EPINOVA

AI-Strategic Node Framework (AI-SNF)

Conceptual and Methodological White Book

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About This White Book

This White Book presents the conceptual foundations, methodological architecture, and interpretive safeguards of the **AI-Strategic Node Framework (AI-SNF)** and its bounded composite diagnostic output, the **AI-Strategic Node Index (AI-SNI) v0.1**. It is intended as a transparency-oriented reference for researchers, policymakers, and governance practitioners examining how AI-mediated systems shape strategic geography through sensing infrastructures, model dependencies, decision-loop timing, infrastructure–governance relationships, and resource–data–compute coupling.

AI-SNF responds to a structural limitation in many existing analytical instruments. Prevailing indices often focus on aggregate capacity, performance, or competitiveness and rely on single-score representations that compress multidimensional complexity. While useful for comparative benchmarking, such approaches are not designed to identify non-substitutable system functions, leverage–control mismatches, or the propagation of localized disruptions across tightly coupled perception–prediction–execution architectures. AI-SNF adopts a complementary analytical premise: in AI-enabled environments, strategic relevance is shaped primarily by structural position, cross-dimensional coupling, and governance implications rather than by numerical magnitude alone. Within this framework, AI-SNI serves as a constrained composite signal to support diagnostic visualization and pattern recognition, rather than as a standalone evaluative or ranking instrument.

This White Book makes that premise explicit and auditable. It defines AI-strategic nodes as a distinct unit of analysis; specifies five core analytical dimensions (D1–D5) and their structural sequencing; documents indicator construction, normalization, and aggregation procedures; establishes a single authoritative composite formulation for AI-SNI; and sets out diagnostic extensions and higher-order interpretive layers, including exposure regimes, structural profiles, and structural class attribution, under a clearly defined hierarchy of interpretive authority. A worked illustrative example is included to demonstrate how methodological design choices translate into traceable analytical outputs, without advancing empirical claims regarding specific real-world nodes.

AI-SNI is not designed as a predictive model, a ranking mechanism, or a decision-automation tool. All numerical values presented are synthetic and used solely to illustrate methodological logic. Any empirical application requires independent data collection, explicit scope definition, evidence grading, and confidence assessment consistent with the uncertainty and transparency principles set out in this document.

AI-SNI v0.1 constitutes a foundational release. Its primary objective is to establish conceptual coherence, methodological integrity, and governance-grade safeguards prior to empirical scaling or operational use. Future iterations may expand indicator coverage or refine data integration approaches, while remaining anchored in the core principles articulated here: transparency, auditability, and restraint in inference.

Table of Contents

Executive Summary 06

Scope and Limitations 08

Methodological Positioning of AI-SNI 09

Part I. Background and Conceptual Foundation 10

1. Background 12

2. Conceptual Definition: AI-Strategic Nodes 12

2.1 Definition 12

2.2 Core Attributes of AI-Strategic Nodes 13

2.3 AI-Strategic Nodes vs. Classical Geostrategy 13

2.4 The Structural Causal Chain 14

2.5 Scope and Analytical Boundaries 14

2.6 Relationship to Existing Global Index Systems 16

Part II. Indicator Overview 16

3. Index Scope and Purpose 16

3.1 Scope of Measurement 16

3.2 Framework Dimensions Aggregated by the Index 17

3.3 Explicit Measurement Exclusions 17

3.4 Intended Use Cases 18

3.5 Prohibited Uses and Interpretive Constraints 19

4. Indicator Architecture 19

4.1 Architectural Logic 19

4.2 Core Dimensions 22

4.3 Dimensional Composition 22

4.4 Aggregation Logic 23

4.5 Risk Interpretation Framework 24

4.6 Modularity and Upgrade Path 25

Part III. Indicator Definitions and Methodology 25

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC) 25

5.1 Conceptual Rationale 26

5.2 From “Sensors” to “Algorithmic Perception Anchors” 26

5.3 The D1 Causal Mechanism 28

5.4 D1 Core Aggregation Formula 29

5.5 Indicator Composition 38

Table of Contents

5.6 Methodological Notes 38

5.7 Why D1 Is Foundational to AI-Strategic Power 38

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD) 39

6.1 Conceptual Rationale 39

6.2 From “Model Accuracy” to “Forecast Dependency” 40

6.3 The D2 Causal Mechanism 41

6.4 D2 Core Aggregation Formula 43

6.5 Indicator Composition 45

6.6 Methodological Notes 55

6.7 Why D2 Is the Pivot Between Perception and Action 56

6.8 Strategic Interpretation 57

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA) 59

7.1 Conceptual Rationale 59

7.2 From “Speed” to “Decision-Loop Dominance” 59

7.3 The D3 Causal Mechanism 60

7.4 D3 Core Aggregation Formula 61

7.5 Indicator Composition 63

7.6 Methodological Notes 71

7.7 Why D3 Converts Knowledge into Action 72

7.8 Strategic Interpretation 72

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC) 74

8.1 Conceptual Rationale 75

8.2 From “Governance Quality” to “Leverage–Control Mismatch” 75

8.3 The IGA Causal Mechanism 76

8.4 Infrastructure–Governance Asymmetry vs. Traditional Security Vulnerability 77

8.5 D4 Core Aggregation Formula 78

8.6 Indicator Composition 80

8.7 Methodological Notes 92

8.8 Policy Interpretation 93

8.9 D4 as the Structural Anchor of AI-SNI 94

8.10 Why Infrastructure–Governance Asymmetry Will Define AI-Era Stability 95

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP) 98

9.1 Conceptual Rationale 98

Table of Contents

9.2 From “Resource Endowment” to “AI-Coupled Value Chains” 99

9.3 The D5 Causal Mechanism 100

9.4 D5 Core Aggregation Formula 102

9.5 Indicator Composition 105

9.6 Methodological Notes 115

9.7 Strategic Interpretation 117

9.8 D5 Within AI-SNI Architecture 118

Part IV. Composite Index Construction and Risk Classification 119

10. Conceptual Architecture 119

10.1 Dimensional Architecture and Structural Roles 120

10.2 Indicator Normalization 121

10.3 Dimensional Directionality 127

10.4 Dimensional Aggregation 129

10.5 Composite Index Formula and Diagnostic Extensions 132

10.6 Interpretation of Composite Scores 140

11. Risk Classification Framework 141

11.1 Exposure Bands 141

11.2 Risk Profiles versus Rankings 144

11.3 Temporal Interpretation and Change Attribution 145

11.4 Use with Other Indices 146

12. Structural Class System 147

12.1. Structural Class as a Higher-Order Interpretive Layer 147

12.2. Relationship to Composite Scores and Exposure Bands 148

12.3. Structural Class Definitions 148

12.4. Interpretive Authority and Analytical Discipline 152

12.5 Governance Implications 153

Part V. Illustrative Example Calculation 154

13. Purpose and Scope of the Example 154

14. Hypothetical Node Description 155

14.1 Dimension D1 156

14.2 Dimension D2 158

14.3 Dimension D3 160

14.4 Dimension D4 162

Table of Contents

14.5 Dimension D5 164

15. Composite Index and Diagnostic Extensions 166

15.1 AI-SNI Score 166

15.2 Diagnostic Extension I 168

15.3 Diagnostic Extension II 169

16. Classification and Interpretation 170

16.1 Tier Assignment 170

16.2 Structural Tagging 171

16.3 Structural Class Attribution 172

17. Analytical Value of the Example 173

Part VI. International Benchmarks and Node Typologies 174

18. Purpose of International Benchmarking 174

19. Benchmarking Principles 175

19.1 Functional Equivalence over Political Equivalence 175

19.2 Profile Comparison over Ordinal Ranking 175

19.3 Risk Visibility over Score Optimization 175

19.4 Contextual Interpretation 176

19.5 Cross-Index Compatibility 176

20. Core AI-Strategic Node Typologies 177

20.1 Type I: Concentrated Leverage with Weak Correction 177

20.2 Type II: Concentrated Leverage with Institutional Buffering 179

20.3 Type III: Diffuse Leverage with Participation Skew 181

20.4 Type IV: Peripheral or Latent Nodes 183

20.5 Typology Assignment Overview 184

21. Interpreting National and Regional Profiles 185

22. Relationship to Existing Global Indices 186

23. Use in Comparative and Policy Analysis 187

Part VII. Data Sources and References 188

24. Data Sources 189

24.1 Dimension D1 189

24.2 Dimension D2 190

24.3 Dimension D3 191

24.4 Dimension D4 193

Table of Contents

24.5 Dimension D5 195

25. Data Availability and Treatment Notes 197

25.1 Missing Data Handling 197

25.2 Extreme Value Treatment 197

25.3 Auditability and Evidence Grading 198

25.4 Scope and Inheritance 199

26. References 200

Appendix A. Uncertainty and Confidence Treatment **202**

Appendix B: Typology Assignment Protocol **213**

Appendix C: AI-SNF / AI-SNI Reporting Template **217**

Appendix D: Abbreviation and Glossary **220**

Note for the White Book **226**

Author and Institutional Affiliation **227**

Disclaimer **228**

Version History **229**

Citation Recommendation **229**

Executive Summary

Artificial intelligence (AI) no longer functions primarily as a set of discrete tools or applications. It increasingly operates as an integrative system layer that reorganizes sensing, prediction, decision-making, and governance across geographic and institutional contexts. Under these conditions, strategic value does not scale linearly with territory, population, or formal sovereignty. Instead, influence tends to concentrate in specific nodes—geographic, infrastructural, or institutional configurations whose position within AI-mediated systems generates disproportionate effects on perception, timing, dependency, and control.

To address this structural shift, this White Book introduces the **AI-Strategic Node Framework (AI-SNF)** and its bounded composite diagnostic output, the **AI-Strategic Node Index (AI-SNI)**. AI-SNI is neither a ranking instrument nor a predictive model. It is a governance-oriented diagnostic index designed to identify where systemic leverage, fragility, and potential failure consequences are concentrated within AI-enabled architectures. AI-SNF reframes strategic geography as an active component of AI-enabled systems, shaped by data generation, model dependence, decision-loop timing, infrastructure–governance alignment, and evolving coupling potential, rather than as static physical terrain.

AI-SNF is structured around five analytically distinct yet interdependent dimensions: **Algorithmic Sensing and Early-Warning Centrality (D1); Predictive Model Leverage and Dependency (D2); Decision-Loop Temporal Advantage (D3); Infrastructure–Governance Asymmetry and Control (D4); and Resource–Data–Compute Coupling Potential (D5)**. Together, these dimensions capture how AI-mediated systems observe environments, condition expectations about future states, translate information into time-sensitive action, allocate control and accountability, and evolve over longer strategic horizons. Dimensions D1–D4 primarily reflect current operational exposure and relevance, while D5 provides a forward-looking assessment of strategic optionality.

A core design principle of AI-SNF is the clear separation between measurement and interpretation. AI-SNI produces a single composite diagnostic score whose procedural role is limited to comparative visualization and pattern recognition. Tiered exposure bands derived from this score function solely as coarse screening devices. Neither composite values nor tier placement imply desirability, controllability, policy priority, or institutional robustness. Higher-order interpretation is governed by an independent **Structural Class System (S/A/B/C)**, which evaluates systemic role and the consequences of degradation, capture, or misgovernance. Structural class attribution is non-derivative and non-optimizing; it cannot be inferred mechanically from numerical outputs and requires cross-dimensional, auditable assessment.

Recognizing that AI-strategic analysis is conducted under conditions of structural opacity and uneven evidence availability, AI-SNF incorporates uncertainty management directly into its analytical architecture. Evidence grading, confidence propagation rules, and explicit interpretive constraints are applied to ensure that analytical outputs do not exceed available evidentiary support. Governance-related assessments, particularly those concerning infrastructure–governance asymmetry, are subject to heightened interpretive discipline, reflecting their exposure to coercion, dependency, and non-observable control dynamics.

Executive Summary

This White Book presents **AI-SNI v0.1** as a foundational release. Its objective is not empirical exhaustiveness or predictive ambition, but the establishment of a coherent, auditable, and governance-grade analytical framework. A worked illustrative example is included to demonstrate how the conceptual principles embedded in AI-SNF translate into disciplined analytical outputs, without advancing empirical claims regarding any specific real-world node.

By shifting analytical emphasis from comparative ranking to the identification of where systemic consequences concentrate, AI-SNF supports a preventive approach to governance. It is intended to assist policymakers, regulators, and institutional analysts in identifying leverage–control mismatches before they manifest as operational or governance failures, while maintaining clear boundaries between diagnosis, interpretation, and decision authority in increasingly AI-mediated strategic environments.

Executive Disclaimer and Reader Guidance

This White Book introduces AI-SNF and its derived diagnostic output, AI-SNI v0.1, as tools for structural diagnosis and governance-relevant analysis within AI-mediated systems.

AI-SNF and AI-SNI are not ranking instruments, predictive models, or decision-automation tools. They do not assess performance, forecast conflict, prescribe policy action, or determine strategic priority. All outputs are bounded by explicit evidentiary, methodological, and interpretive constraints defined in this White Book.

Interpretation of results must remain proportionate to evidence quality, uncertainty, and structural observability. Any use of composite scores, tiers, typologies, or classifications outside these constraints constitutes methodological misuse of the framework.

The analytical purpose of AI-SNF is to enhance governance awareness of structural leverage, fragility, and control asymmetries, not to replace institutional judgment or policy deliberation.

Scope and Limitations

The AI-Strategic Node Framework (AI-SNF) is designed exclusively for analytical and diagnostic purposes. It does not provide policy recommendations, predictive assessments, or prescriptive guidance, nor is it intended to function as a decision-support or forecasting system.

All framework outputs. including dimensional profiles, composite indices, typologies, and illustrative diagnostics, must be interpreted in light of data limitations, contextual assumptions, and explicitly documented uncertainty. Results are contingent on evidentiary coverage, methodological choices, and the defined analytical scope, and do not constitute definitive assessments of institutional capability, strategic intent, or future outcomes.

Accordingly, AI-SNF outputs should be used as inputs to informed analysis and institutional deliberation, rather than as substitutes for judgment, contextual evaluation, or governance decision-making. Any application beyond exploratory or analytical use requires independent assessment and appropriate oversight consistent with the user’s institutional responsibilities.

Methodological Positioning of AI-SNI

The AI-Strategic Node Index (AI-SNI) is the sole, governance-oriented composite diagnostic output generated within the AI-Strategic Node Framework (AI-SNF). Throughout this White Book, the term AI-SNI refers exclusively to the reference composite score specified in Section 10.5.1 and does not denote an independent analytical system, theoretical construct, or interpretive framework.

AI-SNI derives its authority solely from its procedural role within AI-SNF architecture. It functions as a bounded numerical signal for comparative visualization, pattern recognition, and preliminary exposure screening. AI-SNI carries no autonomous interpretive authority, normative status, or policy-prescriptive force beyond the evidentiary, methodological, and interpretive constraints defined by the framework.

Sections 10.5.2 and 10.5.3 introduce analytically constrained diagnostic extensions rather than alternative index formulations. These extensions apply conditional transformations to the reference AI-SNI in order to surface specific structural risk conditions, such as governance fragility and weakest-link sensitivity, under explicitly stated analytical assumptions. Their purpose is limited to stress testing and sensitivity analysis.

Diagnostic extensions do not constitute new indices, do not redefine AI-SNI, and do not carry independent interpretive standing. They must not alter tier thresholds, structural class attribution, or the interpretive authority hierarchy established in Part XII. Outputs generated under these extensions are conditional and must be interpreted as supplementary diagnostic views rather than baseline index values.

Unless explicitly stated otherwise, all references to AI-SNI in this document denote the reference composite score defined in Section 10.5.1. Any use of diagnostic extensions must be clearly declared, methodologically justified, and analytically bounded. Failure to do so constitutes methodological misuse of AI-SNI under the framework’s interpretive discipline.

Part I.
Background and Conceptual Foundation

1. Background

For much of modern strategic analysis, geography has been treated as a relatively stable substrate of power. Strategic value was assumed to derive from territory hosting populations, resources, military assets, and lines of communication, with power scaling primarily with size, control, and ownership. Strategic assessment therefore focused on aggregate capacity embedded within territorially bounded units. Even as technological change altered the means of power projection, the territorial state remained the dominant unit of analysis (Schelling, 1960; Baldwin, 2016). The diffusion of artificial intelligence challenges this assumption.

As sensing, prediction, decision-making, and policy execution become increasingly mediated by algorithmic systems, strategic value is no longer generated primarily through territorial possession. Instead, it emerges from structural position within AI-enabled system chains that integrate sensing infrastructures, data pipelines, predictive models, decision loops, and governance mechanisms into continuous and latency-sensitive processes (Castells, 2010; Bratton, 2016). Under these conditions, geographic scale becomes a weak proxy for strategic importance: relatively small or sparsely populated locations may exert disproportionate influence, while larger territories with limited algorithmic centrality may become strategically marginal.

This shift exposes a growing analytical gap. Consistent with relational conceptions of power, strategic significance in AI-mediated systems cannot be treated as an intrinsic attribute of states or territories, but must be understood as a function of structural dependence, interaction effects, and asymmetric system positioning (Baldwin, 2016). Conventional strategic metrics are not designed to detect systemic dependency, chokepoint dynamics, or nonlinear fragility within tightly coupled AI-enabled architectures (Beck, 1992; Perrow, 1984). As a result, they tend to under-identify nodes whose degradation, capture, misgovernance, or manipulation could trigger cascading effects across perception, prediction, decision, or governance systems well beyond their apparent territorial scale or sovereignty status (Helbing, 2013).

The **AI-Strategic Node Framework (AI-SNF)** is introduced to address this analytical limitation. AI-SNF is a governance-oriented framework designed to identify, characterize, and interpret the systemic role of geographic nodes embedded within AI-enabled architectures. It conceptualizes strategic relevance in terms of algorithmic centrality, dependency relations, temporal leverage, governance alignment, and long-horizon coupling potential, rather than territorial ownership or aggregate capacity.

Within AI-SNF, AI-strategic nodes are examined through a structured set of analytical components, including five core dimensions (D1–D5), cross-dimensional interaction logic, evidence and confidence treatment rules, and an independent Structural Class System assessing systemic role and non-substitutability. Together, these elements support the diagnosis of where AI-mediated systems are most exposed to cascading failure, control asymmetry, or strategic lock-in, and where disruption would have disproportionate implications for system stability, integrity, or future option space (Floridi, 2014; Taleb, 2012).

1. Background

The **AI-Strategic Node Index (AI-SNI)** is introduced within AI-SNF as a bounded composite diagnostic output. Its purpose is to provide a constrained numerical signal for comparative visualization, pattern recognition, and preliminary exposure screening across cases. AI-SNI does not constitute a theoretical framework, does not generate interpretation independently, and does not substitute for the structural analysis conducted within AI-SNF. Detailed interpretive constraints governing composite scores, tier classifications, confidence treatment, and structural class attribution are specified in Parts IV, XI, and Appendix A.

2. Conceptual Definition

2.1 Conceptual Definition: AI-Strategic Nodes

Within AI-SNF, an **AI-Strategic Node** is defined as a geographic space, such as a territory, corridor, facility cluster, or chokepoint, that occupies a structurally central position within AI-mediated systems of perception, prediction, decision-making, or governance. A node is considered strategic where disruption, degradation, or shifts in control generate disproportionate systemic effects relative to the scale of local inputs.

This definition deliberately departs from classical conceptions of strategic geography. Within AI-SNF, AI-Strategic Nodes do not derive relevance from population size, sovereign authority, or conventional military presence. Instead, their strategic significance arises from systemic dependence: the extent to which AI-enabled architectures rely on the node's continued functionality, integrity, or governance alignment to maintain system-wide performance and stability (Baldwin, 2016; Castells, 2010).

Accordingly, AI-Strategic Nodes are defined less by the assets they contain than by the degree to which broader AI-mediated systems cannot reliably operate in their absence. Their importance is therefore relational rather than intrinsic, and structural rather than symbolic (Latour, 2005).

2.2 Core Attributes of AI-Strategic Nodes

Within AI-SNF, AI-Strategic Nodes are characterized by four core attributes:

- **System Dependency**: the degree to which AI-enabled systems rely on node-specific data sources, sensing coverage, infrastructure, or uninterrupted operational continuity.
- **Decision Relevance**: the extent to which information generated at, or transmitted through, the node enters time-sensitive, high-impact, or low-reversibility decision processes.
- **Spillover Leverage**: the scale and reach of downstream effects resulting from disruption, degradation, or manipulation at the node, including cascading impacts across multiple system layers.
- **Governance Asymmetry**: the degree of misalignment between the node's strategic importance within AI-mediated systems and the capacity of local or institutional authorities to regulate, audit, and exercise effective control over that importance (North, 1990; Jasanoff, 2004).

Together, these attributes define the analytical object of AI-SNF. They are subsequently operationalized, under explicitly stated methodological constraints, through AI-SNI as a bounded composite diagnostic output to support comparative analysis and governance-oriented assessment.

2. Conceptual Definition

2.3 AI-Strategic Nodes vs. Classical Geostrategy

Classical geostrategic analysis is largely organized around logics of possession, projection, and denial. Strategic locations derive value from their ability to host forces, defend territory, secure access routes, or enable physical interdiction. Even network-oriented approaches, such as analyses of sea lanes, straits, or chokepoints, ultimately assume that strategic leverage is exercised through visible presence, kinetic capability, or the credible threat of force.

AI-SNF identifies a distinct structural logic governing AI-Strategic Nodes. First, strategic leverage increasingly operates through informational and epistemic control rather than physical dominance. Control over sensing infrastructures, data continuity, calibration baselines, or signal integrity can shape outcomes without physical occupation or overt confrontation (Bratton, 2016; Floridi, 2014). Second, influence is frequently indirect and temporally displaced: disruptions may manifest downstream within forecasts, risk assessments, optimization routines, or automated decision pipelines rather than at the point of intervention itself (Kleinberg et al., 2018; Shiller, 2017). Third, vulnerability is often institutional rather than physical. Governance opacity, ambiguous control rights, misaligned incentives, or external dependency can undermine systemic stability even when physical infrastructure remains intact (Perrow, 1984; Power, 2007).

Accordingly, AI-Strategic Nodes may be strategically significant precisely because they appear peripheral within classical frameworks. Their importance lies not in territorial command or access denial, but in stabilizing or destabilizing the epistemic foundations upon which AI-mediated decision systems depend.

2.4 The Structural Causal Chain

Within AI-SNF, AI-Strategic Nodes are situated along a structural causal chain that increasingly governs strategic outcomes across security, economic coordination, infrastructure management, and governance domains:

Sensing → Data Integrity → Model Calibration → Forecast Outputs → Decision Execution → Global Spillovers

This chain reflects how environmental signals are progressively transformed into authoritative assessments and binding actions within AI-mediated systems. Strategic outcomes therefore depend less on isolated decision moments than on the integrity, timing, and alignment of the entire chain.

2. Conceptual Definition

AI-Strategic Nodes typically occupy one or more structurally sensitive positions within this sequence, including sensing concentration points with non-substitutable data streams, calibration anchors where models are trained or validated, latency-reducing intermediaries that compress decision windows, and governance interfaces where rules, access rights, and accountability structures are defined or remain ambiguous. Disruptions at such positions do not propagate linearly; interference or misalignment at structurally central nodes can amplify uncertainty, bias predictive outputs, distort prioritization logic, or desynchronize governance incentives. These effects are often cascading, delayed, and difficult to attribute, yet may shape outcomes well beyond the node's immediate geographic or institutional context (Helbing, 2013; Beck, 1992).

2.5 Scope and Analytical Boundaries

To maintain analytical clarity and governance relevance, AI-SNF establishes explicit scope limitations for the use of AI-SNI.

Within AI-SNF, AI-SNI is designed to assess:

- Structural dependence within AI-mediated systems;
- Temporal and informational leverage effects;
- Governance–control mismatches;
- System-wide consequences of localized disruption.

Conversely, AI-SNI does not seek to assess:

- Aggregate national power or competitiveness;
- AI research output or technological sophistication in isolation;
- Normative legitimacy of sovereignty or political claims;
- Comprehensive military balances, except where directly embedded within AI-mediated architectures.

These boundaries ensure that AI-SNI functions as a layer-specific structural diagnostic instrument, complementing rather than substituting for existing geopolitical, economic, and security assessment frameworks.

2.6 Relationship to Existing Global Analytical Frameworks

Most global analytical frameworks are actor-centric in design, comparing countries, regions, or institutions on aggregated indicators of capacity, performance, governance quality, or development outcomes. While these approaches provide valuable comparative insights, they are not intended to diagnose how specific positions within complex AI-mediated systems generate disproportionate strategic consequences.

2. Conceptual Definition

AI-SNF addresses this analytical gap by shifting the unit of analysis from actors to nodes. Rather than assessing aggregate strength or governance quality, AI-SNF focuses on positional consequence—the degree to which a particular node shapes outcomes within interconnected AI system chains, irrespective of the overall characteristics of the actor that hosts it.

Within this framework, AI-SNI functions as a bounded composite diagnostic signal. It does not rank actors or evaluate overall performance; instead, it supports the identification of structural leverage, latent dependency, and infrastructure–governance asymmetry that actor-level frameworks are not designed to capture.

When applied alongside existing governance, development, digitalization, security, or competitiveness frameworks, AI-SNI serves as a complementary diagnostic layer. Its role is to augment, not substitute for, actor-centric analyses by revealing system-level vulnerabilities and concentration effects that shape risk propagation and governance exposure in AI-enabled environments.

Part II.

Indicator Overview

3. Index Scope and Purpose

3.1 Scope of Measurement

Within AI-SNF, geographic nodes are considered eligible for assessment where they meet one or more framework-defined conditions of structural relevance within AI-mediated systems. Inclusion is determined by functional role in processes of perception, prediction, decision execution, or governance, rather than by legal status, administrative classification, or territorial scale (Bratton, 2016; Castells, 2010).

Accordingly, nodes fall within the scope of AI-SNI measurement where AI-SNF identifies relevance in relation to one or more of the following conditions:

a) **Sensing Centrality**: the node hosts unique, high-density, or non-substitutable sensing infrastructures that are critical to early warning, situational awareness, environmental monitoring, or the integrity of system-wide perception (Helbing, 2013; Perrow, 1984).

b) **Calibration Relevance**: the node provides data inputs that are materially used to train, tune, validate, or benchmark predictive models whose outputs inform policy, security, economic coordination, or environmental governance decisions (Kleinberg et al., 2018; Jasanoff, 2004).

c) **Temporal Leverage**: the node is embedded within latency-sensitive decision loops in which early detection, accelerated processing, or privileged access to information confers time advantages that materially affect downstream outcomes (Schelling, 1960; Weick, 1988).

d) **Governance Asymmetry**: the node exhibits a structural mismatch between its strategic importance within AI-mediated systems and the capacity of local or institutional authorities to regulate, audit, or exercise effective control over that importance (North, 1990; Power, 2007; Renn, 2008).

e) **Latent Coupling Potential**: the node possesses unrealized or emerging potential for coupling among resources, data, compute, energy, logistics, or infrastructure layers in ways that may amplify future strategic leverage within AI-enabled systems (Taleb, 2012; Bratton, 2016).

Nodes within scope may be terrestrial, maritime, polar, orbital-adjacent, or infrastructural in nature. AI-SNF adopts a deliberately functional and system-oriented conception of space, reflecting how AI-mediated architectures operate across physical, institutional, and temporal domains (Castells, 2010; Bratton, 2016; Latour, 2005). AI-SNI aggregates dimension-level representations of these relevance conditions into a standardized diagnostic signal, without redefining or substituting for the underlying structural criteria.

3.2 Framework Dimensions Aggregated by the Index

AI-SNF defines five analytically distinct yet structurally interdependent dimensions through which AI-mediated systems generate strategic leverage, exposure, and systemic fragility. These dimensions constitute the conceptual core of the framework and are properties of AI-SNF, not of the index itself.

3. Index Scope and Purpose

AI-SNI aggregates these dimensions without collapsing their causal distinctions into a single composite diagnostic score used exclusively for visualization, comparative screening, and pattern recognition. The aggregation does not imply causal equivalence, priority ordering, or normative valuation among dimensions.

The five AI-SNF dimensions are:

a) **Algorithmic Sensing and Early-Warning Centrality (D1);**

a) **Predictive Model Leverage and Dependency (D2);**

b) **Decision-Loop Temporal Advantage (D3);**

c) **Infrastructure–Governance Asymmetry (D4);**

d) **Resource–Data–Compute Coupling Potential (D5).**

Each dimension remains independently interpretable at the framework level. AI-SNI composite reflects their combined effects under explicitly stated aggregation rules, while preserving analytical separability and interpretive discipline (Power, 2007; Renn, 2008).

3.3 Explicit Measurement Exclusions

To avoid conceptual inflation and category error, AI-SNF establishes explicit analytical exclusions governing the interpretation and use of AI-SNI outputs.

Accordingly, AI-SNI does **not** assess:

- aggregate national or regional power;
- AI research output, innovation capacity, or standalone technological sophistication;
- normative governance quality or political legitimacy;
- sovereignty claims or jurisdictional recognition;
- comprehensive military balances, except where military systems are directly embedded within AI-mediated architectures (UNODA, 2023).

These exclusions reflect the core methodological principle of AI-SNF: **structural leverage within AI-mediated systems is analytically distinct from aggregate capability, normative judgment, or legal status** (Castells, 2010; Bratton, 2016).

3.4 Intended Use Cases

Within the scope and constraints defined by AI-SNF, AI-SNI outputs are intended to support diagnostic and interpretive analysis in areas including:

- strategic risk assessment of AI-enabled infrastructures;
- early-warning system resilience and redundancy planning;
- governance, audit, and oversight design for data-intensive nodes;
- infrastructure investment prioritization under uncertainty;

3. Index Scope and Purpose

- scenario analysis involving denial, manipulation, or coercion;
- comparative assessment of AI-era geopolitical exposure.

Across these use cases, AI-SNI functions as a **screening and signaling instrument**, identifying where framework-defined structural exposure concentrates and where targeted governance or institutional intervention may yield disproportionate stabilizing effects (Beck, 1992; Helbing, 2013).

3.5 Prohibited Uses and Interpretive Constraints

AI-SNI outputs **must not** be used to produce ordinal rankings of states, regions, or institutions, nor to justify unilateral policy actions in the absence of contextual, legal, and institutional analysis. Any application of AI-SNI beyond diagnostic visualization, comparative pattern recognition, and interpretation constrained by AI-SNF framework falls outside its methodological scope.

4. Indicator Architecture

4.1 Architectural Logic

AI-SNF adopts a multi-dimensional, modular indicator architecture to reflect the layered and interdependent nature of AI-mediated strategic systems (Bratton, 2016; Castells, 2010). Under AI-enabled conditions, strategic relevance does not derive from any single capability. It emerges from the interaction among sensing coverage, predictive influence, temporal positioning, governance alignment, and long-horizon coupling dynamics (Helbing, 2013; Perrow, 1984). Reducing these interactions to a single indicator risks obscuring critical sources of leverage and fragility (Power, 2007).

Accordingly, node assessment within AI-SNF is structured around an ensemble of analytically distinct dimensions rather than a monolithic score. The framework's indicator architecture is governed by three design principles:

a) **Decomposability:** Each dimension is analytically separable and can be examined independently to identify the specific mechanisms through which a node generates strategic leverage or systemic risk, supporting targeted diagnosis without conflating causal pathways (Renn, 2008; Power, 2007).

b) **Composability:** Dimensions are designed to be combinable through explicitly declared aggregation functions, enabling multiple analytical views, such as risk profiling, scenario analysis, and sensitivity testing, without imposing a single normative weighting or ranking logic (Taleb, 2012; Renn, 2008).

c) **Auditability:** Indicators, particularly those related to governance and control, are anchored in observable and verifiable artifacts, including legal mandates, regulatory frameworks, operational procedures, and documented control rights. This supports transparency, replicability, and institutional review over time (Jasanoff, 2004; NIST, 2023).

Together, these principles ensure that AI-SNF operates as a governance-grade diagnostic architecture rather than a reductive index. Dimensional transparency is preserved while enabling integrated system-level assessment. Within this architecture, AI-SNI functions solely as a bounded composite diagnostic output and does not substitute for framework-level interpretation. Composite values and any associated tier groupings do not constitute ordinal rankings, performance hierarchies, or priority signals and must not be interpreted as measures of comparative superiority or desirability.

4.2 Core Dimensions

AI-SNF v0.1 is structured around five first-level dimensions (D1–D5), each representing a distinct layer of strategic relevance within AI-mediated systems. Taken together, these dimensions describe how geographic nodes shape system perception, predictive influence, decision execution, governance alignment, and longer-term system evolution.

4. Indicator Architecture

The five core dimensions are:

- **D1. Algorithmic Sensing and Early-Warning Centrality (ASEWC)**: Captures the extent to which a node conditions system-wide perception through sensing infrastructures, data acquisition, and early-warning functions.
- **D2. Predictive Model Leverage and Dependency (PMLD)**: Assesses time-based leverage generated by a node through latency reduction, early detection, or accelerated processing within decision pipelines.
- **D3. Decision-Loop Temporal Advantage (DLTA)**: Assesses the time-based leverage generated by a node through latency reduction, early detection, or accelerated processing within decision pipelines.
- **D4. Infrastructure–Governance Asymmetry and Control (IGAC)**: Evaluates structural mismatches between a node's strategic importance within AI-enabled infrastructures and the capacity of governing institutions to regulate, audit, and exercise effective control.
- **D5. Resource–Data–Compute Coupling Potential (RDCCP)**: Examines a node's potential to generate future strategic leverage through emerging or latent coupling among physical resources, data generation, computational infrastructure, energy supply, and logistics systems.

Together, these dimensions capture both **current operational relevance (D1–D4)** and **forward-looking strategic optionality (D5).** Each dimension is independently interpretable at the framework level, while AI-SNF as a whole enables integrated diagnosis of how present-day leverage and long-horizon system evolution interact to shape strategic exposure and systemic risk. AI-SNI aggregates these framework-defined dimensions into a constrained composite diagnostic signal under explicitly specified aggregation rules (see Part IV).

4. Indicator Architecture

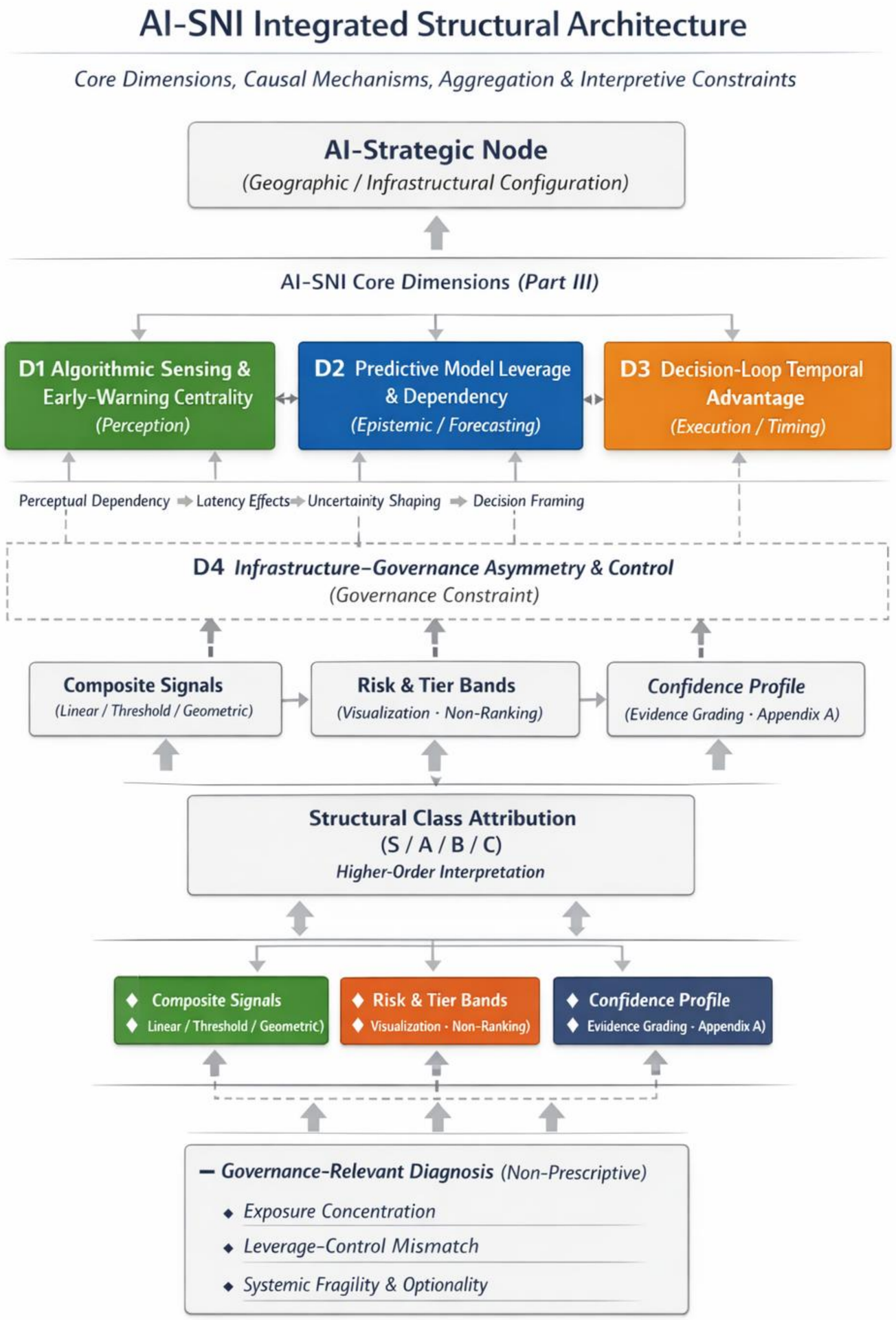

Figure 4.2. Integrated Structural Architecture of AI-SNF and AI-SNI Outputs.

This figure illustrates the layered analytical architecture of AI-SNF. Dimensions D1–D3 capture operational centrality across perception, prediction, and decision-loop execution. Dimension D4 operates as a governance-alignment and fragility layer, conditioning leverage–control relationships, while Dimension D5 reflects forward-looking coupling potential and strategic optionality. Within this architecture, AI-SNI is generated as a bounded composite diagnostic output, accompanied by exposure tier bands and evidence-based confidence profiles to support comparative screening and interpretive discipline. These outputs may inform contextual analysis but do not determine systemic role. Structural class attribution (S/A/B/C) cannot be inferred, calculated, or derived from composite scores, tier groupings, or diagnostic extensions and remains a higher-order interpretive judgment governed by AI-SNF's interpretive authority hierarchy. The framework is intended for governance-relevant diagnosis and structural risk visibility, without predictive, prescriptive, or ranking purpose.

4. Indicator Architecture

4.3 Dimensional Composition

Within AI-SNF, each first-level dimension is operationalized through multiple second-level indicators, each representing a specific operational, technical, or institutional mechanism by which a geographic node generates strategic relevance or systemic fragility within AI-mediated systems. This layered design preserves causal transparency while enabling structured aggregation across dimensions (Renn, 2008; Power, 2007).

Second-level indicators are selected based on three criteria:

- **Causal relevance**: Indicators must capture mechanisms that materially affect the performance, reliability, or stability of AI-mediated systems. Priority is given to variables that directly condition perception integrity, predictive behavior, decision timing, governance alignment, or system evolution, rather than proxy measures of general capacity (Helbing, 2013; Perrow, 1984).
- **Observability and verifiability**: Indicators must be measurable using public data, institutional documentation, or technically verifiable sources, such as infrastructure records, regulatory frameworks, operational disclosures, or validated datasets, to support replicability and limit speculative assessment (NIST, 2023; Jasanoff, 2004).
- **Governance interpretability**: Indicators, particularly those related to dependency, exposure, or control, must be interpretable in governance terms, allowing linkage to institutional responsibilities, regulatory instruments, audit mechanisms, or identifiable gaps in oversight and accountability (North, 1990; Power, 2007).

AI-SNF explicitly distinguishes between capability-oriented and risk-oriented indicators. Variables capturing exposure, dependency, external reliance, or susceptibility to manipulation are flagged and treated asymmetrically in normalization and interpretation. High values on such indicators do not necessarily indicate advantage; they may instead signal elevated systemic vulnerability or governance stress.

This distinction reduces the risk of misinterpretation in composite outputs and supports structured risk profiling. It ensures that AI-SNI reporting highlights not only where strategic leverage concentrates, but also where fragility, contestability, or control deficits are most pronounced.

4.4 Aggregation Logic

AI-SNF specifies a flexible aggregation logic to accommodate different diagnostic objectives while preserving a stable and consistent indicator foundation. The purpose of permitting multiple aggregation views is analytical rather than definitional: to surface distinct structural sensitivities without redefining the index or collapsing interpretation into a single evaluative logic (Renn, 2008; Power, 2007).

4. Indicator Architecture

Within this framework, three aggregation views may be applied to dimension-level scores under explicitly stated conditions:

- **Linear weighted aggregation (reference AI-SNI)**: Aggregates dimension scores using declared weights to produce an interpretable composite diagnostic output. This formulation serves as the authoritative AI-SNI and is intended for baseline reporting, comparative overview, and policy communication, where transparency and decomposability are prioritized.
- **Threshold–penalty aggregation (diagnostic extension)**: Applies conditional penalties where governance-related sufficiency thresholds are not met, highlighting leverage–control fragility in cases where high operational centrality coincides with limited governance capacity.
- **Geometric aggregation (diagnostic extension)**: Accentuates weakest-link effects in tightly coupled systems, where severe underperformance in any critical dimension constrains overall system integrity. This view is intended for stress testing and the identification of bottleneck vulnerabilities.

The coexistence of these aggregation views reflects a deliberate separation between measurement architecture and interpretive intent. Selection of an aggregation view depends on the analyst's stated diagnostic objective and underlying assumptions and does not constitute the creation of alternative indices or independent interpretive authorities.

4.5 Risk Interpretation Framework

AI-SNF explicitly distinguishes strategic centrality from systemic stability. High structural centrality within AI-mediated systems does not imply robustness and often coincides with increased exposure and fragility. Nodes that are most critical to system performance may also be those whose disruption, capture, or misgovernance would generate the most severe cascading effects (Perrow, 1984; Helbing, 2013; Beck, 1992).

Risk interpretation within AI-SNF therefore focuses on identifying and characterizing structural risk vectors, rather than reducing risk to a single residual penalty or adjustment factor (Renn, 2008; Power, 2007). Core risk vectors considered within the framework include:

- **Governance asymmetry**: misalignment between a node's strategic importance and the capacity for effective oversight and control (North, 1990; Power, 2007).
- **External dependency**: reliance on external actors, jurisdictions, or infrastructures that introduce vulnerability through misalignment, coercion, or disruption (Bratton, 2016; North, 1990).
- **Control-rights ambiguity**: fragmented or contested authority over access, operation, or integration interfaces within AI-mediated systems (North, 1990; Power, 2007).
- **Exposure to coercion, denial, or manipulation**: susceptibility to deliberate interference or adversarial exploitation within sensing, modeling, or decision pipelines (Schelling, 1960; Helbing, 2013).

4. Indicator Architecture

- **Environmental and regulatory constraints**: physical, ecological, legal, or regulatory conditions that limit rapid adaptation, redundancy expansion, or system reconfiguration under stress (Renn, 2008).

Rather than aggregating these vectors into a single negative score, AI-SNF preserves them as distinct diagnostic components. This approach enables differentiation between nodes that are structurally central yet governable and those where high leverage coincides with acute control deficits, supporting more targeted and proportionate governance analysis (Renn, 2008; Power, 2007).

4.6 Modularity and Upgrade Path

AI-SNF is designed as an evolving and extensible framework rather than a fixed or closed instrument. Its modular architecture is intended to preserve a stable conceptual core while enabling systematic refinement as AI-mediated systems, governance environments, and data availability develop over time (Power, 2007; Renn, 2008).

Future iterations of the framework may introduce:

- **Sector-specific submodules**, tailored to domains such as climate and Earth-system analytics, space-domain awareness, undersea infrastructure, or critical supply-chain coordination, while maintaining cross-sector comparability at the level of core dimensions (Helbing, 2013).
- **Enhanced uncertainty treatment and confidence scoring**, including improved handling of missing or incomplete data, measurement uncertainty, and sensitivity analysis, alongside clearer confidence disclosure at both dimensional and composite levels (Renn, 2008; NIST, 2023).
- **Cross-node interaction and network-level analysis**, capturing dependency chains, redundancy structures, and systemic clustering in order to extend node-level diagnosis to network-level assessment (Castells, 2010; Helbing, 2013).
- **Integration with complementary governance and risk indices**, enabling multi-layered analysis without diluting AI-SNF’s structural focus or interpretive discipline (NIST, 2023; OECD, 2019).

The v0.1 architecture establishes a stable methodological baseline by defining core dimensions, aggregation views, and interpretive safeguards. This approach preserves comparability and auditability over time while providing a controlled and transparent pathway for refinement and expansion (Renn, 2007; Power, 2007).

Part III.
Indicator Definitions and Methodology

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

Within this White Book, D1 is defined as a framework dimension within AI-SNF. AI-SNI aggregates framework-defined dimensions, including D1, into a bounded composite diagnostic output under explicitly stated aggregation rules. Accordingly, this section sets out the conceptual rationale, causal mechanism, and measurement logic of AI-SNF Dimension D1, rather than introducing an independent index.

5.1 Conceptual Rationale: Perception as the Primary Strategic Bottleneck

All AI-mediated strategic systems are constrained by what they are able to perceive. Perception constitutes the first and foundational bottleneck in the causal chain linking environmental conditions to prediction, decision-making, and action. Where perceptual limitations are structurally embedded, subsequent advances in modeling sophistication, computational capacity, or institutional coordination cannot fully compensate.

AI-mediated systems are particularly exposed to three forms of perceptual constraint: structural blind spots, where geographic, orbital, or infrastructural absence prevents phenomena from entering analytical pipelines; degraded temporal continuity, where intermittent or unreliable sensing undermines trend detection, anomaly recognition, and early warning; and full substitutability, where the loss of a sensing input can be offset without materially affecting system-wide perception or uncertainty.

As AI systems increasingly integrate heterogeneous sensing modalities, such as radar, electro-optical and infrared (EO/IR), signals intelligence (SIGINT), remote sensing, space-domain awareness, and environmental monitoring, strategic relevance no longer derives from sensor quantity alone. Instead, it concentrates at nodes where perception exhibits three properties: density, ensuring persistent and reliable coverage; uniqueness, reflecting non-substitutable geographic, orbital, or functional positioning; and operational integration, whereby perceptual outputs are routinely embedded in downstream analytical, predictive, and decision-execution processes.

Accordingly, AI-SNF Dimension D1 measures perceptual centrality rather than sensing volume. It assesses the extent to which a geographic node functions as a structural perception anchor—one whose degradation, denial, or misalignment would impose disproportionate uncertainty, delay, or distortion across AI-mediated early-warning and situational-awareness architectures. D1 therefore captures a system-level constraint on strategic cognition, rather than a technical inventory of sensing assets. High D1 values indicate nodes whose perceptual role is non-substitutable, temporally binding, and structurally consequential for downstream AI-enabled prediction and decision-making.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

5.2 From “Sensors” to “Algorithmic Perception Anchors”

Conventional strategic assessments typically treat sensing assets as discrete platforms or countable capabilities, emphasizing inventories, technical specifications, nominal coverage, or platform performance. This perspective is increasingly insufficient in AI-mediated systems, where strategic relevance is determined less by possession than by algorithmic embedding.

Within AI-enabled architectures, perception acquires strategic value only when sensing outputs are operationally integrated into algorithmic pipelines that govern early warning, situational awareness, and downstream analytical and decision processes. Sensors that are not embedded in such pipelines, regardless of their technical sophistication, exert limited influence on system behavior. Conversely, geographically constrained or technically modest sensing inputs may become strategically consequential when they function as indispensable reference points within algorithmic perception systems.

Under these conditions, a node’s strategic importance derives not from the quantity or sophistication of sensors it hosts, but from whether its perceptual outputs perform one or more anchoring functions, including:

- **Early-warning temporal anchoring**, by establishing detection timelines that define when threats, anomalies, or environmental changes are first registered across dependent systems;
- **Situational-awareness baseline definition**, by shaping what downstream systems treat as normal, anomalous, or urgent, thereby conditioning alert thresholds, prioritization logic, and attention allocation;
- **Calibration and validation referencing**, by providing data used to train, tune, validate, or continuously update perception models, influencing how uncertainty, confidence, and error propagate system-wide.

By focusing on anchoring functions rather than platform inventories, D1 captures how specific nodes condition what AI-mediated systems are capable of perceiving, anticipating, and responding to prior to explicit human or automated decision.

5.3 The D1 Causal Mechanism

The causal logic underlying Algorithmic Sensing and Early-Warning Centrality (D1) is not one of linear accumulation or direct outcome determination. Instead, it operates through structural conditioning. In AI-mediated strategic systems, perceptual advantage generates influence by reshaping dependency relationships across downstream layers, rather than by directly dictating individual decisions or events.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

At a system level, this mechanism can be summarized as a progression from sensing configuration to strategic centrality:

Sensor Coverage and Uniqueness ↑

↓

Perceptual Dependency ↑

↓

Early-Warning Advantage ↑

↓

Decision-Timing Asymmetry ↑

↓

Strategic Centrality ↑

Influence is therefore exercised not through command or direct control, but through the stabilization of perception as a shared reference point across interconnected analytical, predictive, and decision systems.

Three structural properties characterize this mechanism. First, **path dependence** arises as perceptual baselines become embedded in models, data pipelines, standard operating procedures, and institutional routines, raising switching and integration costs even in the absence of deliberate lock-in. Second, **irreversibility under stress** limits corrective capacity: perceptual gaps cannot be rapidly closed during crises, allowing epistemic uncertainty to persist throughout the decision cycle even when additional data becomes available at later stages. Third, **systemic coupling** links perception quality directly to predictive performance (D2) and constrains execution timing and governance response (D3–D4), such that degradation at the perceptual layer propagates non-linearly across the system.

Dimension D1 therefore captures **upstream structural power** rather than downstream outcomes. It assesses whether a node conditions what AI-mediated systems are able to perceive in the first place, thereby shaping the boundary conditions for prediction, decision, and action across the broader architecture.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

5.4 D1 Core Aggregation Formula

Within AI-SNF, the D1 score is computed as a weighted aggregation of second-level perceptual indicators, adjusted by structural coefficients that account for incomplete temporal coverage and reduced reliability under stress conditions. The formulation is designed to reflect structural perceptual centrality, not sensing volume, platform inventories, nominal coverage density, or downstream decision accuracy.

D1 evaluates whether a node functions as a structural perception anchor within AI-mediated systems—one whose degradation or distortion would generate system-wide epistemic blind spots, disrupt early-warning coherence, or degrade shared situational awareness across dependent analytical and decision architectures.

$$\boldsymbol{D1} = \left(\sum_{\boldsymbol{i=1}}^{\boldsymbol{5}} \boldsymbol{\omega_{1,i}} \times \widehat{\boldsymbol{D_{1-i}}} \right) \times \boldsymbol{C_{coverage}} \times \boldsymbol{C_{reliability}} \quad \textbf{(5.4.1)}$$

Structural Adjustment Coefficients

$$\boldsymbol{C_{coverage}} = \frac{\boldsymbol{T_{observed}}}{\boldsymbol{T_{total}}} \text{ , } \boldsymbol{C_{reliability}} = \boldsymbol{1 - \rho} \quad \textbf{(5.4.2)}$$

Parameter Definitions:

- $\boldsymbol{D1}$**:** Algorithmic Sensing and Early-Warning Centrality (ASEWC). Measures a node's structural perceptual centrality within AI-mediated early-warning and situational awareness architectures. Higher values indicate nodes whose degradation or loss would impose disproportionate system-wide epistemic uncertainty.
- $\boldsymbol{\omega_{1,i}}$: Weight assigned to the *i*-th second-level D1 indicator. AI-SNI v0.1 baseline: $\boldsymbol{\omega_{1,i} = 0.2}$. Equal weighting is applied to avoid premature privileging of any single sensing modality or integration pathway.
- $\widehat{\boldsymbol{D_{1-i}}}$**:** Standardized score of the *i*-th D1 sub-indicator, mapped onto a common **[0,1]** scale. Standardization preserves relative structural importance rather than absolute sensing volume, platform count, or technical performance.
- $\boldsymbol{C_{coverage}}$: Captures the proportion of the required observation horizon during which the node provides continuous, valid, and operationally accessible sensing outputs:
- $\boldsymbol{T_{observed}}$: Effective Observation Time. The cumulative duration within the evaluation window during which sensing outputs are operational, calibrated, and integrated into AI-mediated early-warning or situational awareness pipelines.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

- T_{total}: Required Observation Horizon. The total duration necessary for the node to function as a structurally reliable perception anchor, determined by domain-specific early-warning, monitoring, or planning requirements.
- $C_{reliability}$: Adjusts for the persistence and survivability of perceptual functions under adverse conditions.
- ρ: Estimated degradation probability, representing the likelihood of perceptual failure under conditions such as armed conflict, electronic warfare or jamming, environmental stress, or infrastructure disruption.

5.5 Indicator Composition: Operationalizing D1 (D1 to D1-5)

Within AI-SNF, Dimension D1 is operationalized through five second-level indicators that capture complementary aspects of perceptual centrality. These indicators address, respectively, physical coverage sufficiency, non-substitutability, temporal integrity, model readiness, and institutional embedding. Together, they translate the conceptual notion of algorithmic perception anchoring into measurable components.

5.5.1 D1-1 Sensor Coverage Density (SCD)

SCD assesses the density and structural sufficiency of critical sensing assets within a node's relevant operational domain. It does not measure raw sensor counts or platform inventories. Instead, it evaluates whether sensing coverage is adequate relative to the effective operational domain, taking into account domain relevance, functional availability, and redundancy requirements.

SCD captures the baseline physical viability of perception—that is, whether sufficient sensing coverage exists to support AI-mediated situational awareness prior to higher-order considerations such as non-substitutability, temporal continuity, algorithmic integration, or governance access. As such, SCD is a necessary but not sufficient condition for high perceptual centrality within D1.

A. Core Formula

$$D_{1-1} = \frac{\sum_{k=1}^{K}(\alpha_k \times S_k)}{A_{effective}} \tag{5.5.1.1}$$

Parameter Definitions

- S_k: Effective capacity of critical sensor type k, adjusted for operational availability rather than nominal platform count.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

- $\boldsymbol{\alpha_k}$: Domain relevance weight assigned to sensor type k, reflecting its contribution to early warning and situational awareness within the specific operational context (e.g., radar, EO/IR, SIGINT, space-domain awareness, environmental sensing).
- $\boldsymbol{A_{effective}}$: Normalized effective operational domain area over which sensing coverage is required. This may correspond to land area, maritime zone, airspace volume, orbital regime, or hybrid domains, depending on node characteristics.

B. Standardization

To enable cross-node comparability, the raw SCD value is normalized as follows:

$$\widehat{\boldsymbol{D_{1-1}}} = \frac{\boldsymbol{D_{1-1}} - \boldsymbol{min}(\boldsymbol{D_{1-1}})}{\boldsymbol{max}(\boldsymbol{D_{1-1}}) - \boldsymbol{min}(\boldsymbol{D_{1-1}})}$$

(5.5.1.2)

This normalization preserves relative structural differences in coverage sufficiency across nodes. It does not reflect absolute sensing scale, platform density, or technological sophistication.

C. Interpretive Notes

A high D1-1 (SCD) score indicates that a node provides structurally dense and resilient perceptual coverage relative to its effective operational domain. This satisfies a necessary but not sufficient condition for perceptual centrality within AI-mediated systems.

Conversely, low SCD values indicate baseline perceptual fragility, even where individual sensing platforms may be technologically advanced or high-performing in isolation.

Within D1, SCD functions as the foundational coverage layer. It establishes whether perception is physically and spatially viable before subsequent sub-indicators assess sensing uniqueness, temporal continuity, algorithmic integration, or institutional accessibility. As such, SCD constrains the upper bound of perceptual centrality: without sufficient coverage density, higher-order perceptual advantages cannot be structurally sustained.

5.5.2 D1-2 Sensor Uniqueness Ratio (SUR)

SUR assesses the non-substitutability of sensing functions within the relevant geographic, orbital, or mission-specific context. It evaluates whether functionally equivalent perceptual capabilities can be readily replaced by alternative nodes without materially degrading system-level perception integrity or early-warning performance.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

SUR does not measure sensing volume, technical sophistication, or coverage density. Its analytical focus is structural scarcity—that is, whether the loss or degradation of a node would create persistent perceptual gaps rather than merely reallocate sensing tasks within an existing network.

High SUR values indicate that a node occupies a structurally unique position in AI-mediated sensing architectures, typically characterized by one or more of the following conditions:

- **Limited geographic or orbital alternatives:** Few or no other nodes can provide functionally equivalent sensing coverage within comparable latitude bands, orbital regimes, or spatial configurations.
- **Unique vantage points:** The node offers observational perspectives that cannot be replicated elsewhere due to geometry, environmental constraints, line-of-sight conditions, or spatial positioning.
- **Mission-critical perceptual roles:** The node performs sensing functions essential to specific missions or early-warning timelines, where substitution would introduce unacceptable delay, blind spots, or uncertainty.

Within Dimension D1, SUR captures the irreversibility of perceptual loss, complementing D1-1 (SCD), which assesses baseline coverage sufficiency. While SCD establishes whether perception is physically viable, SUR determines whether that perception is structurally replaceable under stress.

A. Core Formula

$$D_{1-2} = 1 - \frac{N_{substitutable}}{N_{comparable}} \quad \textbf{(5.5.2.1)}$$

Parameter Definitions

- $N_{substitutable}$: The number of alternative nodes capable of providing functionally equivalent sensing outputs, such that loss or degradation of the focal node would not materially alter system-level perception or early-warning performance.
- $N_{comparable}$: The total number of nodes within the relevant geographic, orbital, or mission class considered capable, in principle, of hosting comparable sensing functions.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

B. Boundary condition

$$D_{1-2} \in [0, 1]$$

- D1-2 = 1 indicates complete non-substitutability (no viable alternatives).
- D1-2 = 0 indicates full substitutability (the node is one among many equivalent options).

C. Methodological note

SUR operationalizes non-replaceability as a primary source of upstream leverage in AI-mediated perception systems. Unlike measures of sensing density (D1-1) or temporal and performance robustness (D1-3), SUR assesses whether perceptual functions can be structurally reconstituted elsewhere if a node is degraded or lost.

A node with limited sensing capacity may exhibit a high SUR where its vantage point, geometry, or mission role cannot be replicated by alternative locations or platforms. Conversely, nodes hosting dense sensing infrastructure may score low on SUR where equivalent perceptual functions are widely distributed or readily substitutable across the network.

Within Dimension D1, SUR complements Sensor Coverage Density (D1-1) by distinguishing between perception that is abundant but replaceable and perception that is scarce and structurally anchoring. High SUR values therefore indicate nodes whose degradation would result in irreversible epistemic loss, rather than localized or temporary degradation of sensing performance.

5.5.3 D1-3 Data Freshness and Continuity (DFC)

DFC assesses whether perceptual outputs are sufficiently timely, continuous, and resilient to support early warning, trend detection, and weak-signal identification within AI-mediated systems.

To preserve unit consistency, monotonic interpretability, and structural sufficiency logic, DFC is defined as a multiplicative adequacy measure combining latency sufficiency and continuity sufficiency. This formulation reflects a core design principle: timeliness and continuity are jointly necessary conditions for effective perception. Deficiency in either dimension degrades perceptual effectiveness regardless of performance in the other.

DFC evaluates perceptual performance across three tightly coupled temporal properties:

- **Timeliness**: the extent to which data update latency is sufficiently low to enable early detection and actionable warning before relevant decision windows close.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

- **Continuity**: the degree to which sensing streams remain uninterrupted over the evaluation horizon, enabling the detection of trends, deviations, and weak signals rather than isolated observations.
- **Reliability under stress**: the persistence of perceptual data availability and usability during periods of operational stress, environmental disruption, or adversarial interference.

Taken together, these properties determine whether perception functions as a stable temporal reference within AI-mediated systems, as opposed to an episodic, reactive, or post hoc signal source. Within Dimension D1, DFC complements coverage sufficiency (D1-1) and non-substitutability (D1-2) by assessing whether perceptual inputs remain temporally actionable under routine and stressed conditions.

A. Core Formula

$$\boldsymbol{D_{1-3} = (1 - \delta) \times (1 - \lambda)} \quad \textbf{(5.5.3.1)}$$

Parameter Definitions

- $\boldsymbol{\lambda}$**:** Normalized Average Update Latency. Represents the average time delay between observation and availability within AI-mediated analytical pipelines, normalized against domain-specific early-warning or monitoring requirements. Lower values indicate faster and more operationally relevant updates.
- $\boldsymbol{\delta}$**:** Missing-Data or Outage Ratio. The proportion of the evaluation window during which sensing data is unavailable, incomplete, or invalid due to outages, transmission failure, calibration loss, or access disruption.

B. Standardization

To ensure interpretability and prevent extreme values from disproportionately influencing aggregation, DFC is standardized as follows:

$$\boldsymbol{\widehat{D_{1-3}} = min(1, \frac{D_{1-3}}{D_{1-3}^{benchmark}})} \quad \textbf{(5.5.3.2)}$$

where $D_{1-3}^{benchmark}$ denotes a domain-appropriate reference threshold for early-warning adequacy. Values exceeding the benchmark are capped at 1, reflecting sufficiency rather than superfluity in perceptual timeliness and continuity.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

C. Interpretive Notes

DFC operationalizes the principle that perception delayed is perception degraded. Even sensing infrastructures that are spatially dense (D1-1) or structurally unique (D1-2) do not generate strategic relevance if their outputs arrive too late, too intermittently, or too unreliably to shape early-warning timelines or sustained situational awareness.

Within **Dimension D1**, DFC complements:

- **D1-1 (Sensor Coverage Density)** by ensuring that spatial coverage is temporally usable rather than nominal; and
- **D1-2 (Sensor Uniqueness Ratio)** by ensuring that unique vantage points translate into persistent perceptual leverage rather than sporadic insight.

High DFC scores therefore identify nodes whose sensing outputs function as stable temporal anchors within AI-mediated perception systems. Low DFC scores indicate epistemic fragility: perception may exist in principle, but fails in practice when timing, continuity, and resilience under stress are most consequential.

5.5.4 D1-4 Model-Ready Data Quality (MRDQ)

MRDQ assesses whether sensing outputs can be directly and reliably ingested by machine-learning systems without extensive manual intervention, bespoke preprocessing, or ad hoc correction.

MRDQ does **not** evaluate model performance, algorithmic sophistication, or analytical outcomes. Instead, it captures whether perceptual data streams meet the minimum structural conditions required for automated ingestion, scalable processing, and governance-aligned model deployment within AI-mediated systems.

MRDQ evaluates data readiness across four interdependent quality dimensions:

- **Data Cleanliness:** the extent to which sensing outputs are free from noise, corruption, duplication, or systematic error that would materially degrade automated processing or require corrective preprocessing.
- **Calibration Consistency:** the stability and coherence of calibration parameters across time, platforms, and sensing modalities, ensuring that data distributions remain comparable and analytically meaningful under automated model pipelines.
- **Format Standardization:** the degree to which data formats, schemas, metadata structures, and interfaces conform to standardized or interoperable specifications compatible with automated ingestion and scalable analytics.
- **Provenance and Traceability:** the availability of verifiable information on data origin, collection conditions, processing history, access controls, and governance constraints, supporting auditability, trust calibration, and responsible model use.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

Taken together, these properties determine whether sensing outputs function as model-ready inputs rather than raw, situational, or human-dependent data streams. Within Dimension D1, MRDQ captures the degree to which perception is operationally translatable into automated prediction and decision systems, rather than remaining confined to descriptive or manually mediated analysis.

A. Core Formula

$$D_{1-4} = \frac{\beta_1 \times Q_{clean} + \beta_2 \times Q_{calibration} + \beta_3 \times Q_{standard} + \beta_4 \times Q_{provenance}}{\sum_{j=1}^{4} \beta_j}$$

(5.5.4.1)

Parameter Definitions

- Q_{clean}: Score capturing data cleanliness and noise control. Normalized to the interval [0,1], where higher values indicate greater algorithmic usability.
- $Q_{calibration}$: Score capturing calibration stability and cross-platform consistency. Normalized to the interval **[0,1],** where higher values indicate greater algorithmic usability.
- $Q_{standard}$: Score capturing format, schema, and interface standardization. Normalized to the interval **[0,1]**, where higher values indicate greater algorithmic usability.
- $Q_{provenance}$: Score capturing provenance integrity, traceability, and audit readiness. Normalized to the interval **[0,1],** where higher values indicate greater algorithmic usability.
- β_j: Weight assigned to the *j*-th data quality component. By default, weights are equal unless domain-specific analytical justification exists for differential emphasis.

B. Interpretive Notes

MRDQ operationalizes a core principle of AI-mediated perception: data that cannot be reliably consumed by algorithms does not constitute effective perceptual centrality, regardless of sensing density, uniqueness, or temporal freshness.

Hidden frictions, such as unstable calibration, inconsistent formats, or opaque provenance, introduce latent failure points that degrade early-warning performance, undermine confidence in downstream inference, and constrain scalable deployment under governance and audit requirements.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

Within D1, MRDQ complements:

- **D1-1 (Sensor Coverage Density)** by ensuring that spatial coverage translates into algorithmically usable inputs;
- **D1-2 (Sensor Uniqueness Ratio)** by ensuring that unique vantage points are computationally exploitable rather than observationally isolated;
- **D1-3 (Data Freshness and Continuity)** by ensuring that timely and continuous data remains analytically valid and governance-compliant.

High MRDQ scores therefore identify nodes whose perceptual outputs are natively compatible with AI pipelines, reinforcing their role as structural perception anchors. Low MRDQ scores indicate a binding bottleneck: perception exists, but cannot be operationalized at machine speed, scale, or governance reliability.

5.5.5 D1-5 Operational Integration Index (OII)

OII operationalizes the principle that perception generates strategic relevance only when it is institutionally embedded in decision and execution systems. Perceptual outputs that remain advisory, episodic, or informally consulted do not constitute operational centrality, regardless of their technical quality or uniqueness.

By focusing on formalized uptake rather than connectivity, OII distinguishes between nodes that merely produce information and those that structurally condition monitoring routines, decision timing, and execution pathways under both normal and stressed conditions.

Within D1, OII complements:

a) **D1-1 (Sensor Coverage Density)** by ensuring that available perception is operationally consumed rather than dormant;

b) **D1-2 (Sensor Uniqueness Ratio)** by ensuring that unique perceptual vantage points are institutionally actionable;

c) **D1-3 (Data Freshness and Continuity)** by ensuring that timely perception enters decision loops before windows close;

d) **D1-4 (Model-Ready Data Quality)** by ensuring that algorithmically usable data is also operationally authorized and routinized.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

A. Core Formula

$$D_{1-5} = \frac{I_{ISR} + I_{C2} + I_{SSA} + I_{Allied}}{4} \quad \textbf{(5.5.5.1)}$$

Parameter Definitions

- I_{ISR} : Binary indicator reflecting formal and routine embedding within ISR architectures.
- I_{C2}: Binary indicator reflecting direct and authorized linkage to command-and-control systems.
- I_{SSA} : Binary indicator reflecting integration into space-domain awareness or equivalent strategic monitoring frameworks.
- I_{Allied} **:** Binary indicator reflecting institutionalized participation in allied or multilateral perception networks.

B. Methodological Clarification

The binary specification of OII is intentional. It reflects a threshold property of operational relevance: perceptual outputs either enter decision architectures as standing, authorized inputs, or they do not. Partial, informal, or contingent access does not satisfy the structural condition of operational integration and is therefore coded as **0**.

This design choice avoids false precision and prevents the overstatement of centrality based on episodic cooperation, ad hoc coordination, or goodwill-based data sharing.

C. Interpretive Notes

OII captures institutionalized operational embedding, not technical compatibility or analytical quality. A node may exhibit dense, unique, timely, and model-ready perception (high D1-1 to D1-4) yet score low on OII if its outputs are not incorporated into standing operational systems.

Within D1, OII functions as the final activation layer:

- **D1-1 to D1-4** establish whether perception is structurally viable and algorithmically usable;
- **D1-5** determines whether that perception is structurally consequential.

High OII scores therefore identify nodes whose perceptual outputs are not merely available or usable, but routinely acted upon, anchoring decision timing and execution pathways. Low OII scores indicate latent or under-institutionalized perception: capability exists, but has not been translated into durable operational leverage.

5. Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

5.6 Methodological Notes: Scope and Limitations of D1

Dimension D1 evaluates structural centrality within algorithmic perception networks—that is, whether a node functions as a perception anchor on which broader AI-mediated systems depend for sensing, detection, and early situational awareness.

D1 does not measure downstream decision accuracy, policy effectiveness, operational success, or actor intent. It does not assess whether perception-informed decisions are optimal, ethical, timely, or strategically sound, nor does it evaluate governance quality, command judgment, or execution outcomes.

Accordingly, high D1 values indicate systemic perceptual consequence, not performance superiority or strategic success. A node may score highly on D1 while remaining weakly governed or poorly utilized. Conversely, low D1 values indicate limited perceptual anchoring even where local decision-making or operational competence is strong.

D1 is therefore a structural diagnostic of epistemic positioning, not an evaluative judgment of policy quality, institutional intent, or realized outcomes.

5.7 Why D1 Is Foundational to AI-Strategic Power

In AI-mediated strategic systems, perception precedes prediction, and prediction precedes action. Without structural perceptual centrality, downstream advantages in modeling (D2), compute scale, or execution capability (D3) remain fragile and contingent.

D1 defines the epistemic boundary of algorithmic awareness. It conditions which signals are detectable, which anomalies become visible in time, and which developments enter forecasting and decision pipelines before windows close. In doing so, D1 sets the outer limits of what AI-mediated systems can know and act upon.

D1 is therefore a necessary—though not sufficient—precondition for predictive leverage (D2) and decision-loop advantage (D3). Nodes lacking perceptual anchoring may rely on proxies or external data, but such advantages are structurally exposed to disruption and informational asymmetry.

By serving as the upstream gatekeeper of epistemic access, D1 anchors the durability of downstream power across D3–D5. Where perception is marginal, power is borrowed and reversible; where perception is central, downstream capabilities gain persistence and systemic consequence.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Within AI-SNF, D2 specifies the predictive layer of AI-mediated systems. Its outputs are aggregated with other framework dimensions into the composite AI-SNI under the aggregation rules defined in Section 10. D2 does not constitute an independent index, ranking, or evaluative metric.

6.1 Conceptual Rationale: Prediction as Strategic Leverage

In AI-mediated environments, predictive systems do not merely describe observed conditions; they structure expectations about future states. Under conditions of uncertainty, bounded rationality, and compressed decision cycles, forecasts increasingly function as anticipatory coordination mechanisms, shaping what institutions treat as plausible, urgent, or negligible prior to explicit decision-making.

As predictive models are embedded within planning processes, risk management systems, and automated coordination architectures, their outputs condition institutional behavior in advance of action. Forecasts delimit option spaces, allocate attention, and pre-configure response pathways. Influence over prediction therefore translates into influence over how futures are framed, prioritized, and acted upon, even in the absence of formal decision authority.

Predictive leverage does not derive solely from computational scale or algorithmic sophistication. Structural weaknesses in the predictive layer persist where:

- model calibration depends on fragile, contested, or externally constrained inputs;
- baseline assumptions are unevenly validated or systematically biased; or
- predictive uncertainty is asymmetrically distributed across actors, creating anticipatory advantages for some and residual ambiguity for others.

In AI-mediated strategic systems, predictive leverage arises from structural positioning within forecast generation and reliance chains. As predictive outputs become routinized within institutional processes, leverage concentrates at nodes that:

- anchor model calibration and validation, shaping how systems interpret incoming data and adjust over time;
- materially reduce uncertainty in high-impact domains, such as security, climate risk, financial stability, or infrastructure coordination; or
- condition forecast trajectories whose effects propagate across actors and sectors beyond the node’s immediate context.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Dimension D2 captures this form of forecast-mediated leverage. It measures whether a node occupies a position of structural influence and dependency within predictive architectures—such that its inputs, calibration role, or modeling functions are difficult to bypass, substitute, or neutralize. Within AI-SNF (D1–D5), prediction constitutes a strategic bottleneck, mediating between perception (D1) and downstream action (D3–D5). By shaping how uncertainty is reduced and futures are rendered actionable, the predictive layer conditions the anticipatory environment in which subsequent decisions are made.

6.2 From "Model Accuracy" to "Forecast Dependency"

Conventional assessments of predictive capability typically focus on model accuracy, benchmark performance, algorithmic sophistication, or training scale. While these metrics are essential for technical evaluation, they are insufficient for strategic analysis in AI-mediated systems.

From a strategic perspective, relevance does not depend primarily on which actors develop the most accurate models under controlled conditions. It depends on which nodes predictive systems structurally depend on for calibration, validation, boundary-setting, and continuous updating once models are embedded in real-world decision environments.

In practice, many large-scale predictive architectures, spanning security assessment, climate modeling, financial risk analysis, and infrastructure planning, rely on a limited set of structural anchors. These anchors supply indispensable data streams, reference conditions, or calibration baselines that constrain what models can plausibly forecast. Their role is therefore constitutive rather than merely contributory: they define the feasible prediction space within which models operate.

When such anchors are degraded, distorted, contested, or removed, the resulting effects are rarely linear. Instead:

- predictive uncertainty increases nonlinearly as stable reference points are lost;
- forecast credibility erodes across dependent systems, including actors not directly connected to the disrupted node; and
- previously implicit institutional reliance becomes visible, exposing hidden dependencies and coordination risks.

Dimension D2 accordingly reframes predictive models not as standalone technical artifacts, but as dependency-generating infrastructures. Predictive leverage arises where models become difficult to recalibrate, substitute, or disengage from without incurring systemic uncertainty, coordination failure, or strategic risk.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Within this framework, forecast dependency matters more than forecast precision. A model that is moderately accurate but deeply embedded in institutional workflows may exert greater strategic influence than a technically superior model that remains peripheral, experimental, or readily replaceable.

Dimension D2 captures this shift in analytical focus. It evaluates whether a node contributes to path-dependent reliance in forecast generation and use, shaping how futures are anticipated, coordinated, and acted upon across interconnected systems, rather than whether it produces technically superior predictions in isolation.

6.3 The D2 Causal Mechanism

The causal logic underlying D2 operates through epistemic conditioning rather than operational control. Strategic influence is generated not by issuing directives or exercising authority, but by shaping how uncertainty is reduced, how futures are parameterized, and how risks are internally represented within AI-mediated decision systems.

This mechanism can be summarized as a layered causal sequence:

Calibration Centrality ↑

↓

Forecast Dependency ↑

↓

Asymmetric Uncertainty Reduction ↑

↓

Decision Framing Influence ↑

↓

Strategic Leverage ↑

At each stage, influence is exercised indirectly. Nodes exert leverage by conditioning probability distributions, scenario baselines, confidence intervals, and risk thresholds that structure downstream planning and coordination processes. As predictive outputs become embedded in institutional routines, these epistemic parameters increasingly function as default reference points, constraining what outcomes are considered plausible, urgent, or negligible.

Accordingly, D2 captures a form of structural power that precedes choice and operates upstream of action. It reflects how predictive dependence translates into durable influence over decision framing, even in the absence of formal authority, command relationships, or enforcement capacity.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

A. Mechanism Explanation

a) **Calibration Centrality:** Nodes that anchor model calibration, validation, or baseline assumptions exert disproportionate influence over how predictive systems interpret incoming data and update expectations. Calibration roles define what constitutes "normal," "anomalous," or "critical" within forecast architectures.

b) **Forecast Dependency:** As predictive systems rely on these calibration anchors for coherence and continuity, structural dependency emerges. Disengaging from or substituting these anchors becomes costly, slow, or destabilizing, even where alternative data or models exist in principle.

c) **Asymmetric Uncertainty Reduction:** Dependency enables certain actors or systems to reduce uncertainty earlier, faster, or more consistently than others. This asymmetry does not require formal authority; it arises from unequal access to stabilized forecasts and anticipatory clarity.

d) **Decision Framing Influence:** Forecast outputs shape how decision environments are framed—what scenarios are treated as plausible, which risks are prioritized, and which options are viewed as excessive or infeasible. Over time, forecasts operate as pre-decisional constraints on action.

e) **Strategic Leverage:** When forecast dependency becomes entrenched, influence over calibration points translates into durable strategic leverage. Outcomes need not be dictated directly; shaping expectations is often sufficient to guide behavior across interconnected systems.

B. Key Structural Properties

a) **Indirectness:** Predictive leverage operates through forecasts, baselines, and expectations rather than explicit orders or centralized control. Its effects are therefore diffuse, difficult to attribute, and frequently underestimated.

b) **Amplification:** Minor perturbations at critical calibration points, such as biased inputs, delayed updates, or contested reference values, can generate disproportionate downstream effects across policy, security, economic, and environmental domains.

c) **Institutional Lock-in:** Once predictive outputs are routinized within planning cycles, governance procedures, and automated coordination mechanisms, dependency becomes persistent. Correcting distorted forecasts or re-calibrating models under stress is institutionally and temporally constrained.

Dimension D2 captures structural influence over anticipation, not control over action. It explains how strategic leverage can be exercised without sovereignty, command authority, or overt intervention by shaping how AI-mediated systems construct expectations about the future.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Within AI-SNI architecture, D2 functions as the epistemic hinge between perception (D1) and execution (D3–D5), conditioning uncertainty and expectation in ways that determine which futures enter the decision space—and which remain structurally excluded.

6.4 D2 Core Aggregation Formula

The composite score for D2 is designed to capture structural predictive influence under real-world institutional, dependency, and risk constraints, rather than abstract modeling sophistication or technical forecast accuracy.

Within AI-mediated systems, predictive leverage arises only where forecasts are:

- continuously supported by node-specific data or calibration inputs,
- institutionally embedded within planning, coordination, or decision processes, and
- sufficiently resilient to manipulation, distortion, or governance capture.

Accordingly, D2 measures the extent to which a node anchors predictive architectures on which other actors or systems depend, rather than the performance of individual models in isolation.

D2 does not assess forecast accuracy, methodological quality, or algorithmic sophistication. Instead, it evaluates structural predictive consequence—whether a node's data, calibration role, or forecast outputs condition expectations, scenario baselines, and planning assumptions across dependent systems.

A node may therefore exhibit a high D2 score even where forecasts are contested or uncertain, provided that its predictive role remains difficult to substitute, routinized within institutional workflows, and consequential under operational decision constraints.

A. Core Formula

$$D2 = \sum_{i=1}^{4} \left(\omega_{2,i} \times \widehat{L_i}\right) \times C_{coverage} \times C_{institution} \times (1 - \gamma \times \widehat{R}) \quad \textbf{(6.4.1)}$$

Structural Adjustment Coefficients

$$C_{coverage} = \frac{T_{observed}}{T_{total}}\ , C_{institution} = min(1, \frac{N_{institutional\ citations}}{N^*}) \quad \textbf{(6.4.2)}$$

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Parameter Definitions:

- $\boldsymbol{D2}$**:** Predictive Model Leverage and Dependency (PMLD). Measures a node's structural influence over predictive architectures, conditioned by data sufficiency, institutional embedding, and vulnerability to manipulation.
- $\boldsymbol{\omega_{2,i}}$: Weight of the *i*-th predictive leverage indicator. AI-SNI v0.1 baseline: **0.25**. Equal weighting is applied to avoid premature privileging of any single predictive channel, sector, or application domain in the absence of stable cross-domain calibration standards.
- $\boldsymbol{\widehat{L_i}}$: Standardized leverage score of the *i*-th D2 sub-indicator. $\boldsymbol{\widehat{L_i} \in [0,1]}$ $\boldsymbol{i \in \{1,2,3,4\}}$. Standardization maps heterogeneous measures of calibration dependence, forecast spillover, institutional lock-in, and systemic uptake onto a common interpretive scale while preserving relative structural leverage.
- $\boldsymbol{C_{coverage}}$: Data Coverage Coefficient. Ensures that predictive leverage is assessed only over periods during which node-specific inputs are continuously available and actively used in model calibration, validation, or updating. $\boldsymbol{C_{coverage} \in [0,1]}$**.**
- $\boldsymbol{C_{institution}}$: Institutional Embedding Coefficient. Adjusts predictive leverage by the degree to which node-derived forecasts are routinely embedded in formal decision processes, rather than remaining analytical or advisory outputs. $\boldsymbol{C_{institution} \in [0,1]}$.
- $\boldsymbol{\gamma}$: Risk penalty coefficient. Controls the strength with which predictive leverage is discounted by vulnerability to manipulation or distortion. AI-SNI v0.1 adopts a non-zero but sub-dominant penalty to reflect fragility without erasing structural leverage. $\boldsymbol{\gamma \in [0,1]}$.
- $\boldsymbol{\widehat{R}}$: Standardized risk score. Captures exposure to data poisoning, strategic distortion, adversarial exploitation, governance capture, or opacity-induced bias within predictive pipelines. $\boldsymbol{\widehat{R} \in [0,1]}$**.**
- $\boldsymbol{T_{observed}}$**:** Effective Observation Time. The cumulative duration during which node-derived data actively contribute to predictive model calibration, validation, or updating.
- $\boldsymbol{T_{total}}$**:** Required Observation Horizon. The theoretically necessary time window for reliable forecast anchoring in the relevant strategic context.
- $\boldsymbol{N_{institutional\ citations}}$**:** Number of verified instances in which node-linked forecasts are cited, adopted, or operationalized within:
  - ☐ policy planning documents,
  - ☐ security or contingency frameworks,
  - ☐ financial, insurance, or infrastructure risk models. `
- $\boldsymbol{N^*}$: Institutional Saturation Threshold. Normalization parameter indicating the point at which additional citations no longer materially increase predictive entrenchment, reflecting diminishing marginal effects of institutional uptake.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

6.5 Indicator Composition: Operationalizing D2 (D2-1 to D2-5)

Dimension D2 (Predictive Model Leverage and Dependency) is operationalized through **four leverage-oriented indicators (D2-1 to D2-4)** and **one explicit risk-conditioning indicator (D2-5)**.

The leverage indicators identify the **structural sources of predictive influence and forecast dependency**, while the risk indicator conditions interpretation by identifying circumstances under which such leverage becomes fragile, manipulable, or unreliable. The risk indicator does not redefine or generate leverage; it constrains how leverage may be interpreted in governance-relevant contexts.

Taken together, the five indicators assess **whether, and under what structural and institutional constraints, a node anchors predictive architectures on which other actors, systems, or decision processes depend**.

Specifically, the indicator set captures:

- **Calibration centrality:** whether predictive models structurally rely on node-specific data inputs for calibration, updating, or baseline formation;
- **Forecast spillover:** the extent to which node-linked forecasts propagate downstream across sectors, domains, or decision layers;
- **Substitutability and lock-in:** the feasibility, cost, and systemic disruption associated with replacing node-linked forecasts with alternative sources;
- **Institutional embedding:** the degree to which forecasts are routinized, referenced, or operationalized within formal planning, regulatory, or decision-making processes;
- **Manipulation and distortion risk:** exposure to data poisoning, strategic distortion, governance capture, or opacity that conditions effective predictive leverage.

Importantly, D2-5 functions solely as a risk-conditioning indicator. It does not constitute an additional source of predictive leverage, nor does it modify the underlying leverage structure. Instead, it limits interpretive authority where predictive influence is embedded in fragile, contested, or manipulable pipelines.

This indicator composition reflects the core analytical premise of Dimension D2: predictive power in AI-mediated systems is relational and structural, arising from dependency, entrenchment, and institutional coupling, rather than from model accuracy, technical sophistication, or computational scale in isolation.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

6.5.1 D2-1 Model Calibration Anchor Score (MCAS)

MCAS measures the extent to which node-specific data function as structurally indispensable calibration, validation, or reference inputs for predictive models with strategic relevance. MCAS assesses whether a node conditions how models are tuned, stabilized, and interpreted across operational domains, rather than merely contributing auxiliary or replaceable data streams.

MCAS evaluates whether a node performs one or more of the following structural calibration roles:

a) **Baseline Reference Point:** providing foundational observations that define normal ranges, long-term baselines, or background conditions against which anomalies, deviations, or risks are identified;

b) **High-Sensitivity Calibration Site:** supplying data to which model outputs exhibit disproportionate sensitivity, such that marginal perturbations in node-derived inputs generate non-trivial changes in forecast results;

c) **Cross-Model Validation Anchor:** serving as a shared reference point for validating, harmonizing, or cross-checking multiple model families, thereby increasing system-wide reliance on node-specific conditions.

A. Core Formula

$$D_{2-1} = \sum_{m=1}^{M} \eta_m \times \kappa_m \tag{6.5.1.1}$$

Parameter Definitions

- m**:** Model Family Index. Indexes distinct classes of predictive models, such as climate models, security early-warning systems, financial risk models, supply-chain or logistics forecasts, and infrastructure stress models.
- η_m**:** Strategic Importance Weight of Model Family *m*. Reflects the relative strategic significance of each model family in shaping high-impact decisions. By default, weights are equal.
- κ_m**:** Calibration Dependence Coefficient. Measures the degree to which model family *m* depends on node-specific data for calibration or validation. This may be operationalized through the share of calibration parameters tied to node-derived data, validation dependence on node-specific reference observations, or sensitivity analysis indicating forecast responsiveness to node inputs.$\kappa_m \in [0, 1]$.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

B. Standardization

To enable cross-node and cross-domain comparability, MCAS is standardized as:

$$\widehat{D_{2-1}} = \frac{D_{2-1} - min(D_{2-1})}{max(D_{2-1}) - min(D_{2-1})} \quad \textbf{(6.5.1.2)}$$

This normalization preserves relative calibration anchoring across nodes, rather than reflecting absolute model counts, parameter volume, or computational scale.

C. Interpretive Notes

MCAS operationalizes calibration centrality, the first causal link within Dimension D2. It does not assess model accuracy, algorithmic sophistication, or computing capacity. Instead, it evaluates whether predictive architectures are structurally anchored to node-specific data in ways that generate durable forecast dependency.

High MCAS indicates that degradation, manipulation, or loss of node-derived inputs would propagate epistemic uncertainty across multiple predictive systems and undermine forecast coherence.

Low MCAS indicates that node-linked data, while potentially valuable, remain substitutable or peripheral within calibration and validation processes.

MCAS therefore distinguishes between nodes that contribute data and nodes that define the epistemic reference frame upon which predictive stability and cross-model consistency depend.

6.5.2 D2-2 Global Spillover Sensitivity (GSS)

GSS measures the extent to which localized perturbations at a node propagate into regional or global forecast outputs within AI-mediated predictive systems. It captures how changes in node-specific conditions—environmental, infrastructural, governance-related, or data-induced—reshape predictive baselines, risk distributions, and scenario expectations beyond the node's immediate context.

High GSS values indicate that a node functions as a forecast amplification point, such that relatively small local perturbations generate disproportionate shifts in predictive outputs across interconnected systems.

Specifically, GSS assesses whether perturbations at the node:

a) **Alter regional or global projections**, shifting expected trajectories rather than isolated estimates;

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

b) **Redistribute risk**, changing probability mass, tail risk exposure, or loss expectations; and

c) **Reframe scenario baselines**, redefining what predictive systems treat as "normal," "stress," or "extreme" conditions.

GSS measures the scope and intensity of predictive spillover, not realized downstream outcomes or policy effects. It captures how forecast influence propagates through anticipatory systems, rather than how decisions or impacts ultimately materialize.

A. Core Formula

$$D_{2-2} = \sum_{m=1}^{M} \eta_m \times \frac{|\Delta \widetilde{Y_m}|}{|\Delta X_{node}|}$$

(6.5.2.1)

Parameter Definitions

- η_m: Strategic Importance Weight of Model Family *m*. Reflects the relative significance of each predictive domain. By default, weights are equal unless analytically justified otherwise.
- ΔX_{node}: Standardized Node Perturbation. Represents a controlled or observed change in node conditions, such as data shifts, environmental shocks, access disruption, or calibration drift. Perturbations are normalized to ensure comparability across nodes and domains.
- $\Delta \widetilde{Y_m}$**:** Change in Forecast Outputs for Model Family *m*. Captures the induced change in predictive outputs, including but not limited to:
  - shifts in projected risk distributions,
  - drift in scenario baselines, or
  - changes in expected loss, exposure, or probability-weighted outcomes.
- $\frac{|\Delta \widehat{Y_m}|}{|\Delta X_{node}|}$: Measures forecast amplification, expressing how strongly local perturbations at the node translate into changes in model outputs.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

B. Standardization

To prevent extreme amplification effects from dominating aggregation while preserving interpretive clarity, GSS is standardized as:

$$\widehat{D_{2-2}} = min(1, \frac{D_{2-2}}{D_{2-2}^{benchmark}})$$

(6.5.2.2)

where $D_{2-2}^{benchmark}$ denotes a domain-appropriate reference threshold for systemically consequential forecast spillover. Values exceeding the benchmark are capped at **1**, reflecting sufficiency rather than excess influence.

C. Interpretive Notes

GSS operationalizes the second link in the D2 causal chain, bridging calibration anchoring (MCAS) and system-wide predictive propagation. Whereas MCAS identifies whether predictive models depend on node-specific data, GSS evaluates how far and how forcefully that dependence propagates through interconnected forecasting architectures.

High GSS indicates nodes whose localized perturbation materially reshapes regional or global forecast landscapes, even when the initial change is limited in scope.

Low GSS indicates nodes whose predictive effects remain largely contained, attenuated, or localized within modeling systems.

Importantly, GSS does not measure realized geopolitical, economic, or environmental outcomes. It measures forecast sensitivity—how AI-mediated systems anticipate and redistribute consequences. This anticipatory reshaping conditions planning, coordination, pre-commitment, and institutional risk posture, which is why GSS constitutes predictive leverage rather than ex post impact.

6.5.3 D2-3 Substitutability Gap (SG)

SG measures the incremental degradation in predictive stability or certainty that occurs when node-specific inputs are removed, degraded, delayed, or replaced. It operationalizes forecast lock-in by evaluating how predictive systems perform under a counterfactual condition in which the node no longer fulfills its anchoring role.

SG assesses whether a node functions as a structural dependency in AI-mediated forecasting by examining whether:

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

- **Functional substitutability is constrained**: alternative data sources, proxy variables, or synthetic estimates fail to preserve forecast stability, calibration integrity, or confidence levels;
- **Uncertainty penalties under data loss are material**: removal or degradation of node-linked inputs widens confidence intervals, increases forecast error, or destabilizes scenario ordering; and
- **Forecast reliance is structurally embedded**: predictive models and associated institutional practices have adapted to node-specific inputs in ways that are costly, slow, or politically constrained to reverse.

SG therefore serves as a direct diagnostic of forecast lock-in, rather than an inventory of hypothetical substitute options or a measure of technical redundancy.

A. Core Formula

$$D_{2-3} = \sum_{m=1}^{M} \eta_m \times (E_m^{-node} - E_m^{base})$$

(6.5.3.1)

Parameter Definitions

- m: Model Family Index. Indexes predictive domains such as climate modeling, security early-warning, financial risk forecasting, logistics optimization, or infrastructure stress analysis.
- η_m: Strategic Importance Weight of Model Family *m*. Reflects the relative decision impact of each model family. By default, weights are equal.
- E_m^{base}: Baseline Forecast Error or Uncertainty. Measures predictive error, uncertainty width, or dispersion when node-specific inputs are present and functioning normally.
- E_m^{-node} : Counterfactual Forecast Error or Uncertainty. Measures predictive degradation when node-linked inputs are removed, degraded, delayed, or replaced by substitutes or proxies.
- $(E_m^{-node} - E_m^{base})$**:** Captures the incremental forecast degradation attributable to loss of the node's contribution.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

B. Standardization

To ensure cross-node comparability and prevent scale effects from dominating aggregation, SG is standardized as:

$$\widehat{D_{2-3}} = \min\left(1, \frac{D_{2-3}}{D_{2-3}^{benchmark}}\right)$$

(6.5.3.2)

where $D_{2-3}^{benchmark}$ denotes a domain-appropriate threshold for systemically significant forecast degradation. Values exceeding this threshold are capped at 1, reflecting critical lock-in rather than incremental deterioration.

C. Interpretive Notes

SG operationalizes the third link in the D2 causal chain, advancing from spillover sensitivity (GSS) to dependency persistence. While MCAS identifies calibration anchoring and GSS captures the propagation of localized perturbations, SG evaluates whether predictive systems can credibly disengage from the node without incurring unacceptable epistemic costs.

High SG indicates entrenched forecast dependency and strong path lock-in.

Low SG indicates effective substitutability and limited long-term reliance.

Crucially, SG does not assess whether substitutes exist in principle. It assesses whether substitutes preserve predictive integrity under real-world technical, institutional, and governance constraints. In this sense, SG measures operational substitutability, not theoretical replaceability.

6.5.4 D2-4 Forecast Governance Coupling (FGC)

FGC measures the extent to which node-derived forecasts are institutionally embedded within authoritative governance and decision regimes. It assesses whether predictive outputs linked to a node function as routine, procedurally binding inputs to formal decision cycles, rather than as discretionary analyses or advisory references.

FGC captures institutional uptake and procedural entrenchment, not technical availability, model sophistication, or forecast accuracy. Predictive influence becomes strategically consequential only when forecasts are routinized within governance processes—that is, when they systematically shape priority-setting, resource allocation, and risk definition under formal rules and mandates.

FGC evaluates forecast embedding across four governance domains in which predictive outputs condition authoritative decisions:

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

a) **Official Policy Processes:** Integration of node-derived forecasts into formal policy cycles, strategic plans, regulatory impact assessments, or mandated review procedures.

b) **Financial Risk and Insurance Regimes:** Use of node-linked forecasts in insurance pricing, credit-risk assessment, macroeconomic stress testing, prudential supervision, or compliance frameworks influencing capital allocation and systemic exposure.

c) **Security Planning and Contingency Frameworks:** Formal incorporation into defense posture assessments, early-warning systems, scenario planning, contingency doctrines, or crisis-response simulations.

d) **Infrastructure and Logistics Planning:** Embedding in long-term infrastructure investment decisions, logistics optimization models, supply-chain resilience planning, and critical system design regimes.

FGC therefore indicates whether predictive outputs have transitioned from analytical inputs to governance-relevant constraints, conferring durable influence over how decisions are structured and executed.

A. Core Formula

$$D_{2-4} = \frac{\phi_1 \times G_{policy} + \phi_2 \times G_{finance} + \phi_3 \times G_{security} + \phi_4 \times G_{infra}}{\sum_{j=1}^{4} \phi_j}$$

(6.5.4.1)

Parameter Definitions

- ϕ_{1-4}**:** Governance Domain Weight. Reflects the relative strategic importance of each governance domain. Default as equal weighting is applied unless analytically justified sectoral prioritization is defined.
- G_{policy}: Degree of routinized embedding of node-derived forecasts within official policy cycles, strategic planning documents, or regulatory assessment processes.
- $G_{finance}$**:** Degree of incorporation into financial, insurance, credit, macro-risk, or compliance models that influence capital allocation and systemic risk assessment.
- $G_{security}$**:** Degree of formal integration into security planning, defense posture evaluation, early-warning contingency frameworks, or crisis simulations.
- G_{infra}**:** Degree of embedding within logistics, infrastructure planning, and resilience regimes governing long-term physical and digital systems.
- Each governance coupling variable is normalized to the interval **[0,1]**, where higher values indicate deeper procedural integration and stronger decision relevance.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

B. Interpretive Notes

FGC operationalizes the fourth link in the D2 causal chain, bridging forecast dependency (MCAS, GSS, SG) and institutional entrenchment. Whereas preceding indicators establish whether predictive systems rely on node-linked inputs, FGC assesses whether such reliance has been translated into procedural authority within governance systems.

High FGC indicates that node-derived forecasts are procedurally authoritative, routinely shaping policy agendas, risk thresholds, planning baselines, and institutional expectations under formal decision rules.

Low FGC indicates that forecasts remain advisory, discretionary, or peripheral, constraining strategic leverage despite technical relevance or systemic dependence.

FGC therefore marks the point at which epistemic relevance becomes governance-relevant influence. This transition often occurs without explicit political control, ownership, or coercive mandate, and constitutes a core mechanism through which AI-mediated prediction reshapes strategic authority under conditions of institutional continuity and rule-based governance.

6.5.5 D2-5 Adversarial Manipulation Surface (AMS)

AMS assesses a node's structural exposure to intentional interference capable of undermining, distorting, or weaponizing its predictive leverage. While preceding D2 indicators measure the degree of forecast dependence on node-linked inputs, AMS evaluates the robustness of that dependence under adversarial, competitive, or coercive conditions.

AMS reflects a core paradox of AI-mediated prediction: as predictive influence increases, so does its value as a target. Predictive leverage that lacks resilience does not merely weaken under pressure; it can be reversed into a source of systemic fragility. AMS therefore functions as a risk-conditioning indicator, constraining the strategic reliability of predictive centrality without redefining the underlying leverage structure.

AMS evaluates vulnerability across four analytically distinct manipulation channels:

- **Data Poisoning Exposure (V_{poison}):** susceptibility of node-linked data streams to intentional corruption during collection, transmission, preprocessing, or labeling that materially affects model calibration, validation, or forecast outputs;
- **Strategic Distortion and Incentive-Driven Bias ($V_{distort}$):** vulnerability to systematic bias arising from political pressure, economic incentives, selective reporting, agenda-driven data curation, or institutional misalignment without requiring overt technical attack;
- **Spoofing and Adversarial Perturbation Feasibility (V_{spoof}):** feasibility of inducing false signals, synthetic anomalies, or adversarial perturbations that mislead predictive models while leaving core data pipelines nominally intact;

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

d) **Governance Capture and Insider Manipulation ($V_{capture}$):** risk that opaque governance arrangements, insider access, or weak oversight enable covert manipulation of predictive inputs, assumptions, model parameters, or dissemination pathways.

Each vulnerability component is normalized to the interval [0,1][0,1], where higher values indicate greater exposure. AMS does not assess whether manipulation has occurred; it evaluates whether manipulation is structurally feasible and strategically consequential if attempted.

A. Core Formula

$$D_{2-5} = \frac{\psi_1 \times V_{poison} + \psi_2 \times V_{distort} + \psi_3 \times V_{spoof} + \psi_4 \times V_{capture}}{\sum_{j=1}^{4} \psi_j} \quad \textbf{(6.5.5.1)}$$

Parameter Definitions

- V_{poison}**:** Data Poisoning Exposure. Degree to which adversaries can inject, alter, or degrade node-linked data streams in ways that affect predictive calibration or outputs.
- $V_{distort}$**:** Strategic distortion and incentive-driven bias exposure. Degree to which predictive outputs are vulnerable to systematic bias driven by incentives, pressure, or selective disclosure rather than adversarial technical attack.
- V_{spoof}**:** Spoofing and adversarial perturbation feasibility. Degree to which false signals or adversarial inputs can be introduced to mislead models without breaching core data pipelines.
- $V_{capture}$**:** Governance capture and insider manipulation feasibility. Degree to which governance weaknesses, insider access, or institutional opacity enable covert manipulation of predictive processes.
- ψ_j: Weight assigned to the j-th manipulation channel. AI-SNI v0.1 baseline: $\psi_j = 0.25$. Equal weighting reflects the absence of a stable cross-domain basis for privileging any single manipulation vector ex ante.

B. Interpretive Notes

AMS is explicitly a risk-conditioning indicator, analytically downstream of predictive leverage construction. It does not negate predictive centrality; rather, it conditions the strategic reliability of that centrality under adversarial, competitive, or coercive conditions.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Higher AMS values indicate greater vulnerability of predictive leverage to hostile exploitation and therefore enter directly into the risk discount term of the D2 aggregation:

$$D2 \propto (1 - \gamma \times \hat{R}) \tag{6.5.5.2}$$

where $\hat{R}$ incorporates AMS as a core component of predictive fragility.

Within Dimension D2, high MCAS, GSS, SG, and FGC scores expand predictive leverage while simultaneously enlarging the potential manipulation surface. AMS evaluates whether such predictive influence remains robust, or instead becomes brittle, when exposed to adversarial pressure.

AMS does not assess whether manipulation has occurred. It evaluates whether manipulation is structurally feasible and strategically consequential if attempted.

C. Structural Implication

By analytically separating predictive leverage (D2-1 to D2-4) from predictive vulnerability (D2-5), AI-SNI preserves a critical distinction: **influence and fragility frequently co-evolve**. AMS prevents high predictive centrality from being misinterpreted as an unqualified strategic advantage.

Instead, it enables risk-aware interpretation of forecast dependency and supports targeted interventions in governance, audit, resilience, and control—particularly in environments where predictive authority shapes high-consequence decisions under conditions of asymmetric information and strategic contestation.

6.6 Methodological Notes: Leverage vs. Risk in D2

Dimension D2 is explicitly designed to **separate predictive leverage from predictive vulnerability**. This distinction reflects a core methodological principle of AI-SNF: **strategic centrality must not be conflated with strategic robustness**.

Within D2, the leverage indicators—Model Calibration Anchor Score (MCAS), Global Spillover Sensitivity (GSS), Substitutability Gap (SG), and Forecast Governance Coupling (FGC)—assess the extent to which a node conditions predictive architectures and shapes anticipatory decision environments. Together, they capture how deeply node-linked forecasts are relied upon, how widely their influence propagates, how costly they are to replace, and how firmly they are embedded within formal governance processes.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

By contrast, the risk indicator, the Adversarial Manipulation Surface (AMS), evaluates the **vulnerability of that leverage** to hostile exploitation, distortion, or capture. In AI-mediated systems, predictive influence is inherently ambivalent: the same features that generate leverage often expand incentives and opportunities for manipulation. AMS ensures that this fragility is made explicit rather than obscured by aggregate influence measures.

In AI-SNI v0.1, this separation is operationalized through two design choices:

- **Risk indicators are retained with lower, but non-zero, weights**, reflecting their conditioning role rather than treating risk as an ex post adjustment or exclusion criterion;
- **Predictive leverage is multiplicatively discounted by risk**, via the $(\mathbf{1} - \boldsymbol{\gamma} \times \widehat{\mathbf{R}})$ term, ensuring that vulnerability attenuates without nullifying measured influence.

As a result, D2 functions as a balanced diagnostic, not a celebratory index. It reveals where predictive centrality exists, where it has become institutionally entrenched, and where it remains fragile or contestable under adversarial conditions. It neither rewards forecast dominance nor collapses leverage and risk into a single undifferentiated score.

This separation is essential for correct interpretation. A high D2 score signals structural influence over anticipation, not forecasting superiority, institutional competence, or strategic success. Conversely, a lower D2 score may reflect either limited predictive leverage or deliberately constrained exposure both analytically meaningful and governance-relevant outcomes.

By preserving leverage and risk as distinct but interacting analytical components, D2 supports risk-aware strategic analysis, enabling targeted governance reinforcement, audit and oversight design, and resilience planning rather than simplistic ranking or performance attribution.

6.7 Why D2 Is the Pivot Between Perception and Action

D2 occupies a structural pivot position within the AI-Strategic Node Framework (D1–D5). It mediates the transformation of perceptual capacity into decision-shaping influence, linking what AI-mediated systems can observe with how futures are framed, authorized, and acted upon.

Positioned downstream of perception (D1), D2 inherits the epistemic constraints established at the sensing layer. Predictive systems cannot exceed what is observable: forecasts remain bounded by data availability, temporal continuity, calibration anchors, and perceptual substitutability. Where perception is incomplete, discontinuous, or readily replaceable, predictive leverage is correspondingly constrained, regardless of model sophistication or computational scale.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

At the same time, D2 operates upstream of execution and governance (D3–D4). Decisions and control mechanisms depend not merely on the existence of forecasts, but on their stability, legitimacy, and routinized use. Predictive outputs structure baselines for action, distribute attention across risks, and define acceptable thresholds for intervention. Absent forecast dependency and institutional embedding, execution advantages and governance responses remain reactive and episodic.

D2 therefore performs a unique mediating function: it converts informational advantage into anticipatory authority. Perceptual centrality yields awareness; predictive leverage transforms awareness into anticipation, coordination, and pre-commitment across distributed decision systems.

Without predictive leverage, perceptual advantages remain analytically informative but institutionally inert. With predictive leverage, the same inputs become embedded expectations, shaping planning cycles, risk tolerances, and operational timing across systems that may never directly interact with the originating node.

Within AI-SNI, D2 is neither an extension of sensing nor a proxy for execution capability. It is the epistemic hinge through which observation becomes foresight and foresight becomes structured action. By explicitly identifying this pivot, AI-SNF avoids conflating superior perception or faster execution with strategic advantage, and instead locates power in forecast dependency and legitimacy as the critical intermediary in AI-mediated systems.

6.8 Strategic Interpretation: Forecasts as Quiet Power

Predictive leverage in AI-mediated systems rarely operates through overt coercion. Instead, it functions through anticipatory conditioning, shaping how futures are imagined, prioritized, and acted upon before explicit political or institutional contestation occurs.

Forecasts exercise influence by structuring the pre-decisional environment in three ways. First, they set agendas by determining which risks, trends, and scenarios receive sustained analytical attention, thereby defining what enters institutional consideration. Second, they frame risk by distributing probabilities, defining tail exposures, and shaping thresholds for precaution and intervention. Third, they normalize expectations over time: repeated projections render certain futures baseline or inevitable, while alternatives are discounted as implausible or marginal.

Nodes with high D2 scores occupy positions where these mechanisms are structurally amplified. They need not issue directives or exercise formal authority. By conditioning expectations, they shape which actions appear necessary, legitimate, or unavoidable—often invisibly and without sustained debate.

6. Dimension D2: Predictive Model Leverage and Dependency (PMLD)

This influence is “quiet” not because it is weak, but because it is institutionally normalized. Once embedded in planning cycles, risk models, budgetary processes, and governance routines, forecasts cease to appear as contestable judgments. Dependency replaces persuasion; expectation substitutes for instruction.

In AI-mediated environments, forecast dependency becomes a primary channel of strategic influence. Behavior increasingly aligns with anticipated futures rather than observed realities, and those who condition anticipation acquire leverage disproportionate to formal authority, territorial control, or material scale.

Dimension D2 captures this shift. It identifies how strategic influence is exercised upstream of action—through control over the models, baselines, and dependencies that define what futures are expected, and how the present is governed.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

Dimension D3 captures the temporal–execution layer linking perception (D1) and prediction (D2) to action. In AI-mediated systems, time functions as executable power: advantage accrues to those who can translate anticipation into action earlier and without interruption. D3 assesses whether a node confers structural temporal leverage within decision loops, enabling earlier activation, sustained execution, and pre-emption of alternatives, independent of decision quality or normative judgment.

7.1 Conceptual Rationale: Decision-Loop Temporal Advantage

In AI-enabled strategic systems, time acts as a multiplier of influence, determining whether perceptual and predictive advantages can be operationalized before competing interpretations or responses emerge.

Temporal leverage amplifies influence through three mechanisms:

- **Compression of reaction windows**: shortened detection-to-decision cycles limit others' ability to reassess signals, mobilize countermeasures, or contest interpretations;
- **Pre-emption of interpretive plurality**: pre-authorized or automated responses render dissenting analysis and political deliberation temporally irrelevant;
- **Executional lock-in**: once actions are initiated, such as rerouting, posturing, hedging, or regulatory activation, path dependence constrains reversal even as new information becomes available.

These effects do not depend on superior force or formal authority. They operate through sequencing rather than coercion.

Accordingly, D3 evaluates whether a node structurally amplifies influence by shortening end-to-end decision cycles, preserving executional continuity under stress, and enabling action before contestation or interruption is feasible.

7.2 From "Speed" to "Decision-Loop Dominance"

Speed alone is insufficient. Strategic relevance depends on where and how time is saved across the decision loop as a whole. Gains in raw processing speed are inconsequential if they occur outside binding junctions, are absorbed by downstream bottlenecks, or fail to translate into earlier execution.

In AI-mediated decision loops, three forms of temporal dominance are decisive:

- **Early-detection anchoring:** control over when the decision clock begins;
- **Latency minimization at binding junctions:** compression of delays at points where information becomes commitment;
- **Continuity under stress:** the ability to sustain timing advantages under disruption or contestation.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

Accordingly, D3 measures decision-loop dominance rather than raw speed: whether a node structurally governs timing at initiation, transition, and execution stages, including under adverse conditions.

7.3 The D3 Causal Mechanism

Dimension D3 operates through the structural compression of decision cycles, transforming latency reduction into executional precedence. The mechanism can be summarized as:

Latency Reduction and Early Detection ↑

↓

Decision-Loop Compression ↑

↓

Reaction-Time Asymmetry ↑

↓

Execution Preemption ↑

↓

Strategic Advantage ↑

This mechanism is characterized by three structural properties:

- **Relationality:** Temporal advantage is inherently relative. It exists only in comparison to other decision loops operating on different time scales. Absolute speed is inconsequential if other actors initiate and execute actions earlier within their own loops.
- **Irreversibility under crisis:** Temporal losses cannot be recovered once execution begins. Unlike material setbacks, lost time compounds immediately and persists throughout the decision cycle, constraining all subsequent options.
- **Coupling with automation:** As decision loops compress, opportunities for human deliberation contract. Automated thresholds, alerts, and execution pathways increasingly dominate, reinforcing early advantages and limiting the scope for interruption or correction.

Accordingly, D3 evaluates whether a node reliably converts early detection and reduced latency into repeatable execution pre-emption, rather than merely achieving isolated speed gains.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

7.4 D3 Core Aggregation Formula

Dimension D3 is constructed as a temporal leverage component conditioned by operational coverage and stress reliability, and explicitly discounted by temporal fragility risk, in line with the aggregation logic applied in Dimensions D1 and D2.

This structure reflects the premise that decision-loop advantage is strategically meaningful only when it is continuously exercisable, institutionally embedded, and resilient under stress. Reductions in nominal latency or peak processing time are insufficient if they cannot be sustained through execution or are vulnerable to disruption.

D3 measures temporal leverage, not decision quality or outcome optimality. A high D3 score indicates that a node systematically compresses decision time across perception–prediction–execution loops, and that this advantage remains persistent, executable, and resistant to induced delay. Temporal speed without continuity or resilience does not constitute strategic advantage under AI-SNF.

A. Core Formula

$$D_3 = \left(\sum_{i=1}^{4} \omega_{3,i} \times \widehat{D_{3,i}} \right) \times C_{coverage} \times C_{reliability} \times (1 - \gamma_3 \times \widehat{R_3})$$

(7.4.1)

Structural Adjustment Coefficients

$$C_{coverage} = \frac{T_{observed}}{T_{total}} \text{ , } C_{reliability} = 1 - \rho_3$$

(7.4.2)

Parameter Definitions:

- D_3: Decision-Loop Temporal Advantage (DLTA). Measures the extent to which a node confers decisive and durable time advantage within automated or semi-automated decision loops linking sensing (D1), prediction (D2), and execution. The aggregation structure ensures that temporal advantage is conditioned by continuous loop participation, resilience under stress, and resistance to disruption, rather than by nominal latency reduction or peak processing speed alone.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

- $\boldsymbol{\omega_{3,i}}$**:** Weight of the *i*-th temporal advantage indicator. AI-SNI v0.1 baseline: **0.25**. Equal weighting is applied to avoid premature privileging of any single source of temporal gain, such as early detection, latency minimization, chokepoint positioning, or continuity under stress, in the absence of stable cross-domain calibration standards.
- $\boldsymbol{\widehat{D_{3,i}}}$**:** Standardized score of the *i*-th D3 sub-indicator. $\widehat{D_{3,i}} \in [\mathbf{0}, \mathbf{1}], i = \{\mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4}\}$. Standardization maps heterogeneous measures of detection lead time, junction latency, decision-loop positioning, and execution continuity onto a common interpretive scale, while preserving relative temporal asymmetry across functionally comparable nodes.
- $\boldsymbol{C_{coverage}}$**:** Decision-Loop Coverage Coefficient. Ensures that temporal advantage is assessed only over periods during which the node is continuously engaged in relevant decision-loop operations, including data ingestion, inference routing, authorization gating, or execution triggering. $C_{coverage} \in [\mathbf{0}, \mathbf{1}]$.
- $\boldsymbol{C_{reliability}}$: Stress-Condition Reliability Coefficient. Adjusts temporal advantage by the probability that decision-loop performance persists under adverse conditions, including cyber disruption, physical degradation, surge demand, or crisis-induced overload. $C_{reliability} \in [\mathbf{0}, \mathbf{1}]$.
- $\boldsymbol{\gamma_3}$: Temporal Risk Penalty Coefficient. Controls the strength with which temporal advantage is discounted by fragility and exploitability. AI-SNI v0.1 adopts a non-zero but sub-dominant penalty to reflect that time dominance is valuable only when it remains executable under stress, without erasing structural advantage due to risk exposure alone. $\gamma_3 \in (\mathbf{0}, \mathbf{1}]$.
- $\boldsymbol{\widehat{R_3}}$**:** Standardized Temporal Fragility / Exploitability Risk. $\widehat{R_3} \in [\mathbf{0}, \mathbf{1}]$. Captures vulnerability of the node's decision-loop advantage to adversarial disruption or induced delay, including:
  - Targeted congestion or saturation attacks,
  - Critical link or interface failure,
  - Automation rollback or forced human re-entry,
  - Cascading latency amplification under stress.
- $\boldsymbol{T_{observed}}$**:** Effective Loop-Participation Time. Cumulative duration within the evaluation window during which the node is actively engaged in decision-loop operations, such as data ingestion, inference routing, authorization gating, or execution triggering, without disqualifying outages or disconnections.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

- T_{total}: Required Observation Horizon. Total duration of the theoretically required operational window for assessing decision-loop performance in the relevant strategic context, such as:
  - Continuous 24/7 coverage,
  - Crisis-season or peak-demand windows,
  - Predefined escalation or alert cycles.
- ρ_3: Estimated Degradation Probability under Stress. Represents the probability that the node's decision-loop contribution experiences critical degradation during:
  - Cyber or electronic disruption,
  - Physical or infrastructural damage,
  - Surge demand, overload, or crisis conditions,

  resulting in latency spikes, pipeline interruption, authorization delays, or execution deferral.

7.5 Indicator Composition: Operationalizing D3 (D3-1 to D3-4)

Dimension D3 is operationalized through four interrelated sub-indicators that jointly characterize structural temporal advantage within AI-mediated decision loops. These indicators do not measure raw processing speed or average latency. Instead, they assess where, when, and how timing advantage is generated, propagated, and sustained within decision architectures.

Specifically, the four indicators assess:

- **Decision-loop initiation advantage**: Whether the node anchors early detection, alerting, or warning functions that determine when a decision cycle begins. Nodes scoring highly on this indicator shape the temporal starting point of downstream inference, authorization, and execution, thereby influencing the entire decision horizon.
- **Latency compression at binding junctions**: Whether the node reduces delays at **critical binding transitions**—points where information becomes commitment, authorization becomes executable action, or coordination becomes irreversible. This indicator targets structurally decisive bottlenecks rather than end-to-end average latency.
- **Pipeline positional criticality**: Whether the node occupies structurally central positions within decision pipelines such that temporal gains or losses at the node propagate across multiple downstream decision paths. This captures whether the node functions as a temporal chokepoint, amplifier, or synchronizing junction in complex, multi-stage architectures.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

- **Continuity and resilience under stress**: Whether the node's temporal advantage persists under disruption, including overload, contestation, degradation, or adversarial interference, rather than collapsing at moments of peak strategic relevance. This indicator distinguishes transient acceleration from durable temporal control.

Together, these indicators reflect the core premise of Dimension D3: temporal power is relational and structural. It arises not from raw speed or computational throughput, but from sustained control over when decisions are initiated, when commitments become binding, and when alternatives become temporally infeasible.

By decomposing temporal advantage into initiation control, junction compression, positional propagation, and stress persistence, D3 captures the mechanisms through which time itself becomes a source of strategic leverage—convertible into action only when it is embedded, continuous, and resilient within AI-mediated systems.

7.5.1 D3-1 End-to-End Latency Advantage (ELA)

ELA measures the relative reduction in total decision-loop latency attributable to a node, compared to functionally comparable alternatives. It assesses whether a node structurally accelerates the transition from signal detection to executable action across the full sensing → inference → authorization → execution pipeline.

ELA does not evaluate isolated processing speed, bandwidth, or local latency in isolation. It captures system-level temporal compression, reflecting only those latency reductions that measurably shorten end-to-end time-to-action within AI-mediated decision systems.

Specifically, ELA captures whether the node:

- **Shortens sensing-to-decision cycles** by reducing upstream data acquisition, preprocessing, transmission, or routing delays;
- **Accelerates inference and alert generation** through architectural proximity, queue prioritization, or privileged integration with model pipelines;
- **Reduces execution delays at binding junctions**, where decisions are converted into commitments or actions and temporal advantage becomes operationally decisive.

High ELA values indicate nodes that compress the decision loop in ways that are cumulative, systemic, and consequential, rather than locally efficient but strategically inert.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

A. Core Formula

$$D_{3-1} = \frac{L_{baseline} - L_{node}}{L_{baseline}} \quad \textbf{(7.5.1.1)}$$

Parameter Definitions

- $L_{baseline}$: Baseline End-to-End Latency. The median or representative end-to-end latency observed across a reference set of functionally comparable nodes, measured from initial sensing to execution trigger under normal operating conditions.
- L_{node}: Node-Specific End-to-End Latency. The observed end-to-end latency for the node being evaluated, measured across the same sensing → inference → actuation pathway and under comparable conditions.

B. Standardization

$$\widehat{D_{3-1}} = min(1, max(0, D_{3-1})) \quad \textbf{(7.5.1.2)}$$

Standardization bounds the indicator within **[0,1]**, ensuring interpretability and cross-context comparability across heterogeneous operational environments.

C. Methodological Notes

ELA measures temporal leverage, not decision quality, policy effectiveness, or outcome desirability. Its analytical focus is whether a node compresses decision time at structurally consequential points within AI-mediated decision loops.

The following interpretive constraints apply:

- **Relative, not absolute:** ELA is inherently comparative. Absolute latency values are analytically meaningless unless evaluated against functionally equivalent alternatives.
- **End-to-end relevance:** Partial acceleration (e.g., faster inference alone) does not constitute temporal advantage unless it reduces total sensing-to-execution duration.
- **Structural propagation:** High ELA scores indicate time savings at positions where compression propagates forward into earlier execution, rather than being absorbed by downstream bottlenecks or procedural delays.

Accordingly, ELA identifies nodes whose temporal compression confers executional preemption—the ability to act earlier within binding institutional and operational decision architectures, not merely in principle.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

7.5.2 D3-2 Early-Detection Window (EDW)

EDW measures the relative lead time by which a node detects, classifies, or confirms a strategically relevant event earlier than functionally comparable systems. It evaluates whether a node initiates the decision loop earlier, thereby shaping the temporal conditions under which interpretation, coordination, and action unfold.

EDW focuses on temporal precedence at detection, not downstream processing speed or execution efficiency. A node may exert significant temporal leverage even with modest execution latency if it determines when an event first becomes legible to AI-mediated systems.

Specifically, EDW captures whether the node:

- Detects or classifies events prior to impact, threshold crossing, or benchmark confirmation;
- Establishes the initial interpretive frame, conditioning how subsequent signals are contextualized, validated, or discounted;
- Pre-empts competing detection narratives, determining which actor or system sets the reference timeline for response.

High EDW values therefore indicate control over when the clock starts, conferring upstream temporal leverage that propagates across the entire decision loop, independent of downstream acceleration or execution capacity.

A. Core Formula

$$D_{3-2} = \frac{\Delta t_{node}}{\Delta t_{max}} \tag{7.5.2.1}$$

Parameter Definitions

- Δt_{node}: Node-Specific Detection Lead Time. The time interval by which the node detects, classifies, or confirms a relevant event before the event's manifestation at a predefined reference point (e.g., impact, threshold crossing, or confirmation by a benchmark system).
- Δt_{max}: Maximum Observed Detection Lead Time. The maximum advance warning time observed among all functionally comparable nodes within the same operational and mission context, used for normalization.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

B. Standardization

$$\widehat{D_{3-2}} = \min(1, \max(0, D_{3-2}))$$

(7.5.2.2)

Standardization bounds EDW within **[0,1]**, enabling comparability across heterogeneous domains, event types, and sensing regimes.

C. Methodological Notes

EDW does not assess prediction accuracy, threat severity, or response effectiveness. It measures temporal initiation power—whether a node starts the decision clock earlier than others.

Key interpretive constraints apply:

- **Initiation, not acceleration:** EDW captures when the decision loop begins, not how fast it proceeds once initiated. Downstream speed advantages are addressed separately by D3-1.
- **Event-relative definition:** Detection lead time must be defined relative to a clearly specified event, threshold, or confirmation benchmark to avoid ambiguity or inflated lead-time claims.
- **Structural amplification:** Even modest EDW advantages can produce disproportionate strategic effects when early detection constrains interpretive plurality, anchors early coordination or alerting, or forces other actors into reactive temporal positions.

Accordingly, EDW identifies nodes that exercise temporal agenda-setting power within AI-mediated decision systems, not by acting faster, but by acting first.

7.5.3 D3-3 Decision Pipeline Criticality (DPC)

DPC assesses the extent to which a node occupies a structurally non-bypassable position within decision-making, authorization, or execution pathways. It evaluates whether operational or policy actions must traverse the node in order to be initiated, approved, or implemented, such that disruption, delay, or degradation at the node generates temporal spillover effects across multiple downstream outcomes.

DPC focuses on topological indispensability within execution architectures, rather than on processing speed, operational capacity, or formal decision authority. A node may exercise limited or no autonomous decision-making power while nonetheless exerting substantial temporal and procedural leverage if it functions as a mandatory junction within execution or authorization workflows.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

Specifically, DPC captures whether the node:

- **Functions as a required gate or relay**, such that decisions, approvals, or execution triggers cannot proceed without passing through the node;
- **Constrains alternative routing**, where bypassing the node would require material system redesign, introduce significant delay, or conflict with governance, safety, regulatory, or compliance constraints;
- **Amplifies temporal effects**, insofar as acceleration, delay, or failure at the node simultaneously affects multiple downstream decision or execution processes.

A. Core Formula

$$D_{3-3} = \frac{N_{mandatory\ paths}}{N_{total\ paths}}$$

(7.5.3.1)

Parameter Definitions

- $N_{mandatory\ paths}$: Mandatory Decision Pathways. The number of distinct decision, authorization, or execution pathways for which the node is a required pass-through, such that bypass is not feasible without significant redesign, degradation, or delay.
- $N_{total\ paths}$s: Total Viable Decision Pathways. The total number of functionally viable pathways through which execution can occur within the relevant decision system, including parallel or redundant routes where applicable.

B. Standardization

$$\widehat{D_{3-3}} = min(1, max(0, D_{3-3}))$$

(7.5.3.2)

The standardization procedure constrains Decision Pathway Centrality (DPC) to the closed interval **[0,1]**, ensuring interpretability, scale consistency, and cross-context comparability across heterogeneous decision architectures and institutional environments.

Bounding DPC within a normalized range facilitates comparative analysis without presuming equivalence in institutional form, governance regime, or sectoral function. Standardization serves an analytical normalization purpose only and does not imply linearity of impact or proportional policy significance.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

C. Methodological Notes

DPC does **not** assess decision authority, policy legitimacy, normative control, or operational effectiveness. It measures **structural control over temporal passage** within decision and execution systems, specifically, whether actions, approvals, or implementation steps must traverse the node in order to occur.

Key interpretive constraints apply:

- **Topology, not throughput:** DPC evaluates positional indispensability within decision pipelines rather than processing speed, bandwidth, or execution capacity. A node may operate slowly or inefficiently while remaining structurally critical if it occupies a non-bypassable position.
- **Non-bypassability criterion:** A pathway is classified as mandatory only where bypass would entail structural costs, including but not limited to systemic delay, coordination failure, loss of institutional alignment, or violation of governance, safety, or compliance constraints. Mere inconvenience or marginal efficiency loss does not satisfy the non-bypassability threshold.
- **Temporal amplification:** Nodes with high DPC amplify temporal effects because acceleration, delay, or disruption at the node propagates simultaneously across multiple downstream decision or execution pathways, translating localized timing changes into system-wide temporal shifts.

Within D3, DPC specifies where time structurally accumulates or dissipates within decision systems.If D3-1 characterizes the rate at which decisions progress, and D3-2 determines when decision processes are initiated, D3-3 (DPC) identifies the points through which decision time must necessarily pass.

7.5.4 D3-4 Resilience Under Stress (RUS)

RUS measures the extent to which a node’s decision-loop functionality remains operative under disruptive, contested, or overloaded conditions. It assesses whether temporal advantage—once established under baseline conditions—continues to translate into executable decision and action capacity when systems are subject to stress.

RUS evaluates temporal survivability, not nominal robustness or peak performance. A node may demonstrate high processing speed, early-warning capability, or central positioning within decision pipelines under normal operating conditions, yet fail to deliver strategic advantage if these functions degrade, fragment, or revert precisely when timing becomes critical.

Accordingly, RUS captures whether the node’s contribution to the decision loop:

- **Persists during disruption**, rather than collapsing into delay, functional fragmentation, or reliance on manual or ad hoc fallback mechanisms;

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

- **Maintains timing relevance**, avoiding stress-induced latency spikes, execution deferrals, or synchronization failures that negate earlier temporal gains;
- **Resists stress-induced regression**, including forced human re-entry into automated processes, emergent authorization bottlenecks, loss of system integration, or breakdowns in automation continuity.

A. Core Formula

$$D_{3-4} = 1 - \sigma_3$$

(7.5.4.1)

Parameter Definitions

- σ_3: Stress-Induced Degradation Probability. $\sigma_3 \in$ **[0,1]**. It denotes stress-induced degradation probability that materially affects loop timing (latency spikes, pipeline interruption, forced manual re-entry, execution deferral).

B. Standardization

$$\widehat{D_{3-4}} = min(1, max(0, D_{3-4}))$$

(7.5.4.2)

The standardization procedure constrains RUS to the interval **[0,1]**, ensuring comparability across heterogeneous nodes, stress profiles, and operational contexts.

Normalization supports cross-node and cross-scenario analysis without assuming equivalence in system architecture, institutional design, or threat environment. Standardization does not imply linearity of impact and does not substitute for scenario-specific interpretation under stress conditions.

C. Methodological Notes

RUS does not measure redundancy capacity, cybersecurity maturity, institutional robustness, or system hardening in isolation. It evaluates whether temporal advantage remains operationally and strategically meaningful under adverse conditions, rather than collapsing precisely when timing is most consequential.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

The following interpretive constraints apply:

- **Durability over peak performance:** RUS prioritizes continuity of decision-loop functionality under stress rather than optimal or average performance under ideal operating conditions. High peak efficiency does not compensate for collapse, regression, or loss of executability during disruption.
- **Decision relevance threshold:** Performance degradation is considered analytically relevant only where it materially affects decision-loop timing, authorization flow, or execution viability. Transient, cosmetic, or non-binding disruptions that do not alter decision outcomes or execution timing are excluded.
- **Crisis-weighted assessment:** Estimation of σ_3 places analytical emphasis on worst-case, surge, or adversarial scenarios, rather than steady-state operation. Average performance metrics are insufficient for assessing temporal power, as strategic relevance is determined under conditions of maximal stress.

Within Dimension D3 (Decision-Loop Temporal Advantage), RUS functions as a temporal survivability filter. If D3-1 captures how much time is saved, D3-2 determines when the clock starts, and D3-3 identifies where time must structurally pass, D3-4 (RUS) evaluates whether those temporal advantages persist when the system is subject to maximal stress.

7.6 Methodological Notes: Relational Measurement of Time Advantage

All indicators within Dimension D3 (Decision-Loop Temporal Advantage) are explicitly relational rather than absolute. Temporal advantage is assessed only in relation to functionally comparable nodes operating within a shared mission profile, decision-loop architecture, and institutional context.

The AI-Strategic Node Framework does not reward raw speed, peak throughput, or isolated latency reduction. Instead, D3 identifies structural temporal asymmetry—that is, systematic differences in when decisions translate into executable action and when alternative options become temporally infeasible within a given system configuration.

Accordingly:

- **Temporal advantage is meaningful only in comparison** to alternative pathways, nodes, or configurations capable of performing equivalent functions within the same operational reference class;
- **Absolute latency values are analytically non-informative** unless situated within a common decision architecture, governance regime, and execution environment;
- **Timing gains that fail to propagate through the decision loop**, or that are neutralized by downstream bottlenecks, coordination constraints, or authorization delays, do not constitute temporal leverage.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

This relational design ensures that Dimension D3 measures time as power rather than time as performance. It captures positional advantage within decision architectures, reflecting asymmetric control over temporal sequencing and executability, rather than engineering efficiency or optimization in isolation.

7.7 Why D3 Converts Knowledge into Action

Within AI-SNF, D3 functions as the conversion layer through which perception and prediction are translated into operational precedence.

- **D1** determines what can be observed, detected, and rendered legible within AI-mediated systems;
- **D2** determines how observations are integrated into anticipatory expectations, forecasts, and dependency structures;
- **D3** determines whether those expectations are translated into action before alternative responses can intervene.

Absent D3, perceptual and predictive advantages remain informational in nature. They may inform awareness, planning, or situational understanding, but they do not constrain the timing or feasibility of action by other actors. Informational advantage alone does not close decision windows.

With D3, the same informational advantages become operationally binding. They trigger execution, allocate resources, and initiate sequences that limit or foreclose alternative courses of action. Decision outcomes shift from being contestable options to realized commitments.

Dimension D3 therefore mediates the transition from knowledge to action. It governs who acts first, who sets the tempo of interaction, and whose decisions crystallize into binding facts rather than remaining subject to negotiation, delay, or revision.

In this sense, D3 does not merely accelerate decision-making. It reorders causal sequences within AI-mediated systems, determining which actors pre-empt and which are structurally positioned to respond.

7.8 Strategic Interpretation: Time as Quiet Dominance

Temporal dominance rarely manifests through explicit command, formal authority, or visible coercion. More commonly, it operates through constrained choice, imposed urgency, and reactive positioning, where responses occur only after execution has already taken place.

In AI-mediated strategic systems, control over time constitutes control over choice. Actors that consistently act earlier do not need to persuade, compel, or formally prohibit alternatives. By acting first, they define the conditions under which others must respond.

7. Dimension D3: Decision-Loop Temporal Advantage (DLTA)

This form of dominance is structurally embedded rather than politically asserted:

- Options disappear before they can be deliberated;
- Urgency is imposed without instruction;
- Alternatives become infeasible not through prohibition, but through lateness.

Once temporal advantage is institutionalized, through early-detection windows, non-bypassable decision junctions, and execution pathways resilient under stress, it becomes self-reinforcing. Subsequent responses align around realized outcomes rather than prospective plans.

Dimension D3 captures this mode of power. It reveals how, in AI-mediated environments, strategic influence is often exercised upstream of conflict, regulation, or negotiation, through control over when action becomes possible at all. In such systems, acting first frequently matters more than acting forcefully.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

Dimension D4 captures the governance–control layer that conditions whether the leverage identified in Dimensions D1–D3 is governable, auditable, and enforceable under stress. It is not a governance ranking, compliance score, or normative assessment of institutional quality. Rather, D4 provides a structural diagnosis of alignment between a node's strategic centrality and the effective authority exercised over it.

D4 evaluates whether control rights, accountability mechanisms, and enforcement capacities are commensurate with the node's role within AI-mediated systems, or whether gaps between infrastructure and governance transform leverage into systemic fragility, enabling manipulation, coercion, or cascading failure under adverse conditions.

8.1 Conceptual Rationale: Why Infrastructure–Governance Asymmetry Defines AI-Era Risk

In the AI era, strategic risk increasingly arises not from the absence of capability, but from misalignment between capability and control. AI-enabled infrastructures exhibit three recurrent structural characteristics:

- **Geographical anchoring**, relying on specific locations, facilities, or physical corridors;
- **Global integration**, operating within transnational perception–prediction–decision chains;
- **Institutional disembedding**, functioning across fragmented, overlapping, or externally constrained governance regimes.

As a result, the strategic value generated by infrastructure nodes propagates far beyond local jurisdiction, while the authority to regulate, audit, intervene, or deny use remains local, partial, or weakly enforceable. This condition is defined as the **Infrastructure–Governance Asymmetry (IGA)**.

IGA exists where **the strategic leverage produced by an infrastructure node systematically exceeds the effective capacity to govern that leverage**. Governance capacity in this context encompasses not only formal legal authority, but also institutional competence, resource availability, enforcement instruments, and the practical ability to impose constraints, particularly under stress.

IGA should not be interpreted as a policy failure or regulatory oversight. It is an emergent structural outcome of three interrelated forces:

a) The globalization of data-dependent and AI-mediated systems;

b) The platformization and privatization of operational control over critical infrastructures;

c) The fragmentation of legal authority across jurisdictions, sectors, and governance levels.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

Together, these dynamics decouple the location of strategic value production from the location of effective governance authority, generating latent fragility that becomes operational under stress, contestation, or manipulation.

D4 treats Infrastructure–Governance Asymmetry as a structural risk condition. It explains why AI-strategic nodes may be simultaneously indispensable and difficult to govern, and why AI-era systemic risk increasingly depends on who lacks control over what matters most—at the moment it matters most.

8.1.1 Terminological Mapping Rule

D4 integrates governance sufficiency signals and governance-related risk vectors under a single interpretive construct, while maintaining a clear distinction between structural risk conditions and their operational measurement.

IGA refers to a structural risk condition describing the degree of misalignment between a node’s dependence within AI-relevant infrastructures and the effective capacity to govern, regulate, and constrain the strategic leverage generated by those infrastructures.

IGAC, as operationalized within Dimension D4, denotes the measurable governance sufficiency and control capacity exercised in response to IGA conditions.

IGAC does not redefine or replace IGA. Rather, it represents the governance-side, sufficiency-oriented metric projection of IGA for the purposes of index construction, comparative diagnostics, and stress-oriented analysis.

This mapping rule preserves conceptual clarity by treating IGA as the underlying structural condition, and IGAC as its analytically constrained measurement interface within the AI-Strategic Node Index.

8.2 From “Governance Quality” to “Leverage–Control Mismatch”

Most governance indices evaluate institutional quality, effectiveness, or performance within a defined formal remit. Such approaches implicitly assume that governance challenges scale proportionally with territory, population, or administrative depth.

AI-Strategic Nodes violate this assumption. Nodes with limited autonomy or jurisdictional reach may nonetheless host infrastructures whose outputs are deeply embedded in global, AI-mediated perception–prediction–decision chains. In these cases, the prevailing condition is not deficient governance, but governance overload: responsibilities, exposure, and strategic consequence exceed feasible control, regardless of institutional competence or integrity.

The analytical focus of Dimension D4 is therefore not governance quality, but leverage–control mismatch. D4 assesses whether the scale, scope, and temporal velocity of strategic effects generated at a node are aligned with:

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

- Legal authority and jurisdictional reach;
- Regulatory competence and enforcement capacity;
- Practical intervention options available under stress, contestation, or crisis conditions.

A well-functioning institution may preside over a structurally ungovernable node if strategic leverage propagates faster, farther, or across more domains than governance mechanisms can reach. Conversely, apparent governance failure is frequently misdiagnosed when the underlying issue is structural misalignment, rather than institutional deficiency.

By reframing governance risk as leverage–control mismatch, Dimension D4 enables diagnosis of AI-era systemic fragility without conflating structural constraints with normative judgments about institutional quality or performance.

8.3 The IGA Causal Mechanism

The causal mechanism underlying Infrastructure–Governance Asymmetry (IGA) is structural rather than episodic. It does not arise from isolated policy failures or contingent governance lapses, but from a progressive decoupling of strategic leverage from effective control as AI-enabled infrastructures become increasingly central to system-wide functioning.

At the system level, the mechanism can be summarized as follows:

AI Infrastructure Centrality ↑

↓

Systemic Dependency ↑

↓

External Stakeholder Leverage ↑

↓

Local Governance Control ↓

↓

Structural Fragility ↑

This sequence reflects a shift in which the operational importance of a node grows faster than the institutional capacity to govern, constrain, or reconfigure its use, particularly under stress.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

Three characteristics define this causal mechanism:

- **Nonlinearity:** Small governance constraints, such as delayed audits, partial oversight gaps, narrowly scoped exemptions, or procedural ambiguities, can generate disproportionate downstream effects when dependency structures are dense, tightly coupled, and time-sensitive. Under such conditions, marginal control deficits may cascade into system-level disruption.
- **Opacity:** Many dependency relationships remain latent under normal operating conditions. Their strategic significance becomes visible only during stress, crisis, or contestation, when governance capacity is tested and previously hidden asymmetries translate into operational leverage for external actors.
- **Irreversibility:** Once AI-enabled infrastructures are deeply embedded within global perception–prediction–decision chains, governance deficits cannot be rapidly corrected. Restoring alignment typically requires costly redesign, renegotiation of control rights, cross-jurisdictional coordination, or institutional restructuring, rather than incremental policy adjustment.

Dimension D4 is designed to detect this condition before failure becomes observable. By identifying leverage–control mismatch at the structural level, D4 enables anticipatory diagnosis of AI-era systemic fragility, rather than retrospective attribution after disruption has already occurred.

8.4 Infrastructure–Governance Asymmetry and Traditional Security Vulnerability

IGA must be clearly distinguished from conventional notions of **security vulnerability**.

Traditional security vulnerabilities are asset-centric. They arise from identifiable weaknesses in physical infrastructure, digital systems, or operational procedures, and are typically addressed through hardening, redundancy, segmentation, or defensive protection. Risk within this paradigm is understood as exposure to damage, disruption, or compromise of discrete assets.

IGA, by contrast, is institution-centric and relational. It does not describe weakness in the infrastructure itself, but a misalignment between systemic leverage and enforceable authority. A node may be highly central, indispensable, or dependency-generating within AI-mediated systems, while remaining subject to fragmented, indirect, or externally constrained governance arrangements.

Risk under IGA does not materialize through technical failure alone. It emerges when stress, contestation, or dependency pressure exposes the limits of governance capacity, revealing gaps between who relies on the node for critical functions; and who can legitimately, effectively, and decisively govern its use, modification, or denial.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

As a result, mitigation strategies for IGA differ fundamentally from traditional security responses. Effective mitigation emphasizes:

- **Governance redesign and authority realignment**, rather than asset fortification alone;
- **Auditability and transparency** of infrastructural control interfaces;
- **Clarification of jurisdictional responsibility** across institutional and legal boundaries;
- **Coordination mechanisms** capable of operating under multi-actor, multi-level dependency conditions, particularly under stress.

IGA therefore reframes vulnerability not as a function of defensive strength, but as a question of governability under dependence. Addressing IGA requires institutional adaptation to structural leverage, rather than merely strengthening the protection of the infrastructure through which that leverage is exercised.

8.5 D4 Core Aggregation Formula

Dimension D4 is constructed to diagnose governance sufficiency relative to infrastructure-enabled strategic leverage, rather than to evaluate governance quality in isolation. It assesses whether legally competent authorities possess effective, enforceable, and auditable control capacity that is commensurate with the systemic leverage generated by an AI-strategic node.

D4 is explicitly designed as a fragility diagnostic, not a governance performance score. Higher values indicate lower governance fragility conditional on leverage, while lower values signal elevated exposure to infrastructure–governance asymmetry, external pressure, or institutional bypass under stress.

Accordingly, D4 does not reward formal rule density, institutional complexity, procedural elaboration, or nominal sovereignty. The presence of laws, agencies, or regulatory instruments is analytically insufficient unless accompanied by demonstrable capacity to exercise control when leverage is most consequential.

A high D4 score indicates that infrastructural centrality is matched by enforceable, auditable, and resilient governance control, enabling authorities to intervene, constrain, or reconfigure use under adverse conditions.

A low D4 score indicates that strategic leverage exceeds effective governability. Under such conditions, dependency, coercion, or crisis dynamics may rapidly convert infrastructural centrality into systemic risk, even in the absence of institutional failure or technical malfunction.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

A. Core Formula

$$D4 = \left(\sum_{i \in L_4} \omega_{4,i} \times \widehat{D_{4,i}}\right) \times C_{coverage} \times C_{evidence} \times (1 - \gamma_4 \times \sum_{j \in R_4} v_{4,j} \times \widehat{R_{4,j}})$$

(8.5.1)

Structural Adjustment Coefficients

$$L_4 = \{D_{4-1}, D_{4-3}, D_{4-4}\}, R_4 = \{D_{4-2}, D_{4-5}\}$$

(8.5.2)

$$C_{coverage} = \frac{T_{observed}}{T_{total}}, C_{evidence} = min(1, \frac{N_{verified}}{N^*})$$

(8.5.3)

Parameter Definitions:

- $D4$: Infrastructure–Governance Asymmetry and Control (IGAC). Measures the structural alignment between AI-enabled infrastructural leverage and the effective capacity of legally competent authorities to regulate, audit, constrain, or refuse its use. Higher values indicate greater governance sufficiency relative to leverage; lower values indicate heightened fragility under dependency or contestation.
- $\omega_{4,i}$: Weight assigned to the *i*-th governance-capacity indicator. AI-SNI v0.1 baseline: $\omega_{4,i} = \frac{1}{3}$ for all $i \in L_4$. Equal weighting reflects the complementary and non-substitutable nature of governance capacity, jurisdictional autonomy, and control-rights clarity.
- $\widehat{D_{4,i}}$: standardized governance-capacity indicator. $\widehat{D_{4,i}} \in [0, 1]$. Standardization maps heterogeneous legal, institutional, and control-capacity metrics onto a common interpretive scale while preserving relative asymmetry across nodes.
- $C_{coverage}$: Governance applicability/continuity coefficient over the required horizon.
- $C_{evidence}$: Verifiability coefficient reflecting documented, auditable governance instruments.
- γ_4: Governance Fragility Penalty Coefficient. Controls the strength with which governance capacity is discounted by external dependency and coercion risks. As D4 functions as a structural fragility diagnostic, AI-SNI v0.1 adopts a higher penalty weight than in D2 or D3. $\gamma_4 = 0.5$.
- $v_{4,j}$: Weight assigned to the *j*-th risk indicator. AI-SNI v0.1 baseline: $v_{4,j} = 0.5$.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

- $\widehat{R_{4,j}}$: Standardized governance-risk indicator. Captures exposure to external leverage, dependency pressure, coercion, or institutional bypass that erodes effective control. $\widehat{R_{4,j}} \in [0, 1]$.
- $T_{observed}$: Duration during which governance authority is active, applicable, and enforceable in practice.
- T_{total}: Theoretically required governance horizon corresponding to the infrastructure's strategic role and systemic integration depth.
- $N_{verified}$: Number of verified governance instruments, including laws and statutory authorities, licenses and permits, binding contracts and ownership arrangements, regulatory actions, and audit records or enforcement precedents.
- N^*: Governance Evidence Saturation Threshold. Normalization parameter indicating the point at which additional documentation no longer materially increases effective governance credibility, reflecting diminishing marginal returns of formal evidence.

8.6 Indicator Composition: Operationalizing D4 (D4-1 to D4-5)

Dimension D4 is operationalized through five structurally differentiated indicators, explicitly separated into governance-capacity components and governance-risk components. This separation is foundational to D4's role as a governance fragility diagnostic, rather than a composite assessment of governance quality or institutional performance.

Specifically:

- **D4-1, D4-3, and D4-4** are treated as governance-capacity indicators. These indicators capture legally and institutionally grounded capacities that offset infrastructure-enabled strategic leverage, including jurisdictional authority, enforceable control rights, and operational auditability. They enter the D4 aggregation as positive contributors, conditional on evidentiary coverage, legal enforceability, and verifiability under stress.
- **D4-2 and D4-5** are treated as governance-risk indicators. These indicators capture structural exposure to external leverage, dependency pressure, coercion, or institutional bypass. They enter the aggregation exclusively as penalty terms, discounting governance sufficiency rather than redefining or substituting for it.

This architecture preserves an explicit leverage–risk structure within Dimension D4. Governance capacity and governance fragility are not averaged, substituted, or implicitly traded off. Capacity establishes the potential for control, while risk conditions whether that potential remains effective and enforceable under stress, contestation, or asymmetric dependency.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

By separating capacity and risk at the indicator level, D4 avoids collapsing governance into a single undifferentiated score. The resulting output reflects governance sufficiency relative to infrastructural leverage, rather than institutional virtue, regulatory density, or formal compliance.

This structure ensures that strong formal authority cannot mask exposure to coercion or dependency, and that elevated infrastructural centrality without enforceable governance capacity is diagnosed as fragility rather than strength.

8.6.1 D4-1 Local Governance Capacity (LGC)

LGC measures the extent to which local institutions possess deployable authority and operational capability to regulate, audit, and constrain the use of AI-relevant infrastructure and systems hosted at a strategic node.

LGC captures governance capacity rather than governance outcomes. It evaluates whether the institutional prerequisites for effective control are present and operationally available—not whether such authority has been exercised successfully, consistently, or normatively well in practice. Accordingly, LGC assesses whether a node is governed under conditions that permit meaningful local intervention when AI-enabled strategic leverage generates systemic risk, cross-boundary spillover, or coercive pressure.

Specifically, LGC evaluates whether one or more of the following governance conditions are structurally present and institutionally grounded:

- **Statutory Authority Anchor:** Local institutions possess clear legal mandates and jurisdictional competence over AI-relevant infrastructure, including data flows, licensing regimes, operational constraints, and conditions of use.
- **Regulatory Competence Base:** Authorities maintain sufficient technical, legal, and analytical expertise to understand AI-enabled systems, assess their downstream implications, and design proportionate regulatory responses.
- **Enforcement and Compliance Capacity:** Institutions have access to binding enforcement instruments, including sanctions, conditional approvals, suspension or revocation powers, and mandatory corrective actions.
- **Audit and Oversight Infrastructure:** Formal mechanisms exist for inspection, audit, verification, incident investigation, and post-event review of AI-relevant systems and governance compliance.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

A. Core Formula

$$D_{4-1} = \frac{\alpha_1 \times G_{legal} + \alpha_2 \times G_{expertise} + \alpha_3 \times G_{enforcement} + \alpha_4 \times G_{audit}}{\sum_{k=1}^{4} \alpha_k}$$

(8.6.1.1)

Parameter Definitions

- G_{legal}: Legal Authority Score. Degree to which local institutions possess explicit statutory mandates, jurisdictional clarity, and legal competence over AI-relevant infrastructure, data governance, and system operations. $G_{legal} \in [0, 1]$.
- $G_{expertise}$: Regulatory Expertise Score. Availability of technical, legal, and analytical expertise required to interpret, regulate, and audit AI-enabled systems. $G_{expertise} \in [0, 1]$.
- $G_{enforcement}$: Enforcement Capacity Score. Ability to impose binding regulatory actions, sanctions, operational restrictions, or compliance mechanisms. $G_{enforcement} \in [0, 1]$.
- G_{audit}: Audit and Oversight Capacity Score. Capability to conduct inspections, audits, compliance reviews, and post-incident investigations of AI-relevant infrastructure and governance practices. $G_{audit} \in [0, 1]$.
- α_k: Component Weights. AI-SNI v0.1 adopts equal weighting ($\alpha_k = 1$) to avoid premature normative judgments regarding the relative importance of legal authority, expertise, enforcement, or audit capacity in the absence of stable cross-jurisdictional benchmarks.

B. Standardization

To ensure cross-node and cross-jurisdictional comparability, LGC is standardized as:

$$\widehat{D_{4-1}} = \frac{D_{4-1} - min(D_{4-1})}{max(D_{4-1}) - min(D_{4-1})}$$

(8.6.1.2)

This standardization rescales LGC to the interval **[0,1]**, enabling comparison across heterogeneous institutional settings without assuming equivalence in legal systems, administrative structures, or governance traditions. Normalization serves a comparative and diagnostic purpose only and does not imply linearity of governance impact or proportional policy effectiveness.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

C. Interpretive Notes

LGC operationalizes governance capacity as the primary leverage-offsetting component within Dimension D4. It does not assess political intent, regulatory effectiveness, compliance outcomes, or normative governance quality.

High LGC indicates that governance authority is institutionally feasible and operationally deployable, reducing infrastructure–governance asymmetry even where strategic leverage is high or stress conditions prevail.

Low LGC indicates that the strategic value generated by the node exceeds local governance capacity, increasing exposure to dependency pressure, external leverage, coercion, or governance breakdown under stress.

LGC therefore distinguishes between nodes that are merely hosted by a jurisdiction and nodes that are meaningfully governable by it. The indicator captures the existence and deployability of control capacity, not its historical use, political willingness, or normative adequacy.

8.6.2 D4-2 External Dependency Ratio (EDR)

EDR measures the extent to which the strategic continuity, operability, and adaptive capacity of an AI-Strategic Node depend on actors outside the effective control of local governance institutions.

EDR captures governance fragility arising from external reliance, rather than institutional inefficiency, regulatory weakness, or governance failure per se. It assesses whether critical functions of AI-relevant infrastructure hosted at a node can be sustained, modified, constrained, or suspended without the consent, cooperation, or intervention of external stakeholders.

EDR evaluates dependency across three structurally distinct channels, each of which can independently constrain local governability:

a) **External Capital Dependency:** Reliance on external ownership structures, financing arrangements, or investment vehicles that condition operational continuity, expansion trajectories, or strategic direction beyond the effective discretion of local authorities.

b) **External Platform and Software Dependency:** Dependence on externally governed platforms, cloud services, proprietary software stacks, model access regimes, or AI toolchains that local authorities cannot fully audit, modify, reconfigure, or suspend under stress.

c) **External Personnel and Operational Dependency:** Reliance on non-local specialists, maintenance teams, operators, or critical knowledge holders whose withdrawal, restriction, or strategic realignment would materially impair system functionality or continuity.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

A. Core Formula

$$D_{4-2} = \frac{\beta_1 \times E_{capital} + \beta_2 \times E_{platform} + \beta_3 \times E_{personnel}}{\sum_{k=1}^{3} \beta_k}$$

(8.6.2.1)

Parameter Definitions

- $E_{capital}$: External Capital Dependency Score. Degree of reliance on external financing, ownership, or investment structures that materially influence infrastructure operation, expansion, or strategic alignment. $E_{capital} \in [0, 1]$.
- $E_{platform}$: External Platform Dependency Score. Dependence on externally governed digital platforms, cloud infrastructure, proprietary software, or AI service providers over which local authorities lack direct control, audit rights, or veto power. $E_{platform} \in [0, 1]$.
- $E_{personnel}$: External Personnel Dependency Score. Reliance on non-local or externally controlled specialists, operators, maintenance providers, or technical experts whose availability is not guaranteed under stress, crisis, or political contestation. $E_{personnel} \in [0, 1]$.
- β_k: Dependency Channel Weights.AI-SNI v0.1 applies equal weighting ($\beta_k = 1$) to reflect the absence of a robust cross-sectoral basis for privileging capital, platform, or personnel dependency ex ante. Equal weighting preserves interpretability while avoiding normative assumptions.

B. Standardization

For comparability across nodes and governance contexts, EDR is standardized as:

$$\widehat{D_{4-2}} = \frac{D_{4-2} - min\,(D_{4-2})}{max(D_{4-2}) - min(D_{4-2})}$$

(8.6.2.2)

This transformation rescales EDR to the interval **[0,1]**, enabling comparison across heterogeneous governance contexts and infrastructural configurations. Standardization supports diagnostic comparability only and does not imply linearity of risk or proportional governance impact.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

C. Interpretive Notes

EDR operationalizes external dependency as the primary risk amplifier within Dimension D4. It does not assess the intentions, alignment, or disposition of external actors. Instead, it measures structural exposure—specifically, whether local governance authorities can act unilaterally and decisively when intervention is required.

High EDR indicates that local authorities face constrained autonomy, delayed response capacity, or effective veto exposure when attempting to regulate, suspend, reconfigure, or deny use of AI-relevant infrastructure.

Low EDR indicates that critical operational, financial, and technical functions are locally anchored or locally governable, reducing infrastructure–governance asymmetry and limiting exposure to external leverage under stress.

EDR therefore complements D4-1 (Local Governance Capacity) by identifying cases in which governance capacity exists in principle but is undermined in practice by dependency structures that shift effective control upstream or outside the local jurisdiction.

As a risk indicator, EDR does not negate strategic value or infrastructural importance. Instead, it conditions the fragility of that value, shaping how rapidly centrality, dependence, or leverage may convert into governance stress under pressure, contestation, or system disruption.

8.6.3 D4-3 Rule-Setting Autonomy (RSA)

RSA measures the extent to which local authorities possess effective agenda-setting power to define binding rules governing the use, access, and compliance conditions of AI-enabled systems hosted at a strategic node.

RSA captures regulatory autonomy rather than operational control. It evaluates whether local institutions can set the rules of the game, even when they do not own, operate, or technically manage the underlying AI infrastructure. Ownership, operation, and technical management are neither necessary nor sufficient for RSA.RSA assesses whether local authorities can establish ex ante constraints that shape how AI systems are accessed, deployed, and integrated into broader decision architectures, thereby conditioning behavior upstream of execution and enforcement.

Specifically, RSA evaluates whether local governance institutions can define and enforce binding rules across the following domains:

- **Data Access and Transfer Authority:** The ability to establish binding rules governing data collection, access, sharing, localization, retention, and cross-border transfer for AI-relevant systems.
- **Model Usage and Constraint Authority:** The authority to specify conditions, limitations, safeguards, or prohibitions on how AI models may be trained, deployed, fine-tuned, or applied within the jurisdiction.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

- **Licensing, Certification, and Compliance Authority:** The capacity to impose licensing requirements, certification regimes, compliance obligations, or operational approvals as prerequisites for AI system use, renewal, or expansion.

A. Core Formula

$$D_{4-3} = \frac{\theta_1 \times R_{data} + \theta_2 \times R_{model} + \theta_3 \times R_{licensing}}{\sum_{k=1}^{3} \theta_k}$$

(8.6.3.1)

Parameter Definitions

- R_{data}: Data Governance Authority Score. Degree of local authority over data access, transfer, sharing, localization, and retention rules relevant to AI system operation. $R_{data} \in [0, 1]$.
- R_{model}: Model Usage Authority Score. Extent to which local institutions can impose binding constraints on AI model deployment, usage conditions, retraining, or functional scope. $R_{model} \in [0, 1]$.
- $R_{licensing}$: Licensing and Compliance Authority Score. Capacity to require licensing, certification, regulatory approval, or ongoing compliance audits as conditions for AI system operation. $R_{licensing} \in [0, 1]$.
- θ_k: Rule-Setting Weights. AI-SNI v0.1 applies equal weighting ($\theta_k = 1$) to reflect the absence of a stable cross-jurisdictional basis for privileging data, model, or licensing authority ex ante.

B. Standardization

For cross-node and cross-regime comparability, RSA is standardized as:

$$\widehat{D_{4-3}} = \frac{D_{4-3} - min(D_{4-3})}{max(D_{4-3}) - min(D_{4-3})}$$

(8.6.3.2)

This normalization rescales RSA to the interval **[0,1]**, enabling comparison across heterogeneous regulatory regimes and governance traditions. Standardization serves a structural diagnostic function and does not imply proportional regulatory effectiveness or policy success.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

C. Interpretive Notes

RSA operationalizes agenda-setting power as a central leverage-offsetting component within Dimension D4. It does not evaluate regulatory effectiveness, enforcement outcomes, or compliance rates. Instead, it assesses whether binding rules can be set at all, prior to deployment and execution.

High RSA indicates that local authorities can shape AI system behavior ex ante, defining permissible uses, constraints, and compliance conditions, thereby reducing infrastructure–governance asymmetry even under conditions of high external dependency.

Low RSA indicates that the operative rules governing AI systems are defined externally, contractually locked in, or de facto determined by platform operators, foreign jurisdictions, or transnational governance arrangements beyond local control.

RSA therefore complements:

- **D4-1 (LGC)** by focusing on rule-making autonomy rather than institutional resources or enforcement instruments;
- **D4-2 (EDR)** by identifying cases in which external dependency erodes agenda-setting authority, even where formal governance capacity exists.

RSA distinguishes nodes that merely host AI-relevant infrastructure from those that can define the normative and operational boundaries within which that infrastructure operates.

8.6.4 D4-4 Control-Rights Clarity (CRC)

CRC measures the extent to which ownership, operational authority, and decision-making rights over AI-relevant infrastructure are clearly defined, contractually specified, and practically auditable.

CRC captures the transparency and enforceability of control arrangements, not the strength, legitimacy, or desirability of any particular actor. It evaluates whether governance authority can be identified, traced, and exercised without ambiguity at moments of stress, dispute, escalation, or intervention.

Within AI-Strategic Nodes, ambiguous or fragmented control rights constitute a primary channel through which Infrastructure–Governance Asymmetry becomes exploitable. Even where Local Governance Capacity (D4-1) and Rule-Setting Autonomy (D4-3) exist, unclear control rights can render those capacities inoperable in practice, leading to contestation, delay, or paralysis when timely action is required.

CRC assesses whether control over AI-relevant infrastructure satisfies the following conditions:

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

- **Legally Defined Ownership Rights:** Clear statutory or contractual specification of ownership over physical infrastructure, data assets, models, and critical system components.
- **Operational Authority Clarity:** Explicit allocation of responsibility for system operation, maintenance, configuration, updates, and day-to-day control, including delegation and subcontracting arrangements.
- **Decision and Veto Rights Transparency:** Unambiguous identification of decision-making authority, escalation pathways, and veto powers under both normal operations and exceptional or emergency conditions.
- **Practical Auditability and Traceability:** The extent to which control arrangements can be verified, audited, and reconstructed through documentation, access logs, contracts, governance records, and institutional procedures.

A. Core Formula

$$D_{4-4} = \frac{\phi_1 \times C_{ownership} + \phi_2 \times C_{operation} + \phi_3 \times C_{decision} + \phi_4 \times C_{auditability}}{\sum_{k=1}^{4} \phi_k}$$

(8.6.4.1)

Parameter Definitions

- $C_{ownership}$: Ownership Rights Clarity Score. Degree to which ownership of infrastructure, data assets, and system components is legally defined and free of ambiguity. $C_{ownership} \in [0, 1]$.
- $C_{operation}$: Operational Authority Clarity Score. Clarity regarding who holds responsibility and authority for operating, maintaining, and configuring AI-relevant systems. $C_{operation} \in [0, 1]$.
- $C_{decision}$: Decision and Veto Rights Clarity Score. Transparency of decision-making authority, escalation procedures, and veto rights, particularly under exceptional or crisis conditions. $C_{decision} \in [0, 1]$.
- $C_{auditability}$: Auditability and Traceability Score. Extent to which control rights can be verified and reconstructed through audits, documentation, logs, contracts, and enforcement records. $C_{auditability} \in [0, 1]$.
- ϕ_k: Control-Rights Weights. AI-SNI v0.1 applies equal weighting ($\phi_k = 1$) to avoid privileging any single dimension of control clarity in the absence of a stable empirical basis for cross-domain prioritization.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

B. Standardization

For cross-node and cross-jurisdictional comparability, CRC is standardized as:

$$\widehat{D_{4-4}} = \frac{D_{4-4} - min(D_{4-4})}{max(D_{4-4}) - min(D_{4-4})} \quad \textbf{(8.6.4.2)}$$

This normalization rescales CRC to the interval **[0,1]**, enabling comparison across heterogeneous legal systems, contractual regimes, and institutional arrangements. Standardization serves a diagnostic and comparative purpose only and does not imply proportional control effectiveness or normative adequacy.

C. Interpretive Notes

operationalizes governance legibility as a critical enabling condition for effective control within Dimension D4. It does not assess whether control arrangements are fair, legitimate, optimal, or normatively desirable. Instead, it evaluates whether control relationships are sufficiently clear to be exercised, audited, and enforced when intervention is required.

High CRC indicates that governance authority can be activated rapidly and credibly, reducing the risk that strategic leverage escapes control through legal ambiguity, contractual opacity, or contested mandates.

Low CRC indicates that control is fragmented, opaque, or contestable, creating opportunities for external actors to exploit uncertainty, induce delay, or obstruct governance intervention under stress.

CRC therefore complements:

a) **D4-1 (LGC)** by ensuring that deployable governance capacity is not nullified by ambiguity in ownership or authority;

b) **D4-3 (RSA)** by determining whether ex ante rule-setting authority can be translated into operational control;

c) **D4-2 (EDR)** by revealing cases in which external dependency is compounded by unclear control boundaries, amplifying governance fragility.

CRC thus distinguishes AI-Strategic Nodes that are formally governed from those that are practically governable, particularly under conditions of stress, contestation, or rapid intervention.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

8.6.5 D4-5 Coercion Exposure Index (CEI)

CEI measures the extent to which external actors possess the capability to alter, constrain, or override local governance outcomes through coercive pressure, rather than through formal legal authority or contractual control.

CEI captures conditional loss of governance autonomy under stress. It evaluates whether governance decisions at an AI-Strategic Node remain locally determined under benign conditions, yet become externally malleable when exposed to political, economic, security, or alliance-related pressure.

Unlike External Dependency Ratio (D4-2), which reflects structural reliance embedded in system design, CEI reflects situational vulnerability—the risk that governance authority is compromised when confronted with asymmetric power, leverage, or coercive incentives, particularly during crisis or escalation.

CEI assesses exposure across three primary coercion channels, each capable of conditioning governance outcomes without formal jurisdiction:

- **Economic and Financial Coercion:** Exposure to trade pressure, financial leverage, sanctions risk, investment withdrawal, supply-chain disruption, or market access threats that can influence or constrain governance decisions.
- **Security and Military Leverage:** Vulnerability to explicit or implicit security pressure, including force posture asymmetries, protection dependencies, basing arrangements, security guarantees, or escalation threats that condition regulatory or intervention autonomy.
- **Diplomatic and Alliance Pressure:** Susceptibility to diplomatic coercion, alliance expectations, reputational costs, conditional political support, or coordinated external signaling that limits independent governance action.

A. Core Formula

$$D_{4-5} = \frac{\psi_1 \times V_{economic} + \psi_2 \times V_{security} + \psi_3 \times V_{diplomatic}}{\sum_{k=1}^{3} \psi_k} \quad \textbf{(8.6.5.1)}$$

Parameter Definitions

- $V_{economic}$: Economic Coercion Vulnerability Score. Degree of exposure to economic, financial, or market-based pressure capable of influencing governance decisions, including trade dependence, investment concentration, or sanction susceptibility. $V_{economic} \in [0, 1]$.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

- $V_{security}$: Security Coercion Vulnerability Score. Exposure to security or military leverage that conditions governance autonomy, including defense dependencies, force asymmetries, basing arrangements, or deterrence imbalances. $V_{security} \in [0, 1]$.
- $V_{diplomatic}$: Diplomatic and Alliance Pressure Vulnerability Score. Susceptibility to diplomatic pressure, alliance conditionality, reputational costs, or political isolation risks that constrain independent governance action. $V_{diplomatic} \in [0, 1]$.
- ψ_k: Coercion Channel Weights. AI-SNI v0.1 adopts equal weighting ($\psi_k = 1$) to avoid privileging economic, security, or diplomatic coercion in the absence of stable, cross-context empirical calibration.

B. Standardization

For cross-node and cross-context comparability, CEI is standardized as:

$$\widehat{D_{4-5}} = \frac{D_{4-5} - min(D_{4-5})}{max(D_{4-5}) - min(D_{4-5})} \quad \textbf{(8.6.5.2)}$$

C. Interpretive Notes

operationalizes coercive exposure as the second major risk amplifier within Dimension D4. It does not presume adversarial intent, nor does it imply that coercion is currently being exercised. Instead, CEI measures latent leverage—the capacity of external actors to reshape governance outcomes if pressure were applied.

High CEI indicates that governance autonomy is fragile under stress, crisis, or strategic contestation, even where legal authority, institutional capacity, and formal governance arrangements exist.

Low CEI indicates that local governance decisions are resilient to external pressure across economic, security, and diplomatic domains, preserving autonomy under adverse conditions.

CEI complements:

- **D4-2 (EDR)** by capturing pressure-based, rather than dependency-based, erosion of governance autonomy;
- **D4-3 (RSA)** by identifying conditions under which ex ante rule-setting authority becomes contingent rather than binding;
- **D4-4 (CRC)** by revealing whether formally clear control arrangements can nonetheless be overridden through coercive leverage.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

As a risk indicator, CEI does not negate strategic value or infrastructural importance. Instead, it conditions the governability of that value, shaping how rapidly strategic centrality may translate into governance stress when the node becomes strategically contested.

8.7 Methodological Notes: Why D4 Is Not a “Negative” Dimension

Dimension D4 is neither a normative nor a moral evaluation of governance quality. It does not assign blame, assess institutional virtue, or rank jurisdictions by regulatory competence, effectiveness, or intent. Instead, D4 captures a structural condition: the extent to which AI-enabled strategic leverage generated by infrastructure may outpace the capacity of existing governance arrangements to control, audit, or constrain it.

Infrastructure–governance asymmetry frequently arises not from institutional failure, but from structural transformations inherent to the AI era. These include globalization of data-dependent systems, platformization of operational control, fragmentation of legal authority across jurisdictions, and cross-border dependency chains. Together, these dynamics expand strategic leverage faster than governance authority can be consolidated, producing governance overload as an emergent property of system scale and integration rather than a reflection of deficient intent, competence, or institutional design.

Accordingly, Dimension D4 is deliberately constructed to preserve the interaction between two analytically distinct components:

- **Governance capacity components**, including Local Governance Capacity (D4-1), Rule-Setting Autonomy (D4-3), and Control-Rights Clarity (D4-4), which represent the potential to exercise authority; and
- **Governance risk components**, including External Dependency Ratio (D4-2) and Coercion Exposure Index (D4-5), which capture structural constraints that erode effective control under conditions of stress, contestation, or asymmetric leverage.

This dual structure prevents a common analytical error: interpreting governance fragility as institutional weakness rather than as leverage-induced overload. By separating capacity from risk, D4 avoids conflating limited governability with poor governance and instead highlights situations in which systemic leverage exceeds what any single jurisdiction, institution, or regulatory regime can reasonably absorb.

D4 therefore functions as a diagnostic of structural tension, not as an evaluation of governance performance. Its purpose is to surface points at which strategic leverage and governability diverge, signaling the potential need for authority realignment, cross-jurisdictional coordination, or governance redesign rather than to assign responsibility, assess compliance, or render normative judgment.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

8.8 Policy Interpretation: From Control to Containment

IGA-aware governance reframes policy objectives away from the pursuit of absolute control toward the containment of leverage propagation. In AI-mediated strategic systems, comprehensive control over infrastructure-enabled leverage is frequently infeasible due to scale effects, cross-border integration, platform dependence, and jurisdictional fragmentation. Governance effectiveness therefore depends not on eliminating infrastructure–governance asymmetry, but on preventing asymmetry from cascading into systemic fragility under stress.

Containment-oriented governance prioritizes the management of how leverage propagates, amplifies, and couples across systems, rather than asserting comprehensive command over every technical or institutional component. Within this framework, effective policy action focuses on three core areas:

- **Auditability of critical interfaces.** Ensuring that leverage-generating infrastructures remain observable, traceable, and inspectable at key junctions where data, models, operational authority, or decision rights cross institutional or jurisdictional boundaries. Auditability functions as a prerequisite for timely intervention and coordinated response.
- **Redundancy and fail-safe design.** Reducing single-point dependencies and limiting tightly coupled failure modes, so that loss, manipulation, or withdrawal of a strategic node does not trigger uncontrolled cascading effects across interconnected systems.
- **Multi-jurisdictional coordination and authority alignment**. Recognizing that effective containment often exceeds the capacity of any single sovereign or institutional actor. Shared oversight arrangements, reciprocal constraints, and cooperative governance mechanisms are required where leverage propagation transcends jurisdictional boundaries.

Under this interpretation, governance success is not measured by the ability to fully command AI-enabled systems, but by the capacity to bound risk, dampen amplification, and preserve intervention options when leverage is contested, disrupted, or deliberately exploited.

IGA-aware policy therefore treats infrastructure–governance asymmetry as a persistent structural condition rather than a temporary anomaly. The objective is resilience through containment: ensuring that asymmetry remains manageable, legible, and reversible, rather than allowing it to harden into catastrophic fragility when systems are stressed, contested, or strategically weaponized.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

8.9 D4 as the Structural Anchor of AI-SNI

Within AI-SNF, D4 functions as the governance-conditioning anchor that constrains how upstream leverage signals (D1–D3) are interpreted and applied. It connects measured technical centrality to questions of governability, diagnosing whether infrastructure-enabled leverage is matched by enforceable control, auditable authority, and credible intervention capacity under stress.

In this architecture, the AI-Strategic Node Index (AI-SNI) provides a bounded composite signal for comparative screening and pattern recognition. Dimension D4 governs interpretive legitimacy, determining whether high-leverage profiles should be understood as stable strategic assets or as fragility-prone concentrations of risk. D4 therefore does not add another dimension of "performance"; it conditions the meaning of performance itself.

Dimension D4 performs three indispensable roles within the framework-constrained interpretation of AI-SNI outputs.

- **False-Positive Correction:** High scores in upstream dimensions—such as algorithmic sensing centrality (D1), predictive leverage (D2), or decision-loop temporal advantage (D3)—may be misinterpreted as indicators of durable strategic strength. Dimension D4 corrects for this risk by testing whether technical centrality is matched by effective, enforceable, and institutionally credible governance authority. Absent this correction, nodes that are highly central but weakly governed may appear artificially stable, obscuring latent fragility that manifests only under stress, coercion, dependency pressure, or systemic disruption. In this role, D4 functions as a structural reality check, preventing technical leverage from being mistaken for governable power.
- **Risk Differentiation:** Dimension D4 enables analytical differentiation between nodes that are high-leverage and governable and those that are high-leverage but structurally fragile. By explicitly separating governance capacity and autonomy (e.g., Local Governance Capacity, Rule-Setting Autonomy, Control-Rights Clarity) from external dependency and coercion exposure (e.g., External Dependency Ratio, Coercion Exposure Index), D4 supports classification along a leverage–fragility spectrum, rather than treating similar composite scores as equivalent strategic conditions. This differentiation is critical for identifying nodes whose systemic importance renders them disproportionate sources of cascading risk, even when technical performance, integration depth, or operational efficiency appears robust. In such cases, governance weakness—rather than technical failure—constitutes the dominant risk vector.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

- **Governance Prioritization:** Dimension D4 reorients analytical and policy attention away from the exploitation of leverage toward governance reinforcement and risk containment. Rather than asking how to maximize advantage derived from AI-strategic nodes, D4 identifies where institutional adaptation, rule-setting clarification, dependency mitigation, audit redesign, or multi-jurisdictional coordination would yield disproportionate gains in systemic resilience. In this sense, D4 reframes strategic stability as a function of governability under pressure, rather than technical superiority, speed, or predictive dominance. It directs intervention toward points where modest governance adjustments can prevent large-scale failure propagation.

Absent Dimension D4, AI-SNI outputs risk being interpreted as technical centrality signals alone—useful for mapping influence, but insufficient for diagnosing fragility, contestability, and governance failure modes. With D4 in place, AI-SNF becomes governance-sensitive: it identifies not only where leverage accumulates in AI-mediated systems, but where that leverage becomes unstable, coercible, or dangerous if left weakly governed.

In this sense, Dimension D4 anchors the entire framework in institutional reality. It establishes the interpretive discipline required for policy-relevant diagnosis and ensures that AI-SNI functions not as a celebration of leverage, but as a tool for identifying where leverage demands governance before it becomes systemic risk.

8.10 Why Infrastructure–Governance Asymmetry Will Define AI-Era Stability

As artificial intelligence increasingly integrates sensing, prediction, and execution across borders, institutions, and platforms, the foundations of strategic stability are undergoing a fundamental transformation. In AI-mediated systems, instability no longer arises primarily from shifts in force posture, territorial control, or aggregate capability. Instead, it increasingly originates from mismatches between where strategic leverage is produced and where effective governance authority can be exercised.

IGA should therefore not be understood as a transitional anomaly associated with early-stage AI deployment. It constitutes a persistent structural condition of the AI era, sustained by several convergent dynamics.

- **Spatial concentration with global reach.** AI-enabled infrastructures concentrate strategic relevance in geographically discrete nodes, such as data centers, sensing hubs, compute chokepoints, and model pipelines, while remaining deeply embedded in global networks. These nodes generate leverage whose systemic effects extend far beyond local jurisdiction, legal mandate, or political accountability, creating points of influence that are globally consequential yet locally governed.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

- **Decoupling of operation and authority.** Critical functions, including perception, forecasting, optimization, and execution, are increasingly embedded in privately operated, platform-mediated, or transnational systems. As a result, operational control, economic incentive, and public governance authority become structurally misaligned, even where formal regulatory frameworks nominally exist.
- **Governance fragmentation by design.** Existing governance institutions remain divided across jurisdictions, mandates, and sectoral silos that were not designed to regulate algorithmically mediated, latency-sensitive, and cross-domain power. The resulting condition is not governance failure in a narrow sense, but systemic overload: strategic leverage accumulates faster than enforceable control can adapt.

Under these conditions, strategic risk accumulates silently. AI-mediated systems may appear efficient, cooperative, and predictable under normal operation, even as latent governance fragility deepens. Apparent stability is often maintained not because risks are absent, but because they remain unexercised, uncontested, or untested.

When stress occurs through geopolitical contestation, economic coercion, technological disruption, or crisis escalation, it is governance asymmetry rather than technical malfunction that becomes decisive. Control breakdown, delayed intervention, or constrained authority determines whether AI-mediated systems absorb shock or amplify it.

Infrastructure–Governance Asymmetry thus defines a new fault line of strategic stability in the AI era. It shapes:

- Where cascading failures are most likely to originate within AI-mediated perception–prediction–decision chains;
- Which nodes become points of coercive leverage, even in the absence of overt technical vulnerability;
- How rapidly local disturbances propagate across global decision systems through dependency, synchronization, and model-coupling effects;
- Whether AI-enabled advantages remain governable under stress or become destabilizing sources of systemic risk.

The central contribution of AI-SNF is to render Infrastructure–Governance Asymmetry conceptually diagnosable and methodologically auditable, rather than treating it as an abstract concern or post hoc explanation. Within this framework, AI-SNI provides a bounded composite signal for comparative screening and pattern recognition under explicit interpretive constraints. It is not a standalone measure of stability, strength, or desirability.

8. Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

By explicitly identifying where strategic leverage outpaces governance alignment, the AI-SNF enables anticipatory diagnosis rather than retrospective attribution. It shifts analytical focus away from asking *who is strongest toward asking where systemic stability is structurally most vulnerable, and why*. In doing so, the framework reframes AI-era stability as a problem of institutional adaptation under persistent asymmetry, rather than one of balance restoration through force, ownership, or centralized control.

Dimension D4 anchors this reframing. It ensures that assessments of AI-mediated strategic geography do not conflate technical or infrastructural centrality with durable stability, and that emerging governance risks are rendered visible before asymmetry hardens into systemic failure.

This diagnostic grounding, in turn, prepares the analytical terrain for Dimension D5, where attention shifts from present-day fragility to long-horizon coupling dynamics, path dependence, and strategic optionality from the question of where AI-enabled leverage is concentrated today to the deeper governance challenge of where such leverage may become irreversibly consolidated tomorrow.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

Dimension D5 captures coupling-based optionality—the capacity of a node to become structurally central to future AI-enabled value chains under auditable and credible feasibility conditions. It does not predict outcomes, trajectories, or winners. Instead, it assesses whether physical resources, data infrastructures, and computational capacity can be progressively integrated, recombined, and scaled as technologies, markets, and governance regimes evolve.

D5 treats optionality as latent strategic power, explicitly distinguishing future potential from realized convertibility. A node may exhibit limited present-day utilization or modest operational output, yet possess structural characteristics that enable disproportionate future relevance once coupling pathways mature. Conversely, highly productive nodes may lack meaningful optionality if further integration, recombination, or scaling is structurally constrained.

9.1 Conceptual Rationale: Why Coupling Potential Matters More Than Current Output

AI-Strategic Nodes are not static assets whose strategic significance can be exhaustively inferred from present-day utilization, throughput, or performance metrics. In AI-mediated systems, relevance increasingly derives not from how intensively a node is exploited today, but from whether it can support future integration across domains, scales, and functions.

As AI systems mature, value creation progressively shifts away from isolated efficiency gains toward cross-domain coupling dynamics, in which multiple foundational elements reinforce one another over time:

- **Physical resources** enable sustained data generation, energy provision, and industrial scaling;
- **Data infrastructures** supply the raw material for learning, optimization, and prediction;
- **Compute platforms** transform both resources and data into automation, coordination, and productivity gains.

Strategic advantage emerges where these elements can be progressively coupled, recombined, and scaled into integrated AI-enabled value chains. Crucially, such coupling rarely occurs instantaneously. It unfolds through incremental integration, infrastructural alignment, regulatory accommodation, and institutional learning.

Nodes that facilitate this process accumulate latent optionality: the capacity to be repurposed, upgraded, or absorbed into emerging AI systems even when current utilization remains modest, fragmented, or peripheral.

D5 is designed to capture this option value rather than realized output. It does not ask how much value a node currently produces, how efficiently it operates, or how fully it is exploited. Instead, it asks whether structural conditions exist for future coupling, and whether those conditions are credible, scalable, and evidentially supported.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

By focusing on coupling potential rather than current performance, D5 shifts analytical attention toward three forward-looking concerns:

- **Future pathway formation**, where early structural alignments shape which AI-enabled value chains become feasible over time;
- **Lock-in risk**, where seemingly underutilized nodes quietly accumulate irreversible strategic significance through gradual coupling and institutional embedding;
- **Constraint recognition**, identifying where technical, spatial, regulatory, or governance barriers foreclose future integration regardless of present capability.

Importantly, this forward-looking orientation does not imply prediction. D5 does not assert which pathway will materialize, which application will dominate, or which actor will prevail. It specifies conditions of possibility, not outcomes.

In doing so, Dimension D5 preserves methodological discipline while enabling early diagnosis of where AI-era strategic power may consolidate—not through immediate output or visible dominance, but through the slow, cumulative accumulation of coupling capacity.

9.2 From “Resource Endowment” to “AI-Coupled Value Chains”

Traditional strategic assessments treat resources, infrastructure, data, and compute as separable domains, typically evaluated through parallel indicators of possession, capacity, or output. This compartmentalized approach is increasingly inadequate in AI-mediated systems. In the AI era, strategic relevance no longer derives from ownership or control over any single component. It emerges from the ability to integrate heterogeneous components into AI-coupled value chains, in which physical processes, data generation, and computational intelligence reinforce one another through continuous feedback.

Within such systems, resources cease to be passive inputs. They become active substrates for data production, sensing, and algorithmic mediation. Infrastructure no longer functions merely as transport, storage, or throughput capacity; it increasingly operates as an optimization surface, shaping how flows are monitored, predicted, and coordinated. Compute, in turn, is no longer a fully abstract or freely relocatable utility, but a proximate enabler of real-time perception, prediction, and control, whose strategic value depends on spatial, regulatory, and operational alignment with physical processes.

Accordingly, a node’s strategic significance under Dimension D5 depends not on the scale of its endowment, but on whether it can credibly support coupling across three transformation pathways:

- **Material-to-Data Conversion Capacity:** The extent to which physical resources, environments, or industrial processes at the node can be rendered into continuous, high-value data streams through sensing, monitoring, optimization, and learning loops, enabling iterative AI-mediated improvement rather than one-off extraction.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- **Logistics and Corridor Algorithmization:** The degree to which transport routes, storage systems, and coordination corridors linked to the node can be integrated into algorithmic optimization pipelines, such that movement, timing, allocation, and buffering become controllable variables within AI-driven planning systems rather than fixed constraints.
- **Proximate Compute Anchoring:** Whether the node can host, attract, or interoperate with computational infrastructure sufficiently close to sites of extraction, processing, or sensing, reducing latency, bandwidth friction, and governance discontinuities while enabling near-real-time AI mediation of physical and logistical processes.

Through this lens, Dimension D5 reframes resources not as standalone holdings, but as interdependent elements within evolving AI-coupled systems. What matters is not whether a node supplies inputs to AI-enabled systems located elsewhere, but whether it can participate in—and potentially anchor—value chains in which data accumulation, computation, and physical operations co-evolve locally.

Nodes that satisfy these coupling conditions accumulate strategic optionality. They can be recombined into emerging AI-enabled production, coordination, or governance architectures as technologies, markets, and institutional regimes evolve. Nodes that lack such coupling capacity may remain economically relevant, yet become structurally peripheral—locked into supplier roles within value chains whose strategic logic, data accumulation, and control architectures are defined elsewhere.

In this sense, Dimension D5 distinguishes resource endowment from coupling potential. The former describes what a node possesses today; the latter determines what it can still become within AI-mediated strategic systems.

9.3 The D5 Causal Mechanism

The causal mechanism underlying Dimension D5 operates through progressive alignment and mutual reinforcement across layers, rather than through the immediate conversion of resources into strategic advantage. D5 therefore models option formation, not output realization. Strategic optionality emerges when physical, informational, and computational components can be incrementally integrated into AI-mediated value chains under credible technical, economic, and governance conditions.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

Conceptually, the coupling mechanism can be represented as a layered progression:

Resource Endowment and Accessibility ↑

↓

AI-Enabled Extraction and Sensing ↑

↓

Data Generation and Optimization ↑

↓

Compute Deployment and Integration ↑

↓

Strategic Optionality ↑

This progression does not imply inevitability, linear advancement, or guaranteed escalation. Each layer conditions—but does not determine—the viability of subsequent coupling. Dimension D5 evaluates whether structural preconditions exist at each stage such that integration remains feasible, scalable, and resilient over time, rather than whether a node has already traversed the full sequence.

A. Key Characteristics of the Mechanism

- **Latency and Deferred Payoff:** The strategic value of coupling typically materializes over extended time horizons. Early-stage investments in infrastructure, sensing capacity, or data generation may yield limited immediate returns while laying the groundwork for downstream consolidation once compute platforms, models, and applications mature. D5 therefore treats time lag not as inefficiency, but as an inherent feature of coupling-driven optionality. Nodes are not penalized for delayed realization if structural alignment remains intact.
- **Path Dependence and Partial Irreversibility:** Early decisions regarding infrastructure standards, data architectures, energy provision, connectivity, and governance interfaces progressively constrain future coupling pathways. As integration trajectories solidify, switching costs increase and alternative configurations become increasingly infeasible. This generates partial irreversibility in strategic positioning: nodes may not become dominant, but they may become difficult to bypass, repurpose, or displace within emerging AI-enabled systems.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- **Contestability and Strategic Attention:** Nodes exhibiting high coupling potential often attract competitive and political attention before dominance is realized. Platform operators, external investors, standard-setting bodies, and regulatory actors seek to shape, capture, or constrain emerging value chains at early stages. Contestation therefore intensifies alongside optionality, amplifying both opportunity and governance pressure. D5 explicitly incorporates this dynamic by distinguishing latent potential from secured control, and by recognizing that optionality itself can become a site of strategic competition.

D5 thus measures future leverage space, not present dominance. It identifies where coupling trajectories remain structurally available, and where they are likely to become constrained, externally captured, or prematurely closed. High D5 values indicate that a node remains open to strategic recombination within AI-mediated systems; low values indicate early lock-in elsewhere, foreclosed integration pathways, or loss of relevance before coupling can mature.

By formalizing this causal mechanism, D5 enables the AI-Strategic Node Framework to assess not only where AI-enabled power resides today, but where it can still consolidate tomorrow—and under what structural conditions that consolidation may become durable, contested, or irreversible.

9.4 D5 Core Aggregation Formula

D5 is constructed to diagnose future-oriented strategic optionality relative to AI-enabled value-chain coupling, rather than to evaluate current performance, utilization, or output in isolation. It assesses whether a node possesses credible, scalable, and auditable conditions under which physical resources, data infrastructures, and computational capacity can be progressively integrated into emerging AI-mediated systems.

D5 is explicitly designed as an optionality diagnostic, not a forecast of growth, dominance, or strategic success. Higher values indicate greater openness of future coupling pathways under feasible technical, economic, and governance conditions, while lower values signal early pathway closure, lock-in elsewhere, or structural constraints that limit future integration regardless of present endowment.

Accordingly, D5 does not reward resource abundance, installed capacity, utilization intensity, or policy ambition in isolation. The presence of natural resources, infrastructure assets, data volumes, or compute facilities is analytically insufficient unless accompanied by demonstrable feasibility of integration, recombination, and scaling within AI-coupled value chains.

A high D5 score indicates that a node retains structural optionality: its resources, infrastructures, and institutional interfaces remain amenable to future recombination, upgrading, and absorption into evolving AI-enabled production, coordination, or governance architectures as technologies and regimes change.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

A low D5 score indicates that future strategic leverage is structurally constrained or foreclosed. Under such conditions, a node may remain economically relevant or operationally active, yet its role within AI-mediated systems is likely to be peripheral, dependent, or externally defined. Latent potential fails to materialize not because of poor performance or policy failure, but because coupling pathways have narrowed, closed, or been captured elsewhere.

A. Core Formula

$$\boldsymbol{D5} = \left(\sum_{i \in L_5} \boldsymbol{\omega_{5,i}} \times \widehat{\boldsymbol{D_{5,i}}}\right) \times \boldsymbol{C_{coverage}} \times \boldsymbol{C_{evidence}} \times \left(\mathbf{1} - \boldsymbol{\gamma_5} \times \sum_{j \in R_5} \boldsymbol{v_{5,j}} \times \widehat{\boldsymbol{R_{5,j}}}\right) \quad \textbf{(9.4.1)}$$

Structural Adjustment Coefficients

$$\boldsymbol{L_5} = \{\boldsymbol{D_{5-1}}, \boldsymbol{D_{5-2}}, \boldsymbol{D_{5-3}}\} \textbf{ and } \boldsymbol{R_5} = \{\boldsymbol{D_{5-4}}, \boldsymbol{D_{5-5}}\} \quad \textbf{(9.4.2)}$$

$$\boldsymbol{C_{coverage}} = \frac{\boldsymbol{T_{observed}}}{\boldsymbol{T_{total}}} \textbf{ and } \boldsymbol{C_{evidence}} = \boldsymbol{min}\left(\mathbf{1}, \frac{\boldsymbol{N_{verified}}}{\boldsymbol{N^*}}\right) \quad \textbf{(9.4.3)}$$

Parameter Definitions:

- $\boldsymbol{D5}$: Resource–Data–Compute Coupling Potential (RDCCP). Measures the extent to which a node enables or constrains the progressive coupling of physical resources, data infrastructures, and compute platforms into integrated AI-driven value chains. D5 captures option value and future strategic optionality, not realized output or present operational dominance.
- $\boldsymbol{\omega_{5,i}}$: Weight of the *i*-th opportunity indicator. AI-SNI v0.1 baseline assigns equal weighting ($\boldsymbol{\omega_{5,i}} = \frac{\mathbf{1}}{\mathbf{3}}$.) to reflect that resource endowment, coupling feasibility, and corridor connectivity are jointly necessary and non-substitutable conditions for forming AI-coupled value chains.
- $\widehat{\boldsymbol{D_{5,i}}}$: Standardized opportunity score of the *i*-th D5 sub-indicator. Standardization maps heterogeneous measures of resource accessibility, data-generation feasibility, and compute integration potential onto a common interpretive scale, preserving relative option space rather than absolute capacity. $\widehat{\boldsymbol{D_{5,i}}} \in [\mathbf{0}, \mathbf{1}]$.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- $C_{coverage}$: Coupling-Relevant Coverage Coefficient. Adjusts for whether data on resources, corridors, compute feasibility, and constraints are observable across the required assessment horizon. $C_{coverage} \in [0, 1]$.
- $C_{evidence}$: Evidence Strength Coefficient. Adjusts for the degree to which claims about coupling potential and constraints are supported by auditable, verifiable evidence, rather than speculative projections. $C_{evidence} \in [0, 1]$.
- γ_5: Risk / Constraint Penalty Coefficient. Controls the degree to which coupling potential is discounted by platform capture, regulatory friction, environmental constraints, or geopolitical contestation. In D5, γ_5 is typically moderate: high coupling potential may exist even under significant constraints, but its convertibility into durable strategic leverage becomes uncertain. $\gamma_5 \in (0, 1]$.
- $v_{5,j}$: Weight of the *j*-th risk or constraint indicator. AI-SNI v0.1 baseline assigns equal weighting ($v_{5,j} = 0.5$) to avoid privileging regulatory or capture-related constraints in the absence of stable cross-domain calibration.
- $\widehat{R_{5,j}}$: Standardized risk / constraint score. Captures exposure to platform capture, regulatory blockage, environmental permitting constraints, or geopolitical interference that may limit the realization of coupling potential. $\widehat{R_{5,j}} \in [0, 1]$.
- $T_{observed}$: Effective Observation Time. Cumulative duration within the evaluation window for which reliable information exists regarding resource accessibility, corridor availability, compute feasibility, and relevant constraint regimes.
- T_{total}: Required Observation Horizon. The theoretically necessary assessment window for evaluating coupling potential, typically aligned with multi-year infrastructure planning, permitting cycles, and investment horizons.
- $N_{verified}$: Verified Evidence Items. Auditable sources supporting coupling assessment, including geological and resource surveys, grid and corridor maps, cable route documentation, compute infrastructure plans, permitting records, environmental impact assessments, and investment disclosures.
- N^*: Evidence Saturation Threshold. Normalization threshold beyond which additional evidence yields diminishing improvements in confidence, reflecting informational saturation.

B. Interpretive Notes

D5 does not predict which AI-enabled value chain will materialize, which application will prevail, or which actor will ultimately capture future value. It diagnoses whether structurally plausible coupling pathways remain available, whether those pathways are supported by verifiable evidence, and how existing technical, spatial, regulatory, or governance constraints condition without automatically negating future optionality.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

In this sense, D5 is forward-looking but non-speculative. It does not measure aspirational potential, strategic intent, policy ambition, or projected outcomes. Instead, it evaluates latent strategic space under constraint—the extent to which future integration, recombination, and scaling remain structurally feasible given present conditions.

Accordingly, high D5 values should be interpreted as indicating openness of future coupling trajectories, not inevitability or advantage. Low D5 values indicate early closure or narrowing of feasible pathways, even where resources, infrastructure, or current relevance remain substantial.

D5 therefore functions as a diagnostic of possibility, not a statement of expectation. It clarifies where future AI-enabled leverage could still consolidate under credible conditions—and where such consolidation has already become structurally unlikely, regardless of ambition or intent.

9.5 Indicator Composition: Operationalizing D5 (D5-1 to D5-5)

D5 is operationalized through three optionality (opportunity) indicators and two constraint indicators, reflecting the analytical distinction between latent coupling space and conditional convertibility. This structure ensures that future-oriented potential is assessed independently from current utilization, while remaining explicitly bounded by realistic technical, regulatory, and strategic constraints.

A. Optionality (Opportunity) Components

The optionality indicators capture whether a node possesses the structural preconditions necessary for future AI-coupled value-chain formation, irrespective of present output, intensity of use, or realized economic contribution.

- **D5-1 Resource Endowment and Accessibility:** Assesses whether physical resources, such as energy, materials, land, environmental conditions, or strategic location, are accessible, scalable, and mobilizable for AI-mediated processes. The indicator evaluates practical availability and integration potential, rather than mere physical presence or nominal ownership.
- **D5-2 Data Generation and Sensing Feasibility:** Evaluates whether extraction activities, logistics flows, environmental conditions, or operational processes associated with the node can be translated into continuous, high-value data streams suitable for learning, optimization, and cross-domain reuse. The focus is on data generativity, not existing datasets or current analytics deployment.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- **D5-3 Integration and Corridor Connectivity:** Measures whether resources, data infrastructures, and compute platforms can be structurally linked through physical corridors, digital networks, energy grids, or platform interfaces. This indicator captures the feasibility of progressive coupling across domains, rather than isolated or one-off AI deployment.

Taken together, D5-1 to D5-3 define the option space of a node: whether plausible AI-coupled value-chain pathways exist in principle under credible structural conditions.

B. Risk / Constraint Components

The constraint indicators condition the realizability, durability, and autonomy of coupling potential by capturing structural forces that may foreclose, appropriate, or destabilize emerging value chains.

- **D5-4 Platform Capture and Technological Lock-In Risk:** Assesses whether coupling pathways are likely to be dominated, enclosed, or foreclosed by external platforms, proprietary standards, or vertically integrated ecosystems that limit local agency, recombination capacity, or strategic choice over time.
- **D5-5 Regulatory, Environmental, and Geopolitical Constraints:** Evaluates whether legal regimes, environmental limits, permitting requirements, geopolitical contestation, or cross-border restrictions materially constrain the feasibility, timing, or scalability of future coupling, regardless of technical potential or resource availability.

These indicators do not negate optionality. Instead, they discount convertibility by conditioning how, when, and under whose control latent coupling potential may be realized under realistic institutional, regulatory, and strategic conditions.

C. Interpretive Discipline

The explicit separation between optionality indicators (D5-1 to D5-3) and constraint indicators (D5-4 to D5-5) preserves analytical clarity and prevents the conflation of latent possibility with realizable leverage.

Interpreted jointly, these components yield three analytically distinct configurations:

- **High optionality with low constraints** indicates an expandable and contestable future leverage space, in which multiple AI-coupled value-chain pathways remain structurally feasible and are not yet foreclosed by institutional, technological, or geopolitical barriers.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- **High optionality with high constraints** indicates latent but fragile or capturable potential. Structural preconditions for future coupling exist, but convertibility is conditioned by platform dominance, regulatory bottlenecks, environmental limits, or geopolitical exposure. In such cases, optionality is real but may be externally appropriated, delayed, or destabilized under stress.
- **Low optionality**, regardless of constraint levels, indicates structurally limited future centrality. Even strong present performance, high utilization, or economic relevance does not translate into meaningful future leverage if coupling pathways are absent or closed.

Accordingly, Dimension D5 distinguishes latent optionality from convertible optionality. It ensures that future-oriented assessment remains auditable, feasibility-bounded, and non-speculative, clarifying where AI-enabled strategic power may still consolidate, and where it is structurally unlikely to do so, irrespective of ambition, intent, or short-term success.

9.5.1 D5-1 Critical Material Endowment (CME)

CME measures whether a node possesses material foundations that are structurally relevant and convertible to future AI-enabled value chains, independent of current extraction intensity, utilization rates, or commercial output. The indicator evaluates accessibility and coupling readiness, rather than present profitability, production scale, or realized industrial capacity.

CME assesses whether a node hosts physical inputs, including energy resources, raw materials, land, environmental conditions, or strategically located physical assets, that can be credibly mobilized and integrated into AI-mediated systems as technological capabilities, regulatory regimes, and governance arrangements evolve.

The analytical focus of CME is material convertibility, not material abundance. It evaluates whether physical endowments can function as data-generating substrates, algorithmically optimizable processes, or compute-supporting infrastructures within emerging AI-coupled value chains.

Accordingly, CME evaluates material endowments along three feasibility dimensions:

- **Accessibility and Mobilizability:** Materials can be accessed, transported, or activated without prohibitive physical, legal, or environmental barriers.
- **Scalability and Persistence:** Endowments can support sustained or expandable AI-mediated use over time, rather than one-off extraction or depletion-bound exploitation.
- **Coupling Readiness:** Physical processes associated with the materials can be instrumented, sensed, optimized, or coordinated through AI systems, enabling integration with data and compute layers.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

A. Core Formula

$$D_{5-1} = \frac{\alpha_1 \times M_{energy} + \alpha_2 \times M_{critical} + \alpha_3 \times M_{sensitive}}{\sum_{k=1}^{3} \alpha_k}$$

(9.5.1.1)

Parameter Definitions

- M_{energy}: Energy Resource Availability and Accessibility. Measures the presence and practical accessibility of energy resources relevant to AI-enabled systems, including power generation potential, grid connectivity, and scalability. $M_{energy} \in [0, 1]$.
- $M_{critical}$: AI-Relevant Critical Material Presence. Captures the existence and accessibility of materials essential to AI hardware, sensing infrastructure, energy storage, or compute systems. $M_{critical} \in [0, 1]$.
- $M_{sensitive}$: Strategic or Environmentally Sensitive Inputs. Measures the presence of materials whose extraction or use is subject to heightened strategic, environmental, or geopolitical constraints that condition future AI-coupled exploitation pathways. $M_{sensitive} \in [0, 1]$.
- α_k: Component Weights. In AI-SNI v0.1, all components are equally weighted ($\alpha_k = 1$) to avoid privileging any single material category in the absence of stable cross-domain valuation standards.

B. Interpretive Notes

CME operationalizes the material substrate of optionality, constituting the first enabling link in the D5 causal chain. It does not measure extraction intensity, export capacity, commercial profitability, or immediate contribution to AI system output.

Instead, CME indicates whether a node hosts material conditions that remain structurally mobilizable as AI-coupled systems expand, specifically, whether physical endowments can be translated into data-generating infrastructures, algorithmically optimizable processes, or compute-supporting foundations over time.

A high CME value signals that future AI-enabled value chains may structurally depend on the node’s material base, even when exploitation is delayed, partial, or constrained by non-material factors. A low CME value indicates that the node’s relevance is unlikely to scale through resource–AI coupling, regardless of downstream investment in data, infrastructure, or compute.

CME therefore distinguishes nodes that merely host resources from those that can anchor future AI-enabled industrial and strategic pathways, clarifying where material endowment constitutes a source of latent strategic optionality rather than present economic output.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

9.5.2 D5-2 AI-Enabled Extraction Feasibility (AEEF)

AEEF measures the extent to which a node's material endowment can be credibly converted into AI-mediated operational processes under prevailing technical, institutional, and governance conditions. It evaluates whether artificial intelligence can be realistically deployed to mediate extraction, processing, monitoring, and oversight activities—not whether such deployment is currently profitable, optimized, or deployed at scale.

AEEF captures the feasibility layer of the Dimension D5 causal mechanism. It bridges the gap between the existence of materially relevant resources (D5-1) and the possibility of their integration into AI-coupled value chains (D5-3). The indicator therefore focuses on operational mediability, rather than material presence or downstream connectivity.

Specifically, AEEF assesses whether extraction- or production-related activities associated with a node can be:

- **Instrumented and sensed** through digital or algorithmic interfaces suitable for AI mediation;
- **Operationally standardized or monitored** such that AI systems can meaningfully support optimization, coordination, or compliance functions;
- **Institutionally and legally deployable**, meaning that regulatory regimes, labor arrangements, safety standards, and governance practices do not structurally preclude AI-mediated operation.

A. Core Formula

$$D_{5-2} = \frac{\beta_1 \times F_{technical} + \beta_2 \times F_{institutional} + \beta_3 \times F_{monitoring}}{\sum_{p=1}^{3} \beta_p} \quad \textbf{(9.5.2.1)}$$

Parameter Definitions

- $F_{technical}$: Technical Deployability of AI Systems. Measures whether AI technologies can be practically deployed in resource discovery, extraction optimization, process control, and maintenance under local conditions (infrastructure, connectivity, data availability). $F_{technical} \in [0, 1]$.
- $F_{institutional}$: Institutional Readiness for AI-Enabled Extraction. Captures the presence of regulatory frameworks, skilled labor, organizational capacity, and governance standards that permit AI systems to be adopted and scaled in extraction activities. $F_{institutional} \in [0, 1]$.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- $\boldsymbol{F_{monitoring}}$: Feasibility of AI-Based Environmental Monitoring and Compliance. Measures whether AI can be used to support environmental monitoring, compliance enforcement, safety assurance, and impact mitigation as part of extraction operations. $\boldsymbol{F_{monitoring} \in [0, 1]}$.
- $\boldsymbol{\beta_p}$: Component Weights. In AI-SNI v0.1, all components are equally weighted ($\boldsymbol{\beta_p = 1}$), reflecting the view that technical capability, institutional readiness, and monitoring capacity are jointly necessary and non-substitutable for AI-enabled extraction feasibility.

B. Interpretive Notes

AEEF operationalizes the feasibility link in the D5 causal chain, bridging material endowment (D5-1) and system-level integration pathways (D5-3). It does not measure extraction output, commercial profitability, cost efficiency, or the sophistication of AI currently deployed in operations.

Instead, AEEF evaluates whether AI-mediated extraction, processing, and oversight are realistically attainable under prevailing technical capabilities, institutional arrangements, and governance constraints.

A high AEEF value indicates that material resources can be progressively incorporated into AI-driven production, optimization, monitoring, or compliance systems as enabling conditions mature. A low AEEF value indicates that, even where resources are present and accessible, structural barriers inhibit AI mediation, limiting downstream coupling regardless of investment or intent.

AEEF therefore clarifies whether material endowment constitutes a practical substrate for AI integration, rather than a purely physical or economic asset.

9.5.3 D5-3 Logistics and Corridor Coupling (LCC)

LCC measures whether a node is structurally embedded in transport, energy, and data corridors that enable the scalable integration of material resources, data flows, and computational capacity into AI-coupled value chains.

LCC captures systemic connectability, not current utilization or operational performance. It evaluates whether the physical and digital pathways required for AI-mediated scaling exist, are interoperable, and can be progressively aligned, rather than whether those pathways are presently saturated, efficient, optimized, or politically controlled.

Specifically, LCC assesses whether a node is positioned within corridor configurations that support:

- **Multimodal physical connectivity**, including transport routes and energy networks capable of sustaining coordinated, data-informed flows;

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- **Digital and data connectivity**, enabling low-friction transmission, synchronization, and integration of operational data across systems;
- **Cross-layer interoperability**, allowing physical logistics, data infrastructures, and compute resources to be jointly optimized rather than managed in isolation.

A. Core Formula

$$D_{5-3} = \frac{\theta_1 \times C_{transport} + \theta_2 \times C_{energy} + \theta_3 \times C_{data}}{\sum_{q=1}^{3} \theta_q}$$

(9.5.3.1)

Parameter Definitions

- $C_{transport}$: Transport Corridor Integration Score. Measures the degree of integration into transport corridors such as ports, rail networks, road systems, or maritime routes that enable scalable material and equipment flows. $C_{transport} \in [0, 1]$.
- C_{energy}: Energy Network Connectivity Score. Captures the node's connectivity to energy grids and distribution networks, including reliability, redundancy, and expansion potential relevant to AI-enabled industrial and compute activities. $C_{energy} \in [0, 1]$.
- C_{data}: Data Backbone Connectivity Score. Measures access to high-capacity digital infrastructure, including fiber networks, data backbones, satellite links, or undersea cables that support continuous data exchange and platform integration. $C_{data} \in [0, 1]$.
- θ_q: Component Weights. In AI-SNI v0.1, all components are equally weighted ($\theta_q = 1$), reflecting the view that transport, energy, and data corridors are jointly necessary for scalable AI-coupled systems. Deficiencies in any single corridor can become binding constraints on overall coupling potential.

B. Interpretive Notes

LCC operationalizes the integration pathway in the D5 causal chain, indicating whether a node can function as a convergence and transmission point through which physical resources, energy supply, and data flows may be synchronized into AI-mediated value chains as scale and complexity increase.

LCC does not measure trade volumes, traffic density, logistics efficiency, or ownership and political control of corridor assets. Instead, it assesses whether structural connectivity exists such that future AI-enabled coupling remains feasible under expansion, relocation of compute capacity, or reconfiguration of value chains.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

A high LCC value indicates that a node can transmit, absorb, and amplify AI-mediated flows across physical and digital domains, supporting long-term strategic optionality and path formation beyond local use. A low LCC value indicates that coupling potential remains geographically, infrastructurally, or topologically constrained, even when material endowment (D5-1) and extraction feasibility (D5-2) are present.

LCC therefore distinguishes nodes that are locally endowed from those that are systemically connectable, marking the boundary between isolated potential and scalable AI-strategic relevance.

9.5.4 D5-4 Platform Capture Risk (PCR)

PCR measures the risk that future coupling-derived value is appropriated, conditioned, or governed externally through dominance over compute platforms, proprietary technical standards, orchestration layers, or ecosystem control points.

PCR does not assess current operational efficiency, technological sophistication, or platform performance. Instead, it evaluates whether the option value generated by resource–data–compute coupling is structurally predisposed to external enclosure, thereby limiting a node's capacity to convert latent optionality into autonomous strategic leverage over time.

The focus of PCR is control asymmetry in future value realization. It assesses whether emerging AI-coupled value chains linked to the node are likely to be:

- **Platform-mediated**, such that critical coordination, optimization, or decision layers are controlled externally;
- **Standards-locked**, where proprietary protocols, interfaces, or model ecosystems constrain recombination and local agency;
- **Ecosystem-dependent**, requiring continued alignment with external actors to maintain functionality, scalability, or access.

A. Core Formula

$$D_{5-4} = \frac{\varphi_1 \times P_{compute} + \varphi_2 \times P_{standards} + \varphi_3 \times P_{orchestration}}{\sum_{r=1}^{3} \varphi_r} \tag{9.5.4.1}$$

Parameter Definitions

- $P_{compute}$: Compute Platform Dependence Score. Measures reliance on externally controlled compute infrastructure for AI training, inference, optimization, or scaling. High values indicate limited local autonomy over compute access, cost, prioritization, or continuity. $P_{compute} \in [0, 1]$.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- $P_{standards}$: Standards Imposition Exposure Score. Captures exposure to externally defined data, model, interoperability, or compliance standards that constrain local control over AI system design and evolution. $P_{standards} \in [0, 1]$.
- $P_{orchestration}$: Orchestration Layer Reliance Score. Measures dependence on external platforms for workflow orchestration, pipeline management, optimization logic, or system coordination that mediates coupling outcomes. $P_{orchestration} \in [0, 1]$.
- φ_r: Component Weights. In AI-SNI v0.1, all components are equally weighted ($\varphi_r = 1$), reflecting the view that compute control, standards dominance, and orchestration capture are complementary pathways through which platform power constrains local strategic optionality.

B. Interpretive Notes

PCR operationalizes platform capture as a constraint on convertibility, not as a judgment on platform integration, technological sophistication, or ecosystem participation. Many AI-coupled systems necessarily rely on global platforms to achieve scale, efficiency, and performance. PCR does not imply that such dependence is undesirable, suboptimal, or avoidable.

Instead, PCR evaluates whether the strategic value created through future coupling pathways remains locally governable, renegotiable, or institutionally anchored, or whether it is structurally predisposed to external appropriation through asymmetric control of critical layers in the AI stack.

A high PCR value indicates that increases in coupling potential are likely to disproportionately accrue to external platform owners, limiting the node's ability to convert latent optionality into autonomous strategic leverage over time. A low PCR value indicates that coupling pathways are more likely to remain locally governable, recombinable, or institutionally embedded, preserving option value under future system evolution.

PCR therefore distinguishes technical feasibility of coupling from strategic ownership of its outcomes. It ensures that Dimension D5 reflects not only what a node could become, but who would ultimately govern, appropriate, or condition the value of that becoming.

9.5.5 D5-5 Environmental and Permit Constraint (EPC)

EPC measures conversion friction—the extent to which regulatory, environmental, and social constraints condition the timing, scale, and feasibility of transforming coupling potential into realized AI-enabled value chains.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

EPC is not a normative evaluation of environmental protection, regulatory rigor, or social safeguards. It does not assess whether constraints are desirable, legitimate, or appropriate. Instead, it diagnoses whether such constraints slow, defer, bound, or sequence the mobilization of resource–data–compute coupling, particularly under conditions of strategic urgency, scale-up pressure, or competitive time horizons.

Specifically, EPC evaluates whether future coupling pathways are subject to:

- **Permitting and approval frictions**, including licensing timelines, procedural complexity, or uncertainty that delay deployment or expansion;
- **Environmental and land-use constraints**, such as ecological limits, sustainability thresholds, or conservation requirements that bound scale or location;
- **Social and political contestation**, including community opposition, labor constraints, or legitimacy challenges that condition feasibility even when technical capacity exists.

A. Core Formula

$$D_{5-5} = \frac{\lambda_1 \times E_{regulatory} + \lambda_2 \times E_{environmental} + \lambda_3 \times E_{social}}{\sum_{s=1}^{3} \lambda_s} \quad \textbf{(9.5.5.1)}$$

Parameter Definitions

- $E_{regulatory}$: Regulatory and Permitting Constraint Score. Measures the complexity, duration, and uncertainty of regulatory approvals and permitting processes affecting AI-relevant infrastructure, resource exploitation, or compute deployment. $E_{regulatory} \in [0, 1]$.
- $E_{environmental}$: Environmental Constraint Score. Captures environmental protection limits, ecological sensitivity, emissions constraints, and compliance burdens that restrict or condition coupling pathways. $E_{environmental} \in [0, 1]$.
- E_{social}: Social License and Contestation Score. Measures the risk of social opposition, community resistance, litigation, or political contestation capable of delaying or constraining coupling projects. $E_{social} \in [0, 1]$.
- λ_s: Component Weights. In AI-SNI v0.1, all components are equally weighted ($\lambda_s = 1$), reflecting the view that regulatory, environmental, and social constraints jointly shape the effective convertibility of coupling potential. .

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

B. Interpretive Notes

EPC operationalizes convertibility constraints, not governance deficiencies. A high EPC score does not imply weak institutions, poor governance, or undesirable policy outcomes. In many cases, it reflects high-standard regulatory regimes, strong environmental protections, and robust societal safeguards that deliberately condition the pace and form of system expansion.

A high EPC value indicates that, even where long-term coupling potential is substantial, its realization is likely to be slower, more costly, procedurally contingent, or politically sensitive. Under such conditions, flexibility is reduced in contexts of strategic competition, crisis mobilization, or rapid technological change, as conversion must proceed through sequential approvals, environmental thresholds, or social negotiation.

A low EPC value indicates that coupling pathways can be mobilized more rapidly and at scale, increasing the node's capacity to translate latent optionality into actionable leverage within compressed time horizons.

EPC therefore distinguishes latent potential from deployable potential. It prevents Dimension D5 from overstating future strategic leverage in contexts where environmental, regulatory, or social constraints materially limit the speed, scale, or certainty of AI-enabled system integration.

In combination with D5-4 Platform Capture Risk (PCR), EPC completes the constraint side of Dimension D5. Together, they capture both external appropriation risk (who captures the value) and internal conversion friction (how fast and how far value can be mobilized). This ensures that Resource–Data–Compute Coupling Potential is interpreted as a conditional, governance-bounded option space, rather than an automatic trajectory toward future dominance.

9.6 Methodological Notes: Opportunity, Risk, and Constraint

D5 is explicitly forward-looking but non-predictive. It is designed to identify structurally plausible option pathways, not to forecast outcomes, rank future winners, or assert inevitability. All inferences associated with D5 are therefore strictly conditioned by three methodological gates that bound interpretive authority and prevent speculative inflation.

- **Coverage sufficiency over the required horizon ($C_{coverage}$):** D5 is evaluated only where information on material endowment, AI-enabled feasibility, corridor connectivity, and binding constraints is observable across the relevant planning and investment horizon. Limited temporal or structural coverage constrains the scope of permissible interpretation. Where longitudinal visibility is partial, fragmented, or discontinuous, D5 outputs must be treated as provisional diagnostics rather than stable indicators of future leverage. Coverage sufficiency therefore functions as a first-order gate on interpretive confidence.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

- **Auditable evidence for feasibility and constraint claims ($C_{evidence}$):** Assertions of coupling potential or limitation must be supported by verifiable, auditable evidence, such as documented infrastructure, regulatory instruments, operational precedents, or institutional arrangements. Narrative plausibility, aspirational planning, or projected intent are analytically insufficient. Evidence strength conditions how far optionality may be inferred. Weak or indirect evidence triggers down-weighting or exclusion, ensuring that D5 reflects demonstrable feasibility under constraint, not conjecture about future alignment.
- **Explicit constraint discounting:** Risks of platform capture (D5-4) and environmental, regulatory, or geopolitical conversion friction (D5-5) are incorporated as penalty terms, rather than averaged or offset against opportunity indicators. This prevents latent potential from being misinterpreted as convertible or mobilizable leverage. Constraint discounting ensures that high optionality scores do not imply ease of realization, autonomy of control, or speed of mobilization. Instead, D5 outputs explicitly encode the conditions under which optionality remains bounded, delayed, or externally conditioned.

Within this structure, opportunity, risk, and constraint are not collapsed into a single scalar signal. They are preserved as analytically distinct yet interacting components, ensuring that D5 functions as a diagnostic of option space, not a claim about realized advantage or projected dominance.

Accordingly:

- A high D5 value indicates that irreversible or path-dependent option pathways may be forming, such that future AI-enabled value chains could increasingly depend on the node under plausible conditions. It does not imply present strategic centrality, operational dominance, or guaranteed future control.
- A low D5 value indicates limited recombinability and constrained future coupling space under current structural conditions. It does not imply strategic irrelevance, underdevelopment, or normative deficiency.

Dimension D5 therefore reframes strategic assessment away from output, dominance, or projection, and toward structural optionality under constraint. It identifies where future leverage may become available, contested, or foreclosed—without asserting which trajectory will ultimately prevail.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

9.7 Strategic Interpretation: Optionality as Power

In AI-mediated systems, strategic power increasingly resides not in realized throughput, installed capacity, or current utilization, but in option space—the structured availability of future integration pathways under conditions of uncertainty. As technological trajectories, governance regimes, and market configurations remain fluid, the ability to remain structurally recombinable becomes a decisive source of influence.

Nodes exhibiting high D5 values derive strategic relevance through three interrelated mechanisms.

- **Future Integration Scenarios:** High-D5 nodes occupy positions where multiple AI-coupled value chains could plausibly converge. Their significance lies not in commitment to any single trajectory, but in the preservation of participation and anchoring capacity across alternative configurations as technologies mature, governance regimes adapt, and market structures reconfigure. Optionality here reflects positional openness, not directional choice.
- **Redundancy and Contingency Potential:** Optionality functions as a systemic buffer. Nodes with strong resource–data–compute coupling potential can be reconfigured, repurposed, or substituted into alternative architectures when primary pathways are disrupted, contested, or rendered infeasible. This contingency value becomes most salient under conditions of stress, crisis, or strategic realignment, where flexibility and recombinability outweigh efficiency along any single path.
- **Long-Term Bargaining Leverage:** Even prior to realization, high-D5 nodes shape anticipatory bargaining dynamics. The credible possibility of future centrality alters negotiation positions vis-à-vis platform operators, investors, states, and regulators, influencing terms of access, governance arrangements, and value distribution over time. In this sense, optionality exerts influence before conversion, by conditioning expectations and strategic behavior.

Crucially, these forms of power are conditional rather than automatic. Platform capture risks, regulatory and environmental frictions, and geopolitical contestation may delay realization, redirect integration trajectories, or externalize returns to actors beyond local governance control. Optionality may therefore persist without converting into autonomous leverage.

D5 captures latent strategic leverage, not guaranteed advantage. It identifies where future power could accumulate, where it is likely to be contested, and where it may be structurally foreclosed without asserting inevitability, desirability, or normative preference.

In this sense, optionality constitutes a form of quiet power. Its influence derives not from immediate action or visible dominance, but from the capacity to shape future choice sets for others by preserving pathways, sustaining contingency, and conditioning strategic expectations in AI-mediated systems.

9. Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

9.8 D5 Within AI-SNI Architecture

Within the AI-Strategic Node Framework (AI-SNF), Dimension D5 extends diagnosis beyond present-day leverage (Dimensions D1–D3) and governability under stress (Dimension D4) toward long-horizon pathway formation. It addresses whether a node retains structurally credible option space for future AI-coupled integration, rather than whether such integration is imminent, optimal, or inevitable.

D5 therefore occupies a distinct analytical role. While upstream dimensions identify where leverage is currently generated, executed, and governed, D5 evaluates whether future integration trajectories remain open under observable feasibility conditions. Its focus is on structural possibility, not temporal forecasting or outcome selection.

Within the AI-Strategic Node Index (AI-SNI), D5 contributes a forward-looking but bounded signal to composite screening and comparative pattern recognition. Its influence is explicitly conditioned by evidentiary sufficiency requirements, coverage constraints over the relevant planning horizon, and the interpretive authority hierarchy specified elsewhere in this document.

As a result, D5 does not introduce predictive authority into AI-SNI. It does not elevate nodes on the basis of anticipated success, future dominance, or speculative growth. Instead, it informs interpretation by identifying where option pathways may be forming, narrowing, or closing, and where future leverage could become contingent, contested, or structurally foreclosed.

In this architecture, D5 completes the temporal scope of AI-SNF. It ensures that AI-SNI outputs reflect not only where leverage resides today and whether it is governable, but also whether the conditions for future consolidation remain structurally available. In doing so, D5 reinforces the framework’s diagnostic character, anchoring long-term strategic assessment in feasibility, evidence, and constraint rather than projection or expectation.

Part IV.
Composite Index Calculation and Risk Classification

10. Conceptual Architecture: From Dimensions to Structural Profiles

AI-SNI is not designed to rank nodes by aggregate strength or performance. Its purpose is to diagnose how strategic leverage, temporal advantage, governance alignment, and future optionality interact within AI-mediated systems. Structural diagnosis and risk classification constitute interpretive layers derived from a single composite index.

Interpretive authority, governance-relevant meaning, and permissible usage of composite scores, tiers, and related outputs are formally specified and constrained by the hierarchy established in Section 12 and Appendix A.

AI-SNI is constructed on the premise that AI-mediated strategic power is layered, relational, and system-dependent, rather than additive, actor-centric, or reducible to capability inventories. To reflect this reality, AI-SNI integrates five analytically distinct yet structurally interdependent dimensions, each corresponding to a necessary layer in the production, transmission, control, and evolution of AI-enabled strategic leverage.

Each dimension captures a specific structural function within AI-mediated systems, ranging from perception and forecasting, through decision execution and governance conditioning, to future coupling and option formation. No single dimension is sufficient to characterize a node’s strategic relevance in isolation. Instead, strategic meaning emerges from the configuration and interaction of dimensions, forming a node-specific structural profile rather than a scalar or ordinal measure of “power.”

This architectural approach enables AI-SNI to move beyond capability listings, throughput metrics, or aggregate rankings. By preserving layer ordering, leverage–fragility asymmetries, and the distinction between realized power and latent optionality, the index provides a framework for diagnosing how and where AI-mediated strategic dependence accumulates—and under what structural conditions such dependence becomes resilient, brittle, contested, or destabilizing.

Section 10 formalizes this architectural logic, establishing the conceptual bridge between dimension-level measurement (Part III) and composite index construction and risk classification (Part IV). In doing so, it anchors AI-SNI as a governance-oriented diagnostic instrument, rather than a ranking mechanism or predictive model of strategic outcomes.

10. Conceptual Architecture: From Dimensions to Structural Profiles

10.1 Dimensional Architecture and Structural Roles

Table 10.1 AI-SNI: Dimensional Architecture and Structural Roles

Dimension	Structural Layer	Core Question
D1 Algorithmic Sensing and Early-Warning Centrality	Perception	What can the system see, and from where?
D2 Predictive Model Leverage and Dependency	Forecast	Which futures are shaped by this node?
D3 Decision-Loop Temporal Advantage	Execution	Who acts first, and without interruption?
D4 Infrastructure–Governance Asymmetry	Control	Who governs what depends on this node?
D5 Resource–Data–Compute Coupling Potential	Evolution	Which futures can this node still become central to?

Table 10.1 summarizes the five-dimensional architecture of AI-SNI and clarifies the distinct structural role each dimension plays within AI-mediated strategic systems. The five dimensions are not interchangeable indicators, nor are they independent contributors to a cumulative measure of strength. Instead, they represent ordered layers within a causal strategic sequence:

Perception → Prediction → Execution → Governance → Evolution

Each layer conditions and constrains those that follow. Upstream dimensions establish the informational, temporal, and operational boundaries within which downstream leverage can arise, while downstream dimensions determine whether upstream advantages can be translated into durable, governable, and evolutionarily significant strategic power.

Accordingly, AI-SNI does not interpret high scores as additive measures of “strength.” Each dimension captures a form of position-specific leverage, whose strategic meaning emerges only through cross-dimensional interaction. In particular, interpretation hinges on the configuration and balance between operational centrality and temporal advantage (Dimensions D1–D3), governance alignment and structural fragility under stress (Dimension D4), and future optionality and long-horizon evolutionary potential (Dimension D5).

Read in this way, Table 10.1 provides the conceptual backbone for the composite index construction and risk classification procedures developed in the remainder of Part IV. It establishes the interpretive discipline required to move from dimension-level measurement to governance-relevant diagnosis, without collapsing layered strategic dynamics into a single scalar or ordinal ranking.

10. Conceptual Architecture: From Dimensions to Structural Profiles

B. Implications for Composite Index Construction

Because AI-mediated strategic power is layered, conditional, and relational rather than additive, the aggregation logic of the AI-Strategic Node Index cannot be reduced to a flat summation of dimension scores. Composite index construction must explicitly preserve the following three structural properties.

- **Layer ordering must be respected**. Upstream dimensions establish the preconditions under which downstream leverage can arise. Weakness in early layers, particularly in perception and prediction (D1–D2), cannot be fully offset or compensated by strength in later layers such as execution, governance, or future optionality (D3–D5). Composite aggregation must therefore reflect causal constraint, not substitutability.
- **Leverage and fragility must remain analytically separable**. High strategic leverage may coexist with elevated governance risk. Dimensions that capture leverage accumulation or expansion potential (D1–D3 and D5) must be interpreted in conjunction with, rather than collapsed into, governance-conditioning diagnostics (D4). Aggregation procedures must avoid producing net-positive signals that obscure infrastructure–governance asymmetry, fragility under stress, or coercive exposure.
- **Optionality must be distinguished from realized power**. D5 captures future-oriented coupling potential and evolutionary option space, not present dominance, operational throughput, or control. Its contribution to the composite index therefore differs categorically from dimensions measuring current centrality or temporal advantage. Aggregation must preserve this distinction to prevent future potential from being misread as current strategic strength.

For these reasons, AI-SNI prioritizes structural profiles and exposure bands over ordinal rankings. Composite scores serve as bounded analytical signals that support classification, stress testing, and governance-relevant interpretation. They are not designed to produce definitive hierarchies, competitive league tables, or claims of aggregate “power.”

Part IV formalizes this logic by specifying aggregation rules, adjustment mechanisms, and risk classification frameworks that preserve interpretability while explicitly resisting false precision, compensatory distortion, and unwarranted certainty.

10.2 Indicator Normalization

To ensure cross-node comparability and dimensional coherence, all second-level indicators in the AI-Strategic Node Index (AI-SNI) are normalized to a unit interval **[0,1]** prior to aggregation. Normalization is performed within each indicator class and across the defined comparison set for the relevant evaluation period.

10. Conceptual Architecture: From Dimensions to Structural Profiles

In AI-SNI framework, normalization is not treated as a purely mechanical preprocessing operation. It is a methodologically substantive step that conditions how indicators may be compared, combined, and interpreted. Indicator normalization serves three core purposes.

- **Scale harmonization:** AI-SNI integrates heterogeneous indicators spanning technical performance, infrastructural centrality, institutional capacity, temporal dynamics, and governance conditions. These indicators originate from fundamentally different measurement domains and units. Normalization maps them onto a common interpretive scale, enabling cross-node and cross-dimensional comparison without privileging any single measurement system.
- **Structural differentiation:** Normalization in AI-SNI is designed to preserve relative positional differences among nodes within a given indicator, not absolute magnitudes. Absolute values are often domain-specific, context-dependent, and not meaningfully comparable across technological, institutional, or geopolitical environments. By emphasizing relative positioning, normalization ensures that indicators reflect structural role and leverage relationships rather than raw size, volume, or intensity.
- **Influence discipline:** Without normalization, indicators with wider numerical ranges, higher variance, or more granular measurement units could exert disproportionate influence over composite scores. Normalization constrains such dominance, ensuring that no single indicator or data source can mechanically override others during aggregation. This preserves interpretive balance across dimensions and prevents composite outcomes from being driven by scale artifacts rather than structural significance.

Accordingly, indicator normalization functions as an interpretive discipline within AI-SNI. It regulates how evidence enters the aggregation process, constrains spurious precision, and ensures that subsequent composite construction reflects positional leverage, fragility, and conditionality, rather than unadjusted measurement artifacts.

Normalization therefore underpins the analytical integrity of AI-SNI. It enables disciplined comparison while preserving the conceptual meaning of each indicator, ensuring that composite signals support structural diagnosis and governance-relevant interpretation rather than numerical illusion or implicit ranking.

10.2.1 Normalization of Positive (Monotonic-Benefit) Indicators

For second-level indicators whose higher raw values correspond to greater structural contribution, capacity, or leverage within AI-mediated systems, AI-SNI applies min–max normalization to rescale observed values onto a bounded unit interval **[0,1]**.

10. Conceptual Architecture: From Dimensions to Structural Profiles

This normalization procedure preserves ordinal differentiation within the relevant comparison set while deliberately discarding absolute magnitude claims that are context-dependent, domain-specific, or analytically non-transferable across nodes. The resulting normalized values reflect relative positional standing, not intrinsic strength, efficiency, or desirability.

Positive (monotonic-benefit) indicators include those that capture enabling capacity, functional availability, or leverage-supporting conditions, such as sensing coverage, decision-loop persistence, governance capacity components, or coupling feasibility, where higher values indicate greater structural contribution under otherwise comparable conditions.

Importantly, normalization does not imply linear substitutability or additive equivalence across indicators or dimensions. It functions solely as a scale-alignment mechanism, ensuring that subsequent aggregation reflects comparative structural position rather than raw unit dominance, data variance artifacts, or domain-specific measurement ranges.

A. Core Formula

$$s_{d,k} = \frac{x_{d,k} - \min(x_{d,k})}{\max(x_{d,k}) - \min(x_{d,k})} \quad \textbf{(10.2.1.1)}$$

Parameter Definition

- $s_{d,k}$: Normalized indicator score, bounded in the interval **[0,1]**, where:
  - $s_{d,k} = 0$ represents the weakest observed structural contribution within the comparison class;
  - $s_{d,k} = 1$ represents the strongest observed structural contribution.
- $x_{d,k}$: Raw observed value of the *k*-th second-level indicator within dimension *d* for a given node.
- $\min(x_{d,k})$: Minimum observed value of indicator *k* across the defined comparison set for the evaluation period.
- $\max(x_{d,k})$: Maximum observed value of indicator *k* across the defined comparison set for the evaluation period.

10. Conceptual Architecture: From Dimensions to Structural Profiles

B. Methodological Notes

Min–max normalization preserves relative ordering and proportional distance among nodes for each indicator, ensuring that normalized values retain interpretive meaning tied to structural position within a comparison set, rather than to absolute magnitude, unit scale, or domain-specific measurement conventions.

Within AI-SNI framework, positive (monotonic-benefit) indicators are those for which higher observed values correspond to stronger enabling conditions, leverage-supporting capacity, or feasibility of strategic function under otherwise comparable contexts. These include, but are not limited to:

- Algorithmic sensing coverage, density, and uniqueness indicators (D1), reflecting the breadth and non-substitutability of perception capacity;
- Calibration centrality, anticipatory integration, and forecast spillover indicators (D2), capturing positional influence within predictive architectures;
- Latency reduction, early-detection persistence, and decision-loop execution advantages (D3), measuring temporal precedence rather than raw speed;
- Governance capacity components and control-rights clarity indicators (D4), reflecting the feasibility of enforceable authority rather than governance quality;
- Resource endowment accessibility, AI-enabled coupling feasibility, and corridor connectivity indicators (D5), diagnosing future optionality rather than realized output.

The use of min–max normalization in AI-SNI v0.1 reflects a deliberate methodological preference for transparency, auditability, and cross-domain interpretability. This approach enables consistent comparison across heterogeneous indicator classes while minimizing distortion introduced by unit variance, domain scale, or measurement conventions.

Any deviation from min–max normalization, such as percentile-based scaling, rank transformation, or distributional normalization, must be explicitly justified, formally documented, and applied consistently across the affected indicator class. Such deviations do not constitute neutral technical substitutions; they alter the interpretive properties of normalized values and therefore require explicit methodological disclosure.

10.2.2 Normalization of Risk or Inverse Indicators

For second-level indicators where lower raw values correspond to lower structural risk, higher resilience, or stronger governance alignment, AI-SNI applies an inverse min–max normalization. This procedure preserves directional coherence across the index by ensuring that higher normalized scores consistently represent structurally preferable conditions, regardless of whether the underlying indicator is benefit-oriented or risk-oriented.

10. Conceptual Architecture: From Dimensions to Structural Profiles

A. Core Formula

$$s_{d,k} = 1 - \frac{x_{d,k} - min(x_{d,k})}{max(x_{d,k}) - min(x_{d,k})} \quad \textbf{(10.2.2)}$$

Parameter Definition

- $s_{d,k}$: Directionally aligned normalized score, bounded in the interval **[0,1]**, where:
  - $s_{d,k} = 0$ denotes the **lowest observed risk or strongest structural alignment**;
  - $s_{d,k} = 1$ denotes the **highest observed risk or weakest structural alignment**.
- $x_{d,k}$: Raw observed value of the *k*-th second-level **risk or inverse indicator** within dimension *d* for a given node.
- $\mathbf{min}(x_{d,k})$: Minimum observed value of indicator *k* across the defined comparison set for the evaluation period.
- $\mathbf{max}(x_{d,k})$: Maximum observed value of indicator *k* across the defined comparison set for the evaluation period.

B. Methodological Notes

The use of a common normalized score symbol, $s_{d,k}$, across Sections 10.2.1 and 10.2.2 is deliberate and reflects a core methodological convention of AI-SNI framework.AI-SNI enforces strict directional consistency, under which all normalized indicator scores are aligned such that higher values uniformly correspond to more favorable structural conditions, irrespective of the substantive nature of the underlying indicator.

Accordingly:

- In Section 10.2.1, higher raw values map to higher $s_{d,k}$ for monotonic-benefit indicators, where greater magnitude represents stronger structural contribution or capacity;
- In the present section, lower raw values map to higher $s_{d,k}$ through directional inversion for risk or inverse indicators, where lower magnitude reflects reduced exposure, lower fragility, or stronger alignment.

This design choice ensures interpretive clarity and mathematical coherence during **dimension-level aggregation, risk-penalty application, and structural profile construction**, while preserving the analytical distinction between leverage and risk at the indicator-definition level.

10. Conceptual Architecture: From Dimensions to Structural Profiles

This convention serves three core methodological functions:

- **Interpretive coherence**, ensuring that composite and dimension-level scores remain directionally legible and resistant to misinterpretation, particularly in analytical contexts where indicators of strategic leverage and structural risk coexist within the same evaluative architecture;
- **Aggregation integrity**, enabling mathematically consistent aggregation, penalty application, and sensitivity analysis without introducing sign ambiguity, offsetting artifacts, or compensatory distortion across heterogeneous indicator classes;
- **Analytical separation**, preserving the conceptual distinction between leverage-generating indicators and fragility-conditioning indicators at the level of indicator definition and interpretation, rather than collapsing that distinction during normalization or aggregation.

Directional alignment therefore harmonizes score orientation, not indicator semantics.

Risk indicators remain analytically distinct within AI-SNI framework and retain their role as conditional diagnostics of governability and fragility, rather than as contributors to additive measures of “strength” or performance.

Normalization aligns interpretive direction for aggregation purposes while preserving the underlying structural logic through which leverage and fragility are jointly assessed but not conflated.

10.2.3 Methodological Notes on Normalization Choice

In AI-SNI v0.1, min–max normalization is adopted as the baseline normalization approach. This choice reflects its widespread use in composite indicators developed for policy analysis and governance benchmarking, as well as its transparency, intuitive interpretability, and suitability for cross-sectional comparison across heterogeneous indicators and node types.

Min–max normalization rescales indicator values relative to the observed minimum and maximum within a defined comparison set. As such, normalized values represent relative positional standing within an explicitly defined reference universe, rather than absolute or scale-invariant magnitudes. This property is inherent to the method and is explicitly acknowledged within AI-SNI methodological design.

Within AI-SNI framework, reference-set dependence is treated as a managed methodological condition, not a deficiency. AI-SNI is designed for governance-oriented structural diagnostics under conditions of uncertainty, where analytical clarity, traceability, and interpretive discipline take precedence over claims of universal comparability. In this context, relative positioning within a clearly specified analytical scope is both sufficient and appropriate for identifying structural exposure patterns, leverage concentration, and systemic asymmetries.

10. Conceptual Architecture: From Dimensions to Structural Profiles

To ensure analytical consistency and auditability, AI-SNI applies the following normalization discipline requirements:

- **Explicit scope declaration:** The comparison set (node universe), indicator coverage, and evaluation window used for normalization must be explicitly defined for each benchmarking exercise.
- **Scope consistency for comparability:** Cross-node comparisons are valid only when normalization is performed against the same declared reference set under consistent rules. Results derived from different reference sets constitute distinct analytical frames and must not be directly compared or aggregated.
- **Versioning and auditability:** Any modification to the comparison set definition, sampling rules, indicator inclusion, or evaluation window must be formally documented and versioned, with implications for interpretability clearly disclosed.

AI-SNI further recognizes that alternative normalization strategies may be analytically preferable under specific conditions, including but not limited to:

- **Percentile-based normalization**, where robustness to heavy-tailed distributions or extreme outliers is required;
- **Z-score normalization with sigmoid transformation** (e.g., sigmoid functions), particularly in longitudinal analyses where temporal comparability and distributional stability are prioritized.

Any deviation from the baseline min–max normalization must satisfy all of the following conditions:

- Explicit documentation of the method, its mathematical formulation, and rationale.
- Internal consistency across all nodes and indicators within scope.
- Clear disclosure of implications for aggregation behavior, cross-dimensional interaction, and interpretive boundaries.

Normalization within AI-SNI is therefore not treated as a purely technical preprocessing step, but as a governance-relevant methodological choice. When implemented with explicit scope control, documentation, and version discipline, normalization supports structured comparison while guarding against false precision. This ensures that AI-SNI functions as a diagnostic framework for structural analysis, rather than as a mechanical ranking or performance scoring instrument.

10.3 Dimensional Directionality

AI-SNI explicitly specifies dimensional directionality rather than implicitly assuming that all dimensions contribute positively and symmetrically to a single composite score. This methodological choice reflects a core analytical premise of the framework: strategic leverage and strategic stability are analytically distinct and may diverge in practice.

10. Conceptual Architecture: From Dimensions to Structural Profiles

Accordingly, dimensions within AI-SNI are classified based on their structural function within AI-mediated systems, rather than solely on their numerical contribution to aggregation outcomes. This distinction ensures that composite construction and interpretation remain aligned with the underlying governance logic of the framework.

10.3.1 Leverage-Accruing Dimensions (Positive Contribution)

Several AI-SNI dimensions are designated as leverage-accruing dimensions, reflecting their role in generating strategic centrality, operational advantage, or future optionality within AI-enabled architectures.

For these dimensions, higher scores indicate greater structural relevance within AI-mediated systems. In composite construction, they contribute positively to the identification of nodes exhibiting elevated strategic significance, subject to the application of governance, confidence, and risk-adjustment mechanisms specified elsewhere in the framework.

These dimensions capture where and how strategic influence is produced, rather than whether such influence is effectively governed or contained.

10.3.2 Fragility / Control-Mismatch Dimension (Asymmetric Treatment)

By contrast, D4 – Infrastructure–Governance Asymmetry (IGA) is treated as a structurally asymmetric dimension within AI-SNI framework.

A higher D4 score does not represent an increase in strategic value or advantage. Instead, it signals heightened exposure to structural fragility, arising from misalignment between AI-enabled leverage and the capacity for effective governance, oversight, or control.

Consistent with this interpretation:

- D4 is not inverted into a proxy measure of governance quality or stability;
- D4 is not aggregated additively with leverage-accruing dimensions;
- D4 operates as a risk-modulating and interpretive constraint, shaping how high scores in leverage-oriented dimensions (e.g., D1–D3 or D5) are analytically interpreted.

This asymmetric treatment preserves a clear analytical separation between leverage generation (the production of influence and capability) and leverage governability (the ability to regulate, audit, and contain such influence). It prevents high leverage under weak governance conditions from being misinterpreted as stable or desirable strategic positioning.

10. Conceptual Architecture: From Dimensions to Structural Profiles

10.3.3 Methodological Implications

Treating D4 as directionally distinct addresses a well-documented limitation of composite indicators: the potential for structural risk to be obscured by high technical or operational centrality when all dimensions are aggregated symmetrically and interpreted as value-positive.

Under uniformly additive aggregation, nodes exhibiting substantial AI-enabled leverage but limited governance alignment may be systematically mischaracterized as stable or advantageous strategic assets. Such representations fail to differentiate between the magnitude of influence and the capacity to govern or contain that influence, thereby reducing the diagnostic value of composite outputs.

By enforcing explicit dimensional directionality, AI-SNI ensures that:

- **Strategic relevance is analytically distinguished from strategic robustness**, rather than implicitly equated;
- **High technical or operational centrality cannot mechanically compensate for governance misalignment** within composite interpretation;
- **Composite scores preserve diagnostic integrity**, supporting structured assessment rather than converging toward synthetic performance or “power” rankings.

Dimensional directionality is therefore not treated as a modeling refinement, but as a substantive methodological safeguard. It underpins AI-SNI’s ability to support governance-sensitive structural diagnosis, ensuring that leverage concentration, fragility, and control capacity remain analytically separable. This design choice reinforces the framework’s function as a strategic diagnostic instrument for policy analysis, rather than as a capability inventory or comparative ranking index.

10.4 Dimensional Aggregation

Within AI-SNI framework, each dimensional score D_d is derived through intra-dimensional aggregation of its normalized second-level indicators. This aggregation step consolidates multiple indicator signals into a single, internally coherent dimensional measure, reflecting the structural function captured by that dimension.

Dimensional aggregation is conducted prior to any cross-dimensional aggregation, risk classification, or interpretive assessment. Its purpose is to ensure that each dimension constitutes a stable and analytically meaningful signal, grounded in internally consistent measurement, before being combined with other dimensions or subjected to higher-order interpretation.

By separating intra-dimensional aggregation from cross-dimensional synthesis, AI-SNI preserves analytical clarity between measurement construction and structural interpretation, reducing the risk of premature value attribution or unintended interaction effects across dimensions.

10. Conceptual Architecture: From Dimensions to Structural Profiles

A. Core Formula

$$D_d = \sum_{k=1}^{K} (\omega_{d,k} \times s_{d,k}), \qquad \sum_{k=1}^{K} \omega_{d,k} = 1 \tag{10.4}$$

Parameter Definitions

- K: Number of second-level indicators constituting dimension d.
- D_d: Composite score of dimension d, representing the aggregated structural signal of that dimension after normalization and weighting.
- $\omega_{d,k}$: Weight assigned to indicator k within dimension d, reflecting its relative causal importance in the internal logic of that dimension.
- $s_{d,k}$: Normalized score of the k-th second-level indicator within dimension d, where $s_{d,k} \in [0, 1]$.

B. Weighting Principles

In AI-SNI v0.1, indicator weights within each dimension are fixed and specified ex ante. Weighting decisions are therefore established prior to aggregation and are not adjusted in response to observed outcomes or benchmarking results.

This approach serves three methodological objectives:

- **Cross-node comparability:** Fixing weights prevents post hoc calibration or case-specific adjustment that could compromise the consistency of comparisons across nodes, regions, or analytical exercises.
- **Causal coherence within dimensions:** Weights are intended to reflect theoretical judgments regarding the relative contribution of indicators within a given dimension, rather than empirical outcome optimization, variance maximization, or data-driven fitting.
- **Auditability and reproducibility:** Ex ante fixed weights enable independent replication and methodological review, without reliance on proprietary calibration procedures or opaque optimization routines.

Unless explicitly stated otherwise, equal weighting is applied in AI-SNI v0.1 in cases where robust empirical evidence, cross-domain consensus, or defensible theoretical justification for differential weighting is unavailable. This default treatment is adopted as a transparency-preserving baseline and does not preclude future revisions where stronger justification emerges.

10. Conceptual Architecture: From Dimensions to Structural Profiles

C. Treatment of Risk-Oriented Indicators

Within AI-SNI framework, risk- and fragility-oriented indicators are explicitly retained within dimensional aggregation with non-zero weights. These indicators are treated as integral components of dimensional measurement and are not introduced as optional penalties, ex post corrections, or supplementary adjustments.

This design choice addresses a recurrent methodological distortion in composite indicator construction, whereby selective exclusion or secondary treatment of risk-related indicators leads to systematic inflation of dimensional scores by emphasizing capability- or leverage-enhancing components alone.

Accordingly, AI-SNI applies the following principles:

- Dimensional scores represent net structural conditions, rather than idealized or capability-only capacity profiles;
- Fragility and risk exposure are internal to dimensional measurement, rather than appended through external corrective mechanisms;
- Elevated dimensional scores cannot be obtained through partial indicator reporting, selective omission, or indicator cherry-picking.

By embedding risk-oriented indicators directly within dimensional aggregation, AI-SNI preserves internal coherence between leverage, fragility, and governance conditions at the measurement stage. This treatment reinforces the framework’s function as a diagnostic instrument for structural assessment, rather than as an index of optimized capability or aspirational performance.

D. Interpretive Note

Dimensional aggregation yields internally coherent yet analytically partial signals. A high score in any single dimension does not, in isolation, constitute strategic advantage, stability, or policy relevance.

Within AI-SNI framework, strategic meaning arises only through cross-dimensional interaction, interpreted in light of explicitly defined dimensional directionality (Section 10.3) and the risk classification and interpretive procedures applied at subsequent analytical stages. Dimensional scores are therefore not intended to support standalone judgment, ranking, or prioritization.

Dimensional aggregation is a necessary but intentionally insufficient step in the analytical sequence. Its function is to establish structured, comparable dimensional inputs for higher-order synthesis, rather than to deliver strategic conclusions. This staged design preserves interpretive discipline and prevents premature or reductive inference from isolated measurement outputs.

10. Conceptual Architecture: From Dimensions to Structural Profiles

10.5 Composite Index Formula and Diagnostic Extensions

The interpretive authority of composite scores, tier classifications, and structural profiles produced within AI-SNI framework is formally constrained by the interpretive hierarchy specified in Section 12. All composite outputs must be read in accordance with this hierarchy and do not possess independent decision or ranking authority outside the conditions explicitly defined therein.

AI-SNI is operationalized through a single authoritative composite index formulation, designed to ensure methodological auditability, cross-node comparability, and temporal consistency. This reference formulation constitutes the official AI-SNI index and serves as the sole basis for baseline reporting, benchmarking, and longitudinal analysis.

In addition to the authoritative index, AI-SNI methodology specifies two diagnostic composite extensions. These extensions are introduced for analytical purposes only and are designed to examine specific forms of structural vulnerability, particularly governance fragility and weakest-link sensitivity, that may not be fully captured by a linear aggregation alone.

These diagnostic formulations:

- do not constitute alternative AI-SNI indices;
- do not generate competing estimates of strategic centrality or performance;
- do not carry independent interpretive or comparative authority.

Their function is explicitly diagnostic and stress-oriented: to provide conditional analytical views that surface structural weaknesses under specified assumptions, without redefining the underlying index.

Unless explicitly stated otherwise, all references to “AI-SNI” in this White Book refer exclusively to the authoritative composite index defined in Section 10.5.1. The formulations introduced in Sections 10.5.2 and 10.5.3 are to be interpreted strictly as diagnostic adjustments applied to the reference index, intended for stress testing and risk-sensitivity analysis. They must not be used as standalone measures, substitute indices, or independent bases for comparison.

10.5.1 AI-SNI Composite Index

This formulation defines the sole authoritative composite index referred to as AI-SNI throughout this document. Unless explicitly stated otherwise, all references to AI-SNI correspond exclusively to this formulation and carry the interpretive authority specified in Section 12.

10. Conceptual Architecture: From Dimensions to Structural Profiles

A. Core Formula

$$AI - SNI = \sum_{d=1}^{5} (\alpha_d \times D_d), \qquad \sum_{k=1}^{5} \alpha_d = 1 \tag{10.5.1}$$

Parameter Definitions

- α_d: Weight assigned to dimension D_d, reflecting its relative analytical importance.
- D_d: Normalized score of the *d*-th AI-SNI dimension (D1–D5).

B. Description and Rationale

AI-SNI Composite Index aggregates the five dimensions (D1–D5) using a linear weighted sum. This formulation is selected to ensure a high degree of transparency, traceability, and interpretability in composite construction.

The additive structure allows variations in the composite score to be directly attributed to changes in specific dimensional inputs, thereby supporting systematic decomposition and diagnostic analysis. This property facilitates sensitivity assessment with respect to dimensional weights and supports analytical review of how different structural components contribute to the overall composite signal.

By preserving additivity, AI-SNI Composite Index provides a clear and auditable mechanism for summarizing multidimensional structural information, while remaining compatible with the interpretive and governance constraints defined elsewhere in the framework.

C. Recommended Use Cases

AI-SNI Composite Index is appropriate for use in the following analytical and communication contexts:

- **White papers and flagship analytical reports**, where a transparent and auditable summary measure is required to support structural analysis;
- **Dashboards and cross-node comparative visualizations**, intended to illustrate relative structural positioning within a clearly defined reference set;
- **Policy communication, executive briefings, and public-facing summaries**, where interpretability and traceability are prioritized over technical optimization or predictive precision.

Use of the composite index in these contexts is subject to the interpretive constraints and non-use conditions specified elsewhere in this document.

10. Conceptual Architecture: From Dimensions to Structural Profiles

D. Interpretive Note

AI-SNI Composite Index summarizes aggregate strategic centrality under the explicit assumption that relative weaknesses in individual dimensions may be partially offset by strengths in others through linear aggregation. Accordingly, the composite score is intended to function as a baseline descriptive measure, rather than as a diagnostic indicator of structural fragility, governance failure, or systemic risk.

Use of AI-SNI composite outputs for ordinal ranking, prioritization, or resource allocation decisions in the absence of accompanying risk profile and structural class analysis constitutes a misuse of the AI-Strategic Node Framework.

High scores under this formulation indicate elevated centrality within AI-mediated strategic systems. They do not, in isolation, imply robustness, governability, resilience, or policy desirability, all of which require cross-dimensional interpretation and higher-order assessment as specified elsewhere in the framework.

10.5.2 Diagnostic Extension I: Governance Fragility Adjustment

This diagnostic extension applies a governance fragility adjustment to the reference AI-SNI Composite Index, with the purpose of surfacing structural vulnerability under conditions of infrastructure–governance misalignment.

The adjustment operates through a penalty transformation applied to the authoritative AI-SNI score, generating a conditional analytical view that highlights the sensitivity of aggregate strategic centrality to governance sufficiency constraints. Outputs derived from this formulation are diagnostic in nature and do not constitute independent index values.

Importantly, the penalty mechanism is applied to Infrastructure–Governance Alignment Capacity (IGAC) as a governance sufficiency variable, rather than to Infrastructure–Governance Asymmetry (IGA) as a structural condition. This distinction preserves the conceptual separation between measured misalignment and assessed capacity to govern or mitigate that misalignment.

This formulation does not define an alternative AI-SNI index. It is analytically derived from the authoritative composite index and is intended exclusively for stress testing and risk-sensitivity analysis. Outputs produced under this diagnostic extension must not be used for headline comparison, ordinal ranking, or standalone reporting.

10. Conceptual Architecture: From Dimensions to Structural Profiles

A. Core Formula

$$AI - SNI^{*} = AI - SNI \times (1 - \lambda \times max(0, \tau - D_4)) \quad \textbf{(10.5.2)}$$

Parameter Definitions

- $\boldsymbol{\lambda}$: Penalty intensity coefficient, controlling the sensitivity of the composite score to governance shortfalls.
- $\boldsymbol{\tau}$: Governance sufficiency threshold, represents a minimum governance sufficiency threshold for IGAC under given IGA conditions.
- $\boldsymbol{D_4}$: Infrastructure–Governance Asymmetry dimension, capturing the degree to which strategic leverage exceeds effective governance and control capacity. D_4 is normalized such that higher values indicate greater governance sufficiency relative to infrastructural dependence.

B. Description and Rationale

This formulation introduces an explicit governance fragility adjustment to the reference AI-SNI Composite Index. When measured governance capacity ($\boldsymbol{D_4}$falls below a predefined sufficiency threshold ($\boldsymbol{\tau}$), the baseline AI-SNI score is multiplicatively adjusted downward to reflect increased exposure to governance-related structural vulnerability.

The adjustment is conditionally activated only under insufficiency conditions ($D_4 < \tau$) . This design ensures that governance capacity above the threshold is treated as a satisficing condition, rather than a source of additional leverage, while governance shortfalls below the threshold are explicitly reflected in the adjusted output.

By applying a threshold-based, non-symmetric transformation, the diagnostic extension isolates the effect of governance insufficiency without redefining baseline strategic centrality. The resulting output provides a conditional analytical view of fragility sensitivity, while preserving the interpretive role and authority of the reference AI-SNI index.

C. Analytical Purpose

The governance fragility adjustment is designed to address a specific analytical limitation of linear aggregation: the potential for high sensing or predictive leverage to obscure governance-related vulnerability.

Specifically, this diagnostic extension serves to:

- Prevent nodes exhibiting elevated sensing (D1) or predictive capacity (D2) under weak governance conditions from being analytically characterized as stable strategic assets based solely on aggregate centrality measures;

10. Conceptual Architecture: From Dimensions to Structural Profiles

- Explicitly encode asymmetric vulnerability within the composite structure, ensuring that governance insufficiency constrains the strategic interpretation of otherwise high leverage scores.

Through this adjustment, the framework preserves the distinction between the presence of AI-enabled leverage and the capacity to govern, contain, or sustain that leverage, thereby reinforcing the diagnostic function of AI-SNI methodology under stress and fragility-sensitive analytical conditions.

D. Recommended Use Cases

The governance fragility adjustment is appropriate for use in the following diagnostic analytical contexts:

- **Strategic risk assessment**, where sensitivity to governance insufficiency is analytically relevant;
- **Governance stress analysis**, including scenario-based evaluation of control and oversight constraints under elevated leverage conditions;
- **Long-term stability evaluation**, where the persistence and governability of AI-mediated strategic centrality are examined over extended time horizons.

Outputs generated under this diagnostic extension should be interpreted as conditional analytical views and remain subject to the interpretive constraints specified elsewhere in this framework.

E. Interpretive Note

Diagnostic Extension I operationalizes a core analytical principle of AI-SNI framework: high strategic centrality that is insufficiently governed may increase systemic vulnerability rather than resilience.

A baseline AI-SNI score that is materially reduced under this diagnostic formulation should be interpreted as an indicator of governance-sensitive fragility. Such an outcome signals the need for closer examination of institutional capacity, regulatory alignment, and oversight mechanisms associated with the node in question. It does not, in itself, warrant assumptions of strategic reliability or suitability for dependence.

Outputs produced under this diagnostic extension are intended to inform further institutional and governance analysis, rather than to serve as definitive assessments or bases for immediate strategic reliance.

10. Conceptual Architecture: From Dimensions to Structural Profiles

10.5.3 Diagnostic Extension II: Short-Board Sensitivity Test

This diagnostic extension applies a weakest-link–sensitive aggregation to the reference AI-SNI Composite Index, with the purpose of highlighting structural vulnerability arising from near-zero performance in any single dimension.

The formulation generates a stress-testing analytical view that examines the sensitivity of aggregate strategic centrality to short-board constraints across dimensions. It is intended exclusively for comparative risk diagnosis under stress conditions, rather than for baseline assessment or headline reporting.

Outputs produced under this formulation do not constitute AI-SNI index values. They are analytically derived from the authoritative composite index defined in Section 10.5.1 and must be interpreted relative to that reference formulation, in accordance with the interpretive constraints specified elsewhere in this framework.

A. Core Formula

$$AI - SNI_{GM} = \prod_{d=1}^{5} D_d^{\alpha_d} \tag{10.5.3}$$

Parameter Definitions

- $\boldsymbol{D_d}$: Normalized score of the *d*-th AI-SNI dimension (D1–D5).
- $\boldsymbol{\alpha_d}$: Weight assigned to dimension $\boldsymbol{D_d}$, consistent with the weighting scheme used in AI-SNI Composite Index.
- $\prod$: Multiplicative aggregation operator enforcing cross-dimensional coupling.

B. Description and Rationale

This diagnostic formulation employs a geometric mean aggregation to enforce non-substitutability across dimensions. Under this aggregation logic, strong performance in one or more dimensions cannot compensate for pronounced weakness in another. As a result, near-zero values in any single dimension exert a binding constraint on the composite outcome, irrespective of strengths elsewhere.

The formulation is intended to represent system environments in which AI-mediated strategic effectiveness depends on the satisfaction of minimum-capability conditions across multiple layers, rather than on additive accumulation of strengths. It is particularly relevant in contexts where failure or insufficiency in one critical dimension may propagate through interconnected system components, thereby constraining overall functionality.

10. Conceptual Architecture: From Dimensions to Structural Profiles

By design, this aggregation highlights weakest-link sensitivity without redefining baseline strategic centrality, providing a conditional analytical perspective on structural vulnerability under minimum-threshold constraints.

C. Analytical Purpose

The short-board sensitivity test is designed to surface structural bottlenecks and weakest-link constraints within AI-mediated strategic systems. It facilitates identification of potential single-point failures, where insufficiency in a single dimension may constrain or disrupt overall system performance.

By emphasizing minimum-condition dependence rather than additive contribution, this diagnostic formulation captures aspects of system integrity and cross-dimensional coherence that are not observable through average or aggregate strength measures. The resulting outputs support fragility-aware analysis under conditions where system performance is contingent on the sustained adequacy of all critical dimensions.

D. Recommended Use Cases

The short-board sensitivity test is appropriate for use in the following diagnostic and evaluative contexts:

- **System engineering and architecture-level analysis**, where cross-dimensional dependencies and minimum-capability constraints are of analytical relevance;
- **Resilience assessment and failure-mode stress testing**, including identification of potential single-point failures under adverse or degraded conditions;
- **Scenario-based robustness evaluation**, particularly in tightly coupled systems where insufficiency in one dimension may propagate across the broader architecture.

Outputs generated under this diagnostic extension should be interpreted as conditional stress-test results and remain subject to the interpretive constraints specified elsewhere in this framework.

E. Interpretive Note

Diagnostic Extension II is not intended for general-purpose ranking, headline comparison, or standalone reporting. Its analytical value lies in identifying short-board vulnerabilities—dimensions whose insufficiency imposes a binding constraint on overall system performance.

Divergence between results produced under this diagnostic formulation and those derived from the linear composite index should be interpreted as a diagnostic signal of structural imbalance or weakest-link sensitivity, rather than as a contradiction, methodological inconsistency, or scoring anomaly. Such divergence indicates conditions under which aggregate strength may mask critical dependencies or minimum-capability failures.

10. Conceptual Architecture: From Dimensions to Structural Profiles

Outputs generated under this diagnostic extension are therefore intended to inform deeper structural and resilience-focused analysis, rather than to serve as summary indicators of strategic centrality.

Table 10.5.3 Summary Guidance

Formulation	Core Sensitivity	Primary Analytical Function
AI-SNI Composite Index (Linear)	Average cross-dimensional performance	Communication, baseline comparison, and interpretability
The Diagnostic Extension I (Threshold–Penalty)	Governance-induced fragility	Risk classification and stability assessment
The Diagnostic Extension II (Geometric Mean)	Weakest-link and bottleneck failure	System resilience and robustness analysis

AI-SNI produces a single authoritative composite index score, as defined in Section 10.5.1. This reference formulation constitutes the sole index value to which the term AI-SNI applies throughout this document. Outputs generated under Diagnostic Extension I or Diagnostic Extension II shall not be reported, compared, or cited as standalone indices, and do not alter tier thresholds, structural class attribution, or the interpretive authority hierarchy established in this White Book.

Diagnostic Extensions I and II are introduced to support analytical interpretation under explicit stress assumptions and risk-sensitive perspectives. The decision to apply either diagnostic extension reflects the analyst’s diagnostic objective, institutional risk tolerance, and governance focus, rather than representing alternative definitions, recalibrations, or competing versions of AI-SNI index.

Divergence between the reference composite score and the associated diagnostic formulations should be interpreted as analytically meaningful signals of structural imbalance, governance asymmetry, or system-level vulnerability. Such divergence does not indicate inconsistency, measurement error, or methodological instability, but instead highlights differential exposure under stressed or constrained governance conditions.

When used in combination, the authoritative composite index and its diagnostic extensions ensure that AI-SNI functions not as a unidimensional ranking instrument, but as a governance-grade diagnostic framework capable of distinguishing between strategic centrality, fragility, and resilience within AI-mediated strategic systems.

10. Conceptual Architecture: From Dimensions to Structural Profiles

10.6 Interpretation of Composite Scores

AI-SNI composite scores represent structural strategic centrality within AI-mediated systems. They do not measure desirability, normative legitimacy, political alignment, institutional stability, or policy compliance. A high composite score indicates that a node is deeply embedded within algorithmic sensing, prediction, decision-making, and governance architectures, and therefore occupies a position from which disruption, misgovernance, or strategic contestation may generate disproportionate systemic spillover effects.

Composite scores must not be interpreted in isolation. Meaningful interpretation requires joint examination of multiple analytical layers, including:

- **Dimensional profiles (D1–D5)**, which reveal the configuration of leverage, dependence, and constraint across structural functions;
- **Embedded risk indicators**, including governance asymmetry and fragility-related signals, which condition the interpretation of centrality;
- **Confidence assessments and data-quality annotations**, which specify evidentiary coverage, uncertainty, and interpretive limits.

AI-SNI is explicitly designed as a composite index with embedded diagnostic extensions. It is not a ranking of “leaders” or “winners,” nor does it substitute for institutional judgment, contextual assessment, or policy deliberation. Its analytical purpose is to identify where AI-mediated systems concentrate leverage, fragility, and future optionality, and to signal locations where governance attention, institutional safeguards, and anticipatory regulatory capacity may be most consequential.

11. Risk Classification Framework

Within AI-SNF, the Risk Classification Framework organizes multidimensional structural measurements into exposure regimes and diagnostic categories, rather than rankings or league tables. It integrates signals of centrality, fragility, governance asymmetry, and future optionality to support pattern recognition, comparative diagnostics, and policy screening under uncertainty, without implying competitive superiority or policy prescription. By prioritizing classification over ranking, the framework preserves multidimensional nuance and reflects the principle that risk in AI-mediated systems arises from structural configuration and coupling dynamics, not composite score magnitude alone.

11.1 Exposure Bands

Risk bands represent qualitatively distinct exposure regimes defined by structural leverage concentration and spillover configuration, rather than ordered positions along a common risk continuum.

Exposure bands are categorical screening labels, not ordered performance levels. Tier identifiers are used solely for classification and reference and do not imply monotonic ordering, improvement trajectories, normative hierarchy, or transitive comparability across nodes.

A. Interpretive Note

Tier assignment functions as a coarse screening mechanism and carries no standalone interpretive authority. Meaningful interpretation requires joint consideration of dimensional profiles (D1–D5), embedded risk vectors, particularly governance asymmetry (D4), and structural class attribution, where applicable.

Tier labels must not be treated as conclusions, rankings, or decision outputs, but as preliminary categorical signals that require contextual and cross-layer analysis to acquire analytical or policy relevance.

B. Tier Bands

For purposes of visualization and high-level comparative screening, AI-SNI composite outputs are organized into four exposure-oriented tier bands. These bands serve as categorical signals of structural exposure within AI-mediated systems and do not imply ordinal ranking, performance hierarchy, or normative judgment.

The tier bands are defined as follows:

a) **Tier 1 – Critical Exposure Band**: AI-SNI ≥ 0.80

b) **Tier 2 – High-Exposure Band**: $0.65 \leq$ AI-SNI < 0.80

c) **Tier 3 – Relevant Exposure Band**: $0.50 \leq$ AI-SNI < 0.65

d) **Tier 4 – Peripheral Exposure Band**: AI-SNI < 0.50

11. Risk Classification Framework

Tier thresholds are applied uniformly within a declared reference set and evaluation window. They are intended to support coarse-grained exposure screening and visual differentiation, rather than precise quantitative comparison or standalone interpretation. Interpretation of tier placement remains subject to the constraints specified in Sections 10.6, 11, and 12.

Note:

- Tier identifiers are explicitly non-ordinal. They function as labels for distinct exposure regimes, rather than as ranks, scales of performance, or ordered risk levels.
- Tier membership does not imply priority, desirability, legitimacy, comparative advantage, or policy value. It serves solely as a categorical signal for high-level structural screening.
- Tier thresholds are heuristic governance bands, calibrated to support cross-case visualization and comparative screening within a declared reference set. They do not represent empirical distribution cut-offs, probabilistic risk thresholds, or normative boundaries of acceptability.
- Tier classification must not be used in isolation as a basis for prioritization, sanctioning, funding decisions, or resource allocation. Any such use constitutes a methodological misuse of AI-SNI framework and violates the interpretive constraints specified in this document.

C. Confidence Override

Interpretation of tier assignments is subject to a confidence override mechanism. Where evidentiary coverage, data quality, or validation confidence is assessed as insufficient, tier labels and composite scores must not be escalated, compared, or used as a basis for prioritization, irrespective of their numerical magnitude.

Under such conditions, tier placement carries no standalone interpretive or decision authority. Analytical outputs should be treated as provisional signals and must be accompanied by explicit disclosure of evidentiary limitations.

The confidence override ensures that evidence sufficiency supersedes numerical representation, reinforcing the governance-oriented design of AI-SNI and preventing false precision or over-interpretation under conditions of uncertainty.

D. Non-Comparability Clause

Exposure bands are not mutually comparable in ordinal terms. A node classified in Tier 1 is not, in general terms, “more” or “less” risky than a node classified in Tier 2. Each tier represents a distinct exposure regime, defined by the configuration of leverage concentration and potential spillover pathways, rather than by position along a single continuous risk scale.

11. Risk Classification Framework

Accordingly, tier labels, numerical thresholds, and tier identifiers must not be interpreted as forming an ordered hierarchy, performance ladder, or priority ranking. Any interpretation that treats tier position as ordinal or transitive constitutes a methodological misuse of AI-SNI framework.

Nodes located near tier thresholds may exhibit substantively similar structural profiles despite falling into adjacent exposure bands. Tier boundaries should therefore be interpreted as heuristic classification aids, not as sharp analytical or policy discontinuities.

E. Methodological Flexibility

Tier thresholds may be adjusted for clearly specified analytical purposes, including:

- **Sensitivity analysis**, to assess robustness of tier classification under alternative threshold assumptions;
- **Scenario-specific evaluation**, where exposure regimes are examined under distinct strategic or governance conditions;
- **Sector- or domain-specific application**, where structural characteristics justify tailored exposure band calibration.

Any such adjustment must be explicitly documented and analytically justified. At a minimum, documentation must specify:

- the analytical rationale for threshold modification;
- the alternative threshold values applied;
- the resulting reclassification effects across nodes;
- the implications for cross-node comparability.

Where tier thresholds vary across applications, resulting classifications must be treated as belonging to distinct analytical frames. Outputs derived under different threshold regimes must not be pooled, aggregated, or directly compared without explicit normalization, scope alignment, and disclosure of methodological differences.

This flexibility provision is intended to support analytical rigor under diverse contexts while preserving transparency, auditability, and interpretive discipline.

11. Risk Classification Framework

11.2 Risk Profiles versus Rankings

AI-SNI explicitly discourages the treatment of composite scores as standalone rankings detached from their underlying dimensional structure. Identical or near-identical index values may correspond to fundamentally different risk configurations, depending on how leverage, fragility, governance control, and future optionality are distributed across dimensions D1–D5.

Accordingly, AI-SNF prioritizes risk profiles—the multidimensional configuration of D1–D5—over scalar ordering. Risk profiles preserve structural information that is necessarily lost in one-dimensional rankings and enable analysts to differentiate among structurally distinct cases, including but not limited to nodes that are:

- highly central but weakly governed;
- temporally dominant but governance-fragile;
- moderately central yet institutionally buffered;
- option-preserving in the long horizon but presently peripheral.

This profile-based approach supports diagnostic clarity by emphasizing configuration and interaction effects rather than numerical position.

A. Restricted Use of Rankings

Rankings may be generated only for exploratory visualization or descriptive mapping purposes. They must not be interpreted as:

- policy conclusions or recommendations;
- indicators of desirability, legitimacy, or priority;
- measures of institutional robustness or resilience;
- justification for allocation, intervention, sanctioning, or coercive action.

Any use of rankings beyond exploratory visualization requires accompanying dimensional diagnosis, explicit discussion of the underlying risk configuration, and an interpretive authority statement consistent with the guardrails specified in this framework.

B. Interpretive Guardrail

Within AI-SNF, ranking is strictly subordinate to diagnosis. Policy-relevant interpretation must be grounded in risk profiles and evidence grading, rather than ordinal position. When rankings are presented, they should be framed as non-authoritative visualization artifacts, not as analytic conclusions or decision inputs.

This guardrail ensures that AI-SNI functions as a governance-oriented diagnostic framework, preserving structural nuance and preventing reductive interpretation based on scalar ordering alone.

11. Risk Classification Framework

11.3 Temporal Interpretation and Change Attribution

AI-SNI outputs are time-sensitive and path-dependent. Observed changes in composite or dimensional values do not, in isolation, indicate improvement or deterioration in strategic position. Variations may arise from analytically distinct sources, including:

- **Genuine structural shifts** in AI-mediated sensing, prediction, decision-making, or governance architectures;
- **Changes in data coverage, measurement quality, or evidentiary availability**, which affect confidence levels rather than underlying structure;
- **Governance reforms, regulatory erosion, ownership transitions, or institutional realignment**, altering oversight, control rights, or accountability;
- **Technical integration, decoupling, or architectural reconfiguration**, reshaping coupling intensity and dependency pathways across systems.

Accordingly, temporal comparison requires explicit change-attribution analysis. Simple score differentials are insufficient and may be misleading without attribution. All AI-SNI assessments represent time-stamped diagnostic snapshots, reflecting the structural configuration of a node within a defined observation window.

Longitudinal comparison is permissible only under conditions of methodological consistency, explicit documentation of data updates, and transparent treatment of infrastructural and governance changes. Cross-temporal inference without these controls constitutes methodological misuse.

A. Minimum Requirements for Longitudinal Use

Any longitudinal application of AI-SNI must include, at a minimum:

- **Documentation of methodological consistency**, including scope definition, normalization reference set, indicator weights, and aggregation rules;
- **Identification of primary drivers of change** at both the dimensional and sub-indicator levels;
- **Attribution of observed variation** to structural transformation, governance adjustment, or data-related artifacts;
- **Updated confidence assessment** where evidentiary coverage or quality has changed.

Only with explicit attribution can AI-SNI support temporal diagnostics without conflating measurement noise with genuine strategic evolution.

AI-SNI is not intended for naïve time-series ranking or trend extrapolation absent structural revalidation. Apparent score changes over time may reflect shifts in measurement scope, evidence coverage, governance alignment, or architectural coupling, rather than monotonic improvement or decline in strategic position. Such changes carry no independent interpretive or decision authority without accompanying attribution analysis.

11. Risk Classification Framework

11.4 Use with Other Indices

AI-SNI is designed to complement, rather than replace, existing indices that assess governance quality, economic capacity, technological readiness, security posture, or sustainability. It does not seek to re-evaluate overall national performance or institutional effectiveness along conventional development or capability dimensions.

The principal analytical value of AI-SNI emerges when it is applied as a diagnostic overlay, used to stress-test assumptions and conclusions derived from actor-centric or sector-specific indices. This function is particularly relevant in cases where high scores in governance, development, or technological capability coexist with elevated infrastructure–governance asymmetry (D4), tightly coupled dependencies, or latent forms of systemic fragility.

When used in this complementary manner, AI-SNI helps surface leverage concentrations and governance-relevant vulnerabilities that may remain obscured in aggregate or performance-oriented assessments. It enhances interpretive depth by revealing how AI-mediated systems redistribute risk, control, and spillover potential, without duplicating the scope, metrics, or normative logic of established index frameworks.

12. Structural Class System

The Structural Class System constitutes a distinct, non-derivative, and non-computable interpretive layer within the AI-Strategic Node Framework (AI-SNF). It does not modify composite scores, tier assignments, or diagnostic outputs. Instead, it evaluates systemic role, failure consequences, and governance criticality—properties that are not reducible to scalar aggregation, numerical comparison, or ranking.

Structural class attribution operates external to index construction. It cannot be inferred from composite scores, tier placement, or ordinal position, and it does not emerge from aggregation logic. Attribution requires independent, auditable assessment, grounded in analysis of cross-dimensional coupling, temporal non-substitutability, and failure-propagation dynamics.

12.1. Structural Class as a Higher-Order Interpretive Layer

Structural class attribution represents the highest-order interpretive construct within AI-SNF.

Unlike composite scores or tiered exposure bands, which summarize measured centrality for visualization, screening, and comparative orientation, structural class evaluates whether a node functions, within AI-mediated systems, as one of the following:

- **System-constitutive;**
- **System-stabilizing;**
- **Network-dependent;**
- **Latent / option-preserving.**

These categories describe systemic function, not degree, performance, or exposure level.

Accordingly:

- Structural class cannot be mechanically inferred from composite scores, tier placement, or any form of ordinal ranking;
- Structural class does not scale monotonically with numerical magnitude;
- Structural class does not imply desirability, strength, efficiency, robustness, resilience, security, or policy preference.

Rather, structural class reflects an expert interpretive judgment concerning non-substitutability, cross-dimensional coupling, and failure-propagation dynamics across relevant temporal horizons. Attribution must be grounded in cross-dimensional evidence, institutional and governance analysis, and system-dependence reasoning, rather than score optimization, numerical dominance, or comparative ranking.

12. Structural Class System

A. Non-Computability Guardrail

Structural class is an interpretive construct, not a statistical or algorithmic output. Any attempt to calculate, approximate, derive, or reverse-engineer structural class from index values, tiers, or diagnostic formulations constitutes a methodological violation of AI-SNF and invalidates the interpretive discipline of the framework.

Structural class attribution must therefore remain explicitly separated from index computation, aggregation procedures, and ranking logic.

12.2. Relationship to Composite Scores and Exposure Bands

To prevent methodological ambiguity and interpretive drift, AI-SNF explicitly separates structural classification from all score-based outputs. Each analytical layer serves a distinct and non-substitutable function within the framework:

- **Composite Score (AI-SNI):** A bounded aggregate signal designed for comparative screening, visualization, and descriptive orientation within a declared reference set.
- **Exposure Bands (Tier 1–4):** Coarse-grained categorical labels used for pattern recognition and high-level exposure screening, without ordinal or decision authority.
- **Structural Class (S / A / B / C):** An assessment of systemic role and consequences of failure, capturing properties that are not reducible to numerical aggregation.

Structural class attribution is neither a refinement, extension, nor transformation of composite scoring or tier classification. Nodes exhibiting similar composite scores may occupy fundamentally different structural classes, and nodes assigned to the same structural class may display substantially divergent score levels or tier placements.

Any attempt to infer structural class from score magnitude, tier adjacency, threshold proximity, or ordinal position constitutes a methodological misapplication and is inconsistent with the interpretive discipline of AI-SNF. Structural classification must remain analytically independent of score-based outputs and grounded in cross-dimensional, temporal, and system-dependence assessment as specified elsewhere in this framework.

12.3. Structural Class Definitions

This section defines the structural class categories employed within the AI-Strategic Node Framework (AI-SNF). Structural classes are analytical constructs, not performance labels. They characterize a node’s systemic role and failure implications, rather than aggregate strength, optimization outcomes, policy desirability, or developmental achievement.

Structural class labels (S / A / B / C) function solely as categorical identifiers. Their alphabetical ordering carries no ordinal meaning and must not be interpreted as indicating ranking, hierarchy, priority, or superiority across nodes. Structural classes do not encode progression paths, maturity stages, or normative development trajectories.

12. Structural Class System

Each structural class captures a distinct mode of system participation and consequence of failure within AI-mediated architectures. Classification is therefore role-based rather than score-based, and interpretive rather than computational, consistent with the higher-order function of structural class attribution defined in Sections 12.1 and 12.2.

12.3.1 S-Class: Structural AI Strategic Nodes

S-Class nodes perform system-constitutive functions within AI-mediated architectures. Their presence and integration shape long-horizon option space, calibration integrity, and system-level stability, influencing how AI-enabled systems evolve, coordinate, and remain governable over time.

A. Defining Characteristics

S-Class nodes are characterized by the following properties:

- **High cross-dimensional coupling**, such that interactions among multiple dimensions reinforce one another rather than acting as substitutable or independently compensatory components;
- **Non-linear downstream effects** under conditions of degradation, disruption, or misgovernance, whereby localized failure may propagate gradually across interconnected system layers;
- **Path-dependent governance implications**, in which early institutional, ownership, or regulatory choices constrain future corrective capacity and limit the reversibility of adverse trajectories.

Loss, degradation, or misgovernance of an S-Class node does not necessarily result in immediate system collapse. Instead, it may generate progressive systemic erosion over time, weakening reliability, calibration coherence, or governance alignment across AI-mediated systems.

B. Interpretive Note

An S-Class designation signals governance sensitivity and systemic consequence, not strategic strength, efficiency, security, or priority status. It does not, in isolation, prescribe regulatory action, investment preference, intervention sequencing, or policy urgency.

Structural class attribution serves an interpretive diagnostic function, indicating where governance choices carry long-term, difficult-to-reverse implications, rather than where action is necessarily immediate or desirable.

12. Structural Class System

12.3.2 A-Class: High-Leverage Stabilized Nodes

A-Class nodes exhibit concentrated AI-strategic leverage whose associated risks are institutionally buffered and operationally governable under prevailing arrangements. Within AI-mediated architectures, they function as system-stabilizing anchors, provided that existing governance, oversight, and redundancy mechanisms remain effective.

A. Defining Characteristics

A-Class nodes are characterized by the following properties:

- **Disruptive failure potential that remains locally containable**, without immediate system-wide propagation under current conditions;
- **Clearly defined and enforceable control rights** over critical infrastructure, platforms, or data flows;
- **Redundancy and fallback mechanisms** that limit cascading failure and reduce single-point dependency;
- **Alignment between infrastructural centrality and governance authority**, ensuring that leverage is matched by effective oversight and accountability.

These characteristics reflect a configuration in which leverage concentration is moderated by institutional design rather than by structural substitutability alone.

B. Interpretive Note

An A-Class classification indicates governable leverage under existing institutional and regulatory conditions. It does not imply uniformly low risk across future contingencies, nor does it indicate superior strategic value, desirability, or long-term resilience.

Structural class attribution remains conditional and context-dependent. Changes in governance capacity, ownership structure, regulatory enforcement, or system coupling may alter the stabilizing properties associated with A-Class nodes and warrant reassessment.

12.3.3 B-Class: Distributed or Network-Dependent Nodes

B-Class nodes derive strategic relevance primarily through aggregation and network effects, rather than through singular chokepoint or constitutive functions. Their systemic role is network-dependent, with analytical significance contingent on topology, redundancy configuration, and interaction density within AI-mediated architectures.

12. Structural Class System

A. Defining Characteristics

B-Class nodes are characterized by the following properties:

- **Limited standalone failure impact**, such that isolated disruption or degradation of a single node is generally tolerable at the system level;
- **Systemic relevance emerging from collective participation**, where strategic effect arises through scale, coordination, or cumulative contribution;
- **Sensitivity to network reconfiguration**, including changes in connectivity, redundancy, or coordination patterns, rather than to single-node failure alone.

While individual node failures are typically absorbable, collective degradation, correlated disruption, or synchronized failure across multiple B-Class nodes may materially impair system performance, resilience, or continuity.

B. Interpretive Note

A B-Class designation does not imply dispensability, marginality, or intrinsically low risk. Systemic relevance depends on network density, redundancy structure, and collective degradation dynamics, all of which may vary across contexts and over time.

Accordingly, interpretation of B-Class nodes requires attention to network-level conditions rather than individual node attributes, consistent with the framework’s emphasis on configuration and interaction over scalar magnitude.

12.3.4 C-Class: Peripheral or Latent Nodes

C-Class nodes exhibit low present-day AI-strategic centrality, yet retain potential future relevance under specific technological, infrastructural, regulatory, or geopolitical shifts. They function as latent or option-preserving nodes, whose strategic significance is contingent rather than realized.

A. Defining Characteristics

C-Class nodes are characterized by the following properties:

- **Minimal current systemic impact**, with limited integration into existing AI-mediated sensing, decision, or governance architectures;
- **Relevance contingent on exogenous change**, including technological breakthroughs, infrastructure expansion, regulatory realignment, or shifts in geopolitical configuration;
- **Elevated optionality without immediate leverage**, reflecting the presence of future pathways rather than present influence.

These characteristics indicate unrealized potential rather than operational weakness or marginality.

12. Structural Class System

B. Interpretive Note

A C-Class designation reflects current structural position, not long-term insignificance or strategic irrelevance. Its governance relevance often lies in monitoring pathway formation, preserving future option space, and preventing premature lock-in, capture, or exclusion under evolving conditions.

Accordingly, C-Class nodes warrant anticipatory governance attention, focused on maintaining openness, adaptability, and reversibility as system configurations evolve.

12.4. Interpretive Authority and Analytical Discipline

Within the AI-Strategic Node Framework (AI-SNF), analytical outputs carry explicitly differentiated interpretive authority. Policy-relevant interpretation must adhere to the following hierarchical order, which defines the permissible scope and limits of analytical inference:

a) **Structural Class (S / A / B / C):** Assessment of systemic role and consequences of failure, representing the highest-order interpretive construct.

b) **Risk Profile (configuration of D1–D5):** Evaluation of the distribution of leverage, constraint, fragility, and future optionality across dimensions.

c) **Composite Score (AI-SNI):** A bounded aggregate signal of structural centrality, intended for screening, visualization, and descriptive orientation.

d) **Exposure Bands (Tier 1–4):** Coarse-grained categorical labels used for high-level exposure screening and pattern recognition.

This hierarchy establishes the disciplinary order of interpretation within the framework. Outputs at lower levels may support illustration, comparative visualization, or exploratory analysis, but cannot substitute for, approximate, or be used as proxies for higher-order constructs.

Any interpretation that bypasses higher-authority layers, particularly the use of tier placement or composite scores as proxies for systemic role, governance criticality, or policy priority, constitutes a methodological invalidation of AI-SNF's interpretive discipline.

Where evidence coverage falls below the minimum threshold specified for a given dimension, composite scores and tier assignments may be reported for transparency but must be interpreted as non-authoritative and excluded from comparative or prioritization use.

12. Structural Class System

12.5 Governance Implications

By explicitly separating structural classification from score-based outputs, the AI-Strategic Node Framework (AI-SNF) is designed to support preventive and anticipatory governance, rather than reactive ranking or post hoc performance comparison. Structural class attribution identifies contexts in which governance attention, transparency obligations, institutional safeguards, and coordination mechanisms are likely to be most consequential, even where composite signals or conventional performance indicators appear favorable.

In this sense, structural classification functions as an early-warning instrument for governance stress, not as a measure of achievement, competitiveness, or success. This design reflects a core premise of AI-SNF:

In AI-mediated systems, risk emerges from structural configuration, not from numerical position.

Accordingly, effective governance responses must be oriented toward systemic role, coupling dynamics, and failure-propagation pathways, rather than toward score optimization, ordinal comparison, or headline performance metrics.

Structural classes (S / A / B / C) and node typologies (Type I–IV) serve analytically distinct and non-isomorphic purposes within the framework. Structural class captures systemic role and consequences of failure, while typology abstracts recurring configuration patterns across dimensions. No direct mapping, substitution, or hierarchical correspondence between structural class and node typology should be assumed.

Together, these design principles reinforce the governance-oriented character of AI-SNF, ensuring that analytical outputs support risk-aware institutional design and forward-looking regulatory capacity, rather than retrospective evaluation or competitive signaling.

Part V.

Illustrative Example Calculation

13. Purpose and Scope of the Example

This Part presents a fully worked illustrative calculation to demonstrate the operational logic of the AI-Strategic Node Index (AI-SNI), as specified in Parts III and IV and governed by the interpretive discipline of the AI-Strategic Node Framework (AI-SNF). The purpose of this example is methodological exposition, not empirical assessment.

All numerical values used in this Part are synthetic, hypothetical, and internally consistent. They are provided solely for illustrative purposes and must not be interpreted as descriptive of, or evaluative for, any real-world geographic, institutional, or infrastructural node.

The example is designed to make explicit four core aspects of AI-SNF / AI-SNI analytical system:

- Normalization of heterogeneous indicators across dimensions;
- Aggregation of second-level indicators into dimension-level scores (D1–D5);
- Incorporation of risk, fragility, and governance asymmetry into evaluation and interpretation;
- Interpretation of outputs as structural profiles and risk configurations, rather than as ordinal rankings or comparative judgments of strategic value.

By walking through each calculation step in a transparent and traceable manner, this Part clarifies how a bounded composite index output (AI-SNI) translates framework-defined concepts into auditable analytical signals. The worked example illustrates appropriate use of the index for screening, scenario comparison, and institutional risk diagnostics, while explicitly avoiding empirical claims, rankings, or policy evaluation of any real node.

14. Hypothetical Node Description

Node G is a stylized, hypothetical AI-relevant geographic node, constructed to perform high-latitude sensing and forecasting functions within AI-mediated perception and prediction architectures. It is assumed to exhibit high systemic relevance in upstream data acquisition, modeling, and early-warning processes, while maintaining limited local governance capacity and control authority.

The node is intentionally designed to illustrate a core analytical condition targeted by AI-SNF: leverage–control mismatch. In this condition, a node exerts disproportionate influence over sensing, modeling, or downstream decision processes without commensurate authority over rule-setting, auditability, clarity of control rights, or coercive enforcement capacity. Node G is therefore an analytical device, not a proxy, approximation, or representation of any real-world geographic location, jurisdiction, or infrastructure.

Illustrative Assumptions

a) **Evaluation horizon**:

$$T_{total} = 10 \text{ years}$$

a) **Verified observation / evidence window**:

$$T_{observed} = 8 \text{ years}$$

These assumptions motivate AI-SNF's emphasis on coverage sufficiency and evidence-weighted interpretation in subsequent analysis.

For clarity of exposition, all second-level indicator values presented in the following sections are expressed in normalized form. This presentation choice is intended to foreground aggregation logic, dimensional interaction, and interpretive discipline, rather than raw measurement scale or empirical magnitude.

14. Hypothetical Node Description

14.1 Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

Dimension D1 captures the extent to which a node occupies a structurally central position within AI-mediated sensing, perception, and early-warning architectures. Consistent with the specification in Part III, D1 is constructed from five second-level indicators reflecting sensing density, sensing uniqueness, temporal continuity, model readiness, and operational integration.

All second-level indicators are normalized to the **[0,1]** interval prior to aggregation, ensuring comparability across heterogeneous measurement domains and consistency with the baseline normalization discipline.

Table 14.1 D1 Second-Level Indicators and Normalized Scores

Indicator	Description	Normalized score
D1-1 SCD	High-density polar sensing coverage	0.82
D1-2 SUR	Unique high-latitude sensing geometry	0.90
D1-3 DFC	High data-flow continuity with low missing rates	0.85
D1-4 MRDQ	Strong calibration quality and machine-learning usability	0.80
D1-5 OII	Operational integration with allied ISR systems	0.88

A. Dimension-Level Aggregation

Under the v0.1 baseline specification, equal weights are assigned to all five second-level indicators. The dimension-level score for D1 is therefore calculated as the arithmetic mean:

$$D_1 = \frac{0.82 + 0.90 + 0.85 + 0.80 + 0.885}{5} = 0.85$$

This aggregation yields a bounded dimension-level signal representing relative sensing and early-warning centrality within the declared analytical universe.

14. Hypothetical Node Description

B. Interpretive Note

The resulting D1 score indicates that Node G occupies a high-centrality position within AI-mediated sensing and early-warning systems. In accordance with the interpretive discipline of AI-SNF, this score reflects perceptual and informational centrality only.

It does not imply sovereignty, ownership, governance authority, or controllability of the associated sensing infrastructure. Questions of governance alignment, control capacity, and institutional authority are addressed explicitly in Dimension D4 and must not be inferred from D1 magnitude.

Accordingly, D1 should be interpreted as a structural input to risk profiling and structural classification, rather than as an indicator of strategic robustness or policy desirability.

14. Hypothetical Node Description

14.2 Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Dimension D2 evaluates the extent to which a node functions as a structural anchor within predictive models and forecasting architectures, and the degree to which downstream analytical, policy, or operational systems depend on its inputs.

Consistent with AI-SNF design logic, D2 incorporates both leverage-oriented indicators and an explicit risk-conditioning indicator. Leverage captures predictive centrality and dependency intensity, while risk (captured through the manipulation susceptibility component, AMS) conditions interpretation and aggregation rather than redefining predictive leverage itself.

All second-level indicators are normalized to the **[0,1]** interval prior to aggregation.

Table 14.2 D2 Second-Level Indicators and Normalized Scores

Indicator	Description	Normalized score
D2-1 MCAS	Anchor role in climate and circulation models	0.88
D2-2 GSS	Strong global spillover effects	0.86
D2-3 SG	Low substitutability across model architectures	0.84
D2-4 FGC	Embeddedness in policy-relevant forecasting models	0.80
D2-5 AMS	Moderate algorithmic manipulation surface	0.60

A. Dimension-Level Aggregation

To preserve the D2 aggregation discipline established in Part III, predictive leverage is first aggregated across indicators D2-1 to D2-4, and the resulting leverage signal is then discounted by risk, represented by the estimated risk term $\widehat{R_2}$, with sensitivity parameter $\boldsymbol{\gamma_2}$.

Under the illustrative weighting scheme:

$$\boldsymbol{\omega_{D_{2-1}} = \omega_{D_{2-2}} = \omega_{D_{2-3}} = \omega_{D_{2-4}} = 0.25}$$

Assume:

$$\boldsymbol{\widehat{R_2} = 0.6\ ,\ \gamma_2 = 0.30}$$

14. Hypothetical Node Description

The D2 score is therefore computed as:

$$D_2 = 0.25 \times (0.88 + 0.86 + 0.84 + 0.80) \times (1 - 0.30 \times 0.60) \approx 0.58$$

B. Interpretive Note

The resulting D2 score indicates that Node G exhibits high predictive leverage within AI-mediated forecasting and modeling systems, while simultaneously displaying non-trivial vulnerability to manipulation or distortion.

In accordance with AI-SNF interpretive discipline, D2 must not be interpreted in isolation. Predictive centrality does not imply reliability, robustness, or governability. Proper interpretation requires joint consideration with Dimension D4 (Infrastructure–Governance Asymmetry) to avoid conflating predictive leverage with effective oversight, control, or auditability.

Accordingly, D2 functions as a risk-conditioned leverage signal, contributing to the node's overall risk profile and structural classification rather than serving as an independent indicator of strategic stability or policy suitability.

14. Hypothetical Node Description

14.3 Dimension D3: Decision-Loop Temporal Advantage (DLTA)

Dimension D3 captures the extent to which a node provides temporal advantage within AI-mediated decision loops. It reflects contributions to early detection, latency reduction, pipeline criticality, and operational resilience under stress, all of which shape the timing and sequencing of downstream decisions.

Consistent with AI-SNF specification, all second-level indicators are normalized to the **[0,1]** interval prior to aggregation.

Table 14.3 D3 Second-Level Indicators and Normalized Scores

Indicator	Description	Normalized score
D3-1 LA	Moderate latency advantage	0.70
D3-2 EDW	Strong early-detection window	0.85
D3-3 DPC	Critical position within decision chains	0.88
D3-4 RUS	High resilience under stress conditions	0.78

A. Dimension-Level Aggregation

Under the v0.1 baseline specification, equal weights are assigned to all four second-level indicators. The dimension-level score for D3 is therefore calculated as the arithmetic mean:

$$D_3 = \frac{0.70 + 0.85 + 0.88 + 0.78}{4} = 0.80$$

This yields a bounded signal representing relative temporal advantage within the decision loop.

14. Hypothetical Node Description

B. Interpretive Note

The resulting D3 score indicates that Node G confers a meaningful temporal advantage through early detection capabilities and its position within critical decision pipelines.

In accordance with the interpretive discipline of AI-SNF, D3 represents a temporal leverage signal, not a measure of decision authority, control rights, or institutional mandate. Temporal advantage may amplify the influence of upstream information flows, but it does not imply legitimacy, governability, or policy discretion.

Accordingly, D3 must be interpreted in conjunction with other dimensions, particularly governance alignment and control capacity, to assess whether temporal leverage translates into stable or governable strategic influence.

14. Hypothetical Node Description

14.4 Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

Dimension D4 evaluates the degree of alignment between infrastructural leverage and enforceable governance or control authority. It captures whether a node's centrality within AI-mediated infrastructures is matched by effective mechanisms for oversight, rule enforcement, auditability, and control.

For the purposes of this illustrative example, all D4 second-level indicators are directionally aligned to the [0,1] interval, such that higher values indicate stronger governability and lower structural fragility. This orientation is adopted to facilitate transparent aggregation and interpretation within the worked example and does not alter the underlying conceptual distinction between leverage and control emphasized in AI-SNF.

Table 14.4 D4 Second-Level Indicators and Normalized Scores

Indicator	Description	Normalized score
D4-1 LGC	Limited local governance capacity	0.45
D4-2 EDR	High external dependency on upstream actors	0.35
D4-3 RSA	Weak rule-setting autonomy	0.40
D4-4 CRC	Partially auditable control rights	0.50
D4-5 CEI	High exposure to coercive leverage	0.30

A. Dimension-Level Aggregation

For simplicity of exposition in this example, equal weights are applied and the dimension-level score is computed as the arithmetic mean:

$$D_4 = \frac{0.45 + 0.35 + 0.40 + 0.50 + 0.30}{5} = 0.40$$

This produces a bounded signal representing relative governance alignment and control capacity.

14. Hypothetical Node Description

B. Interpretive Note

The resulting D4 score indicates a pronounced governance and control deficit relative to the node's high upstream leverage in sensing, prediction, and temporal advantage (D1–D3). This configuration corresponds to a high-leverage / low-control structural condition.

Identifying such conditions is a central analytical purpose of AI-SNF. D4 does not assess normative governance quality or policy legitimacy; rather, it diagnoses whether existing institutional and control mechanisms are sufficient to govern the leverage generated elsewhere in the system.

Accordingly, low D4 values serve as a risk-conditioning signal, constraining the interpretation of high scores in leverage-oriented dimensions and informing subsequent diagnostic extensions and structural classification.

14. Hypothetical Node Description

14.5 Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

Dimension D5 evaluates a node's latent coupling potential across resources, data flows, and compute infrastructures. It is forward-looking by design and must be interpreted under explicit evidence sufficiency and constraint discounting principles. In this illustrative example, higher opportunity scores indicate stronger coupling potential, while constraint indicators are treated as discounting factors that condition convertibility.

All values are synthetic and expressed on a normalized **[0,1]** scale for methodological illustration.

Table 14.5 D5 Second-Level Indicators and Normalized Scores

Indicator	Description	Normalized score
D5-1 CME	Moderate availability of critical materials	0.70
D5-2 AEEF	Feasibility of AI-enabled extraction and optimization	0.65
D5-3 LCC	Coupling to emerging logistical and data corridors	0.75
D5-4 PCR	High risk of external platform capture	0.40
D5-5 EPC	Significant environmental and regulatory limits	0.45

A. Dimension-Level Aggregation

For illustrative purposes, D5 is computed as the mean of the opportunity indicators, multiplied by a constraint discount term. Let the constraint sensitivity parameter be:

$$\gamma_5 = 0.40$$

Then, compute the dimension-level score as:

$$D_5 = \left(\frac{0.70 + 0.65 + 0.75}{3} \right) \times (1 - 0.40 \times \frac{0.40 + 0.45}{2}) \approx 0.58$$

This produces a bounded signal representing conditional coupling potential, i.e., option space discounted by constraint intensity under the assumed sensitivity parameter.

14. Hypothetical Node Description

B. Interpretive Note

Node G exhibits moderate coupling optionality, supported by material endowment and corridor connectivity. However, platform capture risk and permitting or regulatory constraints reduce the convertibility of this option space into autonomous future leverage.

Consistent with AI-SNF interpretive discipline, D5 should be interpreted jointly with D4 (Infrastructure–Governance Alignment and Control Capacity). Governance asymmetry often conditions whether optionality translates into resilience and locally governable strategic flexibility, or instead amplifies dependency and exposure to external capture.

15. Composite Index and Diagnostic Extensions

15.1 AI-SNI Score

Under the default specification, equal weights are assigned to all five dimensions:

$$\boldsymbol{\alpha_d = 0.2}, \qquad \sum_{d=1}^{5} \boldsymbol{\alpha_d} = 1$$

The authoritative AI-SNI composite score is defined as the linear weighted sum of the five dimension-level scores:

$$\boldsymbol{AI - SNI = \sum_{d=1}^{5} \alpha_d \times D_d}$$

Substituting the dimension scores derived in Sections 14.1–14.5:

$$\boldsymbol{AI - SNI = 0.2 \times (0.85 + 0.69 + 0.80 + 0.40 + 0.58) \approx 0.66}$$

This yields a bounded composite screening signal within the **[0,1]** interval.

15. Composite Index and Diagnostic Extensions

A. Interpretive Note

AI-SNI composite score represents a bounded aggregate indicator of structural strategic centrality within AI-mediated systems. It is designed to support comparative screening and visual representation, rather than to provide inferences regarding governability, institutional robustness, or system resilience.

In this illustrative case, the relatively low value of D4 (Infrastructure–Governance Alignment and Control Capacity) signals a material infrastructure–governance asymmetry. This configuration exemplifies a core analytical insight of AI-SNF: high structural centrality may coexist with elevated systemic fragility.

Accordingly, interpretation of the composite score requires joint consideration of:

- the full dimensional configuration (D1–D5), capturing the distribution of leverage, constraint, and optionality;
- embedded risk and governance signals, particularly those associated with control, auditability, and enforcement capacity; and
- diagnostic extensions and structural class attribution, which surface fragility, weakest-link constraints, and systemic role beyond scalar aggregation.

Use of the composite score in isolation, as a proxy for stability, control, or policy suitability, constitutes a methodological misuse of the AI-Strategic Node Framework (AI-SNF) and falls outside its intended interpretive authority.

15. Composite Index and Diagnostic Extensions

15.2 Diagnostic Extension I (Non-Index): Governance Fragility Adjustment

This diagnostic extension applies a conditional penalty when D4 falls below a governance sufficiency threshold.

A. Parameter Specification

For the illustrative calculation, the following parameters are applied:

Governance sufficiency threshold:

$$\tau = 0.50$$

Penalty strength parameter:

$$\lambda = 0.30$$

Observed governance score:

$$D_4 = 0.40$$

B. Composite Calculation

The diagnostic fragility-adjusted output (AI-SNI*) is computed as:

$$AI - SNI^* = AI - SNI \times [1 - \lambda \cdot \max(0, \tau - D4)]$$

Substituting the illustrative values:

$$AI - SNI^* = 0.66 \times [1 - 0.30 \times (0.50 - 0.40)] \approx 0.64$$

C. Interpretive Note

Centrality remains, but usable leverage is discounted due to governance insufficiency. This operationalizes the principle: centrality without control amplifies systemic risk.

15. Composite Index and Diagnostic Extensions

15.3 Diagnostic Extension II (Non-Index): Short-Board Sensitivity Test

This diagnostic extension applies a geometric mean aggregation to evaluate system coherence under weakest-link constraints. The formulation is designed to surface structural vulnerability arising from near-minimum performance in any single dimension.

This geometric aggregation is employed exclusively as a diagnostic sensitivity test. It does not constitute an alternative AI-SNI index, does not generate an independent composite score, and carries no standalone interpretive authority.

The diagnostic formulation is defined as:

$$AI - SNI_{GM} = \prod_{d=1}^{5} D_d^{\alpha_d}$$

Substituting the dimension scores derived in Sections 14.1–14.5:

$$AI - SNI_{GM} = (0.85 \times 0.69 \times 0.80 \times 0.40 \times 0.58)^{\left(\frac{1}{5}\right)} \approx 0.64$$

This value represents a conditional diagnostic outcome under a non-substitutability assumption.

A. Interpretive Note

The geometric mean highlights a weakest-link constraint within the system configuration. In this illustrative case, the comparatively low value of D4 (Infrastructure–Governance Alignment and Control Capacity) materially constrains overall coherence, even in the presence of strong performance in leverage-oriented dimensions (D1–D3).

Divergence between the geometric diagnostic outcome and the linear composite score is diagnostically informative rather than inconsistent. It signals structural imbalance and governance-sensitive fragility, not measurement error or index instability.

Accordingly, this diagnostic extension should be interpreted as a stress-test lens on system integrity, complementing—but never replacing—the authoritative AI-SNI composite score defined in Section 10.5.1.

16. Classification and Interpretation

16.1 Tier Assignment

For purposes of visualization and high-level screening, AI-SNI composite outputs may be mapped to exposure bands as defined in the Risk Classification Framework.

Using the reference composite score:

$$\boldsymbol{AI - SNI = 0.66 \Rightarrow \quad Tier\ 2\ (High\ Exposure\ Band)}$$

This tier assignment is derived exclusively from the authoritative composite index defined in Section 10.5.1.

Diagnostic extensions yield an adjusted diagnostic value of approximately **0.64**, positioned near the **Tier 2 / Tier 3 boundary** for sensitivity illustration. Such diagnostic outputs may be examined relative to tier thresholds to assess fragility sensitivity and boundary robustness. However, they **do not generate independent tier assignments, do not redefine exposure bands**, and **do not alter the reference tier classification**.

This example illustrates a core interpretive guardrail of AI-SNF: **tier labels carry analytical meaning only when interpreted in conjunction with dimensional profiles (D1–D5), embedded risk signals, and higher-order interpretive layers**. Tier placement alone does not convey priority, robustness, or policy relevance.

16. Classification and Interpretation

16.2 Structural Tagging

Structural tagging translates multidimensional configurations into interpretable archetypes. Unlike tiering, which groups nodes by composite score ranges for screening and visualization, structural tags capture the internal configuration of leverage, constraint, and fragility across dimensions.

Based on the dimensional profile derived in Sections 14–15, Node G exhibits:

- **high values in D1–D3**, indicating concentrated operational and informational centrality; and
- a **low value in D4**, signaling a material governance and control deficit.

Accordingly, **Node G is structurally tagged as a High-Leverage / High-Fragility configuration.**

A. Governance Implication

For nodes exhibiting this configuration, potential stabilization pathways lie primarily in governance reinforcement, rather than in further leverage maximization. Relevant governance responses include:

- **strengthening auditability and oversight mechanisms;**
- **clarifying and enforcing control rights and institutional authority;**
- **reducing asymmetric or non-transparent dependency relationships; and**
- **enhancing institutional capacity and coordination across relevant domains.**

Structural tagging does not prescribe policy action or intervention priority. Instead, it serves as a diagnostic bridge between dimensional analysis and governance-relevant interpretation, helping to identify where institutional attention is likely to be most consequential.

16. Classification and Interpretation

16.3 Structural Class Attribution

Structural class attribution is conducted as an independent, higher-order interpretive judgment, operating above and outside composite scoring, tiering, and structural tagging. It evaluates systemic role and consequences of failure, rather than aggregate magnitude or relative position.

Structural class determination:

S-Class — Structural AI Strategic Node

A. Justification summary:

- **System-constitutive role:** Dimensions D1–D3 jointly shape perception baselines, forecasting calibration environments, and upstream informational conditions upon which multiple downstream systems depend.
- **High cross-dimensional coupling:** D1–D3 reinforce one another in a non-substitutable manner, such that degradation in one dimension cannot be offset by strength in others.
- **Path-dependent governance consequences:** The low value of D4 indicates that early governance and control deficits constrain future corrective capacity, amplifying long-horizon vulnerability.
- **Non-linear failure propagation:** Failure is unlikely to manifest as discrete collapse. Instead, degradation propagates through cumulative erosion mechanisms, including calibration drift, early-warning distortion, and progressive loss of system trust and reliability.

B. Interpretive Clarification:

Designation as S-Class does not imply strength, efficiency, robustness, security, or automatic policy priority. Rather, it signals systemic consequence and governance criticality: a node at which failure effects concentrate and accumulate, even where short-term operational continuity may appear intact.

Structural class cannot be inferred from composite scores, tier placement, or structural tags. It derives solely from independent assessment of non-substitutability, cross-dimensional coupling, and failure-propagation dynamics across relevant temporal horizons.

17. Analytical Value of the Example

This illustrative calculation is intended to demonstrate the operational logic of AI-SNI, rather than to advance any empirical claim or evaluative judgment. By tracing the analytical pathway from indicator normalization, through dimension-level aggregation, reference composite construction, diagnostic extensions, and higher-order interpretation, the example clarifies how AI-SNF/AI-SNI system generates disciplined, governance-relevant diagnostics under conditions of structural complexity and uncertainty.

Three methodological insights follow:

a) **AI-strategic centrality is irreducibly multidimensional.** No single dimension—whether sensing (D1), predictive leverage (D2), or temporal advantage (D3)—can serve as a proxy for overall systemic role or strategic significance.

b) **Governance asymmetry (D4) constitutes a binding constraint on usable leverage.** Structural centrality without commensurate governance and control capacity does not translate into resilience; instead, it amplifies systemic fragility and risk propagation.

c) **Diagnostic extensions complement—rather than compete with—the reference index.** Extension I surfaces sensitivity to governance fragility, while Extension II reveals weakest-link constraints. Neither redefines AI-SNI index; both function as conditional stress-test lenses that enrich interpretation.

Procedures for uncertainty treatment, evidence grading, and confidence propagation, which govern the permissible scope of interpretation, are specified in Appendix A.

Part VI.
International Benchmarks and Node Typologies

18. Purpose of International Benchmarking

International benchmarking within the AI-Strategic Node Framework (AI-SNF; D1–D5) serves a purpose that is analytically distinct from conventional global indices. Rather than ranking countries, jurisdictions, or institutions by aggregate performance, benchmarking under AI-SNF is designed to diagnose structural roles, dependency configurations, and governance-relevant risk patterns within AI-mediated strategic systems (Baldwin, 2016; Castells, 2010; Bratton, 2016).

The bounded composite output, AI-SNI, may support screening and comparative visualization within this process. However, benchmarking in AI-SNF is not reducible to score comparison. Its orientation is explicitly diagnostic rather than evaluative, emphasizing structural interpretation over performance judgment (Power, 2007; Renn, 2008).

Specifically, benchmarking within AI-SNF aims to:

a) **Identify recurring structural patterns** of AI-era leverage, fragility, and coupling across heterogeneous contexts (Beck, 1992; Helbing, 2013; Perrow, 1984);

b) **Compare nodes with similar functional roles** irrespective of sovereignty, population size, or economic scale, thereby decoupling systemic relevance from actor-centric attributes (Castells, 2010; Bratton, 2016);

c) **Expose infrastructure–governance asymmetries and coupling vulnerabilities** that are typically obscured in aggregate or actor-based assessments (North, 1990; Power, 2007; Renn, 2008); and

d) **Support scenario comparison and stress testing**, rather than competitive scorekeeping or reputational comparison (Kahn, 1962; Taleb, 2012).

Benchmarking under AI-SNF is therefore oriented toward a different guiding question: what kind of node this is, how it is embedded within AI-mediated architectures, and what forms of leverage, fragility, and optionality it generates (Castells, 2010; Helbing, 2013; Taleb, 2012). By shifting the unit of comparison from actors to node functions and structural configurations, AI-SNF enables cross-context learning and anticipatory governance analysis without collapsing heterogeneity into a single ordinal hierarchy (Baldwin, 2016; Power, 2007).

19. Benchmarking Principles

International benchmarking within the AI-Strategic Node Framework (AI-SNF) is governed by five core principles. Taken together, these principles define the interpretive discipline and methodological boundaries required for cross-node comparison to remain structural, contextual, and governance-relevant, rather than ordinal, competitive, or evaluative (Power, 2007; Renn, 2008).

19.1 Functional Equivalence over Political Equivalence

Nodes are compared on the basis of their functional role within AI-mediated systems, rather than legal status, sovereignty, or jurisdictional classification (Castells, 2010; Bratton, 2016). The unit of comparison is defined by system function, such as sensing centrality, forecast dependency, decision-loop positioning, governance asymmetry, or coupling potential, rather than by institutional identity or political form (Latour, 2005).

This principle enables meaningful comparison across heterogeneous entities, including territories, facility clusters, infrastructural corridors, and platform-adjacent hubs, without forcing them into actor-centric or state-based categories (Castells, 2010).

19.2 Profile Comparison over Ordinal Ranking

Benchmarking under AI-SNF prioritizes dimensional profiles (D1–D5) over composite score position (Power, 2007; Renn, 2008). While composite scores (AI-SNI) may support initial grouping, visualization, or descriptive mapping, meaningful comparison requires examination of the underlying multidimensional configuration, as nodes with similar aggregate values may exhibit fundamentally different distributions of risk, resilience, and optionality (Perrow, 1984; Taleb, 2012).

Ordinal ranking—if generated at all—must be treated strictly as a representational artifact, not as an interpretive conclusion. Any ordinal representations produced for exploratory or illustrative purposes fall outside the authoritative outputs of AI-SNF and carry no interpretive or decision-making status. Profile-based comparison remains the primary analytical basis for diagnosis and inference (Baldwin, 2016; Power, 2007).

19.3 Risk Visibility over Score Optimization

Governance asymmetry, coupling fragility, and weakest-link exposure are treated as first-order analytical outcomes, not secondary by-products of aggregation (Perrow, 1984; Helbing, 2013; Renn, 2008). Benchmarking within AI-SNF is not designed to reward score maximization or performance “optimization,” but to surface where structural risk concentrates, particularly where high leverage coexists with high fragility (Beck, 1992; Power, 2007).

19. Benchmarking Principles

Such configurations are analytically meaningful indicators of misalignment between leverage and control, rather than anomalies or measurement error (North, 1990; Renn, 2008). Accordingly, benchmarking emphasizes risk visibility and constraint transparency, including explicit attention to D4-conditioned governability and other binding structural limits.

19.4 Contextual Interpretation

Similar composite scores or dimensional profiles may correspond to divergent risk trajectories depending on environmental, institutional, technological, and geopolitical context (Renn, 2008; Power, 2007). Benchmarking outputs must therefore be interpreted with explicit contextual reference, rather than treated as context-free abstractions or decontextualized signals (Jasanoff, 2004).

Cross-context comparison within AI-SNF is diagnostic rather than prescriptive. Its purpose is to identify structural similarities and differences across nodes, not to generate universal policy prescriptions detached from situational constraints or institutional capacity (Renn, 2008). Contextual interpretation is thus a necessary condition for responsible use of benchmarking results.

19.5 Cross-Index Compatibility

AI-SNI is designed to be read alongside—rather than in place of— established indices of governance quality, security posture, economic development, and technological readiness (Baldwin, 2016; Power, 2007). It functions as a structural diagnostic overlay, interrogating assumptions embedded in conventional actor-centric indices and revealing vulnerabilities, coupling dependencies, or infrastructure–governance asymmetries that such metrics may not capture (Beck, 1992; Helbing, 2013; North, 1990).

Comparative interpretation should therefore be integrative rather than exclusive. No single composite measure—whether AI-SNI or otherwise—should be treated as definitive without reference to complementary frameworks and contextual analysis. Responsible benchmarking requires triangulation across indices, governance assessments, and situational evidence, consistent with international best practice in risk governance and policy evaluation (OECD, 2019; OECD, 2021; NIST, 2023; Renn, 2008; Power, 2007).

20. Core AI-Strategic Node Typologies

Based on recurring structural patterns across AI-SNF dimensions D1–D5, AI-strategic nodes may be grouped into four ideal-typical configurations. These typologies are heuristic reference models intended to support comparative diagnosis, pattern recognition, and scenario analysis, rather than exhaustive, mutually exclusive, or stable categories.

Nodes may exhibit hybrid characteristics or transition between types as AI architectures, governance arrangements, and coupling dynamics evolve over time. Typologies are designed to clarify how leverage, fragility, governance alignment, and optionality tend to co-occur—and why nodes with similar composite signals may generate divergent governance implications.

Typology attribution implies neither ordinal ranking nor policy prescription. It is analytically distinct from structural class attribution (S / A / B / C), which independently evaluates systemic role and failure consequences. No direct or mechanical mapping between typologies and structural classes should be assumed.

20.1 Type I: Concentrated Leverage with Weak Correction

Signature profile: High D1–D3, Low D4, often coupled with elevated D4 risk vectors and/or D5 convertibility or capture constraints.

A. Definition

Type I nodes exhibit concentrated operational leverage, including perceptual centrality, predictive anchoring, and temporal advantage, while lacking sufficient governance, correction, or control capacity. They are system-relevant but structurally fragile, due to a persistent leverage–control mismatch (North, 1990; Power, 2007; Renn, 2008).

B. Structural Characteristics

- **High D1–D3:** Strong sensing centrality, predictive model dependence, and decision-loop temporal advantage, often positioning the node as an upstream anchor within AI-mediated systems (Castells, 2010; Schelling, 1960).
- **Low D4:** Pronounced infrastructure–governance asymmetry, reflected in limited control rights, weak auditability, constrained rule-setting authority, or insufficient corrective and enforcement capacity (North, 1990; Power, 2007).
- **Elevated dependency exposure:** Structural risk vectors are typically visible through D4-related dependency and coercion risks, and may be reinforced by D5 constraints, such as platform capture, regulatory bottlenecks, or low convertibility of future optionality (Helbing, 2013; Bratton, 2016).

20. Core AI-Strategic Node Typologies

C. Diagnostic Value

Type I nodes are analytically salient because disruption, manipulation, or governance failure at such nodes can generate disproportionate downstream effects across perception–prediction–decision chains, while corrective authority remains weak, contested, or externally constrained (Perrow, 1984; Helbing, 2013). The combination of high leverage and limited correction capacity renders these nodes structurally sensitive under both normal operation and stress conditions.

D. Typical Risk Pathways

Type I configurations are commonly associated with the following risk pathways:

- **Dependency growth outpaces correction capacity:** Strategic reliance on the node expands faster than the development of audit, oversight, and control mechanisms, creating widening leverage–control gaps (Power, 2007; NIST, 2023).
- **Silent capture via dependency channels:** External actors may shape system behavior via platforms, capital, standards, or operational dependencies, without overt disruption or formal control transfer (Bratton, 2016; North, 1990).
- **Crisis-time denial / degradation amplification:** Temporal and perceptual centrality magnifies system-wide effects under stress, increasing the impact of delayed detection, distorted signals, or degraded correction (Kahn, 1962; Perrow, 1984; Weick, 1988).

E. Governance Relevance

Attribution as Type I signals that governance sufficiency, auditability, and correction capacity constitute first-order conditions for system stability. These properties must be explicitly assessed, rather than inferred from indicators of centrality, technical sophistication, or operational importance alone (Renn, 2008; Power, 2007; NIST, 2023).

Governance relevance in this context lies not in leverage maximization, but in closing the gap between systemic relevance and effective control.

F. Canonical Typology Illustration

A high-centrality node with leverage–control mismatch.

A Type I AI-strategic node occupies a structurally central position within AI-mediated sensing, forecasting, or time-sensitive decision systems, such that its outputs condition downstream perception and action across multiple domains. Despite this operational leverage, governance authority over data access, system calibration, auditability, and corrective intervention remains fragmented, externally dependent, or institutionally weak.

20. Core AI-Strategic Node Typologies

As a result, the node may appear stable and indispensable under normal operation, yet exhibits latent structural fragility: relatively small governance failures, coercive pressures, or institutional misalignments can propagate disproportionately through tightly coupled systems. The defining characteristic of Type I is therefore not technological weakness, but the absence of effective correction mechanisms commensurate with systemic relevance.

Note: This illustration represents a schematic archetype intended solely for conceptual clarification. It does not describe, correspond to, or imply any specific real-world node.

20.2 Type II: Concentrated Leverage with Institutional Buffering

Signature profile: High D1–D3, High D4, with buffered dependency and coercion exposure

A. Definition

Type II nodes exhibit concentrated AI-mediated leverage across sensing, prediction, and temporal coordination combined with robust institutional buffering and governance capacity. While structural centrality remains high, leverage is largely governable and correctable under stress, reducing the likelihood that disruptions propagate uncontrollably through coupled systems (Renn, 2008; Power, 2007).

B. Structural Characteristics

- **High D1–D3:** Sustained relevance across perception, predictive anchoring, and decision-loop timing, positioning the node as a central but monitored component within AI-mediated architectures (Castells, 2010; Schelling, 1960).
- **High D4:** Sufficient governance and control capacity to support rule-setting, auditability, enforcement, and corrective intervention, including credible escalation and remediation pathways (North, 1990; NIST, 2023).
- **Buffered dependency exposure:** Compared to Type I, Type II nodes exhibit clearer control rights, lower exposure to coercive override, and more effective mechanisms for managing dependency, capture risk, and external influence (North, 1990; Power, 2007).

C. Diagnostic Value

Type II configurations represent managed centrality. Institutional buffering reduces the probability that node-level failures or manipulations propagate system-wide, even where coupling remains tight. Diagnostic significance lies in the alignment between leverage and governability, rather than in leverage magnitude alone (Perrow, 1984; Helbing, 2013).

20. Core AI-Strategic Node Typologies

D. Typical Risk Pathways

Despite stronger governance alignment, Type II nodes remain exposed to characteristic risk pathways:

- **Complacency under prolonged stability:** Governance sufficiency may be assumed rather than actively maintained, audited, and stress-tested, allowing latent vulnerabilities to accumulate (Power, 2007).
- **Underinvestment in redundancy and fail-safes:** Budgetary, political, or institutional constraints may limit investment in backup systems, leading to fragile resilience despite apparently high D4 values (Taleb, 2012; Perrow, 1984).
- **Lagged adaptation to shifting dependencies:** New coupling channels, particularly platform, data, or standards-based dependencies, may emerge faster than institutional updates or regulatory adaptation (North, 1990; Bratton, 2016).

E. Governance Relevance

Attribution as Type II does not imply the absence of risk. Rather, it indicates that relative stability is contingent upon continuous institutional maintenance, including sustained audit discipline, enforcement capacity, and adaptive governance in response to evolving dependency structures. Governance sufficiency should therefore be treated as dynamic and revisable, not as a static property guaranteed by current D4 conditions alone (Renn, 2008; Power, 2007).

F. Canonical Typology Illustration

A governable central node under sustained institutional alignment.

A Type II AI-strategic node combines high AI-mediated centrality with robust institutional buffering. It plays a decisive role in perception, prediction, or decision-loop timing, while operating under governance arrangements that provide clear control rights, auditability, and effective corrective capacity.

Under these conditions, disruptions or anomalies are more likely to be detected, contained, and mitigated locally before cascading across tightly coupled systems. Type II nodes therefore exemplify managed centrality: leverage is present, but it is institutionally bounded rather than structurally exposed.

However, this stability is conditional rather than permanent. It depends on continuous governance upkeep, adaptive regulation, and sustained vigilance against emerging dependency channels and novel forms of capture or coupling.

Note: This illustration represents a schematic archetype intended solely for conceptual clarification. It does not describe, correspond to, or imply any specific real-world node.

20. Core AI-Strategic Node Typologies

20.3 Type III: Diffuse Leverage with Participation Skew

Signature profile: Moderate D1–D3, Variable D4, often conditioned by network topology and external rule-setting environments.

A. Definition

Type III nodes exhibit diffuse, non-chokepoint leverage. Their strategic relevance arises primarily through aggregation, participation, and network effects, rather than through singular control over sensing, prediction, or decision-loop timing. Influence is therefore relational and conditional, embedded within broader architectures rather than concentrated at a decisive node (Castells, 2010; Helbing, 2013).

B. Structural Characteristics

- **Moderate D1–D3:** Contributions to sensing, predictive inputs, or temporal coordination are distributed across multiple systems, typically as enabling or complementary components rather than as primary anchors (Castells, 2010).
- **Secondary or supporting integration:** Type III nodes are commonly integrated as supporting, relay, or auxiliary elements within AI-mediated architectures, with limited standalone leverage (Bratton, 2016).
- **Network-conditioned governability (Variable D4):** Governance and control capacity is highly sensitive to external rule-setting environments, including standards regimes, platform governance, and jurisdictional constraints. Alignment conditions, rather than internal authority alone, shape effective governability (North, 1990; Jasanoff, 2004).

C. Diagnostic Value

Type III nodes are unlikely to generate acute systemic shocks in isolation. Their diagnostic significance lies instead in collective and cumulative effects. System behavior may shift materially through coordinated exclusion, network reconfiguration, or gradual degradation across multiple Type III nodes, even where no single node appears critical on its own (Helbing, 2013; Perrow, 1984).

D. Typical Risk Pathways

Common risk pathways associated with Type III configurations include:

- **Incremental displacement:** Architectural evolution toward tighter coupling or higher concentration may gradually reduce the relevance of Type III nodes, even as overall system performance improves (Castells, 2010; Bratton, 2016).

20. Core AI-Strategic Node Typologies

- **Silent marginalization:** Connectivity may persist, but influence over standards, calibration baselines, or long-term evolution trajectories declines, reducing strategic voice without overt exclusion (Shiller, 2017).
- **Path-dependent lock-in:** External governance regimes, dominant standards, or platform dependencies constrain adaptive capacity and future optionality, limiting strategic maneuverability over time (North, 1990).

E. Governance Relevance

Attribution as Type III directs governance attention toward participation trajectories, dependency alignment, and long-horizon optionality, rather than short-term movements in composite scores or tier position (Renn, 2008; Taleb, 2012). The primary diagnostic question is whether the node's role is becoming structurally substitutable, strategically peripheral, or alternatively poised for reactivation through new coupling pathways.

Governance relevance therefore lies in monitoring how network position evolves over time, rather than in optimizing present-day centrality or leverage indicators.

F. Canonical Typology Illustration

A node whose relevance arises from aggregation rather than chokepoint control.

A Type III AI-strategic node does not function as a decisive chokepoint within AI-mediated systems. Instead, its relevance derives from participation in distributed architectures, contributing data, processing capacity, or enabling functions alongside a plurality of comparable nodes.

Individually, degradation or disruption of a single Type III node is unlikely to generate acute systemic shock. Collectively, however, coordinated exclusion, gradual marginalization, or cumulative degradation across multiple Type III nodes can materially reshape system behavior and resilience.

Governance outcomes for Type III nodes are frequently externally conditioned, shaped by standards regimes, platform governance, and network rules rather than by local control alone. Accordingly, their strategic risk profile is characterized less by sudden failure than by long-term displacement, loss of influence, or path-dependent lock-in.

Note: This illustration represents a schematic archetype intended solely for conceptual clarification. It does not describe, correspond to, or imply any specific real-world node.

20. Core AI-Strategic Node Typologies

20.4 Type IV: Peripheral or Latent Nodes

Signature profile: Low D1–D3, Variable D5, with relevance conditional on future coupling and activation pathways.

A. Definition

Type IV nodes exhibit low present-day influence across AI-mediated sensing, predictive leverage, and decision-loop temporal advantage (low D1–D3). Their strategic relevance, where present, derives from variable coupling or option potential (D5), indicating the possibility of future activation pathways under specific technological, infrastructural, regulatory, or geopolitical conditions (Taleb, 2012).

At present, such nodes are weakly or indirectly integrated into core AI decision and governance architectures, and do not function as operational anchors or chokepoints (Castells, 2010).

B. Diagnostic Value

Type IV configurations function primarily as option spaces rather than immediate leverage points. Their diagnostic value lies in identifying where future strategic relevance could emerge, not in assessing current systemic impact.

Interpretation must therefore focus on coupling pathway formation, constraint relaxation, and convertibility conditions, rather than on present operational dominance or composite score magnitude (Taleb, 2012).

C. Typical Risk Pathways

Common analytical and governance risks associated with Type IV nodes include:

- **Premature securitization:** Latent or speculative potential is misinterpreted as imminent threat, leading to distorted risk perception and disproportionate governance response (Kahn, 1962).
- **Speculative overvaluation:** Future leverage is assumed without evidence of feasible coupling pathways, institutional readiness, or conversion capacity, inflating strategic expectations beyond structural reality (Taleb, 2012).
- **Governance misallocation:** Attention and resources are diverted away from nodes exhibiting immediate systemic relevance or binding governance asymmetry, weakening overall risk management (Power, 2007; Renn, 2008).

20. Core AI-Strategic Node Typologies

D. Governance Relevance

Attribution as Type IV supports calibrated monitoring rather than immediate intervention. The primary governance task is to track whether and under what conditions, coupling feasibility, corridor connectivity, platform constraints, standards regimes, and permitting environments evolve in ways that could activate future centrality.

Type IV attribution therefore functions as a guardrail against both neglect and overreaction: it resists converting speculative optionality into present-day centrality claims, while preserving situational awareness of emerging pathways that may warrant future reassessment (Taleb, 2012; Power, 2007).

E. Canonical Typology Illustration

Low present centrality with future-conditional relevance.

A Type IV AI-strategic node exhibits limited current integration into AI-mediated sensing, prediction, or decision systems. Its present-day leverage is low, and it does not materially condition system behavior or downstream outcomes.

However, such nodes retain latent optionality. Under conditions of technological evolution, infrastructure expansion, regulatory change, or geopolitical realignment, a Type IV node may become relevant as a future coupling site for resources, data, or compute. Its strategic significance is therefore conditional and prospective, rather than immediate or realized.

Type IV nodes function primarily as option spaces rather than active strategic levers. The principal analytical challenge they pose is not acute systemic risk, but interpretive error—either the premature securitization of unrealized potential, or the neglect of early trajectory signals that may indicate future activation pathways.

Note: This illustration represents a schematic archetype intended solely for conceptual clarification. It does not describe, correspond to, or imply any specific real-world node.

20.5 Typology Assignment Overview

AI-strategic node typologies (Type I–IV) are assigned through a structured, non-mechanical diagnostic protocol operating at the level of dimensional profiles (D1–D5). Typology attribution is heuristic rather than algorithmic and does not derive from composite scores, exposure tiers, threshold proximity, or structural class assignment.

Typologies summarize recurring configurations of leverage, governance alignment, and optionality. They do not measure magnitude, imply ordinal ranking, prescribe policy action, or substitute for higher-order interpretive layers.

21. Interpreting National and Regional Profiles

The authoritative typology assignment protocol, including diagnostic steps, mapping logic, documentation standards, and interpretive guardrails, is specified in Appendix B. All typology attributions must conform to that appendix to be considered methodologically valid within the AI-Strategic Node Framework.

A. Portfolio-Based Interpretation

AI-SNI is not designed to assign singular typological labels or composite judgments to countries or regions. Most jurisdictions host multiple AI-strategic nodes of different typologies, embedded in distinct functional roles, governance regimes, and infrastructural contexts (Castells, 2010; Baldwin, 2016).

Accordingly, a mature AI-SNI assessment yields:

a node portfolio, rather than a unitary country- or region-level score; and

a structured distribution of leverage, fragility, and optionality, rather than a singular strategic verdict (Power, 2007; Renn, 2008).

This portfolio-based interpretation directly addresses a core limitation of actor-centric indices: their tendency to collapse heterogeneous infrastructures, institutions, and dependency relations into a single aggregate signal (Castells, 2010).

By contrast, AI-SNF preserves internal differentiation, enabling analysts to identify within the same jurisdiction: highly central but institutionally buffered nodes alongside fragile leverage points with pronounced governance asymmetry; and legacy infrastructures with declining relevance alongside emergent nodes functioning as future option spaces (North, 1990; Helbing, 2013).

B. Interpretive Implication

Interpretation therefore shifts from national ranking to portfolio composition. The analytical focus is not how a country or region “performs” overall, but how different node types coexist, interact, and condition systemic stability within and across jurisdictions.

This perspective supports governance design in functionally diversified and institutionally layered environments, where risk, control, and strategic consequence are unevenly distributed and cannot be inferred from aggregate national indicators alone (Renn, 2008; Power, 2007).

22. Relationship to Existing Global Indices

AI-SNI benchmarking is explicitly designed to complement rather than compete with existing global indices by addressing an analytical question that lies outside the scope of conventional assessment frameworks (Baldwin, 2016; Power, 2007). Its contribution is not an incremental refinement of established metrics, but orthogonal diagnostic coverage focused on structural exposure and governability within AI-mediated systems.

Most established global indices are organized around actor-centric performance questions, including:

- **Governance indices,** assessing the capability, effectiveness, and accountability of public institutions and regulatory systems (North, 1990);
- **Competitiveness and innovation indices,** evaluating productivity, adaptability, and technological advancement within economies or innovation ecosystems (Castells, 2010);
- **Security and defense indices,** measuring deterrence capacity, defensive posture, or force-projection capabilities (Schelling, 1960).

By contrast, AI-SNI poses a structurally distinct diagnostic question:

Where does AI-mediated system dependence concentrate, and to what extent is that dependence governable?

This reframing shifts analysis away from aggregate capacity or performance toward structural exposure, leverage concentration, and control asymmetry—dimensions that are frequently invisible to actor-level indices, yet decisive for systemic stability under conditions of AI-enabled coupling and tight interdependence (Beck, 1992; Perrow, 1984; Renn, 2008).

In this respect, AI-SNI is conceptually aligned with risk-oriented governance approaches, most notably the European Union’s Artificial Intelligence Act, which classifies AI systems according to risk exposure and governance obligations, rather than technological sophistication or economic competitiveness alone (European Commission, 2021). AI-SNI similarly foregrounds structural risk, auditability, and governance alignment, while remaining analytically diagnostic and non-prescriptive with respect to regulatory enforcement or legal compliance.

When used in combination, AI-SNI and conventional indices enable cross-diagnostic validation rather than substitution. AI-SNI functions as a stress-testing overlay, interrogating the implicit stability assumptions embedded in high aggregate scores. In particular, it helps identify false reassurance zones—contexts in which strong governance, development, or innovation indicators coexist with highly central yet weakly governed AI-strategic nodes, whose disruption, capture, or misalignment could generate disproportionate systemic effects (Helbing, 2013; Power, 2007; North, 1990).

23. Use in Comparative and Policy Analysis

AI-SNI benchmarking and typologies are designed to support comparative analysis and governance-facing diagnostics across heterogeneous geopolitical, institutional, and infrastructural environments. Their analytical value lies not in generating policy prescriptions, but in translating structural configurations into governance-relevant questions and scenario-ready interpretations under conditions of uncertainty (Renn, 2008; Power, 2007; NIST, 2023).

Rather than collapsing comparison into ordinal rankings or aggregate performance judgments, AI-SNI enables structural comparison: the systematic examination of how leverage, fragility, governance alignment, and optionality co-occur across nodes and contexts. Within this scope, AI-SNI supports several categories of analytical and policy-relevant use:

- **System stress-testing:** Identifying AI-strategic nodes whose disruption, degradation, or manipulation would generate disproportionate spillover effects across sensing, early-warning, forecasting, or decision-support architectures, even where aggregate system performance appears stable (Helbing, 2013; Perrow, 1984).
- **Governance gap diagnosis:** Clarifying where high operational leverage is insufficiently matched by auditability, control-rights clarity, institutional authority, or corrective capacity, and where such deficits constitute binding constraints on system stability (North, 1990; Power, 2007; NIST, 2023).
- **Cross-jurisdictional coordination analysis:** Identifying nodes whose strategic relevance transcends national or institutional boundaries, thereby requiring cooperative governance arrangements, shared oversight mechanisms, or coordination protocols that cannot be supplied by any single actor (Castells, 2010; Bratton, 2016).
- **Resilience and redundancy design:** Informing diversification, redundancy, and failover strategies in tightly coupled AI-mediated systems, particularly where weakest-link dynamics imply that localized failure can propagate system-wide (Perrow, 1984; Taleb, 2012).
- **Risk-aware infrastructure and system design:** Supporting decisions on architecture configuration, institutional embedding, and governance safeguards without reducing analysis to competitive ranking, optimization, or reputational comparison (Renn, 2008; Power, 2007).

Crucially, AI-SNI is oriented toward preventive governance rather than reactive response. By surfacing latent fragilities, leverage–control mismatches, and asymmetric dependencies before they are activated under crisis conditions, AI-SNI enables anticipatory institutional calibration, targeted oversight enhancement, and cooperative risk reduction across interconnected AI-mediated systems (Beck, 1992; Renn, 2008; Power, 2007).

In this role, AI-SNI does not prescribe policy outcomes or prioritize interventions. Instead, it structures the diagnostic space within which proportionate, accountable, and context-sensitive governance responses can be developed—grounded in structural risk visibility rather than post hoc attribution or crisis-driven escalation.

Part VII.
Data Sources and References

24. Data Sources

Data sourcing within AI-SNF is designed to support structural diagnosis, interpretive assessment, and governance-oriented analysis, rather than score maximization, statistical optimization, or ordinal ranking.

Unlike conventional indices that rely primarily on standardized national statistics, AI-SNF operates under heterogeneous, uneven, and partially observable data conditions. It draws on multi-source, mixed-structure evidence reflecting the infrastructural, algorithmic, and institutional characteristics of AI-strategic nodes embedded in AI-mediated systems.

Given the distributed, transnational, and often non-sovereign nature of many AI-strategic nodes, no single data category is sufficient. AI-SNF therefore integrates diverse forms of evidence, including technical observations, institutional documentation, and analytically assessed indicators, to capture structural centrality, governance alignment, and future coupling potential across dimensions.

To preserve analytical integrity and interpretive transparency, data sources are organized by analytical dimension (D1–D5) and explicitly differentiated by evidentiary function, including:

- **Observational evidence**, such as sensing coverage, latency characteristics, infrastructure capacity, connectivity, operational continuity, and system integration indicators;
- **Institutional and governance documentation**, including regulatory frameworks, control-rights allocation, ownership and custodianship structures, audit and oversight mechanisms, contractual arrangements, and formal coordination or escalation protocols;
- **Assessed or derived indicators**, produced through structured expert evaluation, model-based inference, or analytically constrained estimation where direct observation is unavailable, incomplete, or conceptually inappropriate.

This layered evidentiary architecture enables AI-SNF to remain analytically robust across domains with varying data availability, while maintaining explicit documentation of data provenance, evidentiary limits, and confidence levels. It also supports transparency in cross-node comparison by making clear which dimensions rely primarily on direct observation and which depend on interpretive or inferential inputs.

AI-SNI, as a composite diagnostic output within AI-SNF, inherits these evidentiary foundations but does not define them. Data sources support the framework as a whole; index construction represents only one bounded analytical use of that evidence. Accordingly, evidentiary sufficiency, uncertainty treatment, and confidence assessment apply to AI-SNF system-wide and cannot be inferred solely from index outputs.

24. Data Sources

24.1 Dimension D1: Algorithmic Sensing and Early-Warning Centrality (ASEWC)

Dimension D1 evaluates the degree to which a node contributes to algorithmic sensing coverage and early-warning capacity within AI-mediated systems. Given the infrastructural, distributed, and frequently security-sensitive nature of sensing assets, D1 relies on multi-source triangulation rather than any single authoritative dataset.

D1 does not measure sensor quantity in isolation. Its analytical focus is effective sensing centrality: the extent to which a node's sensing assets materially shape perception completeness, detection timing, and early-warning reliability across tightly coupled analytical, forecasting, or decision-support systems.

Accordingly, D1 captures structural contribution to perception architectures, rather than ownership, sovereignty, or local control capacity (which are assessed separately under D4).

A. Primary Data Sources

Primary evidence for D1 includes, but is not limited to:

- **Publicly documented sensing installations and coverage representations**, including radar sites, satellite ground stations, space situational awareness facilities, and associated coverage maps or footprint disclosures;
- **International or alliance-level ISR integration disclosures**, such as joint early-warning arrangements, interoperability frameworks, data-sharing protocols, or cooperative sensing architectures;
- **Remote sensing and Earth-observation metadata repositories**, describing sensor type, revisit frequency, spatial resolution, coverage geometry, and continuity characteristics;
- **Academic and technical literature** on sensor networks, detection geometry, coverage modeling, and early-warning architectures, including civilian, dual-use, and publicly analyzable systems.

These sources are used to assess not merely asset presence, but systemic relevance, integration depth, redundancy structure, and contribution to early-warning reliability within broader AI-mediated architectures.

B. Acceptable Evidence Forms

Acceptable evidence for D1 assessment includes:

- Official infrastructure disclosures or government-published facility descriptions, where available and verifiable;
- Peer-reviewed geospatial, systems, or network-analysis studies, including coverage simulations, detection-latency analyses, and topology-level assessments;

24. Data Sources

- Verified technical specifications and corroborated operational descriptions from reputable technical, academic, or institutional sources.

Where direct observation or disclosure is incomplete, derived or inferred estimates may be employed. Such estimates must be analytically constrained and accompanied by explicit documentation of:

- underlying assumptions,
- modeling or inference methods,
- uncertainty bounds and confidence implications.

Use of derived estimates does not substitute for evidence; it conditions interpretation and is reflected in confidence grading and downstream analytical constraints.

24.2 Dimension D2: Predictive Model Leverage and Dependency (PMLD)

Dimension D2 evaluates the extent to which a node exerts structural leverage within predictive modeling systems, or is embedded as a critical dependency in forecasting architectures whose outputs materially condition downstream decision-making across policy, operational, economic, environmental, or strategic domains.

D2 does not assess predictive accuracy, forecasting skill, or model validity in a technical sense. Its analytical focus is structural influence: the degree to which a node's data, conditions, or system position anchor model calibration, shape parameter sensitivity, or induce institutional reliance on model outputs in consequential decision contexts.

Accordingly, D2 captures predictive centrality and dependency, rather than epistemic correctness, scientific merit, or governance quality of modeling institutions (the latter addressed under D4).

A. Primary Data Sources

Primary evidence for D2 includes, but is not limited to:

- **Documentation of calibration inputs and boundary conditions** used in climate, environmental, economic, epidemiological, security, or risk-forecasting models, including region-specific datasets, baseline assumptions, and initialization parameters;
- **Policy, regulatory, or institutional references** indicating reliance on specific predictive outputs for planning, allocation, compliance, or strategic decision-making;
- **Scientific and technical literature** identifying high-sensitivity parameters, bottleneck variables, or regions whose perturbation materially affects model outputs or forecast trajectories;

24. Data Sources

- **Model Intercomparison Project (MIP) documentation**, ensemble studies, or sensitivity analyses revealing differential dependence on specific data inputs, geographies, or system components.

These sources are used to assess leverage position within modeling ecosystems, not to adjudicate the correctness or desirability of model conclusions.

B. Acceptable Evidence Forms

Acceptable evidence for D2 assessment includes:

- Model documentation, technical appendices, or supplementary materials detailing input datasets, calibration logic, and sensitivity or robustness analyses;
- Policy impact assessments, regulatory analyses, or strategic planning documents explicitly referencing predictive model outputs as decision inputs;
- Peer-reviewed modeling studies, ensemble comparisons, and validated technical reports demonstrating structural dependence or leverage effects.

Where direct attribution between a node and downstream predictive reliance is infeasible, structured analytical inference may be applied. Such inference must be explicitly documented, including:

- assumptions regarding model architecture or dependency pathways;
- justification for inferred leverage or sensitivity;
- uncertainty characterization and confidence implications.

As with other dimensions, inferred evidence does not substitute for observation; it conditions interpretation and propagates into confidence assessment and downstream analytical constraints.

24.3 Dimension D3: Decision-Loop Temporal Advantage (DLTA)

Dimension D3 evaluates whether and to what extent a node confers temporal advantage within AI-mediated decision loops. This includes reductions in sensing-to-decision latency, preferential positioning within time-critical processing pipelines, continuity of function under stress, and the ability to preserve decision relevance when systems are degraded or contested.

Temporal advantage is treated as a systemic property, not an institutional prerogative. It arises from the interaction of transmission infrastructure, data processing architectures, procedural integration, and resilience mechanisms, rather than from formal decision authority, command hierarchy, or political control (which are addressed under D4).

Accordingly, D3 captures when a node enables earlier, faster, or more persistent decision-relevant signals, not who decides, what decisions are taken, or whether those decisions are normatively justified.

24. Data Sources

A. Primary Data Sources

Primary evidence for D3 includes:

- **Technical assessments of data latency, throughput, and transmission architecture**, including network topology, processing pipelines, and edge–core integration affecting time-to-insight;
- **Documented early-warning and decision timelines** in policy, defense, emergency management, or critical-infrastructure literature, including detection-to-response sequencing and alert escalation protocols;
- **Infrastructure resilience and stress-response studies**, examining system performance under disruption, congestion, denial, or partial failure conditions;
- **Redundancy, failover, and continuity documentation**, detailing backup pathways, parallel processing, or degraded-mode operation that preserve temporal relevance under stress.

These sources are used to assess relative temporal positioning within decision loops, not institutional authority or decision legitimacy.

B. Acceptable Evidence Forms

Acceptable evidence for D3 assessment includes:

- Technical audits, performance benchmarks, and systems-engineering documentation addressing latency, throughput, and continuity characteristics;
- Declassified or publicly available operational descriptions of early-warning, alerting, or time-sensitive decision processes;
- Peer-reviewed systems analyses, resilience studies, and network-performance evaluations.

Where direct measurement of latency or decision-loop positioning is constrained by classification, proprietary limits, or system opacity, bounded analytical estimates may be employed. Such estimates must include:

- explicit statement of assumptions;
- identification of proxy indicators used;
- uncertainty annotation and implications for confidence grading.

As with other dimensions, inferred or estimated evidence conditions interpretation rather than substituting for observation, and must propagate transparently into confidence assessment and downstream analytical constraints.

24. Data Sources

24.4 Dimension D4: Infrastructure–Governance Asymmetry and Control (IGAC)

Dimension D4 evaluates the alignment—or asymmetry—between infrastructural centrality and effective governance authority over AI-strategic nodes. It assesses whether the entities that host, rely upon, or are structurally exposed to critical AI-mediated infrastructures also possess enforceable legal, regulatory, and institutional control sufficient to audit, correct, constrain, or intervene in their operation.

D4 does not measure normative legitimacy, political intent, or formal jurisdiction in isolation. Its analytical focus is effective governability under operational and stress conditions—that is, whether control rights are clear, enforceable, and usable when corrective action is required.

Within AI-SNF, D4 functions as a binding governance constraint: high infrastructural leverage without commensurate governance authority is treated as a first-order source of systemic fragility rather than a secondary risk modifier.

Accordingly, D4 is designated a governance-critical dimension and is subject to the most stringent evidentiary and confidence requirements in the framework.

A. Primary Data Sources

Primary evidence for D4 includes legally and institutionally authoritative materials that establish who can intervene, how, and under what conditions, including:

- **Statutory and regulatory frameworks** governing data control, AI deployment, critical infrastructure oversight, national security review, and emergency powers;
- **Contracts, concessions, licenses, and procurement records** specifying ownership, operational responsibility, audit access, termination rights, and corrective authority;
- **Ownership, control, and operational disclosures**, including public–private arrangements, foreign participation, beneficial ownership structures, and delegated management;
- **Regulatory mandates and oversight instruments**, including inspection powers, audit regimes, sanctioning authority, and escalation mechanisms;
- **International agreements and legal instruments** affecting access rights, interoperability obligations, dispute resolution, jurisdictional override, or coordinated intervention.

These sources are used to assess effective control pathways, not merely formal affiliation or political alignment.

24. Data Sources

B. Acceptable Evidence Forms

Acceptable evidence for D4 assessment is restricted to materials that establish binding authority or enforceable governance capacity, including:

- Codified law, regulations, and legally binding policy instruments;
- Official contracts, licenses, or concession agreements;
- Authoritative institutional reports issued by regulators, courts, or oversight bodies;
- Formal international agreements or treaty-level arrangements.

Secondary reporting, expert commentary, or media analysis may not be used as primary evidence. Such sources may serve only as contextual support and must not substitute for binding documentation.

C. Evidentiary Standard and Confidence Annotation

Because governance capacity is frequently opaque, fragmented, or strategically obscured, D4 applies a conservative evidentiary discipline:

- Where documentation of control rights, enforcement authority, or corrective capacity is incomplete, indirect, or inaccessible, confidence levels must be explicitly downgraded;
- Inferred or assumed governance capacity, including de facto influence, informal coordination, or political leverage, must be clearly distinguished from verified legal or institutional control;
- Absence of evidence must not be interpreted as evidence of governance sufficiency. Unverifiable control defaults to lower governability confidence.

All D4 scores must therefore be accompanied by explicit confidence annotation indicating whether governance alignment is directly documented, partially documented with bounded inference, or weakly evidenced and highly uncertain.

This conservative treatment reflects a core AI-SNF principle: apparent stability without demonstrable control is analytically fragile.

24. Data Sources

24.5 Dimension D5: Resource–Data–Compute Coupling Potential (RDCCP)

Dimension D5 evaluates future-conditional strategic relevance arising from the potential coupling of physical resources, data generation capacity, and computational infrastructure within AI-mediated systems. Unlike dimensions that capture present operational centrality (D1–D3) or governability (D4), D5 is explicitly forward-looking. It measures optionality and trajectory, not realized dominance, current control, or guaranteed strategic leverage.

D5 addresses whether a node could become strategically consequential if and only if multiple coupling conditions materialize—technological feasibility, infrastructural integration, regulatory clearance, platform access, and institutional alignment. High D5 values therefore indicate latent leverage pathways, not current systemic influence.

Within AI-SNF, D5 must always be interpreted under evidence gating and constraint discounting. Optionality that is structurally blocked, institutionally captured, or legally non-convertible does not constitute usable strategic leverage.

A. Primary Data Sources

Primary evidence for D5 focuses on feasible coupling pathways rather than speculative advantage and includes:

- **Geological, energy, and critical-material assessments**, including resource quality, extractability, and proximity to processing or transport corridors;
- **Infrastructure and logistics planning documents**, such as grid expansion plans, fiber corridors, port or hub development, and compute-adjacent facility proposals;
- **Environmental permitting and regulatory filings**, including approval status, conditional constraints, compliance timelines, and litigation exposure;
- **Technology feasibility and integration studies**, addressing scalability, interoperability, latency constraints, and cost thresholds for data–compute coupling;
- **Platform and service-layer market analyses**, identifying access conditions, capture risk, dependency structures, and barriers to autonomous deployment.

These sources are used to evaluate whether coupling is plausibly actionable, not merely theoretically conceivable.

B. Acceptable Evidence Forms

Acceptable evidence for D5 includes:

- Official governmental or intergovernmental reports and planning documents;
- Industry feasibility studies with transparent assumptions and timelines;

24. Data Sources

- Environmental impact statements and permitting records;
- Peer-reviewed technical and systems literature;
- Verified infrastructure development disclosures.

Speculative projections, promotional materials, or scenario narratives must be explicitly identified as such and must not be scored as realized capacity. Where forward projections are used, their dependence on contingent approvals, investment decisions, or external actors must be clearly documented.

C. Constraint Treatment and Convertibility Assessment

D5 explicitly incorporates constraint awareness. High nominal coupling potential must be discounted where one or more of the following apply:

- Regulatory or permitting uncertainty that materially delays or conditions activation;
- Platform capture or dependency that limits autonomous control over data or compute;
- Institutional or ownership arrangements that externalize decision authority;
- Environmental, social, or geopolitical constraints that reduce feasibility or stability.

Accordingly, D5 scores reflect convertible optionality, not raw opportunity. Latent potential that cannot plausibly be converted into controlled leverage within the evaluation horizon must be scored conservatively.

D. Evidentiary Standard and Confidence Annotation

Because D5 concerns future-conditional trajectories, all assessments must include explicit confidence annotation, distinguishing between:

- **Documented coupling pathways** with verified feasibility and bounded uncertainty;
- **Partially evidenced pathways** relying on stated assumptions or conditional approvals;
- **Speculative pathways** lacking institutional, regulatory, or infrastructural grounding.

Uncertainty must be treated as an analytical signal, not as noise. High D5 scores with low confidence require cautious interpretation and must not be treated as indicators of imminent strategic relevance.

Within AI-SNF, D5 therefore functions as an option-space indicator: it highlights where future leverage could emerge, while simultaneously foregrounding the constraints that determine whether optionality becomes resilience, dependency, or unrealized potential.

25. Data Availability and Treatment Notes

This section specifies the operational rules governing the treatment of heterogeneous, incomplete, or uneven data within AI-SNF. These rules apply prior to any index construction, normalization, or aggregation and are designed to preserve interpretive discipline, analytical integrity, and governance relevance under conditions of uncertainty.

AI-SNI inherits these rules as a downstream analytical output. Data treatment decisions are therefore framework-governed rather than index-driven and apply uniformly across all dimensions (D1–D5). No index-level procedure may override or relax these framework-level evidentiary rules.

25.1 Missing Data Handling

AI-SNF applies conservative, explicit, and auditable procedures for incomplete data in order to avoid artificial precision, concealed assumptions, or confidence inflation.

- **Single-indicator gaps:** Where an isolated second-level indicator value is missing, bounded imputation may be applied using the median value of functionally comparable nodes within the same analytical context and observation window. All such cases must be explicitly flagged as Imputed, documented in the methodological annex, and reflected in the node's confidence annotation. Imputation is a transparency-preserving fallback, not a precision-enhancing substitute.
- **Dimension-level gaps (≥ 40%):** Where missing or imputed indicators account for 40% or more of a dimension's total indicator weight, that dimension is treated as structurally under-observed. In such cases, the effective contribution of that dimension to any composite representation (including AI-SNI) is reduced by default (e.g., by 50%, unless otherwise justified); the node's overall confidence profile is downgraded accordingly; and all composite outputs must explicitly disclose the adjustment and its rationale. This rule prevents partial observation from being misinterpreted as full structural assessment.
- **Systematic opacity:** Where governance-, ownership-, or control-related data are persistently unavailable, particularly under Dimension D4 (Infrastructure–Governance Asymmetry and Control), the node is flagged as High-Uncertainty, regardless of apparent centrality, leverage indicators, or composite magnitude. Systematic opacity is treated as an analytical condition, not a neutral absence of information, and constrains permissible interpretation.

25.2 Extreme Value Treatment

To prevent analytical distortion arising from extreme observations, AI-SNF applies explicit and conservative outlier treatment rules across all quantitative indicators prior to normalization or aggregation.

25. Data Availability and Treatment Notes

- **Winsorization prior to normalization:** All raw indicator values are subject to 5% / 95% winsorization before normalization. This rule limits the influence of extreme values driven by reporting artifacts, transient spikes, or uneven measurement practices.
- **Structural justification requirement:** Extreme values are not treated as analytically meaningful by default. Retention of extremity beyond winsorized bounds requires documented structural justification, such as non-replicable infrastructural roles, singular governance or control arrangements and demonstrably irreplaceable system functions. Absent such justification, extreme values are treated as potential artifacts of measurement noise, reporting bias, or transient conditions, and are constrained accordingly.

25.3 Auditability and Evidence Grading

To ensure methodological rigor, transparency, and replicability, AI-SNF applies a three-tier evidence confidence grading scheme across all indicators, dimensions, and derived analytical outputs.

Evidence grading reflects the strength, verifiability, and institutional reliability of underlying sources, not the perceived importance of the node or the magnitude of its measured signal. Confidence grades condition how results may be interpreted and used, rather than altering raw scores ex post.

A. Evidence Confidence Grades

- **Grade A — High Confidence:** Evidence derived from verifiable legal, technical, or institutional documentation, including but not limited to statutory texts, binding agreements, official operational records, or audited technical reports. Grade A evidence supports full diagnostic use within AI-SNF, subject to other framework guardrails.
- **Grade B — Moderate Confidence:** Evidence based on convergent secondary sources, triangulated expert assessments, or well-documented analytical studies where primary documentation is incomplete, restricted, or partially inaccessible. Grade B evidence is admissible for structural diagnosis and comparative analysis but requires explicit uncertainty acknowledgment and may constrain downstream interpretive authority.
- **Grade C — Low Confidence:** Evidence relying on indirect inference, proxy indicators, partial disclosure, or structurally opaque information environments, including cases where governance, ownership, or operational control is intentionally obscured. Grade C evidence may be used to signal potential structural relevance or risk, but it cannot support escalated interpretation, ranking, prioritization, or policy-relevant inference without corroboration.

25. Data Availability and Treatment Notes

B. Mandatory Reporting and Interpretive Conditioning

All AI-SNI dimensional profiles, composite scores, tier assignments, typology attributions, and illustrative diagnostics must be reported together with their corresponding evidence confidence profiles.

Evidence grading is a mandatory reporting attribute and constitutes a binding constraint on permissible interpretation and use. Analytical outputs lacking explicit evidence grading are considered methodologically incomplete within AI-SNF.

25.4 Scope, Inheritance, and Interpretive Authority

The rules specified in this section operate at AI-SNF framework level and govern all downstream analytical outputs, including but not limited to AI-SNI composite scores, exposure band (Tier 1–4) classification, diagnostic extensions and sensitivity tests, typology attribution (Type I–IV), and structural class assessment (S / A / B / C).

No index-level procedure, visualization choice, or comparative exercise may override or bypass these framework-level evidentiary rules.

Interpretive boundaries, uncertainty rationale, confidence propagation logic, and confidence override mechanisms are specified separately in Appendix A. Together, these provisions establish a closed interpretive discipline in which what can be said, compared, or acted upon is explicitly conditioned by evidentiary strength rather than implied by numerical output alone.

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Appendix A. Uncertainty and Confidence Treatment

This appendix specifies the formal principles and procedural rules by which uncertainty is identified, represented, and governed within AI-SNF, and inherited by AI-SNI as a downstream analytical output (OECD, 2019; OECD, 2021; NIST, 2023; Renn, 2008; Power, 2007).

It defines the evidentiary, methodological, and interpretive constraints under which AI-SNI outputs may be generated, communicated, and used for policy-relevant analysis.

Rather than serving as a technical supplement to score construction, this appendix establishes the interpretive discipline that bounds all AI-SNF–derived assessments. Its purpose is to ensure that analytical conclusions remain proportionate to evidentiary strength, institutional transparency, and structural observability across heterogeneous domains.

A.1 Why Uncertainty Treatment Is Central

AI-SNF operates in analytical environments where complete, stable, and fully observable data are structurally unattainable (Beck, 1992; Power, 2007). AI-strategic nodes are frequently embedded in sensitive infrastructures, governed by opaque or partially classified contractual arrangements, and shaped by informal, evolving, or non-codified institutional practices (Jasanoff, 2004; North, 1990).

In such contexts, the absence of explicit uncertainty treatment does not yield analytical clarity; it, and decision-relevant reasoning (Renn, 2008). produces false confidence and interpretive overreach (Power, 2007).

Accordingly, AI-SNF treats uncertainty not as a statistical residual or methodological inconvenience, but as a first-order governance variable (OECD, 2019; Renn, 2008; Power, 2007). The framework does not seek to eliminate uncertainty, nor to conceal it through aggregation or index compression. Instead, it disciplines how uncertainty enters interpretation, comparison, and decision-relevant reasoning.

This appendix therefore establishes a formal framework for:

- distinguishing data absence from data weakness, and separating structural unobservability from remediable information gaps;
- preventing overinterpretation of composite scores, tier placements, or profile classifications beyond their evidentiary support;
- ensuring that analytical leverage does not exceed evidentiary robustness, particularly in governance-sensitive or high-consequence contexts.

By embedding uncertainty and confidence treatment directly into AI-SNF architecture, this appendix reinforces the framework's core premise: **in AI-mediated strategic systems, misplaced certainty constitutes a governance risk in its own right** (Beck, 1992; Power, 2007).

Appendix A. Uncertainty and Confidence Treatment

A.2 Sources of Uncertainty in AI-Strategic Node Analysis

Uncertainty in AI-strategic node analysis arises from four analytically distinct sources. These sources must be treated as non-substitutable and non-conflatable, as each entails different implications for evidence evaluation, confidence grading, and permissible scope of interpretation (Renn, 2008; Power, 2007).

Failure to distinguish among them risks misattributing governance opacity to measurement error, or analytical design choices to empirical instability.

A.2.1 Observational Uncertainty

Observational uncertainty refers to limitations in the direct measurement or verification of physical, technical, or operational attributes associated with AI-strategic nodes. Typical sources include incomplete disclosure of sensing coverage, indirectly inferred latency or resilience metrics, and restricted access to data on operational integration with downstream systems.

Observational uncertainty constrains evidentiary confidence but does not, by itself, imply conceptual ambiguity or indeterminacy regarding a node's structural role. Its primary effect is to limit the degree of auditability and verifiability attached to otherwise well-specified indicators.

A.2.2 Institutional Opacity

Institutional opacity arises from persistent gaps in governance-related information that are institutional, legal, or political in origin rather than technical. Common manifestations include confidential contracts, informal or delegated control arrangements, classified oversight structures, and deliberate non-disclosure of ownership or authority relationships.

Unlike observational uncertainty, institutional opacity is often structural rather than temporary and may not be resolvable through additional data collection alone. It therefore carries heightened interpretive significance for governance-critical dimensions, particularly Dimension D4 (Infrastructure–Governance Asymmetry and Control), where opacity itself constitutes a source of systemic risk.

A.2.3 Temporal Instability

Temporal instability captures uncertainty introduced by dynamic change over time, even when point-in-time observations are accurate and well supported. Relevant sources include shifts in ownership or operational control, changes in regulatory authority or jurisdictional competence, evolving platform dependencies and interoperability regimes, and geopolitical realignment.

Appendix A. Uncertainty and Confidence Treatment

Temporal instability constrains forward validity and limits the interpretability of trends, projections, or comparative time-series analysis. Absent explicit attribution, temporal variation must not be interpreted as evidence of structural improvement, deterioration, or strategic reorientation.

A.2.4 Model-Induced Uncertainty

Model-induced uncertainty originates from analytical design choices embedded within AI-SNF itself. These include choices regarding indicator normalization, weighting assumptions, aggregation functional forms, and boundary definitions.

This form of uncertainty is endogenous, explicit, and in principle controllable through transparency, sensitivity testing, and methodological disclosure. It must be clearly distinguished from data-driven uncertainty to prevent analytical artifacts from being misinterpreted as empirical conditions or governance failures.

A.3 Evidence Grading Framework

Each second-level indicator within AI-SNF is assigned an explicit evidence confidence grade. Evidence grading is a mandatory interpretive constraint that governs how analytical outputs may be interpreted, compared, and used. It does not evaluate indicator importance, substantive validity, or normative credibility.

Evidence grades specify the degree of verifiability, transparency, and institutional accountability associated with the information used to derive an indicator score. They function as limits on interpretive authority rather than as assessments of analytical relevance or policy value.

Table A.3.1 Evidence Grading

Grade	Definition	Typical Evidence Sources
Grade A (High Confidence)	Directly verifiable primary-source evidence with clear provenance and institutional accountability	Statutory law, formal regulations, binding contracts, official infrastructure disclosures, audited technical or financial reports
Grade B (Moderate Confidence)	Convergent secondary sources supported by expert validation and cross-source consistency	Peer-reviewed academic studies, institutional or multilateral reports, documented expert consensus
Grade C (Low Confidence)	Indirect inference, partial disclosure, or proxy-based estimation lacking full verification	Media reporting, proxy indicators, informed estimation, analytical inference based on limited disclosure

Appendix A. Uncertainty and Confidence Treatment

Evidence grades reflect **evidentiary robustness**, not numerical precision or analytical sophistication. A high numerical score supported by weak evidence does not carry high interpretive authority, while a lower score supported by strong evidence may warrant greater analytical weight.

Evidence grades constitute the foundational inputs to the confidence profiling process specified in Section A.4 and do not, by themselves, determine interpretive authority.

A.4 Mapping from Evidence Grades to Confidence Profiles

Within AI-SNF, Evidence Grades assigned at the second-level indicator stage are not themselves interpretable as confidence judgments. Instead, they are systematically aggregated and translated into Confidence Profiles through a formal mapping process that governs interpretive authority at higher analytical levels.

This mapping performs three essential functions:

- to prevent numerical aggregation from masking evidentiary weakness or opacity;
- to ensure that interpretive authority scales with verifiability and institutional transparency rather than score magnitude; and
- to establish explicit and enforceable boundaries on permissible analytical use.

Table A.4.1 Evidence–Confidence Mapping Logic

Evidence Composition (by weighted share)	Resulting Confidence Profile
≥ 60% Grade A evidence	High Confidence
≥ 40% Grade A or Grade B evidence	Moderate Confidence
< 40% Grade A or Grade B evidence	Low Confidence

Evidence Grades characterize source-level robustness and verifiability at the indicator level. Confidence Profiles characterize interpretive authority at the dimension and composite levels. The two are analytically linked through this mapping rule, but they are not interchangeable and must not be conflated.

A Confidence Profile does not alter or rescale numerical values. Instead, it constrains how analytical outputs may be interpreted, compared, communicated, and used. Where evidentiary sufficiency is weak, numerical outputs retain computational validity but do not carry corresponding interpretive authority.

This mapping rule is mandatory and non-discretionary for all AI-SNF and AI-SNI outputs. It applies uniformly across: dimension-level assessments, composite scores (including AI-SNI), tier groupings, and diagnostic extensions.

Appendix A. Uncertainty and Confidence Treatment

Any analytical use that bypasses, overrides, or ignores the Evidence–Confidence mapping constitutes methodological misuse of the framework.

A.5 Evidence Annotation Requirement

All AI-SNF outputs, including indicator-level values, dimension-level assessments, composite indices (AI-SNI), tier assignments, and structural interpretations, **must be reported together with their corresponding evidence confidence profiles**.

Confidence annotation is not ancillary metadata. It is an integral component of interpretation and a binding constraint on permissible analytical use.

Outputs associated with **Low Confidence** profiles must be treated as **provisional analytical signals**. Such outputs are unsuitable for:

- prioritization or escalation,
- comparative ranking or tier advancement,
- policy decision support or governance justification.

Where confidence profiles materially constrain interpretation, this limitation must be explicitly stated in analytical communication. Silence on evidentiary weakness constitutes methodological misuse.

By enforcing evidence annotation as a formal requirement, AI-SNF ensures that analytical leverage remains proportional to evidentiary robustness and that uncertainty is surfaced explicitly rather than absorbed into composite metrics.

A.6 Confidence Propagation Rules

Confidence propagation operates on Confidence Profiles derived through the Evidence–Confidence mapping rules defined in Appendix A.4.

Evidence confidence propagates conservatively and asymmetrically within AI-SNF, from second-level indicators to dimension-level assessments, and from dimensions to composite outputs (including AI-SNI). Confidence propagation is not a statistical smoothing process; it is an interpretive safeguard designed to ensure that analytical authority does not exceed evidentiary robustness in tightly coupled, governance-sensitive systems.

A.6.1 Dimension-Level Confidence

For each dimension $\boldsymbol{D_d}$, dimension-level confidence is determined by the weighted distribution of evidence grades across its constituent second-level indicators, rather than by indicator count or numerical magnitude (Renn, 2008).

Appendix A. Uncertainty and Confidence Treatment

The following rules apply:

- **High Confidence:** Assigned when at least 60% of the dimension's indicator weight is supported by Grade A evidence.
- **Moderate Confidence:** Assigned when at least 40% of the dimension's indicator weight is supported by Grade A or Grade B evidence, but the threshold for High Confidence is not met.
- **Low Confidence:** Assigned when neither of the above conditions is satisfied.

These thresholds are intentionally conservative. They privilege evidentiary dominance over numerical balance, ensuring that a small number of weakly supported indicators cannot be masked through aggregation or averaging (Power, 2007). Dimension-level confidence therefore reflects the robustness of the strongest evidentiary backbone, not the arithmetic mean of inputs.

A.6.2 Composite-Level Confidence

The confidence level of any composite output, including AI-SNI scores, defaults to the lowest dimension-level confidence among D1–D5 (the weakest-link rule).

This rule reflects the systemic character of AI-mediated risk: in tightly coupled strategic systems, uncertainty concentrated in a single critical dimension can materially undermine the interpretive reliability of aggregate representations, regardless of apparent strength elsewhere.

Overrides to the weakest-link rule are permitted only under exceptional circumstances and must be accompanied by:

- explicit identification of the confidence discrepancy;
- a documented rationale explaining why the low-confidence dimension does not materially constrain systemic interpretation; and
- a clear statement of the analytical or institutional basis for the override.

Absent such disclosure, composite-level confidence must default to the lowest dimension-level confidence, and all downstream interpretation must respect this constraint.

A.7 Treatment of Missing, Imputed, and Unobservable Data

AI-SNI explicitly distinguishes among missing data, imputed data, and structurally unobservable data, as each category carries qualitatively different implications for evidentiary confidence, interpretive authority, and permissible analytical use. These distinctions are essential to preventing artificial precision and unwarranted certainty in governance-sensitive analytical contexts (Power, 2007; NIST, 2023).

Within AI-SNF, data absence is treated not as a neutral technical inconvenience, but as a diagnostic condition that constrains interpretation and may itself signal governance-relevant risk.

Appendix A. Uncertainty and Confidence Treatment

A.7.1 Single-Indicator Missingness

When a single second-level indicator is missing for a given node, the following treatment applies:

- The missing value may be imputed using the median of functionally comparable nodes within the same analytical category;
- The indicator must be explicitly flagged as Imputed in all analytical and reporting outputs;
- The corresponding evidence grade is capped at Grade C, regardless of the apparent plausibility or numerical stability of the imputed value (Renn, 2008; NIST, 2023).

This procedure allows dimensional aggregation to proceed while ensuring that imputed values do not acquire interpretive authority beyond their evidentiary basis. Imputation preserves analytical continuity, not evidentiary strength.

A.7.2 Dimension-Level Missingness

When missing or imputed data affect a substantial share of a dimension, the analytical implication escalates from indicator-level caution to dimension-level constraint.

Specifically, if 40% or more of a dimension’s indicator weight consists of missing or imputed data:

- The effective contribution of that dimension to any composite aggregation (including AI-SNI) is reduced by default by 50%, unless an alternative adjustment is explicitly justified and documented;
- The confidence level of the affected dimension is downgraded to Low, irrespective of the numerical values of the remaining indicators (Power, 2007; Renn, 2008).

This rule reflects the principle that dimensional coherence cannot be sustained when evidentiary gaps dominate, even if a subset of indicators remains well supported. Numerical completeness does not substitute for structural observability.

A.7.3 Structural Unobservability

In certain cases, data are not merely missing but structurally unobservable due to persistent institutional opacity, classification, security restrictions, or non-disclosure—most commonly affecting governance-, ownership-, or control-related indicators.

When structural unobservability is identified:

- The node must be explicitly flagged as High-Uncertainty;
- Composite values (including AI-SNI scores) may be computed for exploratory or internal analytical purposes;

Appendix A. Uncertainty and Confidence Treatment

- However, such outputs must not be used for ranking, tier escalation, comparison-based prioritization, or policy decision support.

Structural unobservability constitutes a **hard boundary on interpretive authority**, not a temporary data gap. In AI-SNF, the ability to compute a value does not imply the legitimacy to interpret or act upon it.

A.8 Sensitivity and Robustness Checks

AI-SNF incorporates sensitivity and robustness testing as an **interpretive safeguard**, not as an optimization or score-tuning device. The purpose of these checks is to assess whether substantive analytical conclusions remain stable under reasonable variations in modeling assumptions, rather than to improve or refine numerical outcomes (Renn, 2008; Power, 2007).

Accordingly, AI-SNF supports the following classes of robustness assessment:

- **Weight perturbation tests**, typically within a **±10–20%** range around baseline indicator or dimension weights, to evaluate dependence on specific weighting assumptions;
- **Alternative normalization schemes**, applied to assess whether observed patterns are artifacts of scale transformation rather than underlying structural differences;
- **Aggregation-form comparison**, most notably between linear and geometric formulations, to identify short-board sensitivity, weakest-link effects, and non-linear constraint dynamics (Perrow, 1984; Taleb, 2012).

Sensitivity analysis results do not modify baseline scores by default. Instead, they function as a constraint on interpretation.

Where composite scores, tier placement, or structural interpretations exhibit high sensitivity to reasonable modeling variations, such sensitivity must be explicitly disclosed alongside reported results. High sensitivity constitutes a limitation on interpretive authority and may require:

- qualification of analytical conclusions;
- restriction of permissible use (e.g., exploratory screening rather than comparative assessment);
- escalation to higher-level uncertainty or provisional-use flags.

Conversely, robustness across alternative specifications strengthens interpretive stability but does not substitute for evidentiary confidence, which remains governed by the evidence grading and confidence propagation rules specified in Sections A.3–A.6.

Within the AI-Strategic Node Framework, sensitivity testing ensures that analytical conclusions remain proportionate not only to data reliability, but also to methodological stability. Model-dependent volatility is therefore surfaced as a first-order interpretive signal rather than concealed within apparently precise numerical outputs.

Appendix A. Uncertainty and Confidence Treatment

A.9 Interpretive Guardrails

To preserve analytical integrity and prevent misuse, AI-SNI is governed by a set of non-negotiable interpretive guardrails that constrain how scores, tiers, profiles, and structural classifications may be interpreted and applied (Power, 2007; Renn, 2008).

These guardrails define the outer boundary of permissible inference. They apply to all AI-SNI outputs, irrespective of analytical context, institutional setting, or audience. Tier-specific categorical logic is defined in Section 11 and is not reiterated here.

A.9.1 Scores Do Not Imply Controllability

AI-SNI composite scores represent structural centrality and systemic relevance within AI-mediated systems. They do not imply controllability, ownership, governance authority, or institutional robustness (Baldwin, 2016; North, 1990; Power, 2007).

High AI-SNI scores may coexist with limited local governance capacity, fragmented control rights, or elevated exposure to external coercion. Any interpretation that treats numerical magnitude as evidence of effective control, strategic security, or institutional strength constitutes a methodological misuse of the framework.

A.9.2 Low Confidence Overrides High Scores

Where a node, dimension, or composite output is assigned a Low Confidence rating under the evidence grading and confidence propagation rules (Appendix A.3–A.6), all associated numerical results must be treated as analytical hypotheses, not as substantive conclusions (Renn, 2008; NIST, 2023).

In such cases, high composite scores, favorable tier placement, or apparently strong profiles **carry no interpretive authority** and must not be used to justify prioritization, escalation, or definitive policy claims.

A.9.3 Trends Require Attribution

Temporal variation in AI-SNI scores must not be interpreted as meaningful trends unless explicitly attributed to documented changes in at least one of the following:

- data availability, coverage, or evidentiary quality;
- governance arrangements, control rights, or institutional authority;
- system architecture, integration depth, or coupling dynamics (Renn, 2008; Power, 2007).

Absent such attribution, score fluctuations are analytically indeterminate and must not be treated as evidence of improvement, deterioration, or strategic shift.

Appendix A. Uncertainty and Confidence Treatment

A.9.4 No Automated Policy Triggers

AI-SNI is a diagnostic and interpretive framework, not a decision automation or policy execution system (OECD, 2019; NIST, 2023; Kleinberg et al., 2018).

Its outputs are not designed to trigger automatic regulatory actions, resource allocation, enforcement escalation, or compliance determinations. Any use of AI-SNI outputs as direct decision rules, without contextual analysis, institutional judgment, and governance oversight, violates the framework's design principles and undermines its governance purpose.

Collectively, these guardrails ensure that AI-SNI functions as an instrument of disciplined structural analysis, not mechanized judgment. By constraining how conclusions may be drawn from numerical outputs, the framework prioritizes structural understanding, evidentiary proportionality, and governance responsibility over score-driven decision-making.

A.10 Confidence as a Governance Feature

Within AI-mediated strategic systems, uncertainty is not a methodological deficiency to be minimized or concealed. It is a governable analytical dimension that conditions how structural leverage, exposure, and control asymmetry may be interpreted and acted upon.

Accordingly, confidence treatment within the AI-Strategic Node Framework functions as a governance safeguard, not a technical afterthought. By explicitly constraining interpretive authority, confidence grading prevents numerical centrality from being mistaken for governable control, institutional robustness, or strategic security.

This design enables preventive and proportional governance: high-leverage configurations accompanied by weak evidentiary confidence are surfaced as zones of heightened attention rather than premature prioritization, escalation, or assurance. In this sense, uncertainty recognition strengthens rather than weakens the framework's capacity to support anticipatory risk management and disciplined policy reasoning.

A.11 Relationship to D4 (Infrastructure–Governance Asymmetry)

Uncertainty within the AI-Strategic Node Framework is not evenly distributed across dimensions. Governance-related indicators, most prominently those captured under Dimension D4 (Infrastructure–Governance Asymmetry and Control), are structurally more exposed to institutional opacity, informal authority arrangements, and coercive influence than indicators associated with physical sensing, modeling performance, or technical integration.

This asymmetry has direct methodological and interpretive consequences. Accordingly, AI-SNI applies dimension-specific provisions to D4:

Appendix A. Uncertainty and Confidence Treatment

- Stricter evidentiary thresholds are imposed, reflecting the heightened governance sensitivity of control-related indicators;
- Confidence downgrades propagate more aggressively from D4 to composite-level assessments, consistent with the weakest-link principle;
- Uncertainty amplifies, rather than mitigates, fragility interpretation, signaling elevated governance risk even where operational or predictive centrality appears strong.

This alignment ensures coherence between methodological restraint and strategic caution. Opacity in control is interpreted as risk exposure, not reassurance. Where leverage outpaces verifiable governance authority, uncertainty itself becomes a diagnostic signal requiring heightened interpretive restraint and governance attention.

Appendix B: Typology Assignment Protocol

This appendix sets out a policy-oriented typology assignment protocol for AI-strategic nodes (Types I–IV) within the AI-Strategic Node Framework (AI-SNF, D1–D5). It is intended for use by policy analysts and regulators, strategic risk assessment units, inter-agency coordination bodies, and institutional audit, review, or foresight teams. The protocol does not generate scores, rankings, or priorities; its sole function is to discipline interpretation when assigning typological categories for diagnostic and comparative purposes.

B.1 Core Policy Principles

Typology assignment under AI-SNI is governed by four non-negotiable principles that preserve analytical integrity and prevent misuse:

- **Configuration over magnitude:** Typologies are assigned based on the configuration of dimensions (D1–D5), not on composite index values, exposure tiers, or numerical proximity to thresholds.
- **Judgment-guided, not automated:** Typology assignment structures expert judgment; it does not replace it. No typology is mechanically computed, algorithmically inferred, or automatically produced.
- **Separation from structural class:** Typology attribution is independent of structural class (S/A/B/C). Typologies describe how leverage and fragility co-occur; structural class evaluates systemic role and failure consequence. No conversion or inference between the two is permitted.
- **Auditability before precision:** All typology assignments must be traceable to explicit dimensional evidence and written reasoning. Apparent precision without documentation is treated as analytically invalid.

B.2 Stepwise Diagnostic Logic (Non-Mechanical)

Step 1 — Identify the Operational Leverage Envelope (D1–D3)

The first step determines the node's **current operational relevance** within AI-mediated systems by jointly examining:

- **D1** — Sensing and early-warning centrality
- **D2** — Predictive model leverage and dependency
- **D3** — Decision-loop temporal advantage

For policy diagnostics, these dimensions are assessed **relationally**, using three qualitative envelopes:

- **High operational leverage:** The node performs chokepoint or anchor functions across perception–prediction–decision loops.

Appendix B: Typology Assignment Protocol

- **Moderate operational leverage:** The node contributes meaningfully but not decisively; relevance is distributed or enabling.
- **Low operational leverage:** The node is presently peripheral to core AI-mediated system functioning.

This step establishes *where leverage is concentrated today*, not whether it is desirable or stable.

Step 2 — Assess Governance Correction Capacity (D4)

The second step evaluates whether operational leverage is **matched by effective governance authority**, as captured by **D4: Infrastructure–Governance Asymmetry and Control**.

Assessment focuses on **internal structure**, not headline scores, including:

- clarity of control rights and mandates,
- auditability and oversight mechanisms,
- rule-setting autonomy,
- exposure to external dependency or coercion.

Governance alignment is then characterized as:

- **Buffered / Corrective:** Governance authority plausibly matches infrastructural centrality.
- **Asymmetric / Fragile:** Leverage materially exceeds governance capacity.
- **Context-dependent:** Outcomes hinge on external institutional, legal, or geopolitical conditions.

This step determines whether leverage is **governable, exposed, or externally conditioned**.

Step 3 — Evaluate Optionality and Trajectory Potential (D5)

The third step examines **future-conditional relevance** using **D5: Resource–Data–Compute Coupling Potential**. Key diagnostic questions include:

- Are there credible pathways for deeper future integration?
- Are such pathways constrained by platform capture, regulation, or environmental limits?
- Is optionality latent, contested, or effectively foreclosed?

Optionality is characterized directionally as:

- **Activatable** — plausible pathways exist,
- **Latent but constrained** — potential exists under strict conditions,
- **Minimal** — no credible trajectory toward future centrality.

Appendix B: Typology Assignment Protocol

This step informs **trajectory awareness**, not prediction.

B.3 Typology Mapping Logic (Policy-Safe Summary)

Typology attribution emerges from **joint interpretation** of the three steps above:

- **Type I:** High operational leverage (D1–D3) + governance asymmetry (weak D4 correction).
- **Type II:** High operational leverage (D1–D3) + buffered or robust governance alignment (strong D4).
- **Type III:** Moderate operational leverage, network-conditioned relevance, variable governance outcomes.
- **Type IV:** Low current operational leverage, with relevance contingent on D5-driven future coupling.

No single dimension is decisive. Borderline cases must be explicitly identified as **hybrid** and documented as such.

B.4 Documentation and Review Requirements

Each typology assignment must include:

- a short written justification referencing D1–D5 configurations;
- explicit acknowledgment of uncertainty or boundary conditions;
- confirmation that attribution was conducted without reference to:
    - composite scores,
    - exposure tiers,
    - structural class labels.

Typology labels must **not** be used as proxies for policy priority, regulatory intervention, or resource allocation.

B.5 Interpretive Guardrail for Policy Use

Typologies are **diagnostic instruments**, not decision rules.

They clarify:

- where leverage concentrates,
- where governance alignment holds or fails,
- where optionality may emerge.

Appendix B: Typology Assignment Protocol

They do **not** prescribe:

- policy preferences,
- strategic desirability,
- intervention urgency,
- normative ranking.

Any use of typology labels beyond diagnostic clarification constitutes a misuse of the AI-Strategic Node Framework.

Appendix C: AI-SNF / AI-SNI Reporting Template

This reporting template is designed for analysts, auditors, and governance researchers. It is not intended for decision authorities, enforcement bodies, or automated policy systems.

C.1 General Identification

Field	Description
Node Identifier	Unique internal reference code
Node Description	Functional description of the geographic or infrastructural node
Node Category	Terrestrial / Maritime / Polar / Orbital-adjacent / Infrastructural
Assessment Date	Date of assessment
Evaluation Horizon	Total evaluation horizon (T_{total})
Evidence Window	Verified observation window ($T_{observed}$)
Assessment Purpose	Screening / Scenario analysis / Diagnostic review

C.2 Dimension-Level Profile (D1–D5)

Dimension	Score	Evidence Grade	Confidence Level	Key Supporting Evidence
D1 – Algorithmic Sensing and Early-Warning Centrality				
D2 – Predictive Model Leverage and Dependency				
D3 – Decision-Loop Temporal Advantage				
D4 – Infrastructure–Governance Asymmetry and Control				
D5 – Resource–Data–Compute Coupling Potential				

Notes: Scores are normalized to the **[0,1]** interval. Evidence Grade reflects source reliability, transparency, and coverage, not analytical importance. Confidence Level constrains permissible interpretation and downstream use of all associated scores.

Appendix C: AI-SNF / AI-SNI Reporting Template

C.3 Composite Output

Output	Value	Interpretation Constraint
AI-SNI (Reference Composite)		Diagnostic screening signal only
Confidence Profile		Limits comparative interpretation

Interpretive Guardrail: AI-SNI composite values do not constitute rankings, performance measures, or policy priorities, and must not be used as proxies for controllability, governance quality, or strategic desirability.

C.4 Diagnostic Extensions

Extension	Output	Purpose	Interpretive Status
Governance Fragility Adjustment (Ext. I)		Sensitivity to D4 insufficiency	Diagnostic only
Short-Board Sensitivity Test (Ext. II)		Weakest-link coherence test	Diagnostic only

Guardrail: Diagnostic extensions **do not generate independent indices**, do not modify reference tier assignments, and **must not be used to infer structural class or policy priority**.

C.5 Exposure Tier

Reference AI-SNI	Exposure Tier	Notes
		Tier is descriptive, categorical, and non-ordinal

C.6 Structural Typology

Typology	Justification Summary
Type I / II / III / IV	Profile-based configuration assessment

Note: Typology attribution is heuristic, non-algorithmic, and independent of composite scores, exposure tiers, and diagnostic extensions.

Appendix C: AI-SNF / AI-SNI Reporting Template

C.7 Structural Class Attribution

Structural Class	Justification
S / A / B / C	Non-substitutability, coupling intensity, failure propagation dynamics

Authoritative Constraint: Structural class cannot be inferred, calculated, or derived from AI-SNI scores, exposure tiers, or diagnostic extensions. It represents a higher-order interpretive judgment governed by AI-SNF interpretive authority hierarchy.

C.8 Interpretation Summary

- Key leverage sources:
- Binding fragilities:
- Governance constraints:
- Long-horizon optionality:
- Uncertainty flags and data gaps:

C.9 Use and Disclosure Constraints

This report is diagnostic and interpretive in nature. It does not prescribe policy actions, assign priorities, trigger decisions, or generate evaluative rankings. Any use of this report beyond analytical screening, comparative diagnosis, or governance-oriented interpretation constitutes methodological misuse of AI-SNF / AI-SNI framework.

Appendix D: Abbreviation and Glossary

D.1 Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
AI-SNI	AI-Strategic Node Index
AMS	Adversarial Manipulation Surface
ASEWC	Algorithmic Sensing and Early-Warning Centrality (Dimension D1)
AEEF	AI-Enabled Extraction Feasibility
C2	Command and Control
CEI	Coercion Exposure Index
CME	Critical Materials Endowment
CRC	Control Rights Clarity
DFC	Data Freshness and Continuity
DLTA	Decision-Loop Temporal Advantage (Dimension D3)
EDR	External Dependency Risk
EPC	Environmental and Policy Constraints
FGC	Forecast Governance Coupling
GSS	Global Spillover Strength
HPC	High-Performance Computing
IGAC	Infrastructure–Governance Asymmetry and Control (Dimension D4)
ISR	Intelligence, Surveillance, and Reconnaissance
ELA	End-to-End Latency Advantage
LCC	Logistics and Corridor Coupling
LGC	Local Governance Capacity
MCAS	Model Centrality and Anchoring Strength
ML	Machine Learning
MRDQ	Model-Ready Data Quality
OII	Operational Integration Index
PCR	Platform Capture Risk
PMLD	Predictive Model Leverage and Dependency (Dimension D2)
RDCCP	Resource–Data–Compute Coupling Potential (Dimension D5)
RSA	Rule-Setting Autonomy
RUS	Resilience Under Stress
SCD	Sensor Coverage Density
SG	Substitutability Gap
SSA	Space Situational Awareness
SUR	Sensor Uniqueness Ratio
τ	Governance Sufficiency Threshold (Threshold–Penalty Model)
λ	Penalty Strength Parameter (Threshold–Penalty Model)

Appendix D: Abbreviation and Glossary

D.2 Glossary of Key Terms

Aggregation Logic

The formal method by which dimension-level scores are combined into a composite index (e.g., linear weighted, threshold–penalty, or geometric aggregation), each serving distinct analytical purposes and interpretive constraints.

AI-Strategic Node (ASN)

A geographic, infrastructural, or institutional configuration whose position within AI-mediated systems functions as a structurally irreducible point of leverage over sensing, prediction, decision timing, governance control, or future option space. An AI-Strategic Node is defined by structural role and leverage, not by aggregate technical capacity or performance alone.

AI-Strategic Node Framework (AI-SNF)

A governance-oriented analytical framework designed to identify, characterize, and interpret the systemic roles of AI-Strategic Nodes within AI-enabled architectures. AI-SNF integrates multidimensional indicators, structural classification, and interpretive constraints. It is not a ranking system, predictive model, or decision rule.

AI-Strategic Node Index (AI-SNI)

The authoritative composite index derived from AI-SNF, defined exclusively by the reference aggregation formula specified in Section 10.5.1. AI-SNI provides a diagnostic composite score for comparative analysis and pattern recognition. It does not imply desirability, superiority, controllability, or policy priority.

Algorithmic Sensing and Early-Warning Centrality (D1)

The degree to which a node contributes to AI-enabled perception, detection, and early-warning functions, including sensing coverage, continuity, uniqueness, and integration into operational systems.

Composite Score

An aggregated numerical representation derived from weighted dimension-level scores for analytical comparison and visualization. Composite scores do not imply ranking, optimization, or normative evaluation.

Appendix D: Abbreviation and Glossary

Confidence Profile

A formal assessment of interpretive reliability derived from indicator-level evidence grading, dimension-level aggregation, and weakest-link confidence propagation rules. Confidence profiles constrain permissible interpretation and use of AI-SNF outputs.

Decision-Loop Temporal Advantage (D3)

The degree to which a node compresses, accelerates, or structurally controls AI-mediated decision loops across detection, interpretation, coordination, and execution phases.

Dimension (D1–D5)

A first-order analytical axis within AI-SNF representing a distinct structural function or risk domain relevant to AI-mediated systems. Each dimension aggregates multiple second-order indicators and is independently scored and validated.

Diagnostic Extension

A formally constrained analytical transformation applied to the reference AI-SNI score to surface specific structural risks (e.g., governance fragility or weakest-link sensitivity). Diagnostic extensions do not constitute independent indices and possess no standalone interpretive authority.

Exposure Bands (Tiers)

Categorical groupings that classify AI-Strategic Nodes into distinct regimes of systemic exposure, defined by the configuration and concentration of AI-mediated leverage, spillover potential, and governance alignment. Exposure bands are non-ordinal, non-comparable across categories, and do not represent gradations of risk, performance, or strategic value.

Evidence Grade

A standardized classification of data reliability, coverage, and verifiability assigned to each indicator and propagated upward through the scoring system.

Fragility

A structural condition in which high strategic leverage amplifies systemic risk due to weak governance, low redundancy, or asymmetric failure propagation.

Appendix D: Abbreviation and Glossary

Infrastructure–Governance Asymmetry (IGA)

A structural risk condition describing the misalignment between a node's AI-relevant infrastructure dependence and the corresponding governance, regulatory, or control capacity. IGA is a conceptual and causal condition, not a directly scored index component.

Infrastructure–Governance Asymmetry and Control (IGAC) — D4

A measurable governance-side dimension representing the sufficiency, effectiveness, and enforceability of control mechanisms in response to IGA conditions. Higher IGAC values indicate greater governance coverage and control capacity relative to infrastructure dependence. IGAC serves as the operational governance-side metric corresponding to IGA as a structural condition.

Interpretive Authority Hierarchy

A rule-based hierarchy specifying the relative authority of indicators, dimensions, composite scores, tiers, diagnostic extensions, and structural classes. Higher-order interpretive layers cannot be overridden by lower-order numerical outputs.

Node Profile

The multidimensional configuration of a node across D1–D5, used to assess leverage distribution, constraints, and failure pathways independently of composite scores.

Non-Compensatory Constraint

A methodological rule preventing high performance in certain dimensions from mechanically offsetting critical deficiencies in governance, control, or systemic resilience.

Predictive Model Leverage and Dependency (D2)

The extent to which predictive, forecasting, or decision-support models depend on a node for calibration, accuracy, or global spillover effects, including sensitivity to manipulation or substitution.

Preventive Governance

An approach to governance that emphasizes early identification of structural fragility and leverage–control mismatches before they manifest as crisis or systemic failure.

Appendix D: Abbreviation and Glossary

Risk Band / Tier

The **labeled representation of Exposure Bands (Tiers)** used in AI-SNI outputs for **visualization, grouping, and screening purposes only**. Risk bands (tiers) **do not imply ordinal ranking, performance hierarchy, policy priority, or decision authority**, and must not be interpreted as comparative measures of severity, superiority, or desirability.

Risk Profile

The multidimensional configuration of D1–D5 scores describing the structure and source of exposure, leverage, and fragility.

Short-Board Effect

A systemic constraint in which weakness in a single critical dimension disproportionately limits overall system coherence, despite strength elsewhere.

Strategic Optionality and Lock-In Exposure (D5)

The degree to which a node preserves or constrains future strategic choices within AI-mediated systems, including exit costs, path dependence, reversibility, and long-term lock-in exposure.

Structural Class

A higher-order interpretive construct evaluating whether a node is system-constitutive, system-stabilizing, network-dependent, or option-preserving within AI-mediated architectures.

Systemic Failure Propagation

The process by which degradation, misgovernance, or removal of a node produces cascading effects across sensing, prediction, decision-making, or governance layers.

Threshold–Penalty Aggregation

An aggregation method that conditionally discounts composite scores when governance sufficiency falls below a defined threshold, designed to surface fragility and avoid false stability signals.

Appendix D: Abbreviation and Glossary

Uncertainty Treatment

The explicit identification, categorization, and governance of uncertainty within AI-SNI, including observational limits, institutional opacity, temporal instability, and model-induced uncertainty.

Usable Strategic Leverage

The portion of a node's structural leverage that can be responsibly exercised given existing governance capacity, control rights, and confidence levels.

Note for the White Book

This White Book presents the AI-Strategic Node Framework (AI-SNF) as a foundational analytical architecture for diagnosing structural leverage, governance asymmetry, and systemic fragility within AI-mediated systems.

The AI-Strategic Node Index (AI-SNI) v0.1 introduced herein constitutes a derived diagnostic output of AI-SNF, rather than an autonomous evaluative system. The current release is intentionally conservative in both analytical scope and interpretive ambition. Its design prioritizes structural clarity, evidentiary auditability, and governance relevance over prediction, optimization, or prescriptive ranking.

AI-SNF and its index outputs are not intended to forecast conflict, automate policy decisions, or rank strategic actors by performance. Instead, the framework provides a disciplined diagnostic architecture for identifying where leverage, control, fragility, and systemic consequence intersect across AI-mediated infrastructures and decision environments. Emphasis is placed on transparency of assumptions, explicit treatment of uncertainty, and restraint in inference, particularly in governance-sensitive and high-consequence contexts.

As a foundational release, this White Book establishes the conceptual structure, interpretive discipline, and governance boundaries of the AI-Strategic Node Framework (D1–D5). Future iterations may expand empirical coverage, refine indicator specifications, or introduce additional analytical modules. Such extensions will remain framework-governed and will preserve the core principle articulated herein:

In AI-mediated strategic environments, analytical rigor and interpretive restraint are prerequisites for responsible governance.

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Disclaimer

This White Book presents the **AI-Strategic Node Framework (AI-SNF)** as an analytical construct developed exclusively for research, diagnostic, and policy-analysis purposes. The views, interpretations, and analytical formulations expressed herein do **not** represent the official position of any government, international organization, regulatory authority, or affiliated institution, nor should they be construed as prescribing, endorsing, or advocating specific policy actions, regulatory measures, or strategic decisions.

AI-SNF is intended to support **informed analysis, governance-oriented inquiry, and institutional reflection** by providing structured diagnostic perspectives on AI-mediated systems. All interpretations, applications, and downstream uses of the framework and its derived analytical outputs, including any index-based representations, remain the sole responsibility of the user and must be undertaken in accordance with the **methodological boundaries, uncertainty treatment rules, and interpretive constraints** explicitly articulated in this White Book.

No component of AI-SNF or its derivative outputs is designed to function as an automated decision rule, compliance determination, or policy trigger. Any use of this framework beyond exploratory or analytical purposes requires independent institutional judgment, contextual evaluation, and appropriate governance oversight.

Version History

AI-Strategic Node Framework (AI-SNF) White Book v0.1

Conceptual and methodological foundation

Initial public release: **January 2026**.

This foundational release establishes the AI-Strategic Node Framework (AI-SNF) as a governance-oriented analytical architecture for diagnosing structural leverage, control asymmetry, fragility, and systemic consequence within AI-mediated systems.

Version 0.1 introduces the core conceptual premises of the framework, including the dimensional architecture (D1–D5), indicator logic, evidentiary discipline, uncertainty and confidence treatment, interpretive guardrails, and typological diagnostics. Within this framework, the AI-Strategic Node Index (AI-SNI) is specified as a derived composite representation designed for structured comparison and pattern recognition, operating strictly under the methodological constraints defined by AI-SNF.

This release also includes a fully worked illustrative example to demonstrate application logic and interpretive boundaries. v0.1 prioritizes structural clarity, auditability, and governance relevance, and establishes the analytical and interpretive foundations upon which subsequent empirical expansion, indicator refinement, or modular extensions may be developed.

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