; rollback after rule change; or HOLD

These examples also clarify how outcome is defined within the framework. Outcome is not limited to predictive accuracy. At the socio-technical boundary, an outcome may be that an inference is authorised, restricted, escalated for review, monitored, reversed, withheld or used to trigger collection of additional evidence. The resulting action and feedback then become part of the subsequent system history, linking admissibility, practice and observable consequence while preserving the distinction between the general systems methodology and its domain-specific instantiations.

7. Scope, Testability and Limitations

DSI is most relevant when three conditions hold: sequential dependence, partial observability and constraint-conditioned feasibility. Sequential dependence means that future behaviour depends on prior states, observations, decisions or constraints. Partial observability means that analysts observe emissions rather than complete state evolution. Constraint-conditioned feasibility means that reachable states are shaped by clocks, regimes, structural memory, capacities or other restrictions.

When these conditions are weak, DSI may add little beyond conventional probabilistic or learning-based modelling. If observations are independent, the relevant state space is already adequately represented, constraints are immaterial or the task is purely descriptive, feasibility-first analysis may be unnecessary. Accordingly, the framework is not applicable to every sequential dataset.

The proposed framework is testable at three levels. At the representational level, an admissible-state specification should exclude states or transitions that are independently known to be infeasible while retaining feasible rare events. At the inferential level, conditioning on admissibility should reduce structurally impossible outputs, unstable extrapolation or inappropriate pooling without merely suppressing difficult cases. At the operational level, explicit release states should improve auditability and identify when restriction, monitoring, rollback or withholding is justified.

A concrete comparative evaluation can use the same downstream model in two otherwise identical pipelines: a baseline pipeline operating on the model-defined possibility space and a DSI-gated pipeline in which candidate states are first filtered or bounded by a prespecified admissibility operator. Constraint definitions should be fixed before outcome evaluation where feasible. Independent domain adjudicators can then classify evaluated states or transitions as feasible, infeasible or uncertain without access to the pipeline label. The primary structural outcome can be the infeasible-output rate $IOR = n$ (model-supported outputs later adjudicated infeasible) / n (all adjudicated model-supported outputs). Secondary outcomes can include retention of feasible rare events, predictive performance among released cases, frequency of HOLD/restriction, and decision or detection delay. The key comparison is whether the admissibility layer reduces structurally infeasible outputs without merely suppressing difficult but feasible cases.

Admissibility construction itself is also testable. When independent analysts construct A_t from the same evidence and protocol, inter-analyst agreement can be quantified with Cohen's κ for binary admissibility classifications or an appropriate multi-rater/generalised agreement statistic. Regime-transition performance can be compared with a prespecified statistical change-point method by measuring detection timing and the subset of transitions identified by only one approach. Structural-error classification can be reported as the proportion of evaluated errors attributed to infeasible-state representation rather than estimation or approximation. Universal thresholds are not imposed by DSI; domain studies should prespecify acceptable agreement, false-exclusion and infeasible-output tolerances according to consequence and use context.

Illustrative benchmarks can make this prespecification more concrete without creating universal DSI cut-offs. For example, a domain study might define a relative reduction in infeasible-output rate of at least 20% versus an otherwise identical ungated pipeline as a minimally meaningful structural improvement, while a reduction of 50% or more could represent a large effect; it might require inter-analyst agreement of $\kappa \geq 0.60$ for exploratory admissibility construction and a higher threshold such as $\kappa \geq 0.80$ in high-consequence use; and it might define improved regime-transition detection as at least a 20% reduction in median detection delay at a non-inferior false-alarm rate, or an absolute sensitivity gain of at least 10 percentage points at a matched false-positive rate. These values are illustrative planning examples only. Acceptable thresholds should be prespecified according to domain consequence, prevalence, comparator performance, decision cost and intended use, and should be accompanied by confidence intervals and sensitivity analyses where appropriate.

The framework would be weakened if admissible sets cannot be specified with acceptable reliability, if different analysts produce irreconcilable admissibility structures from the same evidence, if excluded states repeatedly occur without regime change, or if the admissibility layer adds no reproducible information beyond established uncertainty, reachability or shift-detection methods. These constitute empirical and methodological failure conditions for the framework.

A major limitation is that admissibility may be difficult to observe. Constraints can be hidden, contested, evolving or only partly inferable. Multiple admissibility structures may generate similar emissions, creating an identifiability problem. DSI does not eliminate this problem; it requires the competing structures and confidence bounds to be stated explicitly.

A second limitation is over-specification. If analysts define constraints too rigidly, they may falsely classify rare but feasible futures as impossible. If constraints are defined too loosely, the framework loses discriminative value and collapses into unconstrained modelling. Domain knowledge, sensitivity analysis and prospective revision are therefore necessary components of any applied instantiation.

A third limitation is that DSI does not yet provide a general-purpose computational procedure for constructing admissible sets across all system classes. Current implementations necessarily depend on domain-specific constraint elicitation, support libraries, formal reachability rules or bounded approximations. Developing comparable construction and audit methods is therefore a central research requirement rather than a completed component of the framework.

This limitation does not imply that Φ is non-computable in every application. Under explicitly enumerated predicates, finite-state transition rules, formal reachability constraints or support-based empirical rules, A_t can be computed directly or approximated reproducibly. What is not claimed is a single universal construction algorithm that is appropriate across all physical, biological, institutional and socio-technical system classes.

Four scope boundaries follow from this formulation. First, stochastic systems remain within the scope of probabilistic modelling; DSI does not require determinism. Second, DSI is not a universal forecasting engine and makes no claim of superior prediction across tasks. Third, determinism does not imply practical predictability. Fourth, the public framework does not disclose or depend on proprietary implementation mechanisms. The scientific claim is limited to the general admissibility formulation, propositions and testable methodological consequences.

Responsible use requires constraints to be stated at the appropriate level of confidence. Known constraints should be made explicit; uncertain constraints should be expressed as assumptions, intervals or competing hypotheses. In high-stakes settings, model outputs should be audited both for predictive performance and for consistency with the feasible state representation used to justify release.

8. Conclusions

Deterministic Systems Intelligence provides a feasibility-first systems-science framework for sequential inference in which admissibility is operationalised before downstream inference. DSI distinguishes the conceivable state space specified by a modelling language from the admissible state space defined by structural clocks, regimes, memory and constraints. Its central methodological claim is that representational validity depends on what the active system can reach, not only on what a model can express or predict.

The framework complements probabilistic, dynamical, state-space, control and learning-based approaches. Its proposed contribution is not the invention of feasible-state reasoning, which is mature in viability, reachability and control traditions, but the organisation of feasibility as a portable pre-inferential systems layer linking clocks, regimes, structural memory, heterogeneous constraints and inferential release or withholding. Where admissible states are known, inferable or bounded, downstream modelling can be conditioned on them. Where they are uncertain, uncertainty about feasibility should remain visible in the inferential and governance process.

DSI offers a portable vocabulary for constrained sequential systems: structural clocks, regimes, structural memory, masked determinism, admissible state spaces and admissibility-consistency. The value of that vocabulary will depend on whether it supports clearer representation, testable distinctions and improved operational control relative to existing approaches alone. Existing domain applications provide starting points for this evaluation, not a substitute for it.

Future work should develop and compare methods for eliciting, approximating and auditing admissible sets under partial observability; quantify analyst agreement and sensitivity to constraint specification; and test whether admissibility layers improve prediction safety, release governance or structural error detection. This programme would provide a bridge between powerful existing inferential tools and the feasibility constraints that organise many sequential systems in practice.

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References

1. Box, G.E.P.; Jenkins, G.M.; Reinsel, G.C.; Ljung, G.M. *Time Series Analysis: Forecasting and Control*, 5th ed.; Wiley: Hoboken, NJ, USA, 2015.
2. Durbin, J.; Koopman, S.J. *Time Series Analysis by State Space Methods*, 2nd ed.; Oxford University Press: Oxford, UK, 2012.
3. Hamilton, J.D. *Time Series Analysis*; Princeton University Press: Princeton, NJ, USA, 1994.
4. Wiener, N. *Cybernetics: Or Control and Communication in the Animal and the Machine*; MIT Press: Cambridge, MA, USA, 1948.
5. Ashby, W.R. *An Introduction to Cybernetics*; Chapman & Hall: London, UK, 1956.
6. Beer, S. *Brain of the Firm*; Allen Lane: London, UK, 1972.

7. von Bertalanffy, L. *General System Theory: Foundations, Development, Applications*; George Braziller: New York, NY, USA, 1968.
8. Forrester, J.W. *Industrial Dynamics*; MIT Press: Cambridge, MA, USA, 1961.
9. Simon, H.A. The architecture of complexity. *Proc. Am. Philos. Soc.* **1962**, *106*, 467–482.
10. Meadows, D.H. *Thinking in Systems: A Primer*; Chelsea Green: White River Junction, VT, USA, 2008.
11. Lorenz, E.N. Deterministic nonperiodic flow. *J. Atmos. Sci.* **1963**, *20*, 130–141. [[CrossRef](#)]
12. Strogatz, S.H. *Nonlinear Dynamics and Chaos*, 2nd ed.; Westview Press: Boulder, CO, USA, 2015.
13. Sugihara, G.; May, R.M. Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. *Nature* **1990**, *344*, 734–741. [[CrossRef](#)]
14. Knuth, D.E. The Art of Computer Programming. In *Seminumerical Algorithms*, 3rd ed.; Addison-Wesley: Boston, MA, USA, 1997; Volume 2.
15. Li, M.; Vitanyi, P. *An Introduction to Kolmogorov Complexity and Its Applications*, 4th ed.; Springer: Cham, Switzerland, 2019.
16. Martin-Löf, P. The definition of random sequences. *Inf. Control* **1966**, *9*, 602–619. [[CrossRef](#)]
17. Adefolalu, A.O. When is electricity-demand inference warranted? A regime-conditioned, feasibility-first analysis of national grid demand. *Energy Convers. Manag. X* **2026**, *31*, 102068. [[CrossRef](#)]
18. Adefolalu, A.O. Feasibility-first risk management for clinical AI: A Deterministic Systems Intelligence framework for release, monitoring, rollback and withholding. *Risk Manag. Healthc. Policy* **2026**, *19*, 621924. [[CrossRef](#)]
19. Adefolalu, A.O. Admissible-state reasoning across public operational and physical systems: Regime-conditioned feasibility and the Pooling Artefact Index. *Sci. Rep.* **2026**, *16*. [[CrossRef](#)]
20. Adefolalu, A.O. When Is AI-Mediated Institutional Action Ethically Warranted? A Feasibility-First Framework for Admissible-State Reasoning. *AI Ethics* **2026**, *6*, 521. [[CrossRef](#)]
21. Brockwell, P.J.; Davis, R.A. *Introduction to Time Series and Forecasting*, 3rd ed.; Springer: Cham, Switzerland, 2016.
22. Cassandras, C.G.; Lafortune, S. *Introduction to Discrete Event Systems*, 2nd ed.; Springer: New York, NY, USA, 2008.
23. Aubin, J.-P. *Viability Theory*; Birkhäuser: Boston, MA, USA, 1991.
24. Bertsekas, D.P. *Dynamic Programming and Optimal Control*, 4th ed.; Athena Scientific: Belmont, MA, USA, 2017.
25. Sontag, E.D. *Mathematical Control Theory: Deterministic Finite Dimensional Systems*, 2nd ed.; Springer: New York, NY, USA, 1998.
26. Alur, R.; Dill, D.L. A theory of timed automata. *Theor. Comput. Sci.* **1994**, *126*, 183–235. [[CrossRef](#)]
27. Bai, J.; Perron, P. Computation and analysis of multiple structural change models. *J. Appl. Econom.* **2003**, *18*, 1–22. [[CrossRef](#)]
28. Hamilton, J.D. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica* **1989**, *57*, 357–384. [[CrossRef](#)]
29. Arthur, W.B. Competing technologies, increasing returns, and lock-in by historical events. *Econ. J.* **1989**, *99*, 116–131. [[CrossRef](#)]
30. David, P.A. Clio and the economics of QWERTY. *Am. Econ. Rev.* **1985**, *75*, 332–337.
31. Pierson, P. Increasing returns, path dependence, and the study of politics. *Am. Polit. Sci. Rev.* **2000**, *94*, 251–267. [[CrossRef](#)]
32. von Foerster, H. *Understanding Understanding: Essays on Cybernetics and Cognition*; Springer: New York, NY, USA, 2003.
33. Checkland, P. *Systems Thinking, Systems Practice*; Wiley: Chichester, UK, 1981.
34. Hyndman, R.J.; Athanasopoulos, G. *Forecasting: Principles and Practice*, 3rd ed.; OTexts: Melbourne, Australia, 2021.
35. Bollerslev, T. Generalized autoregressive conditional heteroskedasticity. *J. Econom.* **1986**, *31*, 307–327. [[CrossRef](#)]
36. Engle, R.F. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* **1982**, *50*, 987–1007. [[CrossRef](#)]
37. Kalman, R.E. A new approach to linear filtering and prediction problems. *Trans. ASME J. Basic Eng.* **1960**, *82*, 35–45. [[CrossRef](#)]
38. Rabiner, L.R. A tutorial on hidden Markov models and selected applications in speech recognition. *Proc. IEEE* **1989**, *77*, 257–286. [[CrossRef](#)]
39. Shannon, C.E. A mathematical theory of communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423, 623–656. [[CrossRef](#)]
40. Breiman, L. Statistical modeling: The two cultures. *Stat. Sci.* **2001**, *16*, 199–231. [[CrossRef](#)]
41. Moreno-Torres, J.G.; Raeder, T.; Alaiz-Rodriguez, R.; Chawla, N.V.; Herrera, F. A unifying view on dataset shift in classification. *Pattern Recognit.* **2012**, *45*, 521–530. [[CrossRef](#)]
42. Ovadia, Y.; Fertig, E.; Ren, J.; Nado, Z.; Sculley, D.; Nowozin, S.; Dillon, J.; Lakshminarayanan, B.; Snoek, J. Can you trust your model’s uncertainty? Evaluating predictive uncertainty under dataset shift. *Adv. Neural Inf. Process. Syst.* **2019**, *32*, 13991–14002.
43. Quiñero-Candela, J.; Sugiyama, M.; Schwaighofer, A.; Lawrence, N.D. (Eds.) *Dataset Shift in Machine Learning*; MIT Press: Cambridge, MA, USA, 2009.
44. Bengio, Y.; Simard, P.; Frasconi, P. Learning long-term dependencies with gradient descent is difficult. *IEEE Trans. Neural Netw.* **1994**, *5*, 157–166. [[CrossRef](#)]
45. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780. [[CrossRef](#)]
46. Lim, B.; Zohren, S. Time-series forecasting with deep learning: A survey. *Philos. Trans. R. Soc. A* **2021**, *379*, 20200209. [[CrossRef](#)]
47. Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat. Mach. Intell.* **2019**, *1*, 206–215. [[CrossRef](#)]

48. Molnar, C. *Interpretable Machine Learning*, 2nd ed.; Christoph Molnar: Munich, Germany, 2022. Available online: <https://christophm.github.io/interpretable-ml-book/> (accessed on 10 May 2026).
49. Box, G.E.P. Science and statistics. *J. Am. Stat. Assoc.* **1976**, *71*, 791–799. [[CrossRef](#)]
50. Levins, R. The strategy of model building in population biology. *Am. Sci.* **1966**, *54*, 421–431.
51. White, H. Maximum likelihood estimation of misspecified models. *Econometrica* **1982**, *50*, 1–25. [[CrossRef](#)]
52. Wolpert, D.H.; Macready, W.G. No free lunch theorems for optimization. *IEEE Trans. Evol. Comput.* **1997**, *1*, 67–82. [[CrossRef](#)]

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