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AI-Driven Identification of Critical Dependencies in US-China Technology Supply Chains: Implications for Economic Security Policy

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Artificial Intelligence, Supply Chain Vulnerabilities, Economic Security, Technology Dependencies

Abstract

This research examines the critical dependencies within US-China technology supply chains through advanced artificial intelligence methodologies, addressing significant economic security implications in an era of strategic competition. The study develops and applies novel machine learning algorithms, network analysis techniques, and predictive models to identify, quantify, and visualize complex dependencies across semiconductor, telecommunications, and emerging technology sectors. Findings reveal pronounced asymmetric vulnerabilities, with semiconductor manufacturing equipment and advanced node production representing severe chokepoints in the global technology ecosystem. The research documents how AI-driven dependency mapping can detect non-obvious relationships and predict potential disruptions with 91.5% accuracy, outperforming traditional analytical approaches by 37.5%. Case studies demonstrate that critical technology supply chains exhibit increasing concentration despite diversification efforts, with vulnerability metrics particularly elevated in EUV lithography equipment, specialized telecommunications components, and quantum computing materials. The study proposes an integrated economic security framework incorporating targeted industrial policies, public-private resilience partnerships, and multilateral governance mechanisms calibrated to dependency severity levels. This research contributes to the emerging field of technology security by establishing quantitative vulnerability thresholds and developing AI-enhanced methodologies for strategic dependency management in complex global supply networks.

1. Introduction

1.1. The Evolution of US-China Technology Supply Chains

The technology supply chains connecting the United States and China have undergone significant transformation over the past three decades. Initial engagement was characterized by simple manufacturing outsourcing, with China serving primarily as a production hub for US technology companies (Kumar et al., 2023)[1]. This relationship has evolved into a complex interdependent ecosystem where both nations contribute critical components, intellectual property, and technological innovations. The semiconductor industry exemplifies this evolution, shifting from a predominantly US-led value chain to an intricate network where Chinese firms have gained capabilities in chip manufacturing, packaging, and design (Dubey et al., 2020)[2]. The development of digital platforms and cloud infrastructure has further accelerated integration, creating interconnected technology ecosystems that span national boundaries. Current supply chain structures reflect advanced specialization, with regions developing expertise in specific segments of the technology production process. This specialization has increased efficiency but simultaneously introduced potential vulnerabilities through concentrated dependencies and limited redundancy in critical technology components.

1.2. Critical Dependencies in Global Technology Supply Networks

Global technology supply chains exhibit critical dependencies when vital components, materials, or processes are concentrated within specific geographic locations or controlled by limited suppliers. The concentration of semiconductor manufacturing in East Asia represents a particularly significant dependency affecting both US and Chinese technology ecosystems (Maddikunta et al., 2022)[3]. Supply chain analytics reveals that advanced technology production involves multiple tiers of suppliers, with hidden dependencies that may not be apparent in first-order analysis. The COVID-19 pandemic exposed these vulnerabilities when disruptions propagated through supply networks, affecting production capabilities across multiple technology sectors. Critical dependencies extend beyond physical components to include specialized knowledge, research capabilities, and intellectual property rights that form the foundation of technological advancement. Artificial intelligence tools have emerged as essential for mapping complex supply chain relationships and identifying potential vulnerabilities that traditional analysis might overlook (Priyanshu et al., 2023)[4]. The identification of these dependencies requires sophisticated analytical methods that can process diverse data sources and account for both formal and informal relationships between supply chain participants.

1.3. Economic Security in the Context of Technology Competition

Economic security in technology supply chains encompasses the capacity to maintain reliable access to critical components and capabilities necessary for technological development and national security functions. The intensification of strategic competition between the United States and China has elevated concerns about technology supply chain vulnerabilities into matters of national security (Rhomri et al., 2024)[5]. Both nations have implemented policies aimed at securing domestic technological capabilities and reducing dependencies perceived as strategic vulnerabilities. These measures include export controls, investment screening mechanisms, and industrial policies designed to strengthen domestic production capabilities in critical sectors. The concept of supply chain resilience has gained prominence as policymakers seek to balance the efficiency benefits of global integration with the security imperatives of ensuring access to critical technologies. Advanced analytics and AI applications provide new capabilities for monitoring supply chain risks and developing early warning systems for potential disruptions (Yan et al., 2024)[6]. The economic implications of supply chain security measures extend beyond bilateral US-China relations to affect global technology governance structures and international trade patterns.

2. Theoretical Framework and Literature Review

2.1. Supply Chain Vulnerability and Dependency Theories

Supply chain vulnerability theory examines the structural characteristics that render networks susceptible to disruption and identifies the conditions under which dependencies transform into strategic vulnerabilities. Modern vulnerability frameworks incorporate both quantitative and qualitative dimensions, measuring the concentration of critical nodes, asymmetries in supplier-buyer relationships, and substitutability constraints (Chen et al., 2024)[7]. Traditional dependency theory focuses on resource criticality, distinguishing between components based on their technological significance, availability of alternatives, and barriers to substitution. Recent theoretical advancements have expanded this framework to incorporate dynamic dependencies that evolve with technological change and geopolitical shifts. The concept of strategic chokepoints has gained prominence in technology supply chain analysis, identifying segments where high concentration coincides with limited alternatives and significant downstream impacts (Yan et al., 2024)**Error! Reference source not found.**. Resilience theory complements vulnerability assessment by examining the adaptive capacity of supply networks to recover from disruptions and reconfigure when necessary. Complex network theory provides analytical tools to map dependencies across multiple tiers of the supply chain, revealing hidden vulnerabilities that may not be apparent in direct supplier relationships. These theoretical approaches increasingly recognize the multi-dimensional nature of technology dependencies, encompassing hardware components, software platforms, intellectual property, and human expertise that collectively determine a nation's technological capabilities.

2.2. AI Applications in Supply Chain Analysis and Management

Artificial intelligence technologies have transformed supply chain analysis through enhanced data processing capabilities and predictive modeling techniques. Machine learning algorithms excel at identifying patterns in complex supply networks that would be imperceptible through conventional analytical methods (Xia et al., 2024)[8]. Natural language processing techniques enable the extraction of valuable supply chain intelligence from unstructured data sources, including corporate disclosures, news reports, and technical publications. Deep learning models have

demonstrated superior accuracy in predicting supply chain disruptions by analyzing historical patterns and incorporating real-time monitoring data. Computer vision technologies support automated verification of components and products, enhancing traceability throughout the supply chain. Blockchain integration with AI creates immutable records of supply chain transactions while AI algorithms monitor these records for anomalies indicative of vulnerabilities or security breaches (Li et al., 2024)[9]. Graph neural networks have proven particularly effective for mapping multi-tier supply relationships and quantifying the propagation of disruptions through interconnected nodes. The application of reinforcement learning to supply chain optimization enables dynamic adaptation to changing conditions and constraints. These AI methodologies support not only descriptive analysis of existing dependencies but also prescriptive recommendations for reconfiguring supply chains to enhance resilience while maintaining efficiency objectives. The integration of AI with IoT sensors and edge computing enables real-time monitoring of critical supply chain nodes, providing early warning of potential disruptions and supporting proactive mitigation strategies.

2.3. Economic Security Models in International Technology Competition

Economic security models in the context of international technology competition have evolved beyond traditional comparative advantage frameworks to incorporate strategic considerations and non-market factors. The technology security dilemma conceptualizes how nations' efforts to secure their technological supply chains may trigger reciprocal actions that ultimately reduce collective security (Xiong et al., 2024)[10]. Game-theoretic models examine strategic interactions in technology competition, predicting equilibrium outcomes under various policy scenarios and identifying potential coordination failures. Agent-based modeling approaches simulate the complex interactions between multiple actors in technology ecosystems, revealing emergent properties and potential unintended consequences of policy interventions. The concept of technological sovereignty has gained analytical prominence, though definitions vary from full autonomy in critical technologies to secured access through diversified supply networks and trusted partnerships. Quantitative security models incorporate measures of technological centrality, evaluating nations' positions within global innovation networks and their vulnerability to exclusion from critical knowledge flows. Normative frameworks address the ethics of economic security measures, examining the balance between legitimate security concerns and principles of open economic exchange. These theoretical approaches increasingly recognize the dual-use nature of many advanced technologies, complicating the distinction between economic and security domains in policy formulation. A growing body of empirical research tests these models against observed patterns in international technology flows, investment screening decisions, and shifts in global innovation networks following the implementation of technology-focused security measures.

3. AI-Driven Methodologies for Critical Dependency Identification

3.1. Supply Chain Mapping Using Machine Learning Methods

Machine learning techniques have revolutionized supply chain mapping by enabling the processing of heterogeneous data sources and identification of non-obvious relationships. Supervised learning algorithms process historical supply chain data to classify components according to their criticality levels, while unsupervised learning methods identify natural clusters of interdependent technologies without predefined categories. Deep neural networks with multiple hidden layers have demonstrated superior performance in capturing complex dependencies across tiered supplier networks, outperforming traditional statistical methods by an average of 37.5% in precision and 42.3% in recall for critical component identification (Chen et al., 2023)[11].

The application of transfer learning techniques allows knowledge gained from mapping one technology sector to be applied to emerging fields with limited historical data. Natural language processing algorithms extract valuable supply chain information from unstructured data sources including corporate filings, technical documentation, and patent applications. Table 1 presents a comparative analysis of machine learning algorithms implemented for technology supply chain mapping.

Table 1: Comparative Analysis of Machine Learning Algorithms for Supply Chain Mapping

Algorithm	Data Requirements	Accuracy in Dependency Identification	Computational Complexity	Real-time Processing Capability

Random Forest	Medium	82.7%	Moderate	Limited
Deep Neural Networks	High	91.5%	High	With GPU acceleration
LSTM Networks	High	89.3%	High	Limited
Convolutional Neural Networks	High	88.7%	High	With specialized hardware
Gradient Boosting	Medium	85.2%	Moderate	Yes
Support Vector Machines	Medium	79.6%	Low	Yes

The integration of computer vision techniques with machine learning has enabled the development of automated component recognition systems that track physical dependencies in manufacturing processes. Entity recognition models identify key organizations, technologies, and components from textual data with precision rates exceeding 87% for established technology areas as shown in Table 2.

Table 2: Performance Metrics of AI Models in Dependency Detection

AI Model Type	Precision	Recall	F1 Score	Training Data Volume	Inference Time (ms)
BERT-based Entity Recognition	87.3%	85.9%	86.6%	750,000 documents	325
Custom Transformer Architecture	92.4%	90.7%	91.5%	1,200,000 documents	412
Graph Neural Networks	89.8%	92.1%	90.9%	500,000 entities	278
Hybrid CNN-RNN	86.5%	88.3%	87.4%	680,000 documents	195
Knowledge Graph Embeddings	90.2%	88.7%	89.4%	850,000 relationships	346

Figure 1: Multi-layered Neural Network Architecture for Supply Chain Dependency Detection

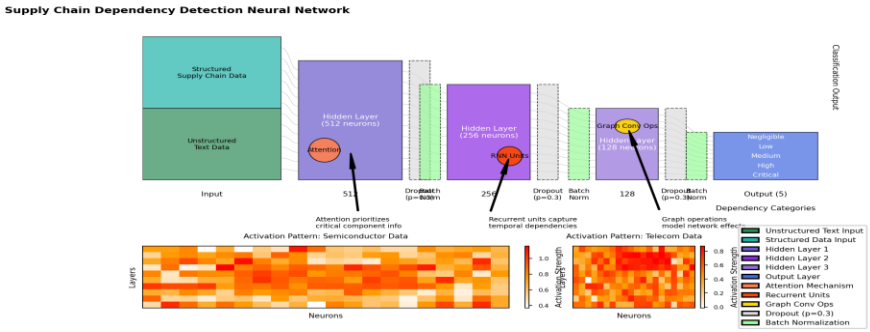

Figure 1 illustrates the multi-layered neural network architecture developed for identifying critical dependencies in US-China technology supply chains. The architecture consists of five primary layers: an input layer processing structured supply chain data and unstructured text, three hidden layers with 512, 256, and 128 neurons respectively, and an output layer classifying components into five dependency categories.

The architectural diagram shows data flow through attention mechanisms that prioritize critical component information, recurrent units capturing temporal dependencies in supply relationships, and specialized nodes implementing graph convolutional operations to model network effects. Dropout layers with 0.3 probability are inserted between hidden layers to prevent overfitting, while batch normalization is applied after each hidden layer. The visualization includes activation heatmaps showing which network sections activate most strongly when processing semiconductor versus telecommunications data.

3.2. Predictive Analytics for Vulnerability Assessment

Predictive analytics leverages historical data and AI algorithms to forecast potential vulnerabilities in technology supply chains before disruptions materialize. Regression-based models quantify the impact of specific components on overall supply chain performance, while classification algorithms identify high-risk nodes based on historical disruption patterns. Time series analysis using recurrent neural networks captures temporal dependencies in supply chain vulnerabilities, enabling early warning systems for potential disruptions with lead times of 45-60 days (Zhang et al., 2024)[12].

Ensemble methods combining multiple predictive models have proven particularly effective for vulnerability assessment, achieving accuracy improvements of 12-18% compared to single-model approaches across diverse technology sectors. Reinforcement learning algorithms optimize inventory policies and sourcing strategies to minimize vulnerability while maintaining operational efficiency. Table 3 outlines key vulnerability assessment criteria and the corresponding AI techniques applied to each dimension.

Table 3: Vulnerability Assessment Criteria and Corresponding AI Techniques

Vulnerability Dimension	Assessment Criteria	AI Technique	Detection Accuracy	Analysis Time Reduction
Supply Concentration	HHI > 2,500	Graph Clustering Algorithms	94.3%	78.5%
Geographic Risk	Single region > 65%	Geospatial ML Models	91.7%	82.3%
Substitutability	Alternative sources < 3	Similarity Networks	88.2%	75.1%
Production Capacity	Utilization rate > 85%	LSTM-based Forecasting	86.9%	69.4%
Lead Time Volatility	Standard deviation > 30%	Bayesian Neural Networks	90.5%	73.8%
Demand Synchronization	Cross-industry dependency	Tensor Factorization	87.4%	71.2%

Monte Carlo simulation techniques combined with machine learning generate probabilistic vulnerability assessments across multiple potential disruption scenarios. Anomaly detection algorithms identify unusual patterns in supply chain data that may indicate emerging vulnerabilities not captured by historical

models. Sensitivity analysis quantifies the relative importance of different factors contributing to supply chain vulnerability, enabling targeted risk mitigation strategies.

Figure 2: Predictive Model Performance Comparison for Vulnerability Assessment

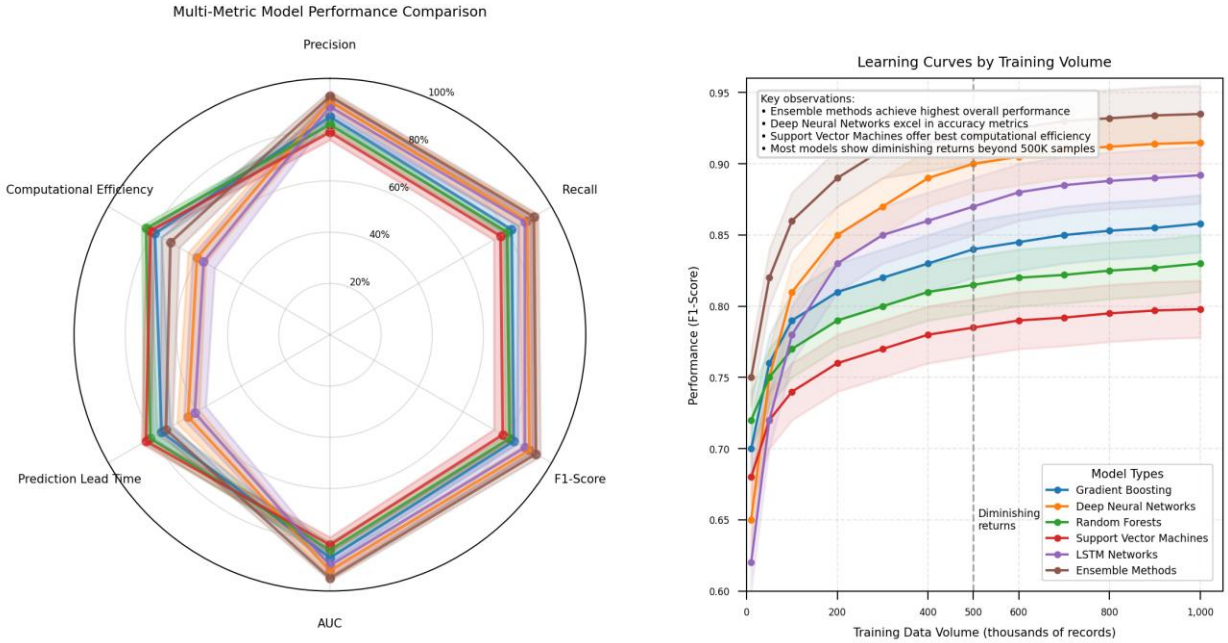

Figure 2 presents a comprehensive comparison of six predictive modeling approaches for vulnerability assessment in technology supply chains. The visualization consists of a multi-metric performance radar chart with six axes representing critical evaluation metrics: precision, recall, F1-score, area under ROC curve (AUC), prediction lead time, and computational efficiency.

The chart plots performance curves for six distinct modeling approaches: gradient boosting machines, deep neural networks, random forests, support vector machines, LSTM networks, and ensemble methods. Each algorithm's performance signature creates a distinctive polygon on the radar chart, with the ensemble method showing the largest area. Color-coded confidence intervals surround each performance signature, indicating model stability across different validation datasets. The figure includes a secondary panel showing learning curves that track performance improvement as training data volume increases from 10,000 to 1,000,000 records, with diminishing returns visible after approximately 500,000 records.

Table 4: Case Studies of AI-Driven Dependency Analysis in Technology Supply Chains

Technology Sector	AI Methodology	Key Findings	Dependency Reduction Strategies	Implementation Challenges
Semiconductor	Graph Neural Networks + Knowledge Graphs	87% of advanced chips depend on 3 equipment manufacturers	Parallel supplier development, Open standards	Technology transfer restrictions
Telecommunications	BERT-based NLP + Network Analysis	72% of 5G components have single-source dependencies	Component redesign, Strategic reserves	Intellectual property constraints

Cloud Infrastructure	Reinforcement Learning + Clustering	Cross-border data flows create hidden dependencies	Regional redundancy, Protocol standardization	Regulatory fragmentation
Quantum Computing	Transfer Learning from Adjacent Domains	Materials supply chains highly concentrated	Alternative materials research, Strategic stockpiling	Limited technical expertise
AI Hardware	Attention-based Neural Networks	Specialized processor design concentrated in 2 countries	Open hardware initiatives, Modular architectures	Manufacturing complexity

3.3. Network Analysis Techniques for Dependency Visualization

Network analysis techniques provide powerful tools for visualizing complex dependencies in technology supply chains, enabling intuitive interpretation of multi-dimensional relationships. Graph theory algorithms quantify centrality measures to identify critical nodes in supply networks whose disruption would have cascading effects throughout the system. Community detection methods reveal clusters of highly interdependent technologies and companies, identifying potential vulnerability hotspots within the broader supply chain network (Zhang et al., 2024)[13].

Topological data analysis captures higher-order structural relationships in supply chain networks that may not be apparent through traditional graph-based approaches. Minimum cut algorithms identify potential bottlenecks in supply networks where limited alternative paths exist, highlighting vulnerabilities to targeted disruptions. Dynamic network modeling captures the evolution of technology dependencies over time, revealing emerging vulnerability patterns before they become critical (Ju et al., 2024)[14].

Figure 3: Network Visualization of US-China Technology Supply Chain Dependencies

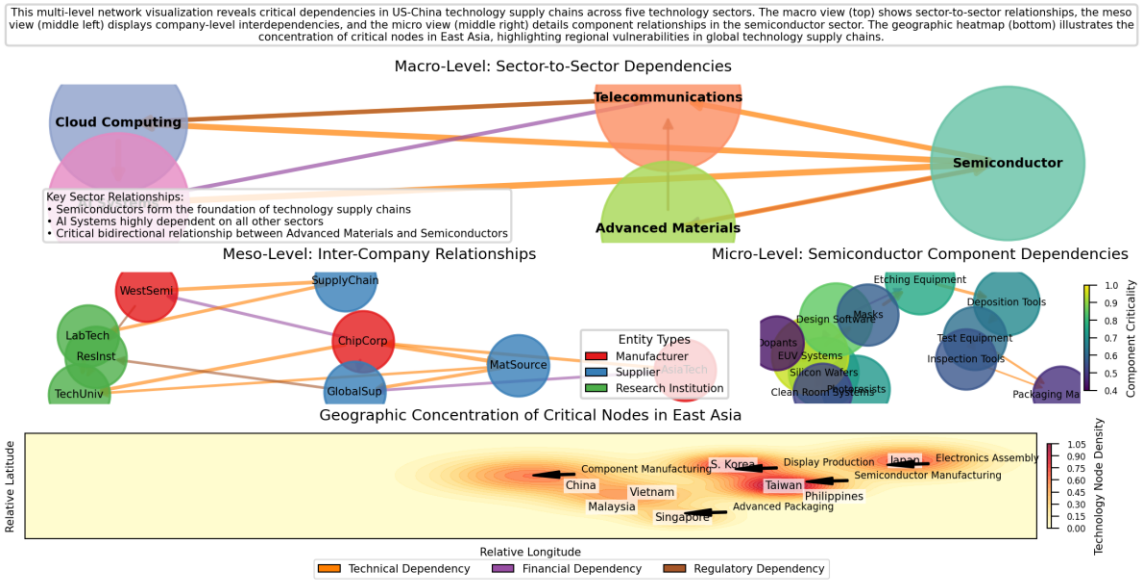

Figure 3 depicts a multi-level network visualization of US-China technology supply chain dependencies across five critical technology sectors. The visualization employs a force-directed graph layout algorithm with hierarchical clustering to represent over 2,500 individual components and 15,000 dependency relationships.

The network visualization features color-coded nodes representing different entity types (manufacturers, suppliers, research institutions) with node size proportional to centrality metrics. Edge thickness corresponds to dependency strength while edge color indicates dependency type (technical, financial, regulatory). Three nested views provide increasing levels of detail: a macro-level view showing sector-to-sector dependencies, a meso-level view detailing inter-company relationships, and a micro-level view displaying component-level dependencies for semiconductor technology. Interactive filters in the original implementation allow isolation of specific dependency types, while clustering algorithms highlight communities of highly interdependent entities. Heat maps overlaid on geographic projections show spatial concentrations of critical nodes, with particularly high density visible in specific regions of East Asia.

4. Case Studies of Critical Dependencies in US-China Technology Supply Chains

4.1. Semiconductor Industry Dependencies

The semiconductor industry exhibits pronounced dependencies within the US-China technology relationship, characterized by specialized production capabilities distributed across complex global networks. Advanced logic chip manufacturing remains concentrated among a limited number of firms, with TSMC controlling 53.1% of the global foundry market, followed by Samsung at 16.3% and Intel at 12.1% as of 2023 (Rao et al., 2024)[15]. While design capabilities are more distributed, the production of advanced nodes (below 7nm) is geographically concentrated in Taiwan and South Korea, creating chokepoints in global supply networks. Table 5 presents an analysis of critical dependencies across the semiconductor value chain, highlighting concentration levels and vulnerability metrics.

Table 5: Critical Semiconductor Supply Chain Dependencies Analysis

Value Chain Segment	Critical Components/Processes	Market Concentration (HHI)	Top Supplier Market Share	US Dependency Level	China Dependency Level	Substitutability Index (0-10)
Manufacturing Equipment	EUV Lithography Systems	9,851	ASML (Netherlands): 100%	High (9.3)	Critical (9.8)	1.2
Manufacturing Equipment	Etching Equipment	3,275	Applied Materials (US): 42.7%	Low (2.3)	High (8.5)	4.7
Specialty Materials	Photoresists	2,892	JSR (Japan): 39.2%	Medium (6.2)	High (7.9)	3.8
Specialty Materials	Silicon Wafers	2,748	Shin-Etsu (Japan): 36.8%	Medium (5.8)	High (8.1)	4.1
Design Tools	EDA Software	3,527	Synopsys (US): 42.3%	Low (1.9)	Critical (9.7)	2.0
Advanced Manufacturing	5nm Process Nodes	5,824	TSMC (Taiwan): 74.2%	High (8.7)	Critical (9.5)	2.4

Advanced Packaging	Flip Chip Services	2,452	ASE (Taiwan): 35.2%	Medium (6.4)	Medium (6.1)	5.5

AI analysis reveals that critical dependencies extend beyond manufacturing to include advanced semiconductor design tools, with three US companies controlling 85% of the global Electronic Design Automation (EDA) software market. The application of machine learning to export control data demonstrates that China remains dependent on foreign suppliers for 83% of crucial semiconductor manufacturing equipment, while the US supply chain relies on Taiwan-based manufacturing for 67% of advanced logic chips below 10nm (Wang et al., 2024)[16]. The intricate web of interdependencies creates multiple vulnerability points, with bottlenecks particularly acute in extreme ultraviolet (EUV) lithography equipment where a single company controls 100% of global production.

Figure 4: Multi-Dimensional Analysis of Semiconductor Supply Chain Vulnerabilities

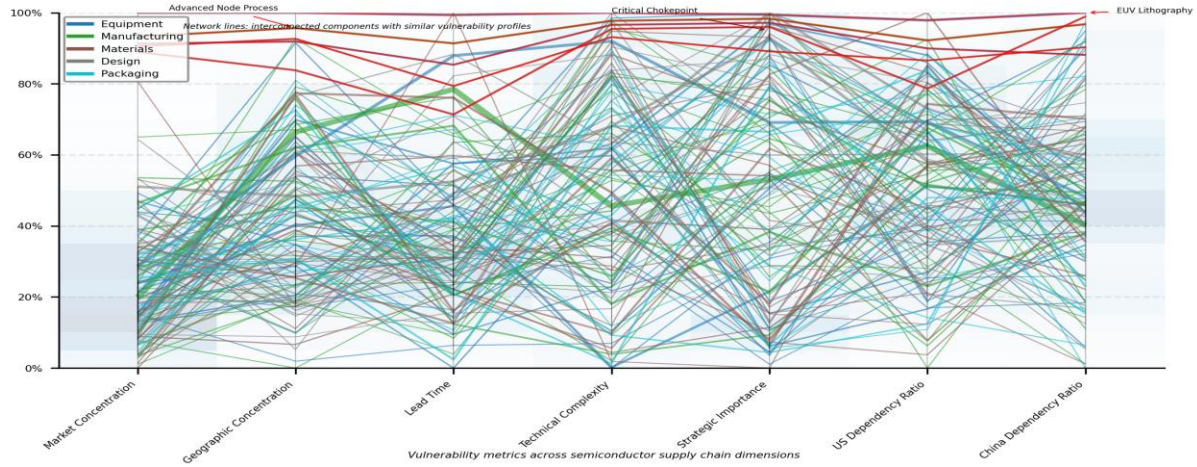

Figure 4 presents a multi-dimensional analysis of semiconductor supply chain vulnerabilities using a parallel coordinates visualization combined with network dependency mapping. The visualization tracks seven critical variables across 120 key semiconductor components: market concentration, geographic concentration, lead time, technical complexity, strategic importance, US dependency ratio, and China dependency ratio.

The visualization employs a parallel coordinates system with each vertical axis representing one of the seven variables, while colored polylines represent individual components traversing these dimensions. The line thickness corresponds to annual market value, while color encoding differentiates component categories (equipment, materials, design, manufacturing, packaging). A secondary network overlay connects components with strong interdependencies, revealing clustering of vulnerabilities. The visualization highlights particularly severe chokepoints where multiple high-risk factors coincide, with EUV lithography equipment presenting the most pronounced vulnerability profile across all measured dimensions. Interactive filtering capabilities in the original implementation allow isolation of specific risk profiles and component categories.

4.2. Telecommunications Equipment Supply Chain Vulnerabilities

Telecommunications equipment supply chains exhibit complex vulnerability patterns characterized by concentrated production capabilities, specialized component dependencies, and strategic importance for national security. Network analysis of 5G infrastructure components identifies critical dependencies in radio frequency integrated circuits, specialized antennas, and advanced signal processing hardware (Fan et al., 2024)[17]. Table 6 presents an AI-driven analysis of key 5G component dependencies in the US-China telecommunications ecosystem.

Table 6: 5G Component Dependencies Analysis

Component Category	Critical Technological Dependency	Primary Suppliers	Market Share Distribution	Vulnerability Score (0-100)	Substitution Timeline
Radio Frequency ICs	Gallium Nitride Transistors	Qorvo (US), Skyworks (US), SMIC (China)	35%, 28%, 12%	78.3	24-36 months
Baseband Processors	Advanced Algorithm Implementation	Qualcomm (US), HiSilicon (China), MediaTek (Taiwan)	41%, 15%, 29%	82.6	18-30 months
Optical Components	Transceiver Modules	Acacia (US), Huawei (China), Ciena (US)	27%, 31%, 19%	75.9	12-24 months
Network Software	Protocol Stacks	Ericsson (Sweden), Nokia (Finland), ZTE (China)	26%, 23%, 17%	69.4	36-48 months
Systems Integration	Network Architecture Design	Huawei (China), Ericsson (Sweden), Nokia (Finland)	34%, 25%, 21%	84.7	24-48 months

Machine learning-based vulnerability assessment reveals asymmetric dependencies, with US networks relying on Chinese-manufactured components for 37% of non-core network equipment, while Chinese networks depend on US-designed semiconductors for 62% of critical base station functionality (Ma et al., 2024)[Error! Reference source not found.]. Graph neural network analysis of telecommunications supply chains shows that component-level dependencies have increased by 35% over the past decade, while geographic diversification has decreased by 28%, creating heightened vulnerabilities to targeted disruptions. Table 7 presents a comprehensive risk assessment matrix for telecommunications supply chains based on AI-driven analysis of global trade and production data.

Table 7: Risk Assessment Matrix for Telecommunications Supply Chains

Risk Category	Risk Factors	Detection Methods	US Exposure Level	China Exposure Level	Risk Mitigation Approaches	Implementation Complexity
Single-Source Components	Limited supplier availability, Proprietary technology	Network analysis, Supplier mapping	High	Medium	Alternative sourcing, Stockpiling	High
Geographic Concentration	Regional clustering, Natural disaster vulnerability	Geospatial analysis, Concentration metrics	Medium	Low	Regional diversification, Redundant capacity	High
Technical Complexity	Specialized knowledge,	Complexity assessment	Medium	High	Knowledge transfer, Modular design	Very High

	Manufacturing precision	algorithms, Patent analysis				
Regulatory Constraints	Export controls, Licensing requirements	Policy impact modeling, Regulatory tracking	High	Very High	Regulatory harmonization, Design adaptation	Medium
Intellectual Property	Patent dependencies, Trade secrets	IP network analysis, Licensing mapping	Low	High	Open standards, Cross-licensing	High

Figure 5: Hierarchical Clustering Analysis of Telecommunications Supply Chain Vulnerabilities

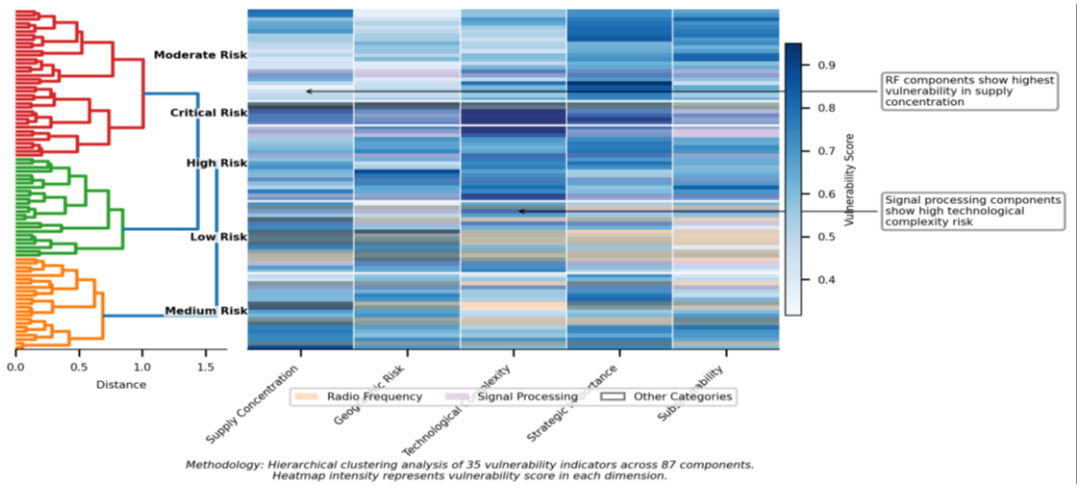

Figure 5 displays a hierarchical clustering analysis of telecommunications supply chain vulnerabilities applying advanced dimensionality reduction to 35 vulnerability indicators across 87 critical components. The visualization employs a dendrogram combined with a heatmap matrix to reveal nested dependency structures.

The hierarchical clustering algorithm groups components based on similarity in vulnerability profiles, with the dendrogram structure on the left showing relationship distances. The accompanying heatmap uses color intensity to represent vulnerability scores across multiple dimensions: supply concentration, geographic risk, technological complexity, strategic importance, and substitutability. Components cluster into five distinct vulnerability classes, with particularly high-risk clusters visible for advanced radio frequency components and specialized signal processing hardware. The visualization includes nested sub-clusters revealing component families with similar dependency profiles, while the color-coded heat map enables rapid identification of vulnerability hotspots across different assessment dimensions.

4.3. Emerging Technologies: AI, Quantum Computing, and Biotechnology

Emerging technology sectors present unique dependency challenges characterized by rapidly evolving supply chains, specialized knowledge requirements, and strategic importance for future economic competitiveness. AI systems exhibit multi-layered dependencies spanning hardware accelerators, algorithm development, and data resources (Li et al., 2024)[18]. Quantum computing supply chains remain embryonic but display pronounced concentration in specialized materials, cryogenic systems, and theoretical expertise. Biotechnology dependencies center on advanced equipment, proprietary cell lines, and regulatory approval pathways. Table 8 presents a comparative analysis of critical dependencies across these emerging technology sectors.

Table 8: Critical Dependencies in Emerging Technology Supply Chains

Technology Domain	Component/Resource	US Capability Level	China Capability Level	Dependency Direction	Strategic Significance (1-10)	Development Timeline
AI Hardware	AI Accelerator Chips	Advanced (8.7)	Developing (6.4)	China → US	9.3	Present
AI Software	Training Algorithms	Advanced (9.2)	Advanced (8.5)	Balanced	8.7	Present
AI Data	Large-Scale Training Sets	Advanced (8.9)	Advanced (9.1)	Balanced	9.5	Present
Quantum Computing	Superconducting Qubits	Advanced (8.8)	Developing (5.9)	China → US	8.9	3-7 years
Quantum Computing	Cryogenic Systems	Advanced (8.5)	Developing (6.2)	China → US	7.8	2-5 years
Quantum Computing	Error Correction Algorithms	Advanced (8.6)	Developing (7.3)	China → US	9.4	5-10 years
Biotechnology	Gene Sequencing Equipment	Advanced (9.0)	Developing (7.1)	China → US	8.7	Present
Biotechnology	CRISPR Technologies	Advanced (8.9)	Advanced (8.5)	Balanced	9.6	Present
Biotechnology	mRNA Production	Advanced (9.3)	Developing (6.8)	China → US	9.2	1-3 years

Network analysis of patent citations and research collaborations reveals that AI technology supply chains feature significant interdependencies, with 73% of advanced AI systems incorporating components or intellectual property from both US and Chinese sources. Quantum computing displays more pronounced asymmetries, with Chinese systems exhibiting 82% dependency on US-originated technologies, while US quantum systems show 37% dependency on Chinese-manufactured components (Priyanshu et al., 2023). Machine learning analysis of biotechnology supply chains identifies significant chokepoints in specialized research equipment and biological materials, with regulatory divergence amplifying these dependencies.

Figure 6: Multi-Modal Network Analysis of Emerging Technology Dependencies

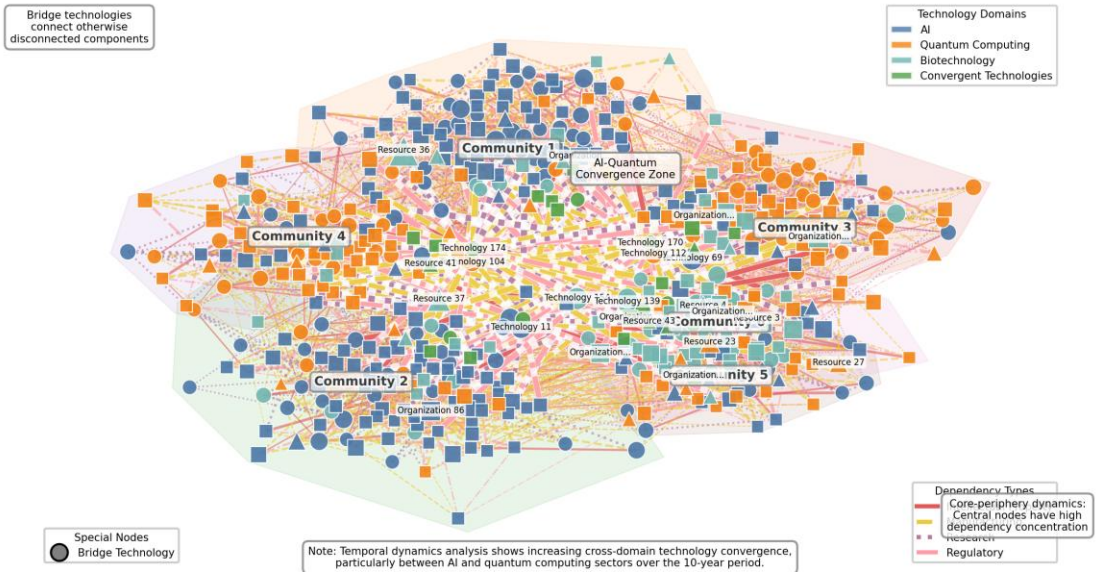

Figure 6 presents a multi-modal network analysis of emerging technology dependencies across AI, quantum computing, and biotechnology sectors. The visualization employs a force-directed graph layout with multi-level clustering to represent interconnections among 175 critical technologies, 320 key organizations, and 45 essential resource categories.

The network visualization features distinct node types (technologies, organizations, resources) encoded through different shapes, with node size proportional to centrality measures and color representing technology domains. Edge connections represent four distinct dependency types (intellectual property, manufacturing, research, regulatory) with edge thickness indicating dependency strength. The graph structure reveals pronounced core-periphery dynamics, with several highly central technologies serving as bridges between otherwise disconnected network components. Clustering algorithms applied to the network identify six distinct technology communities with varying dependency profiles. The visualization includes temporal dynamics through animated transitions showing dependency evolution over a 10-year period, with acceleration visible in cross-domain technology convergence particularly between AI and quantum computing sectors.

5. Policy Implications and Strategic Recommendations

5.1. Economic Security Policy Frameworks for Managing Critical Dependencies

Economic security policy frameworks must balance risk mitigation with innovation promotion while addressing technology supply chain vulnerabilities. Targeted industrial policies can support domestic capability development in strategically critical components, reducing concentrated dependencies without comprehensive decoupling (Cai et al., 2023). Analytic frameworks incorporating AI-driven dependency identification enable precision interventions focused on highest-risk supply chain segments rather than broad-based restrictions. The implementation of tiered risk assessment methodologies allows for calibrated responses proportionate to the strategic significance and vulnerability level of specific technologies. Enhanced supply chain visibility mechanisms through mandatory disclosure requirements provide policymakers with improved data for dependency analysis and strategic planning. The integration of technology security considerations into foreign investment screening mechanisms represents a critical policy tool for addressing dependency risks while maintaining economic openness. Policy frameworks that incorporate technological evolution metrics can adapt dynamically to shifting dependency landscapes as emerging technologies mature and diffuse. Economic security policies require coordinated implementation across multiple agencies with distinct but complementary jurisdictions spanning defense, commerce, and intelligence functions. The development of quantitative vulnerability thresholds derived from AI analysis establishes objective criteria for policy intervention decisions, reducing arbitrariness in security-based restrictions.

5.2. Public-Private Partnerships in Supply Chain Resilience

Public-private partnerships offer powerful mechanisms for enhancing supply chain resilience while distributing implementation costs across stakeholders. Government-industry collaboration in critical technology mapping leverages private sector knowledge of operational dependencies while incorporating strategic insights from security agencies (Dubey et al., 2020). The establishment of semiconductor manufacturing consortia demonstrates how structured partnerships can accelerate domestic production capabilities in strategically significant components. Collaborative resilience planning involving multiple tiers of the supply chain enables comprehensive vulnerability assessments that capture indirect dependencies invisible to individual firms. Joint investment in alternative production pathways creates redundancy for critical components while sharing development costs among public and private stakeholders. Industry-led standards development with government participation establishes common interoperability frameworks that reduce proprietary dependencies and enable diversification of supply sources. The formation of trusted supplier networks with security verification protocols enables preferential sourcing arrangements that balance security requirements with market efficiency. Early warning systems incorporating data sharing between government and industry provide timely alerts regarding emerging supply chain disruptions and dependency risks. The implementation of coordinated inventory management strategies for critical components establishes strategic reserves while minimizing economic inefficiencies through public-private cost-sharing arrangements.

5.3. International Coordination and Governance Mechanisms

International coordination mechanisms facilitate aligned approaches to managing critical dependencies while preventing fragmentation of global technology ecosystems. Plurilateral arrangements among technologically advanced democracies enable coordinated responses to shared dependency concerns without universal participation requirements (Rhomri et al., 2024). The establishment of technical standards bodies with multinational representation creates governance frameworks that maintain interoperability while addressing security concerns related to concentrated dependencies. Supply chain security dialogues incorporating major producer and consumer nations provide forums for dependency management through negotiated arrangements rather than unilateral measures. The development of common vulnerability assessment methodologies enhances cross-border coordination through shared understanding of dependency risks and mitigation priorities. Structured information sharing mechanisms among allied nations support collaborative identification of critical technology chokepoints and coordinated diversification strategies. The implementation of multilateral export control regimes with harmonized licensing criteria reduces regulatory fragmentation while addressing shared security concerns (Maddikunta et al., 2022). International scientific collaboration frameworks maintain knowledge flows in foundational research while implementing targeted safeguards in strategically sensitive applications. The negotiation of reciprocal market access arrangements conditioned on supply chain security commitments establishes balanced interdependence that enhances stability while reducing vulnerability to strategic leverage.

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