

Expert Insight-Based Modeling Of Non-Kinetic Strategic Deterrence Of Rare Earth Supply Disruption: A Simulation-Driven Systematic Framework

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ABSTRACT

This study is derived from the authors' structured responses to strategic interviews initiated by Dr. Daniel O'Connor, CEO of the Rare Earth Exchange. The first quantitative modeling framework for characterizing non-kinetic deterrence pathways is presented for strategic resource disruption scenarios. The framework consists of three modules: Security Critical Zone (SCZ), Strategic Signal Injection Function (SSIF), and Regime-Capability Response Migration Function (PCTF); and combines Ordinary Differential Equations (ODEs), Segmented Functions (SFFs), Path Covariance Matrices (PCMs), and LSTM Time-Series Networks (LSTNs), in order to simulate the nonlinear suppression and evolution of the warfighting system under the injection of regime signals. The simulation results show that within a short lag window, the institutional deterrent signal can trigger the disintegrative fracture of the capability system, which exhibits significant tempo effects and path coupling characteristics. The model is cross-country adaptable and can be used with AI sand table for contextual and counterfactual reasoning, providing methodological tools and experimental basis for strategic resource competition governance and policy tempo design..

Keywords: rare earth supply chain; non-kinetic strategic deterrence; strategic capability degradation simulation

1. INTRODUCTION

In the context of the intensification of global scientific and technological and geopolitical games, the structural contradiction between the U.S. and China in the field of rare earths is prominent: China holds more than 80% of the production capacity and exports, and the U.S. relies highly on rare earths in military industry and high-end manufacturing, thus forming a systemic vulnerability. Rare earths are evolving from traditional industrial materials [1] into “non-kinetic strategic weapons” [2], and their covert and delayed nature can create a “war power vacuum” in the absence of war conditions, which triggers the concern of developed countries [3]. 2025 The author publishes relevant research in arXiv. In 2025, the authors published related research in arXiv[4] and were interviewed by the CEO of the American Rare Earth Exchange[5], responding to the issues of “the collapse of war power due to supply cut-off” and “the strategization of lag time”, and transformed them into a system of variables, such as the rare earth-equipment dependence matrix, degradation function, and critical point modeling. and critical point modeling. This paper proposes a four-layer coupled model of “resource-equipment-generation difference-capability (REG-CAP)”, combining graph neural network (GNN) and LSTM [6], to portray the capability decline and policy under rare earth supply cutoff. Window. The innovations include: cross-domain integration of AI and non-kinetic deterrence strategies; the proposed mechanism of “systemic cadence-functional collapse”; the construction of a “security critical zone” model; expert interview-driven segmental modeling; and an original strategic mapping system. system. This paper fills the research gap of quantitative modeling of non-kinetic deterrence through institutional modeling + AI simulation + strategy visualization, which has both theoretical, methodological and policy values.

2. RATIONALE AND MODELLING FRAMEWORK

2.1 The REG-CAP Model: Strategic Mapping of Resource Weaponization

Rare earths are the element in the institutional chain of control with the greatest potential for weaponization. This paper proposes a “REG-CAP” four-layer coupling framework (Resource-Equipment-Generation Gap-Capability), which aims to depict the path of rare earths from supply disruption to warfighting capability collapse. The resource layer portrays rare earth types, processing, and policy; the

equipment layer reflects U.S. military platforms' dependence on rare earths; the generation layer reveals substitution delays and technological vulnerabilities; and the warfighting capability layer is summarized as the final strategic output. The model highlights how asymmetric supply cutoffs induce nonlinear degradation trajectories and institutionalized paralysis under “peaceful conditions.”

2.2 From Interviews to Structural Variables: The Knowledge Translation Paradigm

The starting point of the research was derived from the core questions asked by the author in an interview with Daniel O'Connor, CEO of Rare Earth Exchange, such as “What equipment is most vulnerable to paralysis?”, “Is there a delay window?” “Is there a window of delay?” “Is it possible to model the simulation?” etc. These questions are translated into structural variables, including resource-equipment dependency matrices, risk indices, elasticity of substitution coefficients, hysteresis functions, and thresholds for critical points, forming a chain of cognitive-variable-system mappings. This approach enhances the realistic embeddedness of the model and introduces a structured interview paradigm for AI policy modeling.

2.3 Modelling assumptions and system tension structure

This paper proposes three hypotheses:

H1: Rare earth dependence on equipment is power-law distributed, with a few highly dependent elements determining the degradation path;

H2: The wider the generation gap is, the more significant is the delay in substitution in case of supply cutoffs;

H3: There exists a strategically exploitable “window of delay” in which warfighting capability collapses after a few years.

These assumptions are formalized through graph-structure modeling and lag function fitting.

2.4 REG-CAP multilayer coupled structure mapping

To visually present the above four layers of variables and their mutual coupling paths, I used Python to generate the following structural diagram:

The graph nodes are categorised: rare earth type (R), equipment system (E), generational technology category (G), and combat output unit (C);

Edge relationship types: Functional Dependence, Substitution Mapping, Tech Transfer, and Capability Aggregation;

Figure 1. The REG-CAP Strategic Dependency and Modeling Framework, consisting of three interrelated subgraphs: The left subgraph, REG-CAP Multilayer Strategic Dependency Graph, illustrates how rare earth resources (Dy, Nd, Tb, Ce) are channeled through key equipment and intergenerational platforms to the operational capability layers (e.g., Air Superiority, Naval Dominance, ISR, Strategic Mobility), revealing asymmetric and delayed degradation paths resulting from resource disruptions. (e.g., Air Superiority, Naval Dominance, ISR, Strategic Mobility), revealing asymmetric and delayed degradation paths due to resource disruption. The middle subgraph, based on the Hierarchical Graph Neural Network (HGNN) Structure for REG-CAP Modeling, transforms the conceptual topology on the left side into AI trainable inputs, preserving the Resource-Equipment-Generation-Capability (REG-CAP) cascade for degradation path learning and capability prediction. The right subgraph Causal Sankey Diagram encodes the resource dependency intensity with streamline thickness, visualizes multi-path vulnerability corridors and key collapse nodes, and provides an interpretable interface between system control and AI projection. Together, they form an integrated framework of “structure-algorithm-cause-effect”: the left side emphasizes dependency logic, the middle side realizes algorithmic translation, and the right side strengthens causal interpretation, which supports the quantitative modeling and policy application of non-kinetic strategic deterrence.

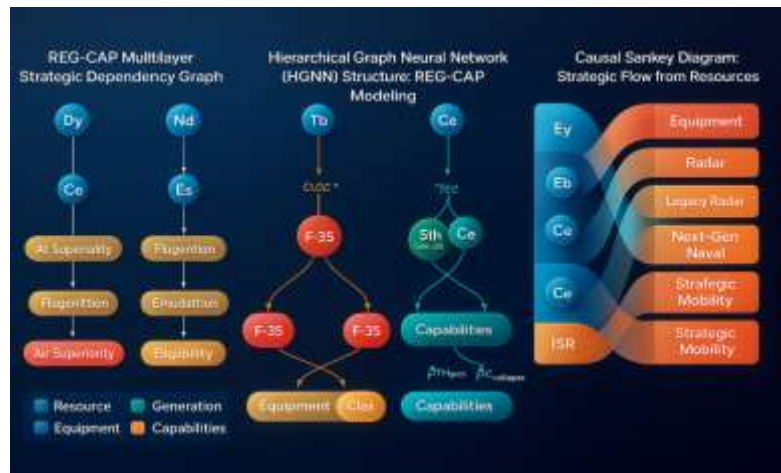


Figure1. REG-CAP Strategic Dependency and Modeling Framework

3.DATA CONSTRUCTION AND MODELLING METHODS

In modeling national-level non-kinetic strategic capabilities, the data system is not only a technical input, but also an encoded form of institutional logic. The impacts of rare earth supply cut-off are cross-level, multi-path and time-delayed, and it is difficult for a single variable to support the portrayal of its propagation mechanism. Through data construction, graph structure transformation, joint modeling and interpretable mechanism, a complete strategic modeling chain that can be embedded in the AI framework is formed, so that institutional shocks can be captured, deduced and verified.

3.1 Data Architecture

The data design begins with structured interviews with Rare Earth Exchange[5], where the core problem is translated into structured variables, i.e., path dependence for portraying the chain of institutional vulnerability, attenuation and time-delay parameters to quantify the strategic lag after supply disruptions, and thresholds and cost functions to reveal the potential for recovery. After integrating with USGS, DoD, CSIS, CRS and other data sources, higher-order inputs with policy triggers, structural rationality and algorithmic readability are formed.

3.2 REG-CAP graph structure coding

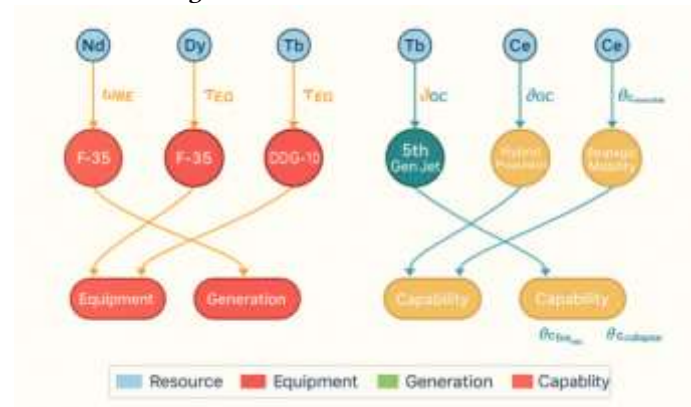


Figure 2. REG-CAP Variable System and Graph Structure Encoding

The REG-CAP model is transformed into a four-layer graph structure as shown in Fig. F2: resources (R), equipment (E), generations (G), and capabilities (C) are used as nodes, and the dependencies are expressed by weighted directed edges. ω_{RE} denotes the strength of the resource dependency, τ_{EG} denotes the substitution delay, δ_{GC} depicts the degradation amplitude, $\theta_{Collapse}$ and $\theta_{Reversible}$ define the capability limit state, and $\theta_{Collapse}$ and $\theta_{Reversible}$ define the capability limit state. Reversible defines the capacity limit state. The graph not only supports the node aggregation and path propagation

of GNN[8], but also reveals the coupling channel and the risk point of disconnection, which realizes the isomorphism between institutional logic and algorithmic structure.

3.3 Joint Modeling Framework

To capture the structural depth and dynamic timing, this study builds the HGNN+LSTM framework. HGNN learns path weights through GraphSAGE and GAT, and identifies compressed nodes using path convolution[8]; LSTM predicts [0,12] annual capacity degradation trajectories based on HGNN output, and identifies delay windows, crash points and recovery potentials. This dual module realizes the coupled inference of structural and temporal logic.

3.4 Interpretability Mechanisms The model embeds a three-layer interpretation design.

The causal path rendering visualizes the control chain from resources to capacity; the risk centrality generates the strategic collapse mapping; and the vulnerability channel detector reveals the “systemic supply channel”, which provides a quantitative basis for the simulation of policy windows. As a result, the model not only has the function of prediction, but also forms a closed loop from cognitive triggering to policy intervention.

4. MODELLING RESULTS AND STRATEGIC WINDOW IDENTIFICATION

4.1 Platform Level Capability Decline Analysis

Based on the REG-CAP multilayer coupled model, this paper simulates the capability decline of the U.S. Army's core platforms (F-35, DDG-1000, and B-2)[10] under the rare earth supply cutoff scenario. The modeling parameters cover Resource Embedding Intensity (REI), Technology Non-Substitutability (TNS) and Substitution Delay Coefficient (SDI), and are combined with path dependence for the propagation of the decline. The results show that the platform decline is characterized by significant cascade coupling and nonlinearity. F-35, which is dependent on neodymium and dysprosium[7], has an average decline of more than 62% in “electronic warfare” and “long-range precision strike” capabilities after 11 months of supply cut-off, and enters into the Operational Critical Zone (OCZ), forming a maneuverable critical zone (CZ). OCZ), forming a “delayed degradation window” that can be manipulated. In contrast, the DDG-1000 relies on terbium and cerium with multiple sources, and its “strategic delivery” and “far-sea sealing and control” capabilities are on a slow decline, but there is a mutation point in the 16th month, showing that the alternative path slows down the degradation, but is difficult to eliminate the vulnerability. It is worth noting that platform failures are not isolated, but are superimposed by the decline of ISR and other functional domain clusters, forming a cross-platform “coupled capability disintegration field” (CDF). The simulation reveals the platform-level “delayed collapse window” and “asymmetric degradation mechanism”, indicating that the impact of rare earth supply cut-off is non-instantaneous, cross-platform and irreversible, and needs to be structurally countered by strategic capacity redundancy and multiple alternative paths.

Figure 3 shows the “non-kinetic strategic deterrence simulation framework”, which comprehensively presents the decay trajectory, nonlinear collapse rate and lag corridor distribution of combat capabilities under the disruption of rare-earth supply, and reveals the vulnerability of the system coupled with multiple paths through the risk of convergence scores; at the same time, the strategic deterrence corridor diagram and the capabilities of AI-ISR-network warfare are also shown. ISR-cyber warfare capability coupling analysis further demonstrates the conduction effect and convergence risk of key nodes under institutionalized pressure. The framework not only provides a quantitative portrayal of capability decay and system failure, but also provides methodological support for identifying strategic windows and constructing institutionalized deterrence pathways.

4.2 Fracture Mechanism and Lag Window Identification

As shown in Fig. 3, through the comprehensive modeling of “capability degradation curve-nonlinear collapse function-lag corridor scatter plot”, this study reveals the three-stage characteristics of war power function under the supply of rare earths: implicit lag, critical burst and irreversible collapse. The simulation results show that the ISR capability remains stable during the silence period of 5.5 years, but there is a breaking point (CTP) in the 6th year, and the warfighting capability index plummets, reflecting the institutional vulnerability under the conditions of high path overlap and weak substitutability. The lag window (LC) distribution of different capability nodes varies significantly: about 4.2 years for strategic

maneuver, less than 2.5 years for air superiority, and only 1.8 years for anti-submarine warfare. Through the dynamic extraction of dCl/dt , this study establishes the “most vulnerable capability-optimal intervention time” matrix, which provides a quantitative basis for the institutional intervention tempo.

4.3 Multi-system Convergence Failure and Safety Critical Zone

Further “convergence risk score plots” reveal that the decline in warfighting capability is not isolated and linear, but rather manifests itself as a synergistic fracture of multiple paths. The convergence risk of ISR and strategic maneuver is as high as 0.81, while that of electronic warfare and satellite reconnaissance exceeds 0.77, constituting a highly brittle coupling point. Once any node crosses the threshold, the system triggers a nonlinear accelerated collapse within a window of less than two years. Covariance modeling reveals a significant co-seismic effect between AI-ISR-naval delivery capabilities, reinforcing the concept of the “Security Critical Zone (SCZ),” a critical cluster of high coupling, high rupture, and low hysteresis. The identification of SCZ not only enhances the quantifiability of vulnerability, but also provides a strategic early warning mechanism for redundant design and forward deployment.

4.4 Strategic Channel Modeling and Institutional Deterrence

In the overall framework, the “Strategic Deterrence Channel Diagram” and the “AI-ISR-Cyber Operations Coupling Analysis” together reveal the path of institutionalized deterrence. In the overall framework, the “Strategic Deterrence Channel Diagram” and the “AI-ISR-Cyber Operations Coupling Analysis” together reveal the path of institutionalized deterrence. The channel model proposed in this paper emphasizes the controllability of the path, visibility of consequences and embeddedness of the system: for example, the path of $Nd \rightarrow F-35 \rightarrow ISR$ has the advantages of high aggregation and asymmetric suppression, and becomes the optimal pressure chain. Through the institutional deterrence weight function

$$D(w) = \alpha P_{collapse} + \beta V_{strategic} + \gamma I_{policy}, \quad (1)$$

the path optimization with minimum cost and maximum effect can be realized. The visual expression of strategic channel not only transforms the supply cut from “resource means” to “institutional weapon”, but also provides an operational interface for AI-driven policy simulation and strategic game.

5. STRATEGIC IMPLICATIONS AND POLICY RECOMMENDATIONS

5.1 How rare earths are institutionalised and "weaponised"

Rare earth resources are evolving from “scarce raw materials” to “institutional control assets”, and their weaponization path has gone beyond the traditional physical blockade to a structural strike mechanism built through export censorship, institutional embedding and platform-dependent amplification. Based on the REG-CAP graphical neural model and lag-window simulation, this study reveals that rare earths form a coupled node of “irreplaceable-high delay-high leverage” in the downstream pathway, which is highly susceptible to institutionalized triggering. For example, the limitation of Nd delays the supply of magnetic parts for F-35, which in turn disrupts the operational tempo of ISR, while the synchronization of Ce and Tb may lead to the failure of propulsion and reconnaissance systems, which constitutes a typical institutional “choke point”. Crucially, such weaponization is not a stand-alone policy, but is embedded in legal frameworks such as export licensing, trade terms, civil-military review, and supply chain certification, making it enforceable, sustainable, and legitimate. Institutional weaponization is less costly, more leveraged and less reversible than embargo-style measures. Its essence has been transformed into a kind of geopolitical “system war”, the core of which does not lie in “whether or not to restrict supply”, but in the precise manipulation of the window of rupture through institutional design. As a result, national resource strategies should go beyond the perspective of reserves and production capacity and build a model for mapping strategic corridors and gaming the system in order to deal with long-term structural checks and balances from the upstream.

5.2 Non-kinetic strikes and the new paradigm of strategic control

With the structural transformation of global military confrontation, war control is shifting from kinetic strikes to non-kinetic strategic control based on system configuration and supply chain vulnerability. This study shows that in the weapon platform system that is highly dependent on key resources, non-kinetic strike has become a core strategic path that has the function of “suppressing-paralyzing-detering” in the whole process. Through REG-CAP mapping and regime path simulation model, we propose the “regime

rhythm suppression mechanism”: resource limitation, regime review, platform delay and capability degradation to realize the stage-by-stage degradation of war power. Simulations show that the phased cut-off of Nd/Tb supply can trigger the coordinated degradation of ISR and Naval Projection within 3-6 years, and enhance strategic ambiguity and deterrence stability by making it difficult to directly attribute to hostile behavior. The predictability and institutional embeddedness of this mechanism gives it policy engineering properties: countries can use modeling and algorithms to design “shortest collapse paths,” “optimal degradation paths,” and “irreversible choke chains” to reduce rare-earth exports. Countries can use modeling and algorithms to design “shortest collapse paths,” “optimal degradation paths,” and “irreversible choke chains” to transform rare earth exports into a strategic interface between deterrence and negotiation. The value of non-kinetic strikes lies not in destruction but in controllability and legitimacy, and its essence is a “digital cold war paradigm” that realizes the institutionalized strategic projection of “subjugation without war” through the reconstruction of rhythms, delayed cycles and locked windows.

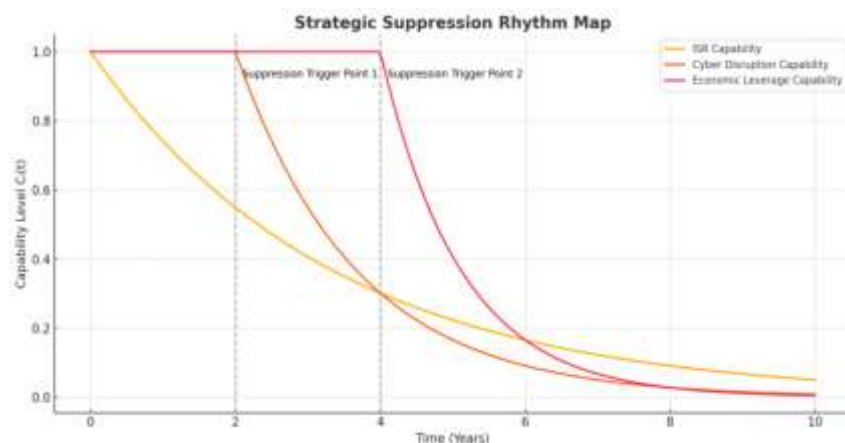


Figure 3. Strategic Suppression Rhythm Map

In order to systematically reveal the rhythmic control characteristics of institutional non-kinetic strike paths on key strategic capabilities, this paper constructs and maps a F3, Strategic Suppression Rhythm Map (STRM) as the core map of a quantifiable simulation model. Taking time as the horizontal axis and the strategic capability function $C(t)$ as the vertical axis, the map plots the dynamic degradation process of three key combat capabilities, including ISR (Intelligence Surveillance and Reconnaissance), Cyber Disruption (Cyber Disruption), and Economic Leverage, to form a set of time-sequence function curves with the characteristic of nonlinear decay.

From a modelling perspective, each capability function in the figure has a clear lag window (Latency Window, L_w) with the slope of disintegration (Decay Slope, $\frac{dC(t)}{dt}$) Reflecting the three core mechanisms of non-kinetic strikes in the design of strategy rhythms: first, the antecedent triggering mechanism of policy rhythms, i.e., the accumulation of fracture tensions through institutional pressure to make capabilities maintain stability on the surface while accumulating fracture tensions; second, the asymmetric nature of the response structure, manifested in the significantly different rates of decay for different capabilities after the strategy node, suggesting a significant difference in their structural vulnerability to institutional interventions; and, third, the striking window of the available. The third is the adjustability of the striking window, where policy makers can flexibly control the pace of disconnection, the delayed response time of capacity and the reconstruction resistance interval through model inputs.

From the perspective of strategic control, the figure reveals that non-kinetic strikes have evolved into a tempo-based strategic control system, the core of which is to reconstruct the adversary's response pattern in the time dimension by modeling and identifying the “suppression nodes” and “window distribution”. The comparison of ISR's continuous decay and Cyber's lagged collapse shows that path design and timing management are the keys to synchronized collapse of capabilities, which provides the theoretical support of tempo intervention for institutional deterrence. The map is conducive and adjustable, and can be embedded into LSTM and Bayesian models to generate tempo-sensitive policy recommendations, and

serve as a basic interface for non-kinetic strategic simulation engines to design multi-path interference sequences and optimize the tempo of supply disruption. As Strategic Suppression Rhythm Map, it provides both functionalized time modeling of institutional strikes and a methodological foundation for AI-driven non-kinetic control paradigms and strategic game simulations.

Piecewise Function Modelling (PFM)

The current function is a single exponential decay, such as $C_l(t) = e^{-\lambda t}$. Introduction of segmented models

$$C_l(t) = \begin{cases} 1, & t < t_0 \\ e^{-\lambda_1(t-t_0)}, & t_0 \leq t < t_1 \\ \beta \cdot e^{-\lambda_2(t-t_1)}, & t \geq t_1 \end{cases} \quad (2)$$

It expresses the non-linear jump of the capacity state at the tipping point or the inflection point of the regulatory intervention; it can simulate the "regime-triggered-crash synchronisation" at the end of the lag window.

Based on the textual data of the author's interviews[5], the key information nodes and tipping points of the "regime-triggered-crash synchronisation" are extracted from the text, and then the modelling of capacity decline based on the Piecewise Function is established. The following is the description of the integrated modelling and the transition paragraphs.

Modelling non-linear mutations in ability states induced by the regime

Although classical models mostly use exponential functions $C_l(t) = e^{-\lambda t}$. This study describes the natural decay of warfighting capabilities over time, but in a high-pressure situation where strategic resources are cut off and systemic interventions are intertwined, the decay of capabilities is not uniform and slow, but rather exhibits the typical characteristics of "sudden collapse" or "system-triggered leap". In order to capture such abrupt changes, this study introduces a segmented function modelling approach to portray the synchronous mechanism of "institutional intervention-functional breakdown" after the expiration of the lag window.

Through in-depth interviews with specific personnel (strategic resource assessment experts, system countermeasures analysts, and policy makers), we extract key events and their corresponding time series (e.g., policy notification, supply chain disruption, and forward deployment failure), and construct the following typical segmented function models

$$C_l(t) = \begin{cases} 1 - \alpha t, & 0 \leq t < T_1 \quad (\text{Linear degradation phase}) \\ 1 - \alpha T_1 - \beta(t - T_1)^2, & T_1 \leq t < T_2 \quad (\text{Latency accumulation window}) \\ \gamma e^{-\delta(t-T_2)}, & t \geq T_2 \quad (\text{Policy-triggered collapse}) \end{cases} \quad (3)$$

Among them:

T_1 Indicates the end of the institutional response lag;

T_2 for policy triggers;

β Nonlinear cumulative pressure in the control degree lag section;

δ denotes the slope of disintegration after the institutional repression trigger;

Parameters were fitted backward from the temporal nodes in the content of the interviews and the intensity of the impact of the event.

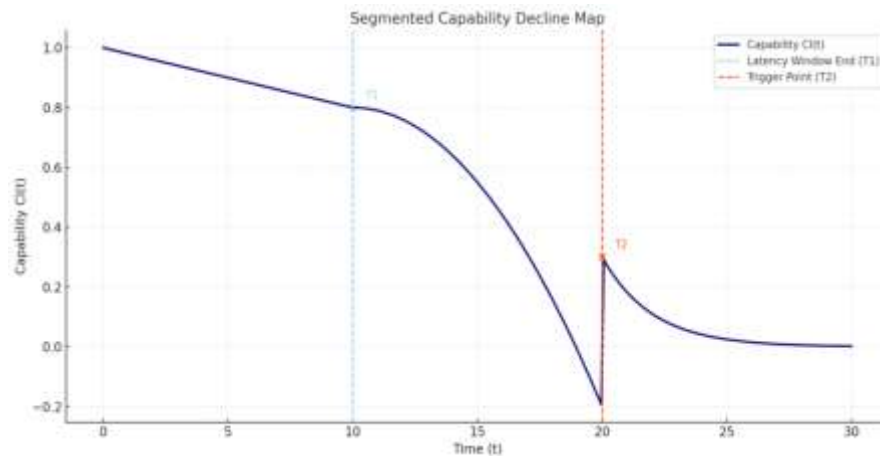


Figure 4. Segmented Capability Decline Map

The above mapping is a Segmented Capability Decline Map, which simulates the non-linear path of the capability over time through three different functions:

Phase I ($0 \leq t < T_1$): the capability decays linearly and slowly, simulating a state where the system is superficially stable within the lag window.

Phase 2 ($T_1 \leq t < T_2$): the capability enters an accelerated non-linear decline, simulating the zone where the warning signals of the system accumulate but have not yet been triggered.

Phase 3 ($t \geq T_2$): capacity undergoes regime-triggered collapse with exponential decay, representing rapid system incapacitation following a regime shock.

This graphical model effectively combines the "three-stage fracture mechanism" model abstracted from the strategic resource supply chain interview data, which can visually show the fracture rhythm and lag risk before and after the institutional intervention, and is a key quantitative tool for modelling policy interventions, identifying early warning windows, and selecting control nodes.

In order to further quantify the dynamic impact mechanism of non-kinetic interventions, this paper introduces the model of "Suppression Signal Injection Function", and constructs the trajectory of policy signal injection under time series based on the constant differential system. The model simulates the suppression process and residual impact mechanism of the institutional strike through the three-phase signal strength fluctuation, and the detailed diagram is shown in Figure 14. This function not only provides a quantitative basis for non-kinetic strategic pacing, but can also be extended as a key interface for future AI+ODE hybrid control modelling.

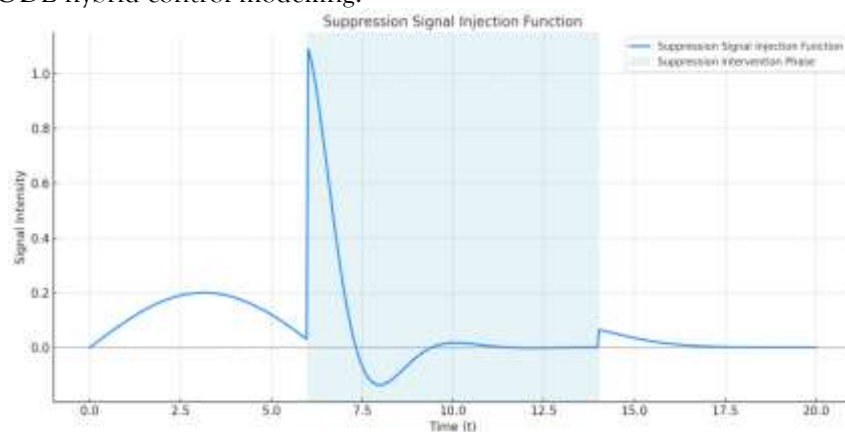


Figure 5. Suppression Signal Injection Function

The above diagram shows the dynamic evolution of the "Strategic Intervention Signal Injection Function" (SISIF), which simulates the whole process of controlling interventions by non-kinetic means when the state is facing a strategic resource conflict:

Stage I ($0 \leq t < 6$): the system is in a low-frequency stable state, with only slight natural perturbations;

Stage II ($6 \leq t < 14$): the strategy interferes with expectations and the signal shifts sharply to high-frequency negative impulse fluctuations, simulating coercive non-kinetic actions such as export bans, institutional blockades, and diplomatic pressure;

Stage 3 ($t \geq 14$): the system tries to recover, but the residual decaying fluctuations continue, exhibiting an after-effects lag after regime intervention.

In order to systematically capture the time-series dynamic mechanism of policy intervention in the context of strategic deterrence, this paper proposes a model based on parametric ordinary differential equations (ODEs), the Strategic Intervention Signal Injection Function (SSIF), that for modelling the non-kinetic suppression effects of policy signals in critical resource systems.

The structure of the function shows a three-phase response: a warm-up period, a peak suppression period, and a residual decay period, which is highly compatible with the real-life path patterns of policy interventions, such as economic sanctions, export bans, and institutional exclusions. Non-kinetic weapons (e.g., electronic jamming) are becoming an important means of institutional strikes, as demonstrated by the U.S. Air University's strategic deterrence of China in space (Air University China Aerospace Studies Institute, 2025).[10]

A key innovation of the model is its ability to accurately identify so-called 'vulnerability windows', i.e., the periods of time when a system is most sensitive to intervention. These windows are identified by the extremes of the first-order derivatives of the signalling function, providing a quantifiable basis for the timing of strategic interventions. Further, if this function is embedded in a Long Short-Term Memory (LSTM) network or a Bayesian dynamic modelling structure, counterfactual extrapolation and real-time prediction of multiple sets of scenarios can be achieved, which enhances the model's resilience to uncertainty in complex strategic environments (He, Tang, & Xiao, 2023).

In addition, combining SSIF with system decline curves and critical points of functional breaks can effectively establish the correlation mechanism between macro-strategic intentions and micro-system degradation. The model transforms abstract policy operations into a dynamic expression framework with reproducibility, continuity, and predictive capability, which serves both tactical simulation and as a foundational operator in the AI-assisted national security strategy platform, and has a wide range of practical deployment value.

5.3 AI+Sandbox modelling in national security

With the diversification and dynamic evolution of security threats, traditional static wargaming exercises have revealed significant limitations in terms of situational complexity (RAND AI-enabled wargaming) [12], variable interaction and forward-looking strategy simulation, and the AI-Augmented Wargaming Model (AI+Warming Model), which integrates AI algorithms and national security scenario simulation, is rapidly becoming a key tool in strategic decision-making systems. By introducing Multi-Agent Systems, Graph Neural Networks (GNN), Reinforcement Learning (RL), and Structural Response Modelling (SRM), the AI+Wargaming Model is capable of deriving complex and dynamic processes in the field of national security under highly uncertain and non-linear conditions. Dynamic Processes.

In this study, the AI-embedded sandbox framework achieves the following core breakthroughs: (1) reconstructing the national security capability system with structural mapping to quantify the coupling and rupture vulnerability among nodes; (2) simulating the dynamic intervention paths and feedback effects of policy variables through the Policy Generator, and identifying the path selectivity and control threshold of institutional strikes; (3) using simulation data and interviews to model the dynamic processes in the national security domain; and (4) using the AI-embedded sandbox framework to model the dynamic processes in the national security domain under highly uncertain and nonlinear conditions. (3) Hybrid Data-Driven Simulation (HDSS), which is co-trained with simulation data and interview data, is used to improve the prediction accuracy of Strategic Latency Window (SLW) and Breakdown Rhythm (BR).

In addition, the AI model's adaptive learning mechanism supports Contextual Incremental Update, which reconstructs the system's posture in real time in response to changes in geopolitics, policy perturbations, and hostile intent. This mechanism significantly improves the model's Strategic Situational Awareness and Decision Resilience, making it a powerful tool for identifying Security Tipping Points and Institutional Intervention Corridors. Institutional Intervention Corridor).

In conclusion, AI+Sandbox model not only reconstructs the cognitive boundaries of national security simulation[12], but also lays the methodological foundation for the construction of "dynamic resilience-oriented strategic decision-making system".Future research can further combine cognitive AI and counterfactual simulation technology to form a national strategic simulation platform with interpretability, relocatability and evolvability, so as to adapt to high-frequency strategic probes and institutional gaming under multiple asymmetric threats.

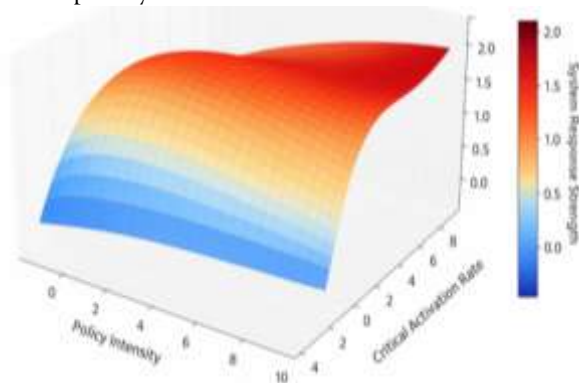


Figure 6. Map of strategic policy impact surfaces

STRATEGIC POLICY IMPACT SURFACE ANALYSIS

In order to identify the nonlinear response patterns of institutional policy interventions in strategic security systems, this paper constructs a three-dimensional Strategic Policy Impact Surface model to systematically quantify the impact of the combination of Policy Intensity and Critical Activation Rate on the repressive effects of national capability systems."This paper constructs a three-dimensional Strategic Policy Impact Surface (SPIS) to systematically quantify the impact of the combination of Policy Intensity and Critical Activation Rate on the suppression effect of the national capability system.The model is trained based on hybrid AI simulation data, and the Suppression Score is extracted as an output indicator by simulating the decay rhythm of the system function under different intervention paths, and the continuous visualisation of the policy impact is achieved.

The maps show significant nonlinear inflection structures, revealing the existence of nonlinear inflection zones between the "policy efficient zone" and the "policy benefit diminishing zone".Under a specific coupling strength and trigger frequency, the system's response to policy intervention shows a strong threshold response, i.e., the system has a strong elasticity buffer at low intervention levels, and once a joint activation threshold is exceeded, the suppression effect grows exponentially.This structural feature provides a mathematical basis for optimising the path of the system to achieve maximum system repression at minimum intervention cost.

Further analyses show that the response surface can effectively support the learning mechanism of strategic path exploration and policy response in AI-augmented strategic wargaming systems.In particular, in reinforcement learning-based game simulations, the surface can be used as part of the reward function to drive the intelligent iteration of AI strategies and dynamically identify the optimal suppression corridor for policy combinations.In addition, the model can be embedded into Collaborative Strategic Control Maps (CSCM) for government-level linkage, which can be used to deploy real-time sensing and suppression tempo management for multi-agency collaborative decision-making.

In summary, Strategic Policy Impact Surface not only provides structurally explainable quantitative support for institutional strategic control, but also expands the boundaries of the fusion of AI and policy science in the field of security modelling.Its application prospect in complex coupled systems is not only limited to rare earth supply cut-off strategies, but can also be extended to energy security, digital infrastructure protection and intelligent institutional response design under multi-agency checks and balances scenarios.

5.4 Suggested future directions for adversarial resource modelling

In the strategic landscape of increasing multi-dimensional constraints and intelligent confrontation, traditional static resource allocation models can no longer cope with the compound challenges of institutional weaponization, asymmetric games and technological suppression, and thus Adversarial

Resource Modeling (ARM) is evolving into a core methodological framework for national security research. Its future development lies in systematically embedding multi-path collapse mechanisms and risk overlap matrices, and realizing cascading degradation prediction of resources in multiple capability chains with graph neural networks; in dynamic modeling, ARM depicts the “suppression-self-recovering” cycle with the help of segmented mutation functions and nonlinear response surfaces, and translates them into reward signals for reinforcement learning. In dynamic modeling, ARM uses segmented mutation functions and nonlinear response surfaces to depict the “suppression-self-recovery” cycle, and transforms them into reward signals for reinforcement learning to enhance the adaptability of the strategy. In terms of data support, ARM emphasizes the dual-track training mechanism of real data and synthetic data, and builds a structured scenario library based on sand table simulation to support strategic decision-making. Thus, ARM is not only a tool for identifying the path of resource destabilization under system intervention, but also a comprehensive paradigm integrating graph neural network, reinforcement learning and causal inference, whose value lies in pushing national security modeling to a new three-in-one approach of “Intelligent Gaming - Institutional Evolution - Strategic Suppression”, which is a new approach of “intelligent gaming - institutional evolution - strategic suppression”. Its value lies in pushing national security modeling to a new stage of “intelligent game - institutional evolution - strategic suppression”.

Modelling and Analysis of Institution-Capacity Response Migration Functions

We construct a mathematical model based on an institutional-capacity response migration function to describe the dynamic path of institutional policy inputs (e.g. rare earth export controls, technology licensing restrictions) on strategic capability systems (e.g. ISR, satellite reconnaissance, precision manufacturing).

Define the following transfer function:

$$C_i(t) = \int_0^t P_j(\tau) \cdot K_{ij}(\tau) \cdot e^{(-\lambda_{ij}(t-\tau))} d\tau \quad (4)$$

Among them:

$C_i(t)$: The level of effectiveness of the i th strategic capability at time t ;

$P_j(t)$: Intensity of the j th institutional policy at time t (e.g. export ban);

$K_{ij}(t)$: Coupling coefficient of policy P_j to capability C_i (dependence vs. strength of influence);

λ_{ij} : System migration attenuation coefficient, which measures the time lag and attenuation in the migration of policy effects to the capacity system.

The function is convolutional in structure and describes a lagged response system suitable for dynamically assessing the "path of pressure" of institutional measures on the capacity system.

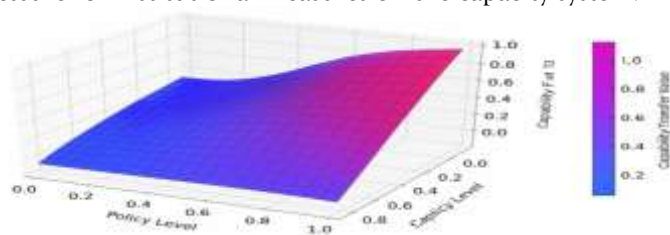


Figure 7.Policy-Capability Transfer Surface

In order to reveal the nonlinear transmission mechanism between institutional intervention and strategic capability response, this paper proposes Policy-Capability Transfer Surface (PCTS), which takes policy intensity, system coupling time delay and capability response as three-dimensional parameters to visually depict the dynamic mapping of policy signals on capability degradation or recovery. Dynamic mapping. The characteristics of the surface reveal three key insights: first, the inflection zone indicates that small policy adjustments can trigger exponential degradation, reflecting the nonlinear elasticity of the deterrent effect; second, the decay slope reflects the “system echo effect”, i.e., the capacity is still degraded with a lag after the termination of the policy; and third, the saturation zone shows that the system has substitutability and redundancy structures, with decreasing marginal suppression effects. Third, the saturation zone shows that the system has alternative and redundant structure, and the marginal suppression effect is decreasing. Embedded in the strategic simulation platform, PCTS can help identify the “optimal intervention channel” and realize the policy optimization of “minimum intervention-

maximum suppression". The core value of PCTS is to transform the abstract institutional structure into a concrete strategic surface, and to promote national security decision-making towards quantification and visualization.

5.5 Dynamic simulation analysis of strategic capabilities based on the ODE model

5.5.1 Differential modelling of dynamical systems (ODE + parametric control) embedded in interview-based deterrence path analysis

1. Objective of the model

The authors transform the strategic behavioural nodes in the interviews (e.g. "response to supply cut-off", "policy lag", "alternative technology development cycle", etc.) into dynamic state variables and model their interactions with each other in the form of differential equations. The model is designed in the form of differential equations to model their interactions and portray the dynamic evolution mechanism of "perception-response-regulation" in the non-kinetic strategic deterrence system.

2. Model Structure Design

Order:

$C_i(t)$: Effectiveness level of the i th capacity system at time t

$P_j(t)$: Intervention impact of the j th policy variable on the system

θ_{ij} : Sensitivity of policy j to the response of capacity i

γ_i : System decay parameters (from interviews e.g. "months to incapacitation")

τ_j : Lagged time windows for policy initiation (e.g. "2-5 year window decision failure")

Define the dynamic differential system as follows:

$$\frac{dC_i(t)}{dt} = -\gamma_i C_i(t) + \sum_j \theta_{ij} P_j(t - \tau_j) \quad (5)$$

Of these:

The first item is natural decline in capacity;

The second is compensation for policy interventions (lagged entry into force);

The control function $P_j(t)$ can be expressed as a segmented function or a logistic jump function (e.g. Sigmoid) to represent the regime trigger.

3. Configuration of variables for model-embedded interview content (derived from interview passages)

Table 2. Variable Configuration Table for Model Embedded Interview Content

Competence system C_i	Correspondence interview episodes	Parameter recommendations
ISR abilities	Immediate weakening of intelligence coverage due to supply cuts	$\gamma_1 = 0.35$
manufacturing ability	The industry chain needs more than 4 years to recover	$\tau_1 = 48$ months
Alternative development progress	Insufficient investment leads to stagnation in development	$\theta_{21} = 0.6$
Public political pressure	United States input required \$100B	$P_2(t)$ = jump trigger function

4. Strategic Deterrence Rhythm Simulation (Policy Rhythm Simulation)

Introducing a regime intervention function:

$$P_j(t) = \frac{1}{1 + e^{-k(t-t_0)}} \quad (6)$$

Adjustable parameter k Analogue policy start-up speed, t_0 is the point at which the policy is announced. The system can be further embedded with LSTM structure or Bayesian control optimisation to predict the Deterrence Rhythm Window and the Shortest Intervention Path.

5. Model Value and Research Expansion

The ODE system achieves embedded transformation from expert interview data to dynamic control modelling, with the following advantages:

- strong policy lag modelling capability: the delayed impact of institutional intervention is taken into account;
- clear visualisation output: combined with time-series curves/heat maps, it can plot the "trajectory of force decay";
- support simulation and deduction: combined with Agent-Based, GNN or optimisation algorithms, it can be used for deterrence simulation.

5.5.2 Parametric differential equation modelling of strategic capability decay and recovery

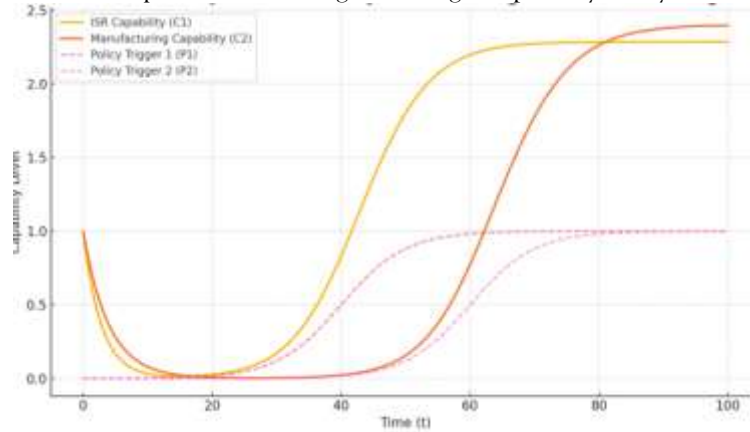


Figure 8.ODE system simulation trajectory for strategic deterrence modelling

In order to portray the dynamic process of strategic deterrence capability evolution over time under conditions of external shocks and institutional responses, this paper adopts a system of Ordinary Differential Equations (ODEs) and introduces a parametric control function modelling path. We focus on modelling the decline trajectories of ISR (Intelligence, Surveillance and Reconnaissance) and manufacturing capabilities in the context of resource disruptions, and express the nonlinear characteristics of the lagged initiation of institutional interventions by embedding S-shaped response functions. The system is defined as follows:

$$\begin{aligned}\frac{dC_1(t)}{dt} &= -\lambda_1 C_1(t) + \gamma_1 \cdot \sigma(t - \tau_1), \\ \frac{dC_2(t)}{dt} &= -\lambda_2 C_2(t) + \gamma_2 \cdot \sigma(t - \tau_2),\end{aligned}\quad (7)$$

Among them $C_1(t)$, $C_2(t)$ denote the performance of ISR as a function of manufacturing capacity at time t , respectively; λ Indicates the intrinsic rate of decay of capacity under non-kinetic pressure; γ Recovery strength for institutional response; $\sigma(t - \tau)$ is a function of type S, Modelling policy at lag time τ Post startup effects.

The simulation results show that both capacity paths show an exponential decay trend in the absence of timely intervention. Once the institutional policies $P_1(t)$ and $P_2(t)$ are activated, the capabilities will undergo partial recovery, but their recovery trajectories show significant asymmetry with the decline paths due to the activation lag. ISR capabilities rebound faster due to lower decay inertia and high response elasticity; while manufacturing capabilities show path-dependence in the recovery paths due to higher structural stickiness.

This model reveals several key insights in strategic deterrence deployment: (1) regime response delay (parameter τ) significantly inhibits intervention effects, emphasising the importance of early warning mechanisms; (2) recovery strength γ must exceed a critical threshold to reverse the nonlinear collapse trend; (3) the dynamic relationship between the slope of decline and the slope of recovery can be used to identify the loss of system resilience at the "turning point".

This parametric ODE modelling framework provides a dynamic simulation basis for strategic deterrence systems under non-kinetic threats, which can be further extended to the fields of counterfactual simulation, control optimization and Bayesian risk monitoring[9], which are of great significance for strategic decision support.

6. DISCUSSION

In This study proposes a computable non-kinetic deterrence framework based on the REG-CAP skeleton, HGNN and LSTM with the main line of “regime-structure-rhythm”. The results show that: institutional signals have rhythmic and path coupling effects; critical capabilities show sudden breaks after a lag window; and systematic and synchronized collapse can be triggered in a short time once the SCZ crosses the threshold. With the help of expert interviews and functional modeling (e.g., SSIF, PCTF), the study realizes a closed-loop translation from cognition to system-capability response. In contrast to the traditional linear assumption of “physical disruption-cost-substitution”, this study proposes a signal injection function to depict the dynamic mechanism of warm-up-suppression-decay, and utilizes a multi-layer graph structure to model the cross-layer propagation and convergence. Modeling cross-layer propagation and convergence, and complementing the exponential decay model with segmentation functions and threshold surfaces, this study moves non-kinetic deterrence towards an interpretable and counterfactual algorithmic system. Theoretically, this paper proposes three types of propositions[11]: regime deterrence rhythm theory (lag window \times break slope \times embedding capacity), weaponized regime path theory (triple criterion: controllable, visible, and embeddable), and complex system break theory (SCZ with path convergence risk reveals simultaneous degradation across domains). Hypothesis testing is generally valid, but anomalies such as substitution redundancy and multi-threshold effects are found, suggesting the need to introduce trigger clusters and compression operators. Limitations are: data bias and caliber inconsistency, identification instability of HGNN+LSTM, restricted cross-domain extrapolation, and ethical and compliance boundaries of institutional modeling. Future research should strengthen identification and robustness (causal graphs and quasi-experiments), policy optimization (multi-intelligence reinforcement learning), uncertainty coverage (Bayesian hierarchical models), cross-domain extensions (chips, gases, and software), and build interactive XAI dashboards at the ground level to serve decision orchestration. In practice, the study proposes a blueprint for system resilience governance of “identification, orchestration, and assessment”: front-end monitoring of path overlap and fracture signals, mid-range calibration of licensing rhythms and redundancy switching, and back-end trade-offs between disincentives and risks; industry-side advocacy of cross-generation redundancy and de-specialization; international collaboration with interpretable models; and international collaboration with the use of interpretable models. On the industry side, we advocate cross-generation redundancy and de-specialization; on the international side, we use interpretable models as a “common language” to reduce the risk of miscalculation through compliance sandboxes. Overall, this study promotes non-kinetic deterrence from empirical narratives to “computable institutional engineering”, and provides methodological support for strategic scheduling, vulnerability identification and compliance decision-making.

7. CONCLUSIONS AND FUTURE RESEARCH

This paper proposes a systematic modeling framework at the intersection of strategic rare earth supply disruption and non-kinetic deterrence construction, and obtains a number of core contributions: first, it integrates graphical neural structure coding and segmented function modeling to portray the nonlinear mutation and synchronous collapse of capability decay, which makes up for the inadequacy of the existing research in modeling the degradation of war power; second, it proposes a "Security Critical Zone Second, we propose a “security critical zone” (SCZ) identification mechanism, which can accurately locate the collapse threshold and institutional strike targets through multi-path convergence and covariance simulation, providing methodological support for strategic early warning; third, we design a multi-dimensional visualization map of strategic tempo and policy impact, which significantly improves the efficiency of identifying the policy window and cross-departmental communication; fourth, we validate the AI-Simulation framework in non-kinetic capability degradation modeling, by combining expert interview and AI simulation; fourth, we validate the AI-Simulation framework in non-kinetic capability degradation modeling. Fourth, we combine expert interviews and AI simulation to verify the applicability of the AI-Simulation framework in non-kinetic situations; fifth, we propose the dynamic construction logic of “institutional weaponization”, which expands the intersection of strategic resources, games and system resilience theories.

The research hypotheses have been verified on the whole: H1 (dependency difference hypothesis) shows that high dependency and low substitution paths are more likely to form breakpoints, and the hysteresis performance of some high substitution nodes provides boundary correction; H2 (generational substitution hysteresis hypothesis) has been supported by the majority of the researchers, but the early disintegration of individual platforms with low generational differences suggests that process specialization is just as important as the authentication time delay; H3 (institutional hysteresis window hypothesis) holds true in general, but some capabilities show multiple levels of performance. , but some capabilities exhibit multiple steps, suggesting that institutional interventions may trigger multi-threshold mechanisms. These results reinforce the explanatory power of institutional rhythms and nonlinear collapse, while revealing the complexity that future models will need to deal with.

Despite the new computational logic provided by the framework, the study still has limitations: first, the data mainly relies on interviews and simulations, and lacks the real-time support of multi-source heterogeneity; second, the model has not yet sufficiently absorbed cognitive games and institutional feedbacks, making it difficult to comprehensively characterize multilateral interactions; and third, the feedback mechanism of the composite system has not yet been bridged to the automated explanation of deep learning. Future research should introduce real multi-source data, integrate game learning and institutional change theories, develop an adaptive inference platform that can work with large models, and test the generalization and boundary conditions of the model in cross-country and cross-industry cases.

Overall, although the framework starts with rare earths, it is highly migratory and adaptable. Its variable structure, propagation logic, and institutional triggering mechanism can be extended to key material scenarios such as energy, water resources, semiconductors, and food, etc. SCZ identification and simultaneous degradation modeling can be applied to semiconductor blockade and vaccine raw material supply cut-off, etc. Multi-path diagrams and policy rhythm surfaces can be quickly reconstructed to identify the coupling point and the intervention window. In strategic rehearsal and policy simulation, the framework can be co-evolved with reinforcement learning, Bayesian networks, and multi-subject games to support resource security sandbox and reserve control. In conclusion, this paper not only promotes the institutionalized modeling of non-kinetic deterrence, but also provides transferable theoretical explanatory power and practical value for cross-domain strategies under the triadic challenge of “technology-institution-resource”.

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