Leveraging Artificial Intelligence to Mitigate Supply Chain Vulnerabilities: Insights from the Malaysia Supply Chain Pressure Index (MSCPI)

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Abstract

The increasing complexity of global supply chains has exposed economies to systemic vulnerabilities arising from pandemics, geopolitical tensions, logistics constraints, commodity price volatility and climate-related disruptions. Malaysia is highly sensitive to these pressures because its trade, manufacturing, port and logistics systems are closely linked to regional and global production networks. Previous work on the Malaysia Supply Chain Pressure Index (MSCPI) provides a Malaysia-specific measurement of supply chain stress using Principal Component Analysis and indicators related to transportation, trade, production, logistics, labor, climate and macroeconomic conditions. However, an index-based monitoring approach remains primarily descriptive unless it is connected to predictive analytics and decision-support mechanisms. This conceptual article proposes an Artificial Intelligence (AI)-enabled framework that leverages MSCPI as a structured analytical input for forecasting supply chain stress, detecting early warning signals, identifying vulnerability drivers and supporting mitigation decisions. The proposed framework integrates MSCPI with machine learning and time-series modelling approaches, including Random Forest, gradient-based models and statistical thresholding; sequence-learning models such as LSTM are reserved for future high-frequency extensions, to capture nonlinear and lagged relationships between macroeconomic indicators and supply chain stress. The models are presented as potential analytical components within the proposed framework; however, they are not subjected to empirical testing in this study. The article argues that AI can transform MSCPI from a retrospective stress indicator into a forward-looking policy intelligence tool. The discussion suggests that transportation costs, trade fluctuations, industrial production, labor dynamics, exchange rate movements and climate variables are useful inputs for risk prediction. The study contributes conceptually by linking

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index construction, AI-based prediction and resilience-oriented policy action within the Malaysian supply chain context. It offers practical guidance for policymakers, industry stakeholders and researchers seeking to strengthen proactive supply chain vulnerability mitigation.

Keywords: *Artificial Intelligence, Supply Chain Vulnerability, Malaysia Supply Chain Pressure Index, Machine Learning, Predictive Analytics*

1. Introduction

The resilience of supply chain systems has become a major concern for national economic stability. Global supply chains connect production, transportation, warehousing, trade, retail and consumption activities across borders. When this network is stable, firms can obtain input, move goods efficiently and respond to market demand. When the network is disrupted, production delays, cost increases, shortages and inflationary pressures can spread across sectors. The COVID-19 pandemic, semiconductor shortages, rising global logistics costs, climate-related disruptions and geopolitical tensions have shown that supply chain vulnerability is not only an operational issue but also a strategic national concern [1], [2].

Malaysia is particularly exposed to supply chain vulnerability because of its role as a trade-oriented economy located along major maritime routes, including the Straits of Malacca and the South China Sea. The country is supported by key logistics infrastructure such as seaports, airports, road networks and rail connectivity. These advantages strengthen Malaysia's position as a regional supply chain node, but they also increase exposure to external shocks. Disruptions in global transportation, fuel markets, production cycles, labour availability or international trade can quickly affect domestic logistics performance and economic activity [1].

To understand such vulnerability, researchers have developed composite indices that summarize supply chain pressure. The Global Supply Chain Pressure Index (GSCPI) by the Federal Reserve Bank of New York is widely used to monitor global bottlenecks and logistics stress[3]. However, the GSCPI does not directly capture Malaysia-specific conditions. The Malaysia Supply Chain Pressure Index (MSCPI) was therefore introduced to represent domestic supply chain stress by combining relevant Malaysian indicators through Principal Component Analysis (PCA) [1]. The MSCPI provides a structured measurement of supply chain pressure from 1990 to 2023 and highlights how Malaysia's supply chain stress changes across economic cycles.

Although MSCPI is valuable as a monitoring tool, the next research challenge is to transform it into a predictive and actionable instrument. Traditional index construction explains what happened, but policymakers and industry players need to know what is likely to happen, which variables are driving the risk, and which mitigation actions should be prioritized. Artificial Intelligence (AI) offers a practical way to address this gap. By learning nonlinear and lagged relationships from MSCPI and related indicators, AI can support forecasting, anomaly detection, risk classification and scenario analysis. This article therefore develops an AI-enabled conceptual framework for mitigating supply chain vulnerability using MSCPI as the core input.

Specifically, this article is guided by the following research objectives. First, it aims to examine how MSCPI can be positioned as a structured analytical input for AI-based supply chain vulnerability analysis. Second, it seeks to conceptualize an AI-enabled framework that links MSCPI-related indicators with forecasting, risk classification, anomaly detection and driver identification. Third, it aims to explain how AI-generated insights can support early warning, scenario analysis and mitigation-oriented decision-making for policymakers and industry stakeholders. These objectives provide the basis for the subsequent sections of the article, particularly the discussion on AI-based predictive resilience, framework development, modelling strategy and policy implications.

2. Literature Review

2.1. Supply chain vulnerability, resilience and stress measurement

Supply chain vulnerability refers to the exposure of a supply network to disruptions that reduce its ability to deliver goods and services effectively. Vulnerability may arise from external shocks such as pandemics, wars, commodity price changes and natural disasters, or from internal weaknesses such as inadequate logistics capacity, limited inventory, labor shortages and poor coordination. In highly integrated economies, such disruptions may affect production cost, delivery time, trade flows and consumer access to goods [2], [4]. Recent supply chain studies further show that disruption risk is multidimensional because shocks may spread across transportation, production, procurement, supplier relationships, inventory systems and final demand[5], [6].

Supply chain resilience therefore requires not only recovery after disruption, but also anticipation, absorption and adaptation to changing risk conditions. The COVID-19 pandemic, geopolitical instability and climate-related events have reinforced the importance of visibility, flexibility, redundancy, supplier diversification and data-driven decision-making in supply chain management[5], [6]. In this context, vulnerability measurement is important because decision makers need systematic indicators that can identify stress patterns before they develop into more serious disruptions.

Index-based measurement is useful because supply chain stress cannot be captured by one variable alone. The Global Supply Chain Pressure Index (GSCPI) combines transportation and manufacturing-related indicators to measure global supply chain pressure [7]. The MSCPI extends the logic of composite measurement to Malaysia by adapting variables that reflect transportation cost, logistics performance, industrial production, trade activities, labor conditions, climate factors and macroeconomic risks [1]. In this sense, MSCPI creates a local evidence base for analysing vulnerabilities that may not be visible in global indicators.

The MSCPI study demonstrates that Malaysia experienced different levels of supply chain pressure across major economic periods. Lower and more stable stress was observed during the early 1990s, while pressure increased during periods associated with global financial turbulence, trade expansion, fuel cost increases, labor shifts and climate-related variations [1]. This historical pattern is consistent with wider evidence that fuel price movements, physical climate exposure and labor constraints can affect supply chain performance, operating costs and network resilience [8], [9], [10].

2.2. Composite indices and alternative approaches to supply chain pressure measurement

Composite indicators are commonly used when a complex phenomenon cannot be represented adequately by a single variable. Methodological guidance from the OECD and the Joint Research Centre emphasizes that composite index construction requires careful selection of indicators, normalization, weighting, aggregation and sensitivity analysis to ensure that the final index is meaningful for policy interpretation[11],[12]. PCA is frequently used in composite indicator construction because it can reduce correlated variables into a smaller number of components while preserving common variation in the data [13].

In supply chain research, the GSCPI is an important benchmark because it captures global supply chain pressure using multiple transportation and manufacturing-related indicators [7]. However, global indices may not fully reflect country-specific logistics structures, trade patterns, labor conditions, climate exposure and macroeconomic vulnerabilities. This limitation supports the development of local or national indices such as MSCPI, which can incorporate domestic variables and provide a more context-sensitive interpretation of supply chain stress [1].

Alternative index-based approaches may use equal weighting, expert weighting, factor analysis, PCA, dynamic factor models or dashboard-style indicator systems. Each approach has strengths and limitations. Equal weighting is simple but may overlook the relative influence of individual variables. Expert weighting is context-sensitive but may introduce subjectivity. PCA reduces dimensionality statistically, but the resulting component requires careful interpretation. For this reason, MSCPI is useful as a structured monitoring tool, but its policy value can be strengthened when it is connected to predictive analytics, explainable modelling and scenario-based decision support.

2.3. Artificial Intelligence for predictive supply chain resilience

AI has become increasingly relevant to supply chain management because modern supply networks generate heterogeneous data from trade, logistics, prices, production, weather, finance and market behavior. Systematic literature reviews show that AI applications in supply chain management include demand forecasting, supplier selection, inventory optimization, disruption prediction, production planning, transportation routing and risk assessment [14][15]. Unlike conventional linear models, AI methods can handle nonlinear relationships, high-dimensional inputs, interactions among variables and complex temporal patterns.

Recent AI-for-supply-chain studies highlight that AI can enhance resilience by improving visibility, risk sensing, sourcing flexibility, distribution planning and business continuity capabilities[16]. AI-based approaches are also increasingly used to support supply chain risk assessment, especially where decision makers need to process large volumes of structured and unstructured data under uncertainty[15]. In the context of MSCPI, this means that AI can be used not only to describe past pressure, but also to estimate future stress, classify risk regimes and identify the most influential vulnerability drivers.

Traditional monitoring and index-based approaches are useful for summarizing supply chain conditions and identifying periods of stress after they have occurred. However, these methods are generally descriptive and rely on historical indicators to explain past or current pressure. AI-based predictive methods extend this capability by learning from historical and real-time data to anticipate future disruptions, detect early warning signals and identify the key variables contributing to supply chain vulnerability. Therefore, while traditional indices such as MSCPI provide a structured measurement of supply chain stress, AI models can potentially enhance their value by transforming them into forward-looking decision-support tools.

Random Forest is suitable for supply chain vulnerability analysis because it can model nonlinear relationships and produce variable importance scores that improve interpretability[17]. Gradient boosting models may further improve predictive performance where multiple weak learners are combined, and recent reviews of AI-based supply chain risk assessment highlight the relevance of Random Forest, XGBoost and hybrid models for predictive risk analysis [18]. LSTM networks are recognized for modelling temporal dependence[18], but they are not proposed as a primary model for the current annual MSCPI series because the 1990-2023 data provide only 34 observations. In this article, LSTM is retained only as a possible future extension if monthly or quarterly MSCPI-related proxy indicators become available.

2.4. Explainable AI for policy trust and decision support

Although AI models can improve predictive capability, their usefulness for policy depends on interpretability and trust. Many machine learning models, especially ensemble and deep learning models, are often treated as black boxes because their internal decision logic is difficult for non-technical users to understand [19]. This is a major concern in public policy and supply chain governance because decision makers must be able to justify why a warning is issued, which variables are driving the risk and what mitigation action should be prioritized.

Explainable AI (XAI) provides methods for interpreting model outputs and increasing transparency. LIME explains individual predictions by approximating complex models locally with interpretable models[19], while SHAP assigns contribution values to features based on Shapley values and is widely used for feature attribution [20]. In supply chain decision support, XAI can help translate model outputs into explanations such as whether fuel price, trade volatility, industrial production, climate indicators or labor conditions are contributing most strongly to predicted stress[21].

Recent literature on XAI in supply chain decision support emphasizes that explainability supports trust, accountability and adoption of AI-based recommendations[21]. For an AI-enhanced MSCPI framework, XAI is important because policymakers and industry stakeholders need more than a forecasted index value. They also need to understand the drivers behind the forecast, the confidence of the warning and the practical implications of different mitigation options. Therefore, explainability should be treated as a core design requirement rather than an optional technical feature.

2.5. Malaysian logistics, trade and industrial policy context

Malaysia's supply chain vulnerability must also be understood within its national logistics, trade and industrial policy context. The National Transport Policy 2019-2030 provides strategic direction for developing an efficient, integrated and sustainable transport system, including improvements in connectivity, logistics efficiency and institutional coordination[22]. The National Trade Blueprint 2021-2025 focuses on strengthening Malaysia's export competitiveness and addressing challenges across the export ecosystem[23] [23]. These policies are relevant to MSCPI because transportation efficiency and trade performance are key components of supply chain pressure.

The New Industrial Master Plan 2030 further emphasizes industrial upgrading, supply chain resilience, manufacturing competitiveness and Malaysia's positioning within changing global production networks[24]. The Twelfth Malaysia Plan also highlights the need to strengthen economic resilience, improve logistics services and support competitiveness in global value chains [25]. In addition, the World Bank Logistics Performance Index provides an international benchmark for trade logistics performance and can complement local indicators when assessing Malaysia's logistics capability [26].

Taken together, the literature suggests four gaps that motivate this article. First, existing supply chain pressure indices are useful for monitoring but are often less developed as predictive tools. Second, AI applications in supply chain resilience are growing, but country-specific integration with a national supply chain pressure index remains limited. Third, XAI is increasingly recognized as necessary for trust and transparency, yet it is rarely embedded explicitly into index-based supply chain monitoring frameworks. Fourth, Malaysia's logistics and trade policy environment requires decision-support tools that can connect data, prediction, risk interpretation and mitigation action. This article addresses these gaps by proposing an AI-enabled MSCPI framework for supply chain vulnerability mitigation.

3. Methods and Theory

3.1. Conceptual Research Design

This article adopts a conceptual and analytical framework approach. It synthesizes the MSCPI construction logic with AI-based predictive analytics to propose a practical decision-support framework. The framework is designed for researchers, policymakers and industry stakeholders who need to monitor supply chain stress, anticipate vulnerability and select mitigation actions. The approach is not limited to a single algorithm; instead, it defines a layered architecture in which MSCPI and supporting indicators are transformed into risk intelligence.

The proposed framework consists of four interconnected layers that operate in a sequential and complementary manner layers. The data layer provides the foundation of the framework by capturing MSCPI and supporting indicators, including transportation cost, trade, industrial production, logistics, labor, macroeconomic and climate variables. These data are then processed in the AI analytics layer, where feature engineering, machine learning, time-series forecasting and anomaly detection are applied to extract patterns, trends and abnormal signals. The analytical outputs are subsequently translated into the risk intelligence layer, which converts model results into interpretable decision inputs such as driver importance, stress probability, risk categories and early-warning thresholds. The decision layer then uses these insights to guide policy intervention, industry mitigation planning and supply chain resilience programs. Therefore, the relationship between the layers reflects a continuous flow from raw data input to AI-based analysis, to risk interpretation, and finally to actionable decision support.

To illustrate the overall structure of the proposed approach, Figure 1 presents the AI-enabled MSCPI framework for supply chain vulnerability mitigation. The figure shows how the framework is organized into four interconnected layers, beginning with data input, followed by AI-based analytics, risk interpretation, and finally decision support for mitigation and resilience planning.

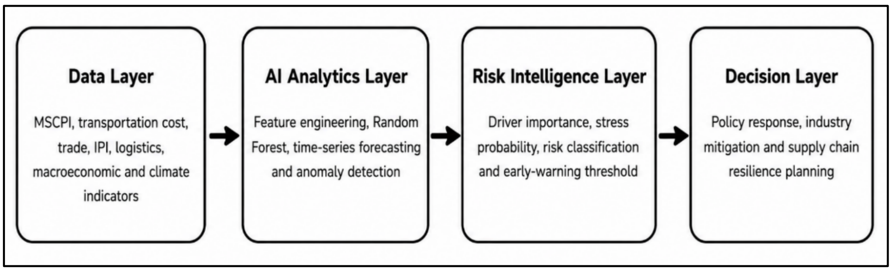

Figure 1. AI-Enabled MSCPI Framework for Supply Chain Vulnerability Mitigation

3.2. MSCPI as the core analytical input

The MSCPI is constructed using PCA, which transforms a set of correlated indicators into uncorrelated principal components. This method is appropriate because supply chain stress is multidimensional and involves variables that may move together, such as fuel price, cargo movement, trade activity and macroeconomic indicators. PCA reduces the dimensionality of the data while preserving the largest amount of variation[1], [27].

The standardisation of each input variable is necessary because the indicators are measured in different units. A standardized variable may be expressed as follows:

$$Zij = (Xij - \mu j) / \sigma j \qquad (1)$$

where Zij is the standardized value of variable j for observation i, Xij is the original value, μj is the mean of variable j and σj is the standard deviation of variable j. The standardized data is then used to compute the covariance matrix:

$$C = (1 / (n - 1))\, Z^{T}Z \qquad (2)$$

where C is the covariance matrix and n are the number of observations. The eigenvalue problem is then solved as:

$$Cv = \lambda v \qquad (3)$$

where λ is the eigenvalue and v are the corresponding eigenvector. The principal component score can be obtained using:

$$Y = ZV \qquad (4)$$

where Y is the matrix of principal component scores and V is the matrix of selected eigenvectors. In the MSCPI context, the first principal component can be interpreted as a summary measure of supply chain pressure when it captures the dominant common variation across the selected indicators [1].

3.3. Data Variables and AI Features

Table 1. MSCPI-Related Variables and AI Feature Use

Category	Variables / Proxies	Role in AI Model	Expected Supply Chain Interpretation
Transportation	Fuel price, cargo handling by seaport, airport and railway	Predictors and lagged predictors	Higher transport cost or abnormal cargo movement may signal logistics pressure
Trade	Exports, imports, net exports and balance of payments	Predictors, growth rates and volatility features	Trade fluctuations may indicate changes in external demand or bottlenecks
Production	Industrial Production Index and manufacturing-related indicators	Predictors and interaction terms	Lower production or sudden changes may reflect supply-side stress
Logistics	Logistics Performance Index and related capacity indicators	Structural predictors	Weak logistics capability may intensify disruption effects
Macroeconomic	Exchange rate, interest rate, inflation and GDP-related variables	Predictors and scenario variables	Macroeconomic volatility may affect import costs, financing and firm operations
Labor and Climate	Labor force, unemployment, temperature and rainfall	Risk modifiers and external shock indicators	Labor shortages and climate events may disrupt production and delivery

Table 1 summarizes how the MSCPI-related variables can be translated into AI features. In addition to using the original variables, the framework may include lagged values, percentage changes, moving averages, volatility measures and interaction terms. These transformations help the AI model capture delayed effects and nonlinear risk relationships.

3.4. AI modelling strategy

The proposed AI modelling strategy involves four main tasks. First, forecasting models estimate future MSCPI values based on historical MSCPI and explanatory variables. Second, classification models categorize stress conditions into low, moderate and high-risk regimes. Third, variable-importance analysis identifies the main vulnerability drivers. Fourth, anomaly detection flags unusual movements that may require attention before a crisis becomes visible in conventional reports. In this framework, an unusual stress signal may include abnormal forecasting residuals, sudden changes in MSCPI values or deviations beyond a specified statistical threshold. For example, an anomaly may be identified when the gap between actual and predicted MSCPI exceeds one or two standard deviations from the historical residual mean, when MSCPI records an unusually sharp period-to-period increase, or when the index moves beyond an upper percentile or z-score boundary. These criteria allow anomaly detection to function as an early warning mechanism by highlighting abnormal supply chain stress patterns that require further investigation.

The low, moderate and high-risk categories may be determined using a combination of statistical and contextual criteria. Statistically, MSCPI values can be divided using percentile thresholds, such as below the 33rd percentile for low risk, between the 33rd and 66th percentiles for moderate risk, and above the 66th percentile for high risk. A z-score or standard deviation approach may also be applied, where values substantially above the historical mean indicate higher stress conditions. These thresholds should be validated against known crisis periods, such as financial crises, fuel price shocks, COVID-19-related disruptions and major trade disturbances. Expert judgement may further refine the thresholds to ensure that the risk classification is relevant for policy and industry decision-making.

Random Forest can be applied as a baseline machine learning model because it is robust, handles nonlinear interactions and provides interpretable importance rankings [28]. Gradient boosting models may improve predictive accuracy when multiple weak learners are combined, and AI-based supply chain risk assessment reviews indicate that ensemble and hybrid models are relevant for predictive risk analysis [29]. However, LSTM is not proposed as a primary model for the current annual MSCPI dataset because the series contains only 34 annual observations from 1990 to 2023, which creates a serious overfitting risk[30]. LSTM should therefore be considered only in future work if higher-frequency data, such as monthly port activity, fuel prices, trade flows, industrial production, shipping indicators, weather data and logistics proxies, are developed. Model evaluation should include forecast accuracy, classification performance and practical usefulness for early warning. For policy application, interpretability is as important as accuracy because decision makers must understand why the model is issuing a warning.

Given that MSCPI is time-series data, model validation should follow a temporal validation strategy rather than random data splitting. The dataset may first be divided using a time-based train-test split, where earlier observations are used for model training and later observations are reserved for out-of-sample testing. Rolling window validation or expanding window validation can also be applied to assess whether the model remains stable when new observations become available over time. In addition, back testing can be conducted by comparing predicted MSCPI values or predicted risk categories with actual historical outcomes during known disruption periods. Model performance should therefore be evaluated using forecast accuracy measures, such as RMSE, MAE or MAPE, classification measures such as accuracy, precision, recall and F1-score, and practical early-warning usefulness, including whether the model can detect stress signals before major supply chain disruptions occur.

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Table 2. Proposed AI Modelling Tasks for MSCPI-Based Vulnerability Analysis

Task	Model Examples	Input	Output	Decision Value
Forecasting	ARIMA, Random Forest and Gradient Boosting	MSCPI and lagged indicators	Predicted MSCPI level	Anticipates future pressure
Risk Classification	Random Forest, Logistic Model, Support Vector Machine	Engineered features and thresholds	Low, moderate or high-risk regime	Prioritizes response level
Driver Identification	Tree-based importance, SHAP-based explanation	All predictors	Ranked vulnerability drivers	Supports targeted mitigation
Anomaly Detection	Isolation Forest, statistical thresholding	MSCPI residuals and feature patterns	Unusual stress signal	Triggers early warning review

4. Conceptual Discussions

4.1. MSCPI trend as a historical risk signal

The MSCPI trend provides an important empirical basis for AI-based analysis. As shown in Figure 2, the Malaysia Supply Chain Pressure Index from 1990 to 2023 illustrates how supply chain stress changed across different economic periods. The figure shows that Malaysia’s supply chain pressure was relatively low and stable during the early 1990s, reflecting a period of stronger economic stability and lower stress. However, the index increased after the mid-2000s and fluctuated more noticeably during periods associated with trade expansion, the global financial crisis, fuel price increases, labor dynamics, climate variation and global uncertainty[1]. Therefore, Figure 2 supports the discussion by showing that MSCPI can serve as a historical risk signal for identifying changes in supply chain vulnerability over time.

The historical trend suggests that supply chain vulnerability is not caused by a single factor. Instead, stress emerges when transportation, trade, production, labor, macroeconomic and climate-related pressures interact. This finding supports the use of AI models because such models can learn interactions among multiple variables and detect patterns that may not be easily visible through descriptive analysis alone.

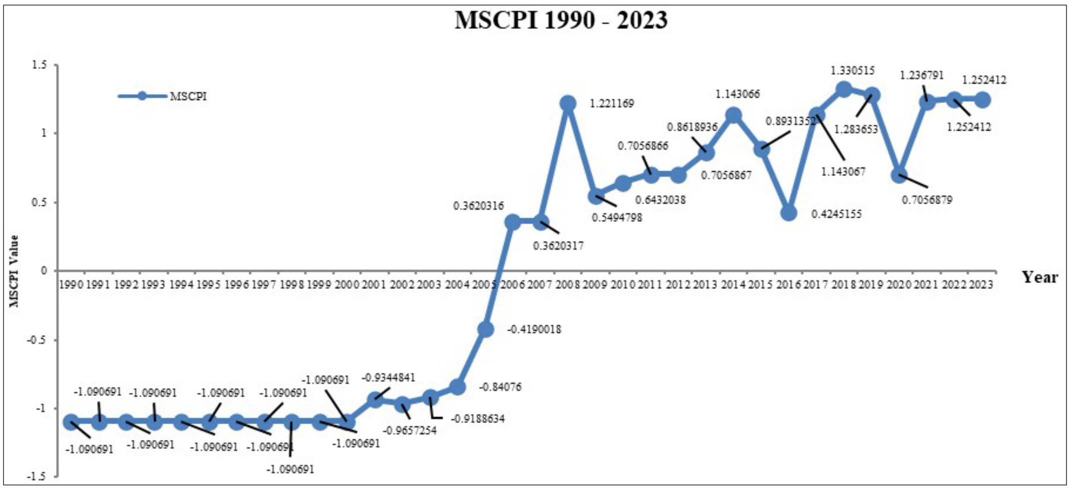

Figure 2. Malaysia Supply Chain Pressure Index Trend, 1990-2023 [1]

4.2. AI interpretation of vulnerability drivers

An AI-enabled MSCPI framework can identify which indicators contribute most strongly to supply chain stress. For example, transportation cost variables such as fuel prices may be highly influential because fuel price changes directly affect logistics cost, business operating cost and delivery decisions. Trade variables such as exports and imports may also be important because Malaysia's manufacturing and logistics sectors are closely linked to external demand and cross-border movement [1].Industrial production can provide a signal of supply-side capacity, while labor and climate indicators may highlight operational and environmental sources of vulnerability. To demonstrate how these AI-generated insights can inform practical action, Table 3 presents examples of possible AI signals, supply chain risks and corresponding mitigation responses. The table shows how dominant drivers can be translated into targeted responses, such as route optimization, supplier diversification, production monitoring, workforce planning and climate-related contingency logistics.

Table 3. Example AI-Driven Insights and Mitigation Responses

Dominant Driver	Possible AI Signal	Supply Chain Risk	Mitigation Response
Fuel price and transport cost	High variable importance and rising lagged trend	Higher logistics cost and delivery disruption	Fuel cost monitoring, route optimization and logistics support
Exports and imports	Trade volatility and abnormal movement	External demand shock or bottleneck	Supplier diversification, trade facilitation and inventory planning
Industrial production	Declining production trend	Supply shortage or weak manufacturing capacity	Production monitoring and sector-specific support
Labor dynamics	Falling labor participation or shortage signal	Operational delays and lower capacity	Workforce planning, automation and skills support
Climate variables	Extreme rainfall or temperature anomaly	Transportation and production disruption	Climate risk monitoring and contingency logistics

4.3. From descriptive monitoring to predictive early warning

The most important contribution of AI is its ability to convert MSCPI from a descriptive index into a predictive early warning system. A descriptive index informs users that pressure has increased after the event has occurred. A predictive system estimates whether pressure is likely to rise soon. This distinction is important because mitigation must occur before disruptions escalate into shortages, price increases or production losses.

In practice, an early AI warning system could define threshold levels for MSCPI and stress probability. When the forecasted MSCPI exceeds the threshold, the system may trigger a policy or industry review. The warning can also be accompanied by driver explanations, such as fuel price pressure, trade volatility or production slowdown. This allows agencies and firms to respond more precisely rather than relying on broad and delayed assessments.

The framework can also support scenario analysis by estimating how specific shocks may influence predicted MSCPI values. For example, a 10% fuel price increase may raise logistics and transportation costs, leading the model to predict higher supply chain pressure, as fuel and energy price volatility has been shown to affect procurement cost, inventory management and supply chain operating expenses. An exchange rate depreciation scenario may increase import costs and external trade exposure, thereby raising the likelihood of a higher MSCPI forecast, particularly in trade-dependent supply chains exposed to currency fluctuation risk. A trade contraction scenario, such as a decline in exports or imports, may signal weaker demand, reduced cargo movement or production bottlenecks, which can affect supply chain performance and resilience. Similarly, an extreme rainfall event may disrupt transportation routes, agricultural supply, port activities or delivery schedules, since extreme weather conditions have been linked to disruptions in transport systems, logistics operations and global supply chains. By adjusting these input variables, the AI model can generate revised MSCPI predictions, stress probabilities and risk classifications. This allows policymakers and industry stakeholders to evaluate potential shocks before they develop into wider supply chain disruptions.

Such scenario analysis can help policymakers compare mitigation options and design targeted interventions. It also supports industry stakeholders in procurement planning, inventory management and logistics contingency planning.

4.4. Policy and industry implications

For policymakers, AI-enhanced MSCPI can support proactive policy formulation. Instead of reacting only after disruption occurs, policymakers can monitor early signals and identify which sector or variable requires intervention. This is especially useful for a trade-oriented economy such as Malaysia, where external shocks can affect domestic costs and production systems. The framework can support coordination among agencies responsible for trade, transport, industry, labor, agriculture, climate and statistics.

Specific policy actions may be linked to the type of risk signal generated by the AI-enhanced MSCPI framework. Fuel price or transport cost pressure may require logistics support, fuel cost monitoring, route optimization and port efficiency measures. Trade-related pressure may require trade route diversification, supplier diversification, customs facilitation and closer monitoring of export-import flows. Labor-related risks may be addressed through workforce planning, skills training, temporary labor support and automation incentives. Climate-related risks may require contingency logistics, alternative transport routes, emergency stockpiles and coordination with disaster management and agriculture agencies. In this way, the framework helps policymakers move from general monitoring toward targeted and timely mitigation actions.

For industry stakeholders, the framework provides a structured approach to operational resilience. Firms can use MSCPI forecasts and risk classification as part of procurement planning, inventory buffers, supplier selection, logistics scheduling and contingency planning. When the model shows that transport cost pressure is increasing, firms may review shipping routes or negotiate logistics capacity. When trade volatility becomes the main signal, firms may diversify suppliers or markets.

For researchers, the framework opens a pathway for future empirical testing. The proposed model can be validated using historical data, out-of-sample forecasting and real-time indicators. Future research may compare model performance across Random Forest, gradient boosting and hybrid models, while LSTM should be reserved for future high-frequency MSCPI extensions. It may also apply explainable AI techniques to strengthen model transparency and policy trust.

4.5. Challenges and limitations

The proposed framework must be implemented carefully. First, data quality is critical. AI models are only useful when input data are reliable, consistent and updated. Missing values, measurement changes and different reporting frequencies can reduce predictive performance. Second, model interpretability is essential. A highly accurate model that cannot explain its warning may be difficult for policymakers to trust. Third, AI predictions should not be interpreted as certainty. Supply chain systems are affected by sudden shocks that may not be present in historical data. Therefore, AI should support human judgement rather than replace it. Fourth, the MSCPI is annual in its existing form, while real-time decision support may require monthly, weekly or even daily indicators. Future work should explore high-frequency data sources, including port activity, shipping data, commodity prices, news signals and weather alerts.

5. Conclusions

Future research should empirically test the proposed framework using historical MSCPI data and high-frequency indicators. It should also compare data-efficient models, conduct out-of-sample and rolling-window validation, incorporate explainable AI and evaluate how predictive insights can be embedded into national supply chain monitoring systems. With careful implementation, AI-enhanced MSCPI can become a practical tool for building a more resilient and responsive Malaysian supply chain ecosystem.

The proposed framework suggests that these indicators could be combined with data-efficient machine learning, time-series modelling and explainable AI techniques to support future stress anticipation and targeted mitigation planning. However, the framework remains conceptual and requires empirical validation. Given the limited number of annual MSCPI observations, deep learning models such as LSTM should be reserved for future work using monthly or quarterly proxy indicators, transfer learning or simulation-based augmentation.

The expanded literature review shows that recent AI-for-supply-chain studies, composite index methods, explainable AI and Malaysian logistics and trade policy references provide a stronger foundation for positioning MSCPI as a forward-looking decision-support tool. Transportation costs, trade fluctuations, industrial production, labor dynamics, exchange rate movements and climate variables are important inputs for AI-based vulnerability analysis.

This article proposes an AI-enabled framework for mitigating supply chain vulnerabilities using the Malaysia Supply Chain Pressure Index as the core analytical input. The MSCPI provides a valuable Malaysia-specific measure of supply chain stress, while the proposed AI integration conceptually extends its usefulness by enabling forecasting, early warning, driver identification, anomaly detection and decision support.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

References

[1] M. Kyizzad Mesran, A. Azam, S. @ Mohamad, and R. H. Zakaria, "Assessing Malaysia Supply Chain Vulnerabilities Construction of Comprehensive Stress Index," *International Journal of Business and Technology Management*, vol. 6, no. S4, pp. 23–48, 2024, doi: 10.55057/ijbtm.2024.6.S4.2.

[2] G. Alessandria, S. Y. Khan, A. Khederlarian, C. Mix, and K. J. Ruhl, "The Aggregate Effects of Global and Local Supply Chain Disruptions," *Policy Research Working Paper*, 2023, [Online]. Available: http://www.worldbank.org/prwp.

[3] G. Benigno, | Julian Di Giovanni, J. J. J. Groen, J. Di Giovanni, and A. I. Noble, "The GSCPI: A New Barometer of Global Supply Chain Pressures N O. 1 0 1 7 M A Y 2 0 2 2 The GSCPI: A New Barometer of Global Supply Chain Pressures," 2022. [Online]. Available: https://www.newyorkfed.org/research/staff_reports/sr1017.html.

[4] M. Bi, G. Chen, D. M. Tilbury, S. Shen, and K. Barton, "A Model-based Multi-agent Framework to Enable an Agile Response to Supply Chain Disruptions," Jul. 2022, doi: 10.1109/CASE49997.2022.9926559.

[5] D. Ivanov, "Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case," *Transp. Res. E Logist. Transp. Rev.*, vol. 136, Apr. 2020, doi: 10.1016/j.tre.2020.101922.

[6] M. M. Queiroz, D. Ivanov, A. Dolgui, and S. Fosso Wamba, "Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review," *Ann. Oper. Res.*, vol. 319, no. 1, pp. 1159–1196, Dec. 2022, doi: 10.1007/s10479-020-03685-7.

[7] G. Benigno, | Julian Di Giovanni, J. J. J. Groen, J. Di Giovanni, and A. I. Noble, "The GSCPI: A New Barometer of Global Supply Chain Pressures," 2022. [Online]. Available: https://www.newyorkfed.org/research/staff_reports/sr1017.html.

[8] K. Kpodar and B. Liu, "The Distributional Implications of the Impact of Fuel Price Increases on Inflation," Nov. 2021. Accessed: Jun. 25, 2026. [Online]. Available: https://www.imf.org/-/media/files/publications/wp/2021/english/wpiea2021271-print-pdf.pdf

[9] N. M. C. Pankratz and C. M. Schiller, "Climate Change and Adaptation in Global Supply-Chain Networks," *Finance and Economics Discussion Series*, vol. 2022.0, no. 56, Aug. 2022, doi: 10.17016/feds.2022.056.

[10] A. Nagurney, "Supply chain game theory network modeling under labor constraints: Applications to the Covid-19 pandemic," *Eur. J. Oper. Res.*, vol. 293, no. 3, pp. 880–891, Sep. 2021, doi: 10.1016/j.ejor.2020.12.054.

[11] Organization For Economic Co-Operation and Development, "Handbook on Constructing Composite Indicators," 2008. [Online]. Available: www.oecd.org/publishing/corrigenda.

[12] M. Nardo, M. Saisana, A. Saltelli, and S. Tarantola, "Tools for Composite Indicators Building," 2005. [Online]. Available: http://europa.eu.int

[13] I. T. Jollife and J. Cadima, "Principal component analysis: A review and recent developments," Apr. 13, 2016, *Royal Society of London*. doi: 10.1098/rsta.2015.0202.

[14] R. Toorajipour, V. Sohrabpour, A. Nazarpour, P. Oghazi, and M. Fischl, "Artificial intelligence in supply chain management: A systematic literature review," *J. Bus. Res.*, vol. 122, pp. 502–517, Jan. 2021, doi: 10.1016/j.jbusres.2020.09.009.

[15] A. R. Teixeira, J. V. Ferreira, and A. L. Ramos, "Intelligent Supply Chain Management: A Systematic Literature Review on Artificial Intelligence Contributions," May 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/info16050399.

[16] A. Belhadi, V. Mani, S. S. Kamble, S. A. R. Khan, and S. Verma, "Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation," *Ann. Oper. Res.*, vol. 333, no. 2–3, pp. 627–652, Feb. 2024, doi: 10.1007/s10479-021-03956-x.

[17] L. Safra Zaabar, M. Ridzwan Yaakub, M. Iqbal, and A. Latiffi, "Combination of Lexicon Based and Machine Learning Techniques in the Development of Political Tweet Sentiment Analysis Model," 2022.

[18] L. Safra Zaabar, *Enhancement of Kansei Model for Political Security Threat Prediction using Bi-LSTM*. 2024. doi: 10.1007/978-981-97-9890-2_10.

[19] A. Barredo Arrieta *et al.*, "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Information Fusion*, vol. 58, pp. 82–115, Jun. 2020, doi: 10.1016/j.inffus.2019.12.012.

[20] S. M. Lundberg, P. G. Allen, and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," 2017. [Online]. Available: https://github.com/slundberg/shap

[21] F. Olan, K. Spanaki, W. Ahmed, and G. Zhao, "Enabling explainable artificial intelligence capabilities in supply chain decision support making," *Production Planning and Control*, vol. 36, no. 6, pp. 808–819, 2025, doi: 10.1080/09537287.2024.2313514.

[22] Ministry of Transport Malaysia, "Malaysia National Transport Policy," 2019.

[23] Ministry of International Trade and Industry Malaysia, "Malaysia National Trade Blueprint," 2021.

[24] MITI MALAYSIA, "New Industrial Master Plan 2030," 2023.

[25] Economic Planning Unit, "TWELFTH MALAYSIA PLAN 2021-2025," 2021.

[26] J.-F. Arvis *et al.*, "Connecting to Compete 2023 Trade Logistics in an Uncertain Global Economy The Logistics Performance Index and Its Indicators Developing Trade Consultants," 2023. [Online]. Available: www.worldbank.org

[27] I. T. Jollife and J. Cadima, "Principal component analysis: A review and recent developments," Apr. 13, 2016, *Royal Society of London*. doi: 10.1098/rsta.2015.0202.

[28] M. Imani, A. Beikmohammadi, and H. R. Arabnia, "Comprehensive Analysis of Random Forest and XGBoost Performance with SMOTE, ADASYN, and GNUS Under Varying Imbalance Levels," *Technologies (Basel).*, vol. 13, no. 3, Mar. 2025, doi: 10.3390/technologies13030088.

[29] X. Jiang, W. Yan, H. Xing, P. Feng, J. Sun, and Y. Fan, "A highly accurate and interpretable gradient boosting machine learning model for predicting permeability in strongly heterogeneous reservoirs using the Optuna framework," *Journal of Geophysics and Engineering*, vol. 22, no. 3, pp. 810–823, Jun. 2025, doi: 10.1093/jge/gxaf039.

[30] M. Krichen and A. Mihoub, "Long Short-Term Memory Networks: A Comprehensive Survey," Sep. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/ai6090215.