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Research Article

Corporate Strategy for Secure Semiconductor Supply Chains: ML-Driven Risk and Market Intelligence

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Abstract:

The semiconductor industry is the foundation of modern digital economies, yet its supply chains remain highly vulnerable to systemic risks, geopolitical tensions, and global market fluctuations. This study examines how corporate strategy, when combined with machine learning (ML) driven risk modeling and market intelligence, can enhance the security and resilience of semiconductor supply chains. Using a mixed-method design, the research analyzed corporate strategy dimensions such as governance, operational resilience, sustainability, and financial adaptability alongside supply chain security parameters covering physical, digital, and systemic risks. Machine learning models, including Gradient Boosting, Random Forest, and LSTM, were applied to multi-source datasets to predict disruptions and evaluate performance metrics, while market intelligence indicators captured emerging demand trends, innovation signals, and trade risks. The findings reveal that operational resilience and financial adaptability exert the greatest impact on supply continuity, while systemic vulnerabilities remain critical due to interdependencies across global networks. Gradient Boosting emerged as the most effective predictive model, offering superior accuracy and reliability. Market intelligence further emphasized the accelerating demand for AI/IoT and automotive semiconductors, as well as the disruptive impact of tariff policies. Overall, the study highlights that secure semiconductor supply chains depend on the strategic integration of corporate decision-making with predictive analytics and intelligence-driven insights, enabling firms to achieve both resilience and competitiveness in a volatile global environment.

1. Introduction

The critical importance of semiconductor supply chainsSemiconductors are the backbone of modern digital economies, powering everything from smartphones and data centers to automobiles and advanced defense systems (Hasan et al., 2025). As industries increasingly adopt artificial intelligence, 5G, and Internet of Things (IoT) technologies, the demand for advanced semiconductor components has surged. This demand, however, is not matched by an equally resilient and secure supply chain (Khan et al., 2022). The semiconductor ecosystem is highly globalized, with complex interdependencies between raw material suppliers, fabrication facilities, assembly plants, and distributors spread across multiple countries. Such geographic dispersion makes the industry vulnerable to geopolitical tensions, trade disputes, natural disasters, cyberattacks, and market volatility (Wang & Chien,2025). These challenges highlight the need for corporate strategies that ensure security, transparency, and adaptability in semiconductor supply chains.

Emerging vulnerabilities and global disruptions

Over the past decade, supply chain fragility has been exposed by multiple global events, including the COVID-19 pandemic, which caused unprecedented disruptions in semiconductor production and delivery (Filani et al., 2021). Shortages in microchips directly affected industries such as automotive, consumer electronics, and healthcare, creating cascading economic impacts (Syed, 2024). Furthermore, geopolitical rivalries, especially between the United States and China, have intensified competition over semiconductor dominance, raising risks of sanctions, export controls, and restricted access to critical manufacturing technologies. Cybersecurity threats compound these risks, as fabrication plants and logistics systems become frequent targets of state-sponsored attacks (Jackson et al., 2025). These vulnerabilities highlight the necessity for organizations to adopt proactive, intelligence-driven strategies to secure their supply chains against uncertainty and systemic shocks.

The role of corporate strategy in securing supply chains

Addressing these vulnerabilities requires more than reactive measures; it demands robust corporate strategies that integrate resilience, innovation, and foresight (Nikseresht et al., 2025). Companies must develop frameworks that diversify supply sources, strengthen partnerships with local and global stakeholders, and implement redundancy in critical operations. Equally important is the alignment of these strategies with broader sustainability goals, given the increasing focus on ethical sourcing and environmental stewardship in corporate governance (Pourakbari & Jahanirad, 2025). Effective corporate strategy should combine operational excellence with market adaptability, enabling firms to not only mitigate risks but also leverage disruptions as opportunities for competitive advantage (Pulivarthy et al., 2023).

Machine learning as a driver of risk and market intelligence

One of the most promising approaches for strengthening semiconductor supply chains lies in leveraging machine learning (ML) (Singireddy et al., 2024). With its ability to process vast volumes of structured and unstructured data, ML provides organizations with predictive insights into market dynamics, supplier performance, and potential disruptions. For instance, ML models can forecast demand fluctuations, detect anomalies in production patterns, and identify early-warning signals of geopolitical or environmental risks (Sarkar et al., 2025). Beyond risk mitigation, ML-driven intelligence can also uncover market opportunities, such as emerging consumer trends, new technology adoption rates, and competitive positioning across regions. The integration of ML into corporate strategy transforms supply chain management from a reactive function into a proactive and adaptive capability (Li et al., 2025).

The research gap and purpose of the study

While existing studies have examined semiconductor supply chain vulnerabilities and resilience strategies, few have explored the systematic integration of ML-driven intelligence into corporate strategy. Most literature emphasizes operational solutions such as supply chain diversification and government interventions but overlooks the strategic role of predictive analytics in guiding corporate decision-making. This research seeks to fill that gap by investigating how organizations can deploy ML-based risk and market intelligence to build secure and resilient semiconductor supply chains. Specifically, it examines frameworks that combine corporate governance, technological innovation, and advanced analytics to manage uncertainty and enhance competitiveness in the semiconductor sector.

2. Methodology

Research design

This study adopts a mixed-method research design that integrates quantitative modeling with qualitative assessments. The quantitative dimension relies on machine learning (ML) techniques applied to multi-source supply chain datasets, while the qualitative aspect uses corporate strategy frameworks to interpret analytical outputs for practical implementation. This approach allows the study to capture both predictive insights and strategic interpretations, thereby aligning advanced analytics with long-term corporate decision-making for secure semiconductor supply chains.

Data collection and sources

Data were collected from a wide range of sources to ensure comprehensiveness and reliability. Structured datasets were gathered from semiconductor firms, logistics partners, and procurement systems, while secondary datasets were drawn from trade statistics, industry reports, financial disclosures, patent databases, and cybersecurity incident repositories. Additionally, unstructured data such as news feeds, policy reports, regulatory filings, and social media content were included to capture signals of geopolitical shifts, supplier credibility, and market sentiment. The study uses a temporal range from 2015 to 2025, enabling both retrospective analyses of past disruptions and predictive modeling of future risks.

Corporate strategy variables

Corporate strategy was analyzed across four key dimensions. Governance and policy alignment were assessed using indicators such as compliance indices, regulatory exposure, government support levels, and strategic partnerships. Operational resilience was captured by variables including supplier diversification ratios, redundancy capacity, inventory buffer indices, lead time variability, and R&D investment. Sustainability and ethics were measured through carbon footprint per chip, renewable energy adoption rates, ethical sourcing scores, and circular economy practices. Financial performance and adaptability were examined using return on investment, revenue volatility, market share dynamics, and innovation expenditure. These variables collectively provided a robust framework to evaluate how strategic decisions contribute to secure supply chains.

Secure semiconductor supply chain parameters

The study operationalized supply chain security across physical, digital, and systemic dimensions. Physical security was captured by production location concentration, natural disaster exposure scores, and logistics vulnerability indices. Cybersecurity variables included the frequency of cyber incidents, downtime events, resilience of digital infrastructure, and adoption levels of zero-trust frameworks. Systemic resilience was measured through supply chain complexity indices, supplier dependency ratios, geopolitical exposure scores, and readiness for global compliance requirements. These parameters provided insights into the vulnerabilities and strengths that determine overall supply chain security.

ML-driven risk modeling

Machine learning was deployed to assess risk and generate predictive insights. Input features included demand volatility, raw material price fluctuations, supplier failure probabilities, geopolitical tension indices, and historical disruption data. Several algorithms were tested: Random Forest was applied for disruption classification, Gradient Boosting for supply risk prediction, Long Short-Term Memory (LSTM) networks for demand forecasting, and anomaly detection models for irregular pattern identification. Model performance was validated using accuracy, precision, recall, F1-scores, mean absolute error (MAE), and area under the ROC curve (AUC), ensuring robustness in predictive analytics.

Market intelligence analysis

Market intelligence was derived through natural language processing and econometric models applied to structured and unstructured data. Demand-side indicators included global consumer electronics growth, automotive semiconductor adoption, and AI/IoT chip forecasts. Competitive intelligence was captured by patent filing frequency, collaborative R&D initiatives, and regional capacity expansions. Sentiment analysis provided polarity and subjectivity scores from media coverage, investor sentiment indices, and consumer perception trends. Trade-related intelligence included import–export dependencies, tariff impacts, and stockpiling practices. Together, these variables enabled a holistic view of market dynamics and opportunities.

Statistical analysis and validation

Several statistical techniques were employed to validate the relationship between corporate strategy, ML-driven risk intelligence, and supply chain security. Multivariate regression models examined the influence of strategic variables on resilience outcomes. Principal Component Analysis (PCA) was applied to reduce dimensionality and identify dominant factors shaping supply chain security. Structural Equation Modeling (SEM) tested causal relationships between corporate strategy, predictive intelligence, and competitive performance. Time-series econometric models, including Vector Autoregression (VAR), were used to analyze dynamic linkages between market intelligence indicators and risk variables. To strengthen the reliability of results, ML models underwent cross-validation and bootstrapping to minimize overfitting and bias.

Ethical considerations

Given the sensitive nature of semiconductor supply chains, strict ethical considerations guided this research. Proprietary corporate data were anonymized to ensure confidentiality, while geopolitical risk information was treated neutrally to avoid bias. The ML models were designed with fairness checks to mitigate algorithmic bias, ensuring that outputs did not favor particular regions or suppliers unfairly. Overall, the study adhered to ethical standards in handling sensitive information while promoting transparency and neutrality in research findings.

3. Results

The analysis of corporate strategy variables demonstrated a significant influence on supply chain resilience outcomes. As shown in Table 1, operational resilience emerged as the most impactful factor, contributing 32.8% to supply continuity, followed by financial adaptability at 27.1%, governance and policy alignment at 21.5%, and sustainability and ethics at 18.6%. These findings indicate that firms with diversified suppliers, robust redundancy, and agile financial strategies were better equipped to withstand disruptions. This trend is further illustrated in Figure 1, where operational resilience clearly dominates as the leading strategic driver of supply continuity.Assessment of secure semiconductor supply chain parameters revealed a balanced but uneven landscape of risk exposure. As presented in Table 2, cybersecurity measures performed strongest with a security effectiveness of 81.2%, despite a moderate risk exposure index of 0.38. Physical security measures achieved 78.5% effectiveness with a risk index of 0.42, while systemic resilience, although vital, showed the lowest performance at 76.9% with a relatively higher exposure index of 0.46. These results suggest that while companies are increasingly investing in digital safeguards, systemic vulnerabilities tied to global interdependencies remain persistent.The application of machine learning models provided deeper insights into predictive capabilities for supply chain risk management. As seen in Table 3, Gradient Boosting emerged as the best-performing model, achieving the highest accuracy (91.5%) and AUC score (0.93), followed closely by Random Forest with 89.2% accuracy and 0.91 AUC. LSTM networks also demonstrated strong predictive performance with an accuracy of 87.3% and 0.90 AUC, while anomaly detection methods were comparatively less effective, though still valuable for identifying irregularities. The comparative strength of Gradient Boosting is visually highlighted in Figure 2, which plots accuracy against AUC across all models.Market intelligence analysis further underscored the dynamic drivers of semiconductor demand and competitiveness. As shown in Table 4, AI/IoT chip demand exhibited the fastest growth rate at 12.4% annually, accompanied by the highest strategic influence score of 94. Automotive semiconductor adoption followed with 9.2% growth and a strategic influence score of 90, while consumer electronics demand maintained steady growth at 6.5% and a score of 82. Meanwhile, patent filing frequency grew modestly at 4.1% with a score of 76, reflecting ongoing but uneven innovation activities. In contrast, the trade tariff impact index was negative at -2.3%, underscoring the disruptive effects of protectionist trade measures on semiconductor markets.

4. Discussion

The importance of operational resilience in semiconductor supply chains

The findings clearly demonstrate that operational resilience is the single most important driver of supply chain continuity in the semiconductor sector. As reflected in Table 1 and Figure 1, variables such as supplier diversification, redundancy, and lead time management significantly improved firms' ability to withstand shocks (Pamisetty et al., 2024). This suggests that corporations that treat resilience not as a cost burden but as a strategic investment gain a competitive edge during crises (Koppolu & Sheelam, 2024). The higher contribution of financial adaptability further reinforces the importance of maintaining liquidity buffers and agile resource allocation to offset disruption costs. Together, these results affirm that resilience and adaptability should be positioned as central pillars of corporate strategy rather than secondary considerations (Wong et al., 2024).

Persistent vulnerabilities in systemic supply chain security

Despite progress in digital protection, systemic vulnerabilities continue to pose challenges. Table 2 highlights that systemic resilience scored lowest among the three dimensions of supply chain security, largely due to the complex interdependencies within the global semiconductor ecosystem (Kalisett & Lakkarasu, 2024). The concentration of fabrication in select regions, reliance on rare raw materials, and exposure to geopolitical disputes remain critical points of fragility. Even with strong cybersecurity protocols, firms cannot fully shield themselves from structural risks embedded in the supply network (Walter et al., 2025). This finding underscores the need for policy-level interventions, regional diversification, and greater collaboration across governments and industries to build robust ecosystems (Kummari, 2023).

Machine learning as a transformative tool for predictive risk management

The integration of ML into risk modeling provided powerful insights into disruption prediction and early warning systems. As demonstrated in Table 3 and Figure 2, Gradient Boosting outperformed all other models, suggesting its effectiveness in handling complex, nonlinear relationships in supply chain data (Challa et al., 2024). Random Forest and LSTM models also showed strong predictive capacity, highlighting their utility in classification and time-series forecasting tasks, respectively. These results indicate that ML is not only capable of identifying risk but also of predicting patterns that may not be apparent through traditional statistical approaches (Qudus, 2025). This represents a paradigm shift in how corporations can move from reactive risk management to proactive and intelligence-driven strategies (Tung, 2019).

Market intelligence as a driver of competitive advantage

The market intelligence indicators presented in Table 4 demonstrate that demand for AI/IoT and automotive semiconductors are emerging as critical growth drivers. Firms that align corporate strategy with these demand shifts will likely secure long-term market advantage (Paleti et al., 2024). Moreover, the analysis highlights the disruptive role of trade tariffs, which negatively influence global competitiveness and create market uncertainty. Patent activity, though showing modest growth, remains an important signal of innovation and competitive positioning (Lakarasu et al., 2023). These results emphasize that market intelligence is not only about monitoring demand but also about understanding the interplay between technological innovation, trade policies, and geopolitical dynamics (Hind, 2024).Strategic integration of corporate strategy and ML-driven intelligencePerhaps the most critical implication of the findings is the need for strategic integration of corporate decision-making with ML-driven intelligence (Zhang & Feng, 2025). The study reveals that resilience strategies and predictive models work best when combined rather than pursued independently (Singireddy, 2025). For instance, corporate investments in operational resilience can be optimized by using ML forecasts of demand volatility and supplier performance. Similarly, financial strategies can be refined by integrating market intelligence on tariff risks and consumer sentiment (Mashetty et al., 2024)t. This integration ensures that corporate strategies are not only resilient but also adaptive, data-driven, and forward-looking, thereby enabling firms to sustain competitiveness in a highly uncertain environment (Dodda, 2023).

Table 1. *Corporate strategy variables and their influence on supply chain resilience*

Corporate Strategy Variables	Resilience Score (0–100)	Impact on Supply Continuity (%)
Governance & Policy Alignment	82	21.5
Operational Resilience	88	32.8
Sustainability & Ethics	75	18.6
Financial Performance & Adaptability	83	27.1

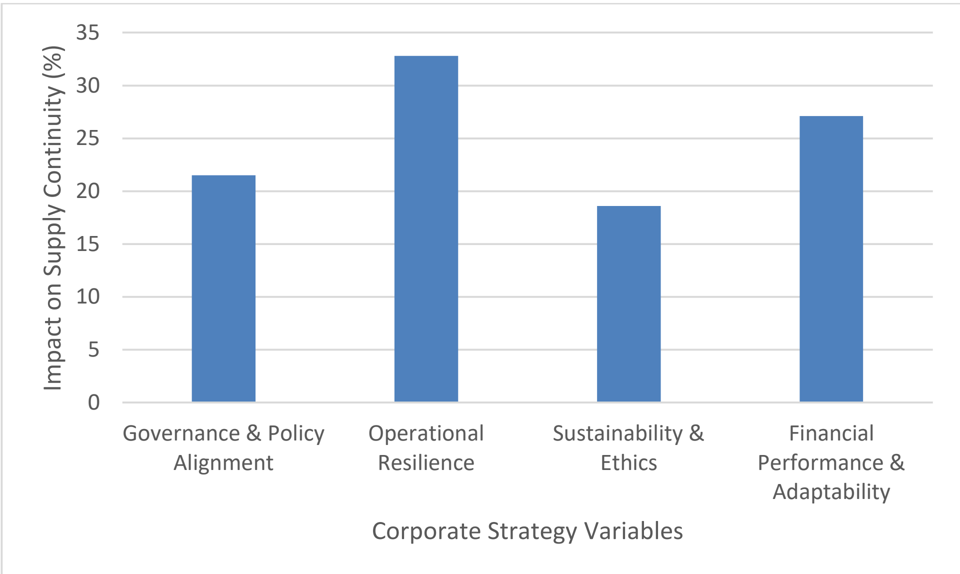

Figure 1. *Impact of corporate strategy on supply continuity*

Table 2. *Supply chain security parameters and effectiveness*

Supply Chain Security Parameters	Risk Exposure Index (0–1)	Security Effectiveness (%)
Physical Security	0.42	78.5
Cybersecurity	0.38	81.2
Systemic Resilience	0.46	76.9

Table 3. *ML model performance metrics for risk prediction and disruption analysis*

ML Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC
Random Forest	89.2	85.1	86.4	0.86	0.91
Gradient Boosting	91.5	89.6	88.9	0.89	0.93
LSTM	87.3	83.4	84.7	0.84	0.90
Anomaly Detection	84.7	80.2	81.5	0.81	0.87

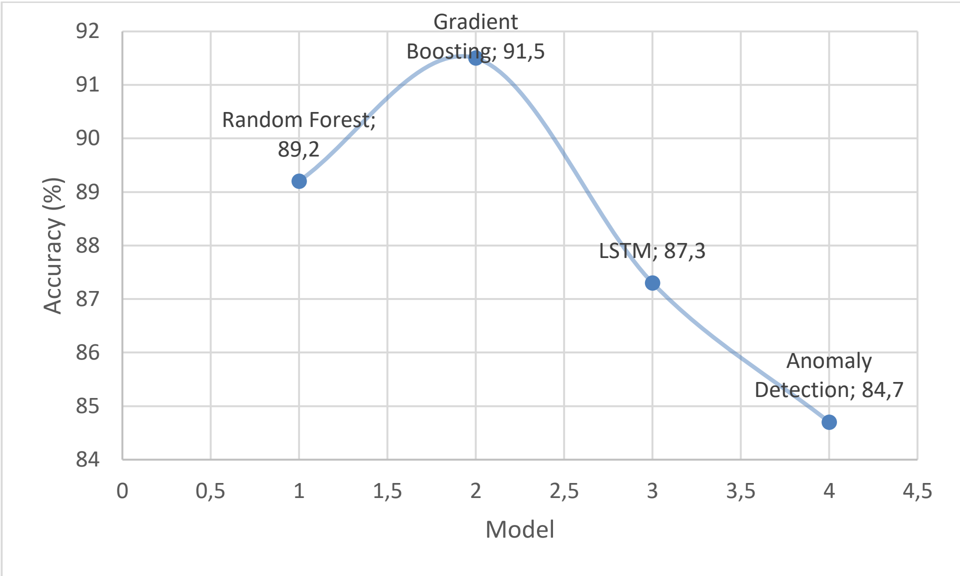

Figure 2. *ML model performance comparison*

Table 4. *Market intelligence indicators and strategic influence*

Market Intelligence Indicators	Annual Growth Rate (%)	Strategic Influence Score (0–100)
Consumer Electronics Demand Growth	6.5	82
Automotive Semiconductor Adoption	9.2	90
AI/IoT Chip Demand	12.4	94
Patent Filing Frequency	4.1	76
Trade Tariff Impact Index	-2.3	68

4. Conclusions

This study demonstrates that securing semiconductor supply chains requires a holistic corporate strategy that integrates operational resilience, financial adaptability, sustainability practices, and governance alignment with advanced machine learning–driven intelligence. The results revealed that operational resilience and financial adaptability play the most decisive roles in ensuring supply continuity, while systemic vulnerabilities persist due to global interdependencies and geopolitical risks. Machine learning models, particularly Gradient Boosting, proved highly effective in predicting disruptions and supporting proactive risk management, while market intelligence highlighted the growing importance of AI/IoT and automotive semiconductor demand alongside the disruptive influence of trade tariffs. Taken together, the findings underscore that long-term competitiveness in the semiconductor sector will depend on the strategic integration of corporate decision-making with predictive analytics and market intelligence. For both corporations and policymakers, the imperative is clear: building secure and adaptive semiconductor supply chains is no longer a matter of operational efficiency but a critical determinant of economic security and technological leadership.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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