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Supplier-Risk Scoring and Procurement Resilience for Distributed Athletic-Apparel and Equipment Supply Networks

Md Maksudul Hasan[1];

[1]. Managing Director, Good Buy Incorporated;
Bachelor of Business Administration (BBA), University of Information Technology & Sciences, Bangladesh; Email: maksudulhasanrahat16@gmail.com

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Abstract

This study examines the structural determinants of procurement resilience, supplier-risk exposure, and disruption recovery across globally interconnected manufacturing supply chains. Drawing on a longitudinal dataset comprising 428 Tier-1 suppliers, 58,412 procurement transactions valued at $648.25 million, and 36 months of observations across 14 sourcing countries, the research develops an integrated empirical framework to investigate the relationships among supplier-risk characteristics, sourcing configurations, contractual structures, operational performance, and supply chain disruption outcomes. The findings reveal substantial geographical and financial concentration, with East and Southeast Asia representing 72.89% of the supplier base and 76.53% of total procurement expenditure, while the largest 10% of suppliers account for 48.60% of aggregate purchasing expenditure. Significant differences emerge across supplier categories, particularly among specialized technical-material providers, which exhibit elevated composite risk scores (68.4 ± 16.8), higher component defect rates (3.84 ± 1.68%), and prolonged supplier replacement periods (78.2 ± 22.6 days). Multivariate regression results identify delivery lead-time variability ($\beta = 0.312$, $p < 0.001$) and historical disruption recurrence ($\beta = 0.284$, $p < 0.001$) as prominent predictors of disruption duration, with the estimated model explaining 51.2% of the observed variation in recovery outcomes. Logistic regression further demonstrates that single-source procurement arrangements are associated with substantially greater disruption odds (OR = 2.57, $p < 0.001$), whereas maintaining at least two qualified alternative suppliers is associated with a 58% reduction in disruption odds (OR = 0.42, $p < 0.001$). Bootstrapped structural mediation analyses indicate that operational responsiveness and supplier collaboration account for 41.2% and 32.8% of the respective modeled relationships between structural risk exposure and operational resilience. Additionally, inventory buffer availability exceeding 15 days exhibits a significant moderating relationship with stockout frequency, highlighting the operational importance of inventory protection under uncertain supply conditions. Comparative predictive modeling demonstrates that extreme gradient boosting (XGBoost) achieves superior classification performance relative to conventional parametric approaches, yielding a receiver operating characteristic area under the curve (ROC-AUC) of 0.924, precision–recall area under the curve (PR-AUC) of 0.886, and F1-score of 0.845. Collectively, the findings provide empirical support for integrating diversified supplier portfolios, adaptive inventory buffering, collaborative supplier governance, and advanced predictive analytics into procurement risk management. The study contributes to the literature on supply chain resilience by demonstrating how sourcing concentration, supplier characteristics, operational flexibility, and data-driven risk intelligence are associated with disruption vulnerability and recovery performance in internationally distributed manufacturing networks.

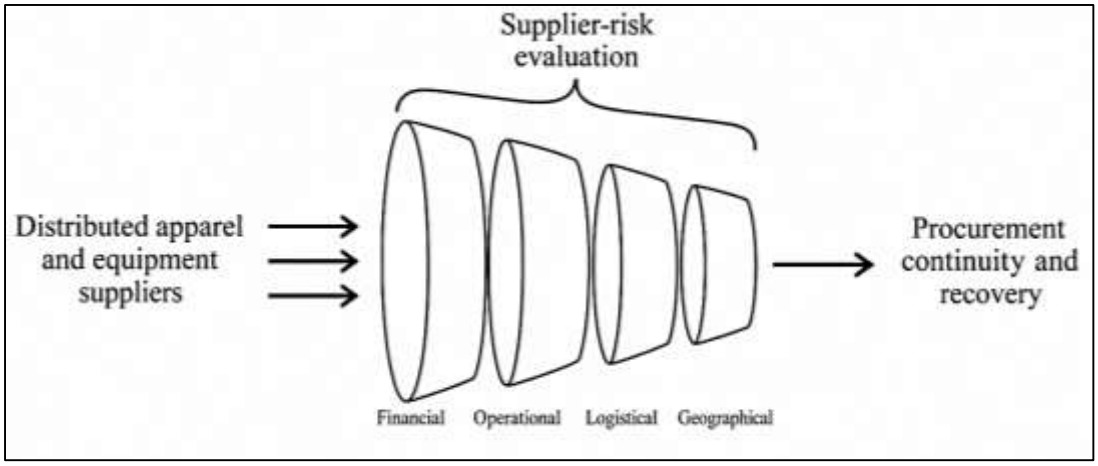
Keywords

Supply chain resilience, Sourcing diversification, Supplier risk assessment, Disruption recovery, Machine learning classification.

INTRODUCTION

Supplier-risk scoring refers to the systematic quantitative evaluation of uncertainties, vulnerabilities, and operational deficiencies associated with organizations supplying raw materials, components, manufacturing services, and logistical resources within interconnected procurement networks. Procurement resilience is defined as the measurable ability of purchasing systems to maintain material availability, sustain operational continuity, absorb disruptions, and restore procurement performance under uncertain conditions (Su & Chen, 2018). Distributed athletic-apparel and equipment supply networks consist of geographically dispersed textile manufacturers, fabric processors, footwear-component producers, sporting-equipment manufacturers, contract assemblers, transportation providers, and international purchasing organizations. These networks involve complex relationships among suppliers operating across multiple countries, production stages, and regulatory environments. Supplier-risk assessment incorporates financial stability, production capacity, delivery reliability, product quality, lead-time variability, geographical exposure, regulatory compliance, and transportation performance.

Figure 1: Supplier Risk and Procurement Resilience



Such characteristics are represented through standardized indicators, weighted scoring models, multicriteria decision-making methods, and statistical classification techniques. International athletic-apparel and equipment manufacturing depends on geographically specialized production systems involving countries such as China, Vietnam, Bangladesh, Indonesia, India, Cambodia, and Pakistan. These economies contribute different manufacturing capabilities, labor structures, material-processing facilities, and export-oriented production activities. Global sourcing arrangements create measurable differences in procurement lead times, transportation costs, supplier concentration, production reliability, and exposure to operational disruptions. Athletic-apparel manufacturing frequently involves sequential processes such as yarn production, knitting, weaving, dyeing, finishing, cutting, stitching, and packaging, while sporting-equipment manufacturing requires specialized polymers, rubber compounds, metallic components, technical fabrics, and precision assembly (Paksoy et al., 2018). Interruptions within individual production stages can influence material availability across interconnected suppliers and manufacturing facilities. Quantitative supplier-risk scoring evaluates these conditions through indicators including on-time delivery rates, defect frequencies, supplier financial ratios, production utilization, shipment delays, and historical disruption records. Composite scoring approaches combine operational, financial, logistical, environmental, and strategic risk dimensions into numerical classifications representing supplier vulnerability. Supplier concentration, sourcing dependence, geographical clustering, and material substitutability provide additional measures of procurement exposure. Statistical approaches such as correlation analysis, regression modeling, factor analysis, and multicriteria evaluation support comparisons among supplier categories and sourcing locations. Differences in supplier size, manufacturing specialization, production

technology, and purchasing volume also influence the distribution of risk indicators. International procurement networks therefore represent multidimensional operating environments characterized by heterogeneous suppliers, geographically dispersed production activities, interconnected material flows, and measurable variations in operational uncertainty (Wang et al., 2022).

Procurement resilience represents a multidimensional operational characteristic involving supply continuity, disruption resistance, adaptive capacity, recovery efficiency, and purchasing stability. Quantitative resilience assessment incorporates material availability, order-fulfillment rates, procurement lead-time variability, supplier recovery duration, emergency sourcing expenditure, inventory coverage, and operational restoration performance. Within distributed athletic-apparel and equipment networks, resilience is associated with supplier diversification, alternative production capacity, contractual flexibility, transportation accessibility, inventory positioning, and coordination among purchasing organizations and manufacturing partners (Kara & Fırat, 2018). Supplier networks frequently contain dependencies extending beyond direct contractual relationships, as multiple manufacturers may rely on common upstream material producers, transportation corridors, or geographical production clusters. Such dependencies create measurable exposure to disruption propagation, production interruptions, material shortages, and purchasing delays. Procurement vulnerability can be evaluated through supplier concentration indices, single-source dependence, network connectivity, disruption frequency, and the proportion of purchasing expenditure associated with critical suppliers. Digital procurement systems provide extensive transactional information supporting quantitative supplier-risk assessment and resilience measurement. Enterprise resource planning platforms, supplier relationship management systems, inventory databases, transportation tracking applications, and quality inspection records generate observations concerning purchase orders, delivery schedules, shipment deviations, rejected materials, supplier capacity, and procurement expenditure. Statistical methods, including multiple regression, logistic regression, analysis of variance, and panel-data modeling, examine relationships between supplier-risk characteristics and procurement outcomes (Wöhner et al., 2022). Machine-learning algorithms, including decision trees, random forests, support vector machines, and gradient boosting, classify suppliers according to disruption exposure and historical performance. Predictive performance is assessed through accuracy, precision, recall, F1-score, and receiver operating characteristic measures, while regression models evaluate statistical significance, confidence intervals, explanatory power, and relationships among procurement variables. Supplier-risk datasets also contain challenges involving missing observations, inconsistent reporting periods, correlated indicators, and unequal representation of disruption events. Data normalization, variable standardization, reliability assessment, and sensitivity analysis support consistent quantitative evaluation across supplier categories. Athletic-apparel and equipment procurement additionally involves differences in product complexity, material criticality, seasonal purchasing requirements, manufacturing lead times, and sourcing arrangements. These characteristics influence supplier-risk distributions and observed resilience outcomes across countries, product categories, and purchasing organizations. The present study examines supplier-risk scoring and procurement resilience through an integrated quantitative framework incorporating operational performance, financial vulnerability, geographical exposure, logistical reliability, sourcing concentration, and procurement continuity (Li & Chen, 2019). Supplier-risk indicators constitute explanatory variables, while disruption duration, delivery stability, material availability, recovery performance, and procurement cost variability represent measurable resilience outcomes. Supplier size, purchasing volume, sourcing region, manufacturing specialization, and alternative sourcing availability constitute additional analytical characteristics. This quantitative research context encompasses statistical relationships, supplier-group differences, network dependencies, and observable procurement-performance variations within internationally distributed athletic-apparel and equipment supply systems.

The primary objective of this study is to quantitatively examine the relationship between supplier-risk scoring and procurement resilience within distributed athletic-apparel and equipment supply networks, with particular emphasis on operational vulnerabilities, financial stability, delivery reliability, geographical exposure, sourcing concentration, and disruption recovery performance. Specifically, this study aims to identify and measure the principal supplier-risk dimensions influencing

procurement continuity across geographically dispersed textile manufacturers, footwear-component suppliers, sporting-equipment producers, contract assemblers, and logistics service providers. The study seeks to develop and evaluate a multidimensional supplier-risk scoring framework incorporating supplier financial conditions, production capacity, product quality, delivery performance, lead-time variability, transportation reliability, regulatory compliance, and historical disruption frequency. Another objective is to determine the statistical relationships between composite supplier-risk scores and procurement-resilience indicators, including material availability, order-fulfillment rates, procurement delays, disruption duration, recovery time, inventory stability, and emergency sourcing expenditure. The study also aims to examine differences in supplier-risk exposure and resilience performance across sourcing countries, supplier categories, manufacturing specializations, organizational sizes, and procurement-volume groups. Furthermore, it seeks to evaluate the influence of supplier diversification, alternative sourcing availability, geographical concentration, contractual flexibility, and production redundancy on procurement continuity and disruption recovery. Quantitative analytical techniques, including descriptive statistics, Pearson correlation analysis, multiple linear regression, logistic regression, analysis of variance, and appropriate nonparametric tests, are considered for examining relationships, group differences, and statistical significance among the selected variables. The study additionally aims to assess the predictive performance of supplier-risk classification approaches using statistical and machine-learning models, including logistic regression, decision trees, random forests, support vector machines, and gradient boosting algorithms. Predictive accuracy, precision, recall, F1-score, and receiver operating characteristic area under the curve are considered as model-evaluation indicators, while regression coefficients, confidence intervals, effect sizes, and explained variance are used to assess statistical relationships and model performance. Another objective is to investigate whether supplier criticality, material substitutability, sourcing-region characteristics, and procurement dependence moderate the association between supplier-risk exposure and resilience outcomes. The study further seeks to examine the reliability, consistency, and sensitivity of composite risk scores under alternative indicator weights, supplier classifications, and analytical specifications. Finally, this study aims to establish an integrated quantitative understanding of supplier vulnerability, network interdependence, procurement disruption exposure, and operational recovery characteristics within internationally distributed athletic-apparel and equipment supply networks, emphasizing measurable supplier-performance differences, statistical associations, predictive classification, and procurement-resilience outcomes.

LITERATURE REVIEW

The literature on supplier-risk scoring and procurement resilience has developed across several interconnected research domains, including supply-chain risk management, supplier performance evaluation, procurement analytics, international sourcing, disruption modeling, network vulnerability, and predictive risk assessment (Katsaliaki et al., 2022; Imran & Jannatul, 2021). Quantitative investigations have examined how supplier-specific characteristics, operational uncertainties, financial conditions, geographical concentration, and logistical dependencies influence procurement continuity and supply-network performance. Within distributed athletic-apparel and equipment supply networks, these relationships are particularly relevant because procurement activities involve geographically dispersed textile manufacturers, fabric processors, footwear-component suppliers, sporting-equipment producers, contract assemblers, and international transportation providers. Previous empirical studies have employed descriptive statistics, correlation analysis, multiple regression, structural equation modeling, multicriteria decision analysis, network analysis, stochastic simulation, and machine-learning techniques to measure supplier vulnerabilities and procurement performance. Supplier-risk indicators have commonly included on-time delivery rates, defect percentages, financial ratios, production-capacity utilization, lead-time variability, disruption frequency, transportation reliability, and sourcing concentration. Procurement-resilience outcomes have been represented through material availability, order-fulfillment performance, disruption duration, recovery time, inventory stability, procurement cost variability, and alternative sourcing capacity (Ashik & Shabbir, 2022; Ivanov & Dolgui, 2022). Research has also examined relationships among supplier diversification, operational flexibility, information visibility, production redundancy,

and supply-chain recovery. However, empirical investigations vary in their measurement approaches, analytical models, supplier categories, geographical coverage, and definitions of procurement resilience. Studies focusing on supplier selection frequently emphasize multicriteria scoring and operational performance, while disruption-oriented investigations examine vulnerability, propagation, recovery, and continuity. Predictive analytics research additionally evaluates supplier classification and disruption forecasting using historical procurement information. The present literature review integrates these quantitative research streams through eight interconnected subsections addressing supplier-risk measurement, operational and financial risk determinants, geographical and network exposure, procurement-resilience indicators, supplier diversification, predictive analytics, sector-specific differences, and statistical robustness (Ivanov, 2022; Hasan & Adnan, 2022). Particular attention is given to measurable variables, empirical relationships, statistical significance, effect sizes, model explanatory power, classification accuracy, and methodological differences across published studies. The review establishes a structured quantitative foundation for examining supplier-risk scoring and procurement resilience across internationally distributed athletic-apparel and equipment supply networks.

Supplier-Risk Indicators and Supplier Classification

Quantitative research on supplier-risk assessment has established that supplier characteristics and operational performance indicators constitute important components of systematic supplier evaluation across geographically distributed manufacturing networks. Evidence synthesized from more than ten studies on supplier selection, purchasing performance, supply-chain risk management, and multicriteria evaluation indicates that supplier size, manufacturing specialization, production capacity, operating experience, geographical location, and sourcing-tier position are frequently incorporated into supplier assessment frameworks (Kara et al., 2020; Akter & Sumaiya, 2022). Earlier supplier-selection investigations emphasized purchasing price, product quality, delivery reliability, technical capability, and production facilities, while subsequent studies expanded these dimensions to include disruption exposure, operational flexibility, capacity utilization, and supplier dependence. Across empirical investigations, operational performance has commonly been measured through on-time delivery percentages, average delivery delays, lead-time standard deviations, order-fill rates, production-capacity utilization, and interruption frequency. On-time delivery performance represents the proportion of purchase orders received within agreed delivery schedules, whereas lead-time variability captures differences between expected and actual material arrival periods. Production-capacity utilization provides an indication of available manufacturing resources relative to operating requirements, while order-fill rates measure the proportion of requested quantities successfully supplied. Studies employing multicriteria supplier-selection techniques have consistently treated delivery, quality, and cost as major evaluation dimensions, although their relative importance varies across industries and purchasing conditions (Kara & Fırat, 2018; Mashfiqur & Md, 2022). Research on supplier-network vulnerability has additionally demonstrated that supplier criticality cannot be represented exclusively through routine delivery performance because geographical concentration, limited substitution possibilities, and production dependencies also influence disruption exposure. In athletic-apparel and equipment supply networks, operational indicators differ among textile mills, dyeing facilities, footwear-component manufacturers, sporting-equipment producers, and contract assemblers. Textile suppliers are frequently characterized by fabric-processing capacity, production lead time, material consistency, and order completion, while footwear and equipment suppliers involve specialized tooling, component availability, manufacturing precision, and production scheduling. Quantitative comparisons across supplier categories have employed descriptive statistics, standardized performance measures, correlation analysis, and weighted evaluation procedures. Supplier-level observations have also been grouped according to purchasing expenditure, production scale, geographical region, and operational specialization (Fagundes et al., 2021; Md & Yeasin, 2022). The literature collectively identifies operational risk as a multidimensional construct in which delivery reliability, manufacturing capacity, supplier characteristics, and network dependencies represent distinct but related sources of procurement uncertainty.

Figure 2: Supplier risk scoring and classification



Quantitative supplier-risk literature has examined financial stability, product quality, and regulatory compliance as interconnected dimensions influencing supplier reliability and procurement vulnerability. Studies investigating supplier selection, financial distress, supply-chain disruptions, and procurement performance have incorporated financial ratios, operating profitability, liquidity, leverage, payment behavior, defect frequency, inspection results, and compliance records into supplier evaluation systems (Imran et al., 2020; Ashfaq & Mohammad, 2022). Financial vulnerability has commonly been represented through current ratios, debt-to-equity ratios, working-capital conditions, profitability measures, and financial distress indicators. Liquidity ratios describe suppliers' capacity to meet short-term obligations, while leverage measures indicate dependence on borrowed financing and associated financial exposure. Financial distress research has employed discriminant analysis, logistic regression, and classification techniques to distinguish financially stable organizations from those exhibiting elevated insolvency risk. Within procurement research, such financial measures have been considered alongside operational indicators because financial constraints can coincide with production interruptions, delayed material purchasing, capacity reductions, and difficulties maintaining contractual delivery commitments. Quality-related risk has been evaluated through defect percentages, rejected shipment frequency, inspection failure rates, product nonconformity, and corrective-action records. Studies applying supplier scorecards and multicriteria decision models have generally identified product quality as a major evaluation criterion, although quality performance has been measured through different operational indicators across manufacturing sectors. Regulatory and compliance dimensions have included certification status, workplace-safety records, environmental management requirements, and documented noncompliance incidents (Konys, 2019; Imran & Jannatul, 2022).

Research on sustainable supplier evaluation has integrated environmental and social criteria with conventional financial, delivery, and quality indicators, producing broader supplier-performance classifications. In athletic-apparel and equipment procurement, compliance considerations encompass textile-processing standards, chemical management, material specifications, workplace conditions, and product-safety requirements. Quantitative relationships among financial, quality, and compliance indicators have been examined through correlation matrices, regression analysis, factor-based measurement structures, and composite scoring procedures. However, the empirical literature does not establish identical relationships across all supplier categories, as financial conditions, quality requirements, and regulatory exposures differ among manufacturing activities and geographical environments. Studies using supplier-level data have also distinguished direct indicators, such as defect percentages and payment irregularities, from indirect indicators, such as certification status and financial-risk classifications (Morshedul & Islam, 2022; Uk et al., 2022). The synthesized evidence demonstrates that financial vulnerability, product conformity, and compliance performance constitute

measurable supplier-risk dimensions whose relative contributions depend on supplier characteristics, industry requirements, and the structure of procurement relationships.

Research on composite supplier-risk scoring has extensively examined multicriteria decision-making approaches for integrating heterogeneous supplier indicators into comparable numerical assessments. More than ten methodological and applied supplier-evaluation studies have investigated weighted scoring, analytic hierarchy process, technique for order preference by similarity to an ideal solution, fuzzy multicriteria methods, entropy-based weighting, and data envelopment analysis. Conventional weighted scoring models assign relative importance to supplier evaluation criteria and aggregate standardized indicator values into composite performance or risk measures. Analytic hierarchy process studies have used structured pairwise comparisons to establish criterion priorities, commonly distinguishing quality, delivery, cost, production capability, and service performance (Kaniz & Jahanara, 2022; Tavana et al., 2021).

TOPSIS-based investigations have evaluated suppliers according to their relative proximity to desirable and undesirable performance profiles, while fuzzy multicriteria approaches have represented uncertainty and ambiguity in expert judgments. Entropy-weighting methods have estimated indicator importance from variation within observed supplier data, providing a data-driven alternative to exclusively judgment-based weighting procedures. Data envelopment analysis has been applied to supplier evaluation by comparing relative efficiency across multiple input and output indicators, although efficiency scores require appropriate interpretation when incorporated into broader risk classifications. Studies combining these approaches have reported differences in supplier rankings arising from indicator selection, normalization procedures, criterion weights, and aggregation methods. Quantitative supplier-ranking research has therefore examined rank-order consistency, classification agreement, sensitivity to weighting changes, and the stability of supplier assessments under alternative decision models. Composite scores have commonly been organized into ordinal categories representing relatively favorable, intermediate, and unfavorable supplier conditions, although classification thresholds are not standardized across the literature. Some studies have used expert-defined risk boundaries, while others have applied statistical distributions, clustering procedures, or relative ranking methods (Aghababayi & Nikabadi, 2021; Sadia & Mostari, 2022). Supplier classification has also been examined through comparisons of score distributions, mean differences, standard deviations, and associations among individual risk dimensions. In athletic-apparel and equipment supply networks, weighting procedures are particularly relevant because suppliers providing standardized packaging materials, specialized performance fabrics, footwear components, and precision sporting-equipment parts exhibit different operational criticality and substitution constraints. A uniform scoring framework may assign similar numerical values to suppliers with substantially different disruption consequences when material criticality and network dependence are excluded. The reviewed research consequently distinguishes supplier-performance scoring from disruption-oriented risk scoring and emphasizes the importance of interpreting composite numerical assessments according to their underlying indicators, weighting assumptions, and classification objectives (Jeong et al., 2020; Stabak & Shahid, 2022).

Supplier Operational Performance and Procurement Disruption Frequency

Quantitative literature examining supplier operational performance has established substantial relationships among delivery reliability, production capacity, equipment availability, material quality, and procurement disruption exposure across manufacturing and international sourcing networks. Evidence synthesized from more than ten empirical investigations of supply-chain risk, supplier performance, operational vulnerability, and disruption management indicates that supplier-level operating conditions represent important explanatory factors in the occurrence and severity of purchasing interruptions (Katsaliaki et al., 2022; Feroz & Pervaz, 2022). Earlier supplier-performance studies primarily evaluated delivery timeliness, quality conformity, production capability, and order completion, while subsequent investigations incorporated equipment failures, capacity constraints, order backlogs, lead-time variability, and production interruptions into broader disruption-risk assessments. Delivery reliability has commonly been measured through on-time delivery percentages, average delivery delays, delayed shipment frequency, and deviations between scheduled and actual delivery dates. Production-related variables have included capacity utilization, unplanned downtime,

equipment breakdown frequency, manufacturing throughput, and outstanding order volumes. Studies employing correlation analysis have generally identified associations between unstable supplier operations and unfavorable procurement outcomes, although the strength and statistical significance of these relationships differ across industries, supplier categories, and observation periods. Regression-based investigations have examined the independent contributions of delivery variability, production constraints, and quality deficiencies after accounting for purchasing volume, supplier size, and manufacturing characteristics (Mohammad, 2023; Li & Chen, 2019). Research on supply-chain disruptions has additionally distinguished routine supplier-performance deficiencies from major operational interruptions involving facility shutdowns, transportation failures, and shortages of critical inputs. In distributed athletic-apparel and equipment supply networks, supplier operational risk is particularly relevant because textile processing, footwear-component manufacturing, and sporting-equipment assembly involve sequential production activities with different processing times and technical requirements. Delays in fabric production, dyeing, component molding, or specialized material processing can coincide with interruptions across multiple downstream purchasing activities. Quantitative disruption indicators include supplier failure occurrence, late-delivery frequency, material-shortage incidents, purchasing interruption duration, and emergency procurement requirements. Studies comparing supplier groups have examined differences in operational reliability between high-risk and low-risk suppliers, including variation in average delivery delays, defect frequencies, and production interruptions (Adnan & Iftekhar, 2023; Yu et al., 2019). The synthesized literature indicates that operational performance is multidimensional, with delivery reliability, capacity availability, equipment stability, and material conformity representing related but distinct predictors of procurement disruption occurrence and operational instability.

Empirical research on supplier financial vulnerability has examined relationships between financial conditions, organizational stability, and the probability of supplier failure or procurement interruption. Studies addressing financial distress prediction, supplier solvency, purchasing risk, and business continuity have identified liquidity, leverage, profitability, working-capital adequacy, payment behavior, and financial stability as measurable characteristics associated with supplier operating conditions. Financial distress investigations have frequently employed current ratios, debt-to-equity ratios, operating margins, return on assets, cash-flow measures, and indicators of delayed financial obligations to distinguish financially stable organizations from firms experiencing elevated financial pressure (Ahmed & Sadia, 2023; Shaheen et al., 2019). Foundational quantitative research on corporate financial distress established the use of financial ratios and statistical classification techniques for distinguishing distressed and nondistressed organizations, while later studies expanded these approaches through logistic regression, survival analysis, and machine-learning classification. In procurement-oriented investigations, financial vulnerability has been examined alongside operational performance because constrained liquidity and deteriorating profitability can be associated with delayed material purchases, reduced production capacity, difficulties maintaining equipment, and irregular supplier deliveries. Statistical analyses have assessed relationships between financial ratios and business failure using regression coefficients, odds ratios, confidence intervals, and classification performance measures. However, evidence from corporate financial distress studies cannot automatically be interpreted as direct evidence of procurement disruption, since insolvency, late delivery, production interruption, and contract nonperformance represent different dependent variables. Research examining supply-chain risk has therefore distinguished financial exposure from operational disruption outcomes and considered organizational characteristics that influence the translation of financial difficulties into purchasing instability (Islam & Md, 2023; Monostori, 2021). Comparative investigations have evaluated financially stable and financially vulnerable organizations according to profitability, liquidity, payment irregularities, and business continuity indicators. Supplier size has also been considered because large manufacturers and small or medium-sized enterprises frequently differ in financial resources, borrowing conditions, working-capital flexibility, and dependence on major customers. Within athletic-apparel and equipment supply networks, financial vulnerability is relevant to textile mills, component manufacturers, subcontractors, and specialized material producers operating under varying payment arrangements and purchasing commitments. Quantitative analysis has incorporated supplier financial indicators into composite risk

classifications and examined their associations with supplier failure probability, delivery instability, and operational continuity. The synthesized evidence identifies liquidity, leverage, profitability, and payment behavior as distinct financial-risk dimensions whose statistical relationships with procurement disruption depend on the selected outcome, organizational characteristics, and underlying economic conditions (Asheke, 2023; Chu et al., 2020).

Figure 3: Supplier risk and disruption relationships



Quantitative studies investigating supply-chain disruption severity have examined the combined contributions of supplier operational performance, financial vulnerability, purchasing dependence, and production-network characteristics to procurement interruption outcomes. Research on supplier risk and disruption management has distinguished disruption occurrence from disruption frequency, duration, and economic consequences, recognizing that these outcomes represent different dimensions of procurement instability (Yeasin, 2023; Rodgers & Singham, 2020). Operational predictors have included on-time delivery performance, lead-time variability, production downtime, capacity utilization, equipment failure frequency, material defects, and outstanding order backlogs, while financial predictors have included liquidity constraints, financial distress classifications, leverage, profitability, and payment irregularities. Dependent variables have encompassed the number of delayed orders, material-shortage frequency, interruption duration, emergency sourcing expenditure, and purchasing cost deviations. Empirical studies have applied Pearson and Spearman correlation analysis to examine associations among continuous or ordinal supplier indicators, while multiple regression has been used to evaluate the relationships between several predictors and procurement-performance outcomes. Logistic regression has been applied when disruption occurrence or supplier failure is represented as a binary outcome, with odds ratios and confidence intervals describing estimated associations between explanatory variables and event probabilities. Research on supply-chain disruptions has also examined organizational responses, supply-network characteristics, and recovery capabilities using regression-based and multivariate approaches. Studies of disruption consequences have identified the relevance of network complexity, supplier dependence, and limited sourcing flexibility when interpreting the severity of operational disturbances (Aldrighetti et al., 2019; Jahanara & Kaniz, 2023). However, operational and financial predictors may be statistically correlated, requiring attention to multicollinearity and the separate interpretation of their estimated effects. For

example, suppliers experiencing financial constraints may also exhibit production instability, while manufacturers operating near capacity limits may experience increased delivery variability without exhibiting financial distress. The empirical literature has therefore treated financial vulnerability and operational instability as potentially related but analytically distinguishable dimensions. Within athletic-apparel and equipment procurement, disruption severity also varies according to material criticality, product specialization, purchasing lead times, and the availability of qualified substitute suppliers. Specialized performance fabrics, technical footwear components, and precision equipment materials may involve longer replacement periods than standardized procurement items (Grzybowska & Stachowiak, 2022; Sheak & Tahmedur, 2023). Quantitative comparisons across supplier categories have examined average disruption duration, purchasing delays, and emergency procurement requirements under different operational conditions. The synthesized literature indicates that the relative statistical importance of operational and financial risk factors is conditional on disruption measurement, supplier characteristics, sourcing dependencies, and the analytical controls included in empirical models.

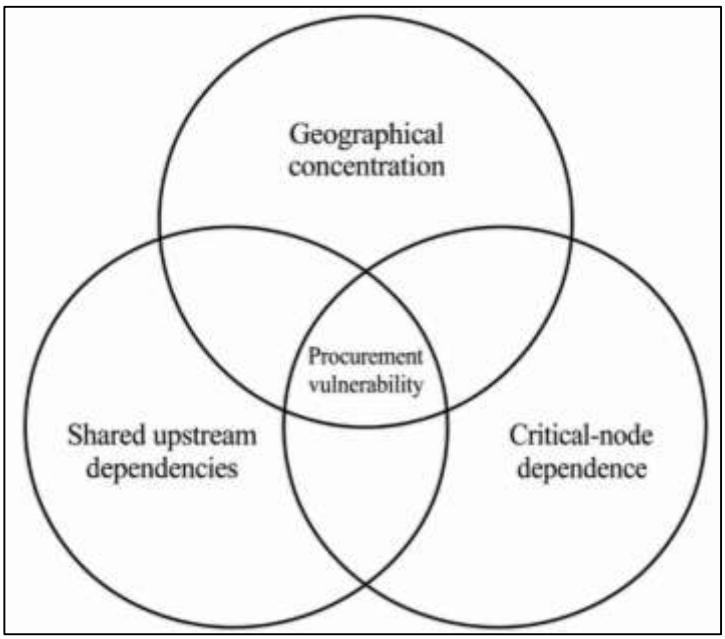
Empirical literature comparing supplier-risk categories has examined whether differences in operational performance, financial stability, organizational scale, and sourcing characteristics correspond with statistically distinguishable procurement disruption outcomes. Quantitative supplier-evaluation studies have classified organizations according to composite risk scores, delivery reliability, financial distress indicators, production capability, and quality performance, while supply-chain disruption investigations have assessed differences in interruption frequency, disruption severity, and recovery characteristics (Kaium, 2023; Sharma et al., 2022). High-risk and low-risk supplier groups have been compared using descriptive statistics, mean differences, distributional measures, and inferential procedures, although the criteria defining these groups vary considerably across studies. Independent-samples tests have been used to evaluate differences between two supplier categories when the measurement assumptions were appropriate, while analysis of variance has supported comparisons across multiple risk classifications or organizational groups. Nonparametric procedures, including Mann–Whitney and Kruskal–Wallis tests, have provided alternatives for skewed outcomes, ordinal risk measures, and datasets that do not satisfy conventional parametric assumptions. Research involving supplier financial conditions has compared organizations according to liquidity, leverage, profitability, and financial distress classifications, while operational investigations have distinguished suppliers through delivery performance, capacity constraints, quality defects, and production interruptions. Statistical significance thresholds such as $p < 0.05$ have been commonly employed in quantitative research, with confidence intervals and standardized effect sizes providing additional information about the precision and magnitude of estimated differences. However, statistical significance does not establish operational importance, and the literature has emphasized the distinction between measurable differences and practically consequential disruption exposure (Gurtu & Johny, 2021; Pervaz, 2023). Studies incorporating regression analysis have examined whether supplier-risk categories remain associated with procurement outcomes after controlling for organizational size, purchasing expenditure, industry characteristics, and geographical location. Comparative evidence concerning large manufacturers and small or medium-sized suppliers has reflected differences in resource availability, production flexibility, financial capacity, and customer concentration, although these characteristics do not produce uniform risk rankings across all manufacturing contexts. In international athletic-apparel and equipment networks, supplier comparisons are further influenced by textile-processing specialization, component complexity, country-level operating conditions, and sourcing-tier position. Supplier groups may differ in the frequency of late deliveries, material shortages, production interruptions, and emergency purchasing even when their aggregate risk scores appear similar (Khalil et al., 2022; Badrul & Mominul, 2023). Quantitative robustness assessments have therefore examined alternative classification thresholds, different indicator combinations, and sensitivity to influential observations. The synthesized literature establishes that supplier operational performance and financial vulnerability can be evaluated through complementary statistical approaches, while the magnitude, direction, and significance of their relationships with procurement disruption depend on supplier-group definitions, measurement quality, model specification, and the characteristics of distributed sourcing networks.

Geographical Sourcing Concentration and Quantitative Disruption Propagation

Quantitative literature examining geographical sourcing concentration has established that supplier location, regional manufacturing specialization, sourcing distance, transportation connectivity, and international trade conditions represent important dimensions of procurement risk exposure within distributed supply networks. Research spanning global sourcing, supply-chain disruption management, international production networks, and geographical diversification has examined how the spatial distribution of suppliers relates to purchasing continuity, delivery reliability, and operational vulnerability (Katsaliaki et al., 2022; Nishat, 2023). Across more than ten relevant empirical and modeling studies, geographical exposure has been represented through supplier-country distributions, regional sourcing shares, transportation distances, manufacturing concentration, border-crossing requirements, and country-level operating conditions. Studies of international sourcing have documented substantial variation in supplier dependence across countries and manufacturing clusters, particularly in industries characterized by labor-intensive production, specialized materials, and sequential manufacturing activities. Geographical concentration has commonly been measured using country-level purchasing expenditure, procurement-volume shares, supplier counts, and concentration indices such as the Herfindahl–Hirschman Index. These measures distinguish procurement systems that depend heavily on a limited number of sourcing locations from those distributing purchasing activities across multiple countries. Research examining global production networks has also considered transportation infrastructure, customs procedures, political and regulatory conditions, and the availability of alternative manufacturing locations. Sourcing distance has been evaluated through geographical separation, transportation lead time, freight movement, and international shipment requirements, while border-crossing frequency has represented an additional dimension of logistical complexity (Ivanov, 2018; Sadia, 2023).

Empirical studies have examined associations between international sourcing configurations and operational outcomes, including delivery variability, purchasing costs, inventory requirements, and exposure to transportation interruptions. Within athletic-apparel and equipment manufacturing, geographical sourcing patterns frequently involve textile processing, footwear-component production, technical-material manufacturing, and finished-product assembly distributed across Asian manufacturing economies and international consumer markets. Suppliers operating within the same industrial cluster may share electricity infrastructure, transportation routes, raw-material providers, and export facilities, creating common exposure to regional disturbances. Quantitative comparisons between single-country and multicountry sourcing arrangements have considered supplier availability, procurement concentration, logistical complexity, and operational continuity (Ivanov, 2021; Stabak & Siam, 2023). The synthesized literature indicates that geographical diversification and geographical vulnerability are not interchangeable measures because the number of sourcing countries does not independently capture shared upstream dependencies, supplier substitutability, or the distribution of purchasing volume across production regions. Quantitative investigations of supply-network topology have examined how supplier connectivity, sourcing-tier depth, network density, centrality, and structural dependence influence the distribution and severity of procurement disruptions. Research using complex-network theory, graph-based modeling, supply-chain mapping, and empirical supplier relationship data has demonstrated that procurement networks consist of interconnected organizations whose operational dependencies extend beyond direct buyer–supplier contracts (Najafi et al., 2021; Feroz, 2023). Studies examining supply-network structures have represented manufacturers, suppliers, logistics providers, and production facilities as network nodes, while material flows, purchasing relationships, and transportation connections have been represented as links between these nodes. Supplier count provides a basic measure of network scale, whereas sourcing-tier depth describes the number of sequential supplier relationships separating upstream material producers from downstream purchasing organizations. Network density measures the extent of observed interconnections relative to possible relationships, while degree centrality identifies organizations with comparatively large numbers of direct connections.

Figure 4: Geographical sourcing and network vulnerability



Betweenness centrality has been used to examine the extent to which particular suppliers occupy connecting positions between other network participants, and critical-node dependence describes reliance on suppliers whose interruption could affect substantial portions of material flow. Empirical and simulation-based investigations have shown that network topology influences the distribution of disruption exposure, although the direction and magnitude of effects depend on production relationships, inventory availability, substitution possibilities, and network design (Tahmedur & Rifat, 2023; Wei & Pan, 2021). Highly connected suppliers may support multiple purchasing relationships while simultaneously representing common points of operational dependence. Research examining multitier supply networks has also identified the importance of shared upstream suppliers, particularly when nominally independent manufacturers purchase essential materials from the same production facilities. Within distributed athletic-apparel and equipment networks, several garment manufacturers may depend on common fabric mills, dyeing facilities, chemical suppliers, or transportation providers, while footwear manufacturers may share producers of rubber compounds, synthetic materials, and specialized cushioning components. Such relationships create structural interdependence that is not fully represented by direct supplier counts. Quantitative studies have assessed network vulnerability through connectivity measures, supplier centrality distributions, affected-node counts, and changes in material-flow accessibility following simulated disruptions. Comparisons among centralized, decentralized, and distributed procurement structures have examined differences in critical-node exposure, network redundancy, and operational coordination (Mohammad, 2024; Shuang et al., 2019). The synthesized literature establishes that supplier-network vulnerability depends on both the geographical distribution of production activities and the structural organization of material dependencies across sourcing tiers.

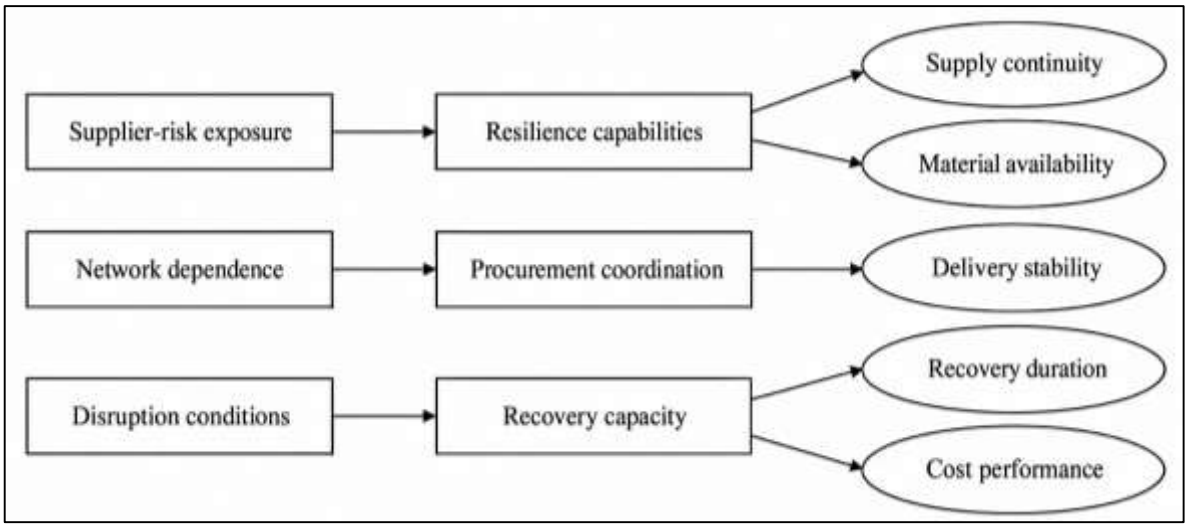
Quantitative Procurement Resilience Measurement

Quantitative literature examining procurement resilience has established that supply continuity, material availability, order-fulfillment performance, and purchasing service reliability constitute important operational dimensions of resilience within geographically distributed manufacturing networks (Ahmed, 2024; Katsaliaki et al., 2022). Evidence synthesized from more than ten empirical studies addressing supply-chain resilience, disruption management, supplier collaboration, and operational performance indicates that procurement continuity is commonly assessed through material availability percentages, procurement service levels, order-fill rates, stockout frequency, and the proportion of purchasing activities maintained during operational disturbances. Earlier supply-chain

performance investigations primarily emphasized routine delivery reliability, inventory availability, and purchasing efficiency, while subsequent resilience-oriented research incorporated disruption resistance, operational continuity, recovery capability, and performance stability under uncertain conditions. Material availability has been represented through the proportion of required inputs accessible within specified procurement periods, while order-fulfillment rates describe the percentage of purchasing requirements satisfied within agreed quantities and delivery schedules. Stockout frequency and material-shortage duration have been examined as indicators of purchasing interruptions, particularly in manufacturing environments dependent on sequential production activities (Islam, 2024; Gkanatsas & Krikke, 2020).

Empirical studies using survey-based structural equation modeling have investigated relationships among resilience capabilities, organizational responsiveness, collaboration, and supply-chain performance, while operational-data studies have evaluated service levels, inventory behavior, and disruption-related delivery outcomes. Quantitative findings have generally associated stronger supply-chain resilience capabilities with more favorable continuity and operational performance measures, although the magnitude and statistical significance of these relationships vary according to industry, measurement framework, and disruption conditions. Research has also distinguished routine procurement efficiency from resilience performance because high service levels under stable operating conditions do not necessarily demonstrate the ability to maintain material availability during supplier failures or transportation interruptions. Within athletic-apparel and equipment supply networks, continuity indicators are particularly relevant to textile mills, fabric processors, footwear-component suppliers, and specialized equipment manufacturers whose production activities depend on coordinated material flows. Interruptions involving technical fabrics, synthetic materials, rubber compounds, or precision components can affect downstream purchasing and assembly operations (Asheke, 2024; Trabucco & Giovanni, 2021).

Figure 5: Quantitative procurement resilience measurement framework



Quantitative comparisons have examined continuity performance across supplier categories, sourcing configurations, and organizational capability levels using descriptive statistics, correlation analysis, regression models, and group-difference tests. The synthesized literature identifies material availability, order fulfillment, stockout occurrence, and purchasing continuity as complementary indicators of procurement resilience, with their interpretation depending on disruption exposure, inventory conditions, supplier criticality, and production requirements. Empirical and quantitative modeling research on procurement resilience has examined disruption recovery through time to recover, time to survive, supplier replacement duration, operational restoration rates, and the persistence of purchasing interruptions. Studies investigating supply-chain resilience, disruption propagation, business continuity, and operational recovery have distinguished the ability to withstand

an initial disturbance from the capacity to restore acceptable performance after material flows or supplier operations have been interrupted (Ashrafuzzaman, 2024; Shishodia et al., 2019). Time to recover has been used to describe the duration required for an affected supplier, facility, or supply network to restore a defined level of operational functionality, while time to survive represents the period during which downstream activities can continue following a supply interruption before available resources become insufficient.

These measures have been examined through simulation, disruption scenarios, inventory-based analysis, and empirical observations of supply-chain interruptions. Supplier replacement duration has been represented through the time required to identify, qualify, contract, and activate an alternative supplier, while operational restoration has been assessed through recovered production capacity, resumed delivery volumes, and the proportion of purchasing activities restored after disruption. Research using network simulation and stochastic modeling has demonstrated that recovery outcomes depend on supplier criticality, inventory availability, alternative production capacity, transportation accessibility, and the duration of upstream interruptions (Ghezelhesar & Bozorgi-Amiri, 2022; Jannatul, 2024). Empirical studies examining resilience capabilities have also investigated relationships between flexibility, responsiveness, collaboration, and organizational recovery performance. Statistical approaches have included multiple regression, structural equation modeling, and comparative analysis of disruption-response capabilities, although direct recovery-time observations are less consistently available than survey-based measures of perceived resilience. Studies comparing disrupted and less-disrupted organizations have examined differences in operational recovery, business continuity, and performance deterioration, while simulation-based investigations have evaluated recovery trajectories under alternative supplier-failure and inventory conditions. In distributed athletic-apparel and equipment manufacturing, recovery duration is influenced by material specialization, production sequencing, tooling requirements, supplier qualification procedures, and international transportation lead times. Replacement of standardized packaging materials may involve different recovery requirements from substitution of certified performance fabrics, specialized footwear cushioning, or precision sporting-equipment components (Trump, et al., 2021; Kynatun & Saba, 2024). Quantitative resilience assessments have therefore considered supplier replacement capability alongside inventory buffers, sourcing redundancy, and operational flexibility. The synthesized literature establishes that recovery duration and restoration performance represent distinct measurable characteristics of procurement resilience, with recovery outcomes varying according to disruption severity, supplier dependencies, material substitutability, and the availability of operational alternatives.

Quantitative research on procurement resilience has examined delivery stability and purchasing cost performance as interconnected operational and financial outcomes associated with supplier disruptions. Studies addressing supplier performance, international sourcing, supply-chain risk management, and disruption recovery have incorporated average procurement lead time, lead-time standard deviation, delayed shipment percentage, delivery schedule adherence, emergency purchasing expenditure, expedited transportation costs, inventory carrying costs, and disruption-related financial losses (Mashiat, 2024; Sureeyatanapas et al., 2020). Delivery stability has commonly been assessed through the consistency of actual material arrival times relative to scheduled delivery requirements, while lead-time variability has represented uncertainty in procurement scheduling and material replenishment. Research examining supply-chain disruptions has identified delivery instability as an important characteristic of operational vulnerability because variation in supplier lead times can coincide with increased inventory requirements, production scheduling difficulties, and emergency purchasing activities. Quantitative investigations have used correlation analysis and regression modeling to examine associations among supplier delivery performance, operational uncertainty, inventory management, and purchasing outcomes. Studies of disruption consequences have also documented relationships between supply interruptions and organizational performance deterioration, although procurement-specific financial losses have not been measured uniformly across empirical settings. Emergency procurement expenditure has been represented through additional costs associated with substitute suppliers, urgent material acquisition, and purchasing under constrained availability. Expedited transportation expenditure has included premium freight charges and alternative shipping arrangements, while inventory carrying costs have reflected storage, financing,

handling, and material-holding requirements. Simulation and optimization studies have examined trade-offs between inventory protection, sourcing flexibility, transportation expenditure, and disruption exposure under alternative uncertainty assumptions. Within international athletic-apparel and equipment procurement, lead-time stability is affected by textile-processing schedules, component manufacturing requirements, shipment consolidation, international freight arrangements, and customs procedures (Ocicka et al., 2022; Sumaiya, 2024). Seasonal purchasing cycles and product-specific manufacturing requirements can introduce additional variation in procurement schedules and purchasing costs. Statistical comparisons between routine and disrupted operating periods have examined changes in delivery delays, inventory levels, service performance, and purchasing expenditure, while multivariate approaches have assessed relationships after accounting for supplier characteristics and operational conditions. However, the magnitude of disruption-related costs depends on the definition of purchasing losses, the observation period, inventory accounting procedures, and the inclusion of indirect production consequences. The synthesized literature demonstrates that procurement resilience encompasses both operational delivery stability and financial performance, with lead-time variability, delayed shipment frequency, emergency sourcing expenditure, and inventory-related costs providing measurable but analytically distinct indicators of disruption consequences (Mohammed et al., 2021; Feroz, 2024).

Quantitative literature investigating procurement resilience capabilities has examined how flexibility, redundancy, responsiveness, supplier collaboration, information visibility, and alternative sourcing availability relate to purchasing continuity, recovery performance, delivery reliability, and disruption-related costs. Empirical research involving supply-chain resilience, relational competencies, risk-management capabilities, and organizational performance has frequently employed survey-based measurement models, multiple regression, and structural equation modeling to evaluate relationships among organizational capabilities and resilience outcomes. Flexibility has been measured through the ability to adjust sourcing arrangements, purchasing volumes, production schedules, and supplier allocations, while redundancy has been represented through backup suppliers, reserve production capacity, alternative transportation routes, and inventory buffers (Mital et al., 2018). Responsiveness has been assessed through disruption-detection speed, decision-making timeliness, and operational adjustment capability, whereas supplier collaboration has included information exchange, joint planning, coordination, and relationship quality. Information visibility has been examined through access to supplier inventory records, production status, shipment information, and procurement-performance data. Studies applying structural equation modeling have reported associations between collaborative capabilities, risk-management practices, resilience, and operational performance, with standardized path coefficients, explained variance, and model-fit measures used to evaluate estimated relationships. Mediation analyses have examined whether resilience capabilities statistically account for relationships between organizational practices and performance outcomes, while moderation analyses have assessed differences in these relationships under varying levels of uncertainty and disruption exposure. Comparative research has also distinguished suppliers or purchasing organizations according to risk classifications, resource availability, and operational flexibility, although composite supplier-risk categories and resilience capabilities have not always been examined within the same empirical model. Independent-samples tests, analysis of variance, and nonparametric comparisons have been used where appropriate to assess differences among organizational groups, while confidence intervals and standardized effect sizes have supported interpretation beyond statistical significance alone (Mahoney, et al., 2021).

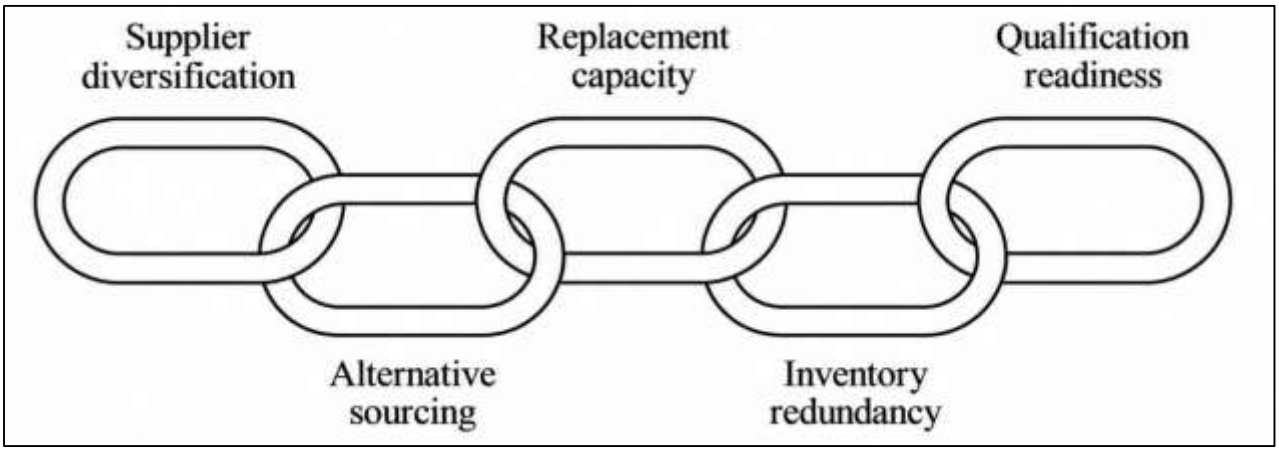
Research examining disruption responses has identified the relevance of supplier dependence, organizational preparedness, and network structure when evaluating resilience performance. Within athletic-apparel and equipment supply networks, alternative sourcing capacity and supplier collaboration are influenced by material specifications, manufacturing specialization, geographical dispersion, and contractual arrangements. Statistical relationships may also vary between standardized materials and specialized components because substitution requirements and recovery constraints differ across procurement categories. The synthesized evidence indicates that procurement resilience is represented through multiple interacting capabilities rather than a single operational indicator. Empirical distinctions between routine performance and disruption-specific outcomes remain

important, as favorable delivery records, low purchasing costs, or high inventory availability during stable conditions do not independently establish strong recovery performance under supplier failure. The literature consequently characterizes resilience measurement through the combined assessment of continuity, recovery, delivery stability, purchasing costs, and organizational capabilities, with statistical interpretation dependent on measurement validity, supplier-risk exposure, analytical controls, and the operational conditions represented in the underlying studies (Zhu & Wu, 2022).

Supplier Diversification and Procurement Resilience

Quantitative literature examining supplier diversification has established that sourcing configuration, supplier concentration, geographical distribution, and procurement-volume allocation represent important dimensions of supply-chain resilience and purchasing continuity. Evidence synthesized across more than ten empirical and quantitative modeling studies has examined relationships between the number of qualified suppliers, sourcing concentration, supply disruption exposure, and operational performance under uncertain manufacturing conditions (Katsaliaki et al., 2022). Earlier supplier-selection and purchasing studies primarily evaluated sourcing efficiency, supplier performance, and purchasing costs, while subsequent research incorporated disruption probability, supplier redundancy, geographical exposure, and recovery capabilities into quantitative sourcing assessments. Supplier diversification has commonly been measured through the number of active or qualified suppliers, purchasing expenditure distributed across suppliers, geographical sourcing diversity, and concentration indices such as the Herfindahl–Hirschman Index. Single-source dependence has been represented through the proportion of purchasing requirements allocated to one supplier, while multisource procurement has been characterized by the distribution of purchasing volumes among alternative manufacturers.

Figure 6: Supplier diversification and procurement resilience



Quantitative optimization and simulation studies have demonstrated that diversification can reduce dependence on individual supplier failures when alternative suppliers possess sufficient independent capacity and operational availability. However, empirical relationships between supplier count and procurement resilience have varied according to geographical clustering, shared upstream dependencies, supplier qualification requirements, and purchasing coordination costs. Research examining international sourcing has also identified differences between geographical diversification and effective risk independence because suppliers operating in separate locations may remain dependent on common raw-material producers or transportation infrastructure (Helgeson & Roa-Henriquez, 2022). Multiple regression and panel-data approaches have been applied in related procurement research to examine associations among sourcing characteristics, supplier performance, and purchasing outcomes, while simulation studies have compared expected disruption losses under alternative sourcing allocations. Within distributed athletic-apparel and equipment networks, supplier diversification involves textile mills, fabric processors, footwear-component manufacturers, technical-

material producers, and finished-product assemblers operating across multiple production regions. The distribution of procurement volumes among these suppliers influences exposure to regional interruptions, manufacturing constraints, and transportation disturbances. Studies comparing concentrated and diversified sourcing configurations have assessed procurement continuity, order-fulfillment performance, disruption duration, and purchasing cost variability (Cohen et al., 2022). The synthesized literature indicates that the relationship between diversification and resilience depends on supplier independence, geographical exposure, material compatibility, and the availability of operationally qualified alternatives rather than supplier numbers alone.

Empirical and quantitative modeling research on alternative sourcing has examined the relationships among backup supplier availability, qualification duration, replacement production capacity, supplier-switching time, and procurement recovery following operational disruptions. Studies addressing supply-chain flexibility, disruption management, sourcing redundancy, and supplier selection have distinguished nominal supplier availability from the practical ability of alternative manufacturers to satisfy purchasing requirements within acceptable operational periods. Backup supplier availability has commonly been represented through the number of qualified substitute suppliers, while replacement capacity has been measured through available production volume, manufacturing capability, and the proportion of disrupted purchasing requirements that alternative suppliers can accommodate (Ivanov et al., 2019). Supplier qualification duration incorporates the time required to verify production capabilities, assess product conformity, complete technical inspections, and establish contractual purchasing arrangements. Supplier-switching duration additionally reflects production scheduling, transportation arrangements, material availability, and the transfer of purchasing volumes between manufacturers. Quantitative studies using stochastic optimization, scenario analysis, and disruption simulation have examined how backup supplier capacity and switching constraints affect expected shortages, unmet demand, recovery duration, and additional procurement expenditure. Research on supply-chain flexibility has also investigated the relationship between alternative sourcing arrangements and operational responsiveness, while resilience-oriented empirical studies have examined sourcing flexibility alongside collaboration, information sharing, and organizational recovery capabilities. Statistical investigations have assessed associations among supplier flexibility, operational performance, and resilience using regression and structural equation modeling, although direct observations of supplier-switching duration are less consistently reported than survey-based measures of sourcing flexibility. Within athletic-apparel and equipment manufacturing, alternative sourcing capacity differs considerably across material categories (Piprani et al., 2022). Standardized packaging, common textile inputs, and widely available accessories may involve relatively broad supplier availability, whereas specialized performance fabrics, proprietary footwear components, technical coatings, and precision sporting-equipment materials require more extensive qualification and manufacturing compatibility. These differences influence replacement duration and the proportion of purchasing requirements recoverable through alternative suppliers. Comparative studies have examined sourcing flexibility under different disruption conditions, including individual supplier failure, regional production interruption, and simultaneous capacity constraints. Quantitative outcomes have included material-shortage duration, order-fulfillment recovery, procurement service levels, and emergency sourcing costs (Zavala-Alcívar et al., 2020). The synthesized literature establishes that alternative sourcing contributes to procurement resilience through a combination of supplier availability, qualification readiness, replacement capacity, and switching efficiency, with the observed magnitude of resilience benefits depending on material criticality, production specialization, and disruption severity.

Quantitative literature on inventory redundancy has examined how safety-stock coverage, buffer inventory, inventory turnover, and days of supply influence procurement continuity, material shortages, and operational recovery during supplier disruptions. Research on inventory management, supply-chain uncertainty, disruption-risk mitigation, and resilient sourcing has evaluated the relationship between inventory availability and the ability of purchasing organizations to maintain manufacturing operations when replenishment activities are interrupted (Hosseini & Ivanov, 2022). Safety-stock coverage has commonly been measured through inventory quantities relative to expected consumption, while days of supply represents the period during which available inventory can support

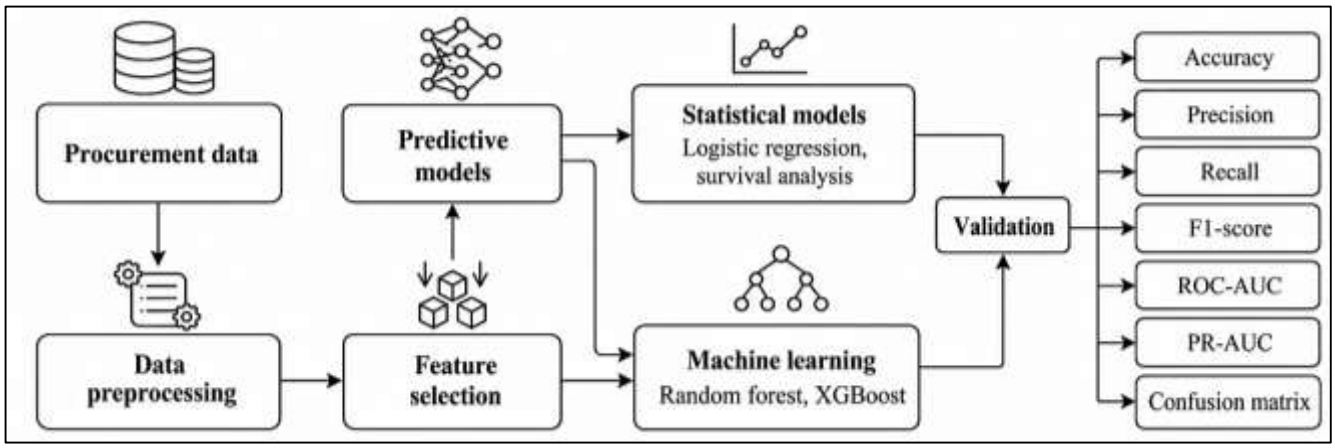
purchasing or production requirements. Inventory turnover has been used to characterize the rate at which materials are consumed and replenished, whereas stockout frequency measures the occurrence of insufficient material availability during specified observation periods. Quantitative inventory studies have employed stochastic demand models, optimization techniques, simulation, and empirical performance analysis to evaluate inventory behavior under uncertain supplier lead times and variable demand conditions. Research examining supply disruptions has demonstrated that inventory buffers can extend operational continuity during temporary interruptions, although the extent of protection depends on disruption duration, demand variability, replenishment frequency, and material consumption rates. Inventory redundancy has also been associated with financial and operational trade-offs involving storage expenditure, working-capital requirements, material deterioration, and inventory obsolescence (Ivanov, 2018). Studies evaluating supply-chain resilience have distinguished inventory-based redundancy from supplier-based redundancy because the former provides immediately available material protection, while the latter depends on alternative production and delivery capabilities. Statistical analyses of inventory performance have examined relationships among lead-time variability, inventory levels, service performance, and stockout outcomes, while simulation-based studies have compared expected shortages and costs across alternative buffer-stock policies. Within athletic-apparel and equipment procurement, inventory requirements differ according to fabric characteristics, product seasonality, component standardization, storage conditions, and manufacturing lead times. Technical fabrics, adhesives, synthetic materials, rubber compounds, and specialized equipment components may exhibit different storage requirements and substitution possibilities. Excess inventory of product-specific materials can also create financial exposure when production requirements change (Tavana et al., 2021). Quantitative disruption assessments have therefore examined both operational benefits and purchasing costs associated with inventory buffers. Interaction between inventory redundancy and disruption severity has been represented through comparisons of inventory sufficiency under interruptions of different durations and intensities. The synthesized literature indicates that inventory redundancy contributes to resilience through material availability and temporary continuity protection, while its effectiveness depends on inventory coverage, replenishment uncertainty, disruption duration, and the economic characteristics of stored materials.

Predictive Supplier-Risk Classification and Procurement Transaction Data

Quantitative literature examining predictive supplier-risk classification has established that procurement transaction records, supplier operational characteristics, financial indicators, and historical disruption information constitute important data sources for statistical and machine-learning risk assessment. Research spanning supplier evaluation, financial distress prediction, supply-chain risk management, procurement analytics, and operational disruption modeling has investigated the classification of suppliers according to observed performance deficiencies and estimated disruption exposure (Kumar et al., 2022). More than ten relevant empirical studies across these research domains have examined combinations of delivery delays, defect rates, financial ratios, supplier capacity, geographical exposure, purchasing dependence, and historical disruption frequency as explanatory variables. Procurement transaction datasets have commonly included purchase-order quantities, scheduled delivery dates, actual receipt dates, rejected material quantities, supplier identification, purchasing expenditure, and order-completion records. Delivery-related predictors have been represented through late-delivery percentages, average shipment delays, lead-time standard deviations, and previous fulfillment failures, while quality indicators have included defect frequency, inspection rejection rates, and product nonconformity. Financial predictors have incorporated liquidity, leverage, profitability, cash-flow conditions, and financial distress classifications. Supplier capacity and geographical exposure have been measured through production capability, facility location, regional concentration, transportation accessibility, and sourcing dependence. Quantitative classification studies have distinguished binary disruption outcomes from multicategory risk classifications and continuous supplier-risk scores. Binary outcomes have included supplier failure versus nonfailure, delayed versus on-time delivery, and financially distressed versus financially stable organizations. Multicategory approaches have classified suppliers into low-, moderate-, and high-risk groups using predefined thresholds or statistical classification procedures. Research involving

transactional datasets has also identified methodological difficulties associated with missing observations, inconsistent reporting periods, correlated predictors, unequal supplier representation, and relatively infrequent severe disruption events (Baryannis et al., 2019). Class imbalance has been particularly relevant when major supplier failures represent a small proportion of recorded procurement transactions. Within athletic-apparel and equipment supply networks, predictive variables differ among textile processors, footwear-component manufacturers, technical-material suppliers, and sporting-equipment assemblers because production requirements, delivery schedules, and material specifications vary across supplier categories. Historical procurement data may also contain repeated observations for individual suppliers, creating dependencies between records that require consideration during model development and validation. The synthesized literature indicates that supplier-risk classification depends on the operational definition of disruption, the quality and temporal availability of predictor variables, and the correspondence between model-generated risk categories and observed procurement outcomes (Brintrup et al., 2022).

Figure 7: Predictive supplier risk classification framework



Empirical research on statistical risk prediction has extensively examined logistic regression, discriminant analysis, survival modeling, and probabilistic classification as methods for estimating organizational failure, operational instability, and disruption-related outcomes. Foundational financial distress studies established the use of accounting ratios and multivariate statistical techniques to distinguish financially vulnerable organizations from financially stable firms, while subsequent investigations incorporated additional operational and organizational indicators into predictive classification frameworks (Allal-Chérif et al., 2021). Logistic regression has frequently been applied to binary outcomes because it estimates the relationship between explanatory variables and the probability of a specified event. In supplier-risk assessment, relevant predictors include delivery reliability, financial liquidity, leverage, profitability, defect frequency, capacity utilization, and historical disruption occurrence. Regression coefficients and odds ratios have been used to interpret the direction and relative magnitude of estimated associations, while confidence intervals and statistical significance tests have provided information about estimation uncertainty. Discriminant analysis has been applied in organizational failure research to classify observations using combinations of financial and operational characteristics, although its performance depends on data distributions, group characteristics, and modeling assumptions. Survival analysis has examined the timing of organizational failure or operational events, incorporating observation periods, event occurrence, and censored cases. Such approaches are analytically relevant when supplier disruption risk concerns not only whether an interruption occurs but also the duration until failure or the timing of operational recovery (Jayender & Kundu, 2021). Quantitative investigations have compared statistical models using classification accuracy, sensitivity, specificity, receiver operating characteristic measures, and error rates. Research on financial distress has demonstrated that predictor selection, observation

horizon, industry composition, and class distribution influence estimated model performance. However, financial distress prediction and procurement disruption prediction represent different classification tasks, and strong performance in identifying financially distressed firms does not independently establish equivalent accuracy in predicting late deliveries or material shortages. Statistical supplier-risk models have also been examined for multicollinearity, nonlinear predictor relationships, missing financial information, and instability across observation periods. Within distributed athletic-apparel and equipment procurement, logistic regression can represent associations between supplier characteristics and recorded disruption events, while survival-oriented approaches can describe time-dependent supplier failure or interruption outcomes (Hong et al., 2018). Comparative evidence indicates that conventional statistical models provide interpretable coefficients and probability estimates, although predictive performance varies according to outcome definitions, supplier heterogeneity, data quality, and the extent to which operational relationships satisfy model assumptions.

Quantitative literature on machine-learning risk classification has examined decision trees, random forests, support vector machines, gradient boosting, XGBoost, and artificial neural networks for predicting financial distress, delivery failures, operational disruptions, and supply-chain risk categories. Empirical studies in these related domains have compared conventional statistical classifiers with nonlinear machine-learning approaches using structured financial, operational, and transactional datasets. Decision trees have provided interpretable classification rules based on predictor thresholds, while random forests have combined multiple trees to represent complex relationships and reduce the instability associated with individual tree structures. Support vector machines have been applied to classification problems involving multiple correlated indicators and potentially nonlinear decision boundaries (Kara & Fırat, 2018). Gradient boosting and XGBoost have been investigated for their capacity to represent interactions among financial ratios, supplier characteristics, operational variability, and historical event patterns. Artificial neural networks have been applied to organizational failure prediction and supply-chain analytics where relationships among explanatory variables are complex. Comparative studies have reported varying model rankings across datasets, with no single algorithm consistently demonstrating superior performance across all financial distress and operational disruption settings. Classification accuracy has been used to measure the overall proportion of correctly classified observations, while precision has represented the proportion of predicted risk events that corresponded to actual events. Recall has measured the proportion of observed risk events correctly identified, and specificity has assessed the identification of nonevent observations. F1-score has combined precision and recall into a single performance measure, while ROC-AUC and PR-AUC have evaluated discrimination across classification thresholds. Research involving imbalanced datasets has emphasized that high overall accuracy can coexist with poor detection of relatively rare supplier failures. Precision–recall evaluation has therefore been particularly informative when disruption events represent a small minority of recorded observations (Pradhan et al., 2022). Confusion matrices have provided additional information about false-positive and false-negative classifications, which carry different operational consequences in procurement risk management. Within athletic-apparel and equipment supply networks, missed disruption predictions may coincide with material shortages and production interruptions, whereas excessive false-positive classifications may lead to unnecessary supplier reviews or sourcing adjustments. Machine-learning investigations have also examined predictor importance, model complexity, training sample size, and the influence of correlated variables (Žigienė et al., 2022). The synthesized literature indicates that predictive model performance depends on the characteristics of the supplier dataset, the frequency of disruption events, the classification threshold, and the balance between identifying vulnerable suppliers and limiting incorrect risk classifications.

Quantitative research evaluating predictive risk models has examined cross-validation procedures, independent testing, class-imbalance adjustments, model interpretation, and performance stability across organizational groups and observation periods. Empirical investigations of financial distress classification, procurement analytics, and supply-chain disruption prediction have used training-testing partitions, stratified cross-validation, temporal validation, and independent holdout samples to assess whether predictive relationships remain consistent beyond the data used for model estimation.

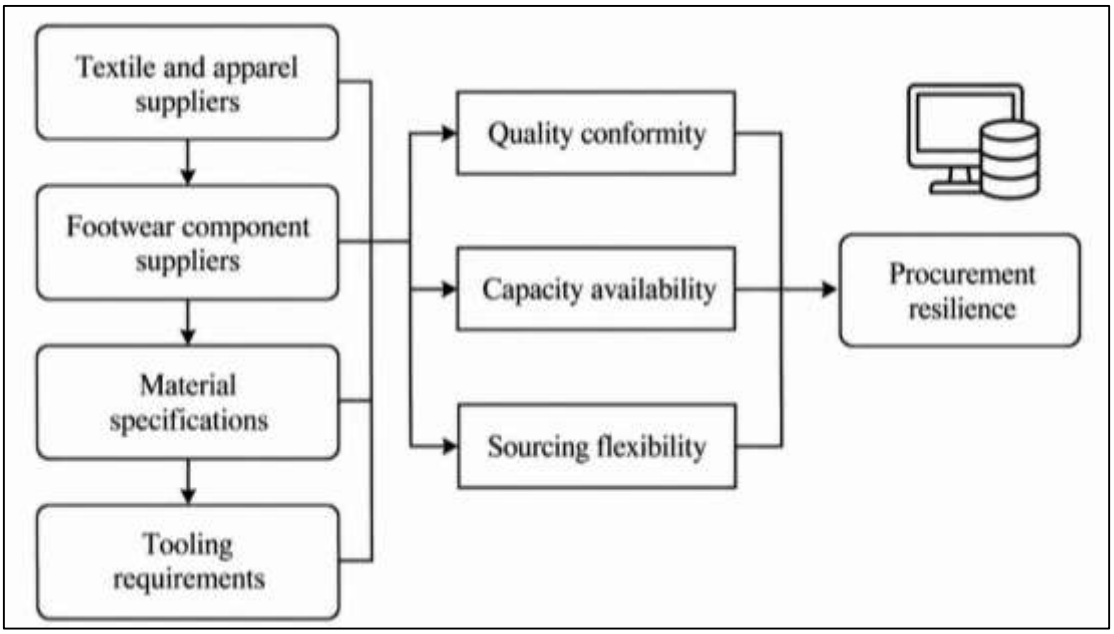
Stratified k-fold cross-validation has been applied to maintain approximate class proportions across evaluation partitions, while chronological training-testing procedures have been used when predictor information and disruption outcomes follow a temporal sequence (Rejeb & Appolloni, 2022). Independent holdout testing has provided an additional assessment of generalization to observations excluded from model development. Research involving repeated organizational observations has also highlighted the importance of separating records appropriately because transactions from the same supplier may contain correlated information. Randomly dividing such records across training and testing samples can overstate predictive performance when supplier-specific characteristics are shared between partitions. Class-imbalance methods have included random oversampling, undersampling, synthetic minority oversampling, and class-weighted learning. Comparative studies have examined how these procedures affect recall, precision, F1-score, ROC-AUC, and PR-AUC, although improvements in detecting minority events have sometimes been accompanied by increased false-positive classifications. Model explainability has been evaluated through decision-tree rules, regression coefficients, feature importance, permutation importance, and SHAP-based interpretation. These methods have been used to examine the relative contributions of delivery delays, financial indicators, supplier capacity, purchasing dependence, and geographical exposure to predicted classifications (Chu et al., 2020). However, feature importance does not independently establish causal relationships between supplier characteristics and disruption occurrence. Research on predictive model robustness has also considered changes in predictor distributions, observation periods, supplier populations, and classification thresholds. Sensitivity analysis has examined whether model performance remains stable when alternative variables, training samples, and parameter settings are used. Within distributed athletic-apparel and equipment procurement, generalizability is influenced by differences in supplier size, manufacturing specialization, sourcing region, material criticality, and transaction frequency. Models developed using large textile manufacturers may exhibit different classification performance when applied to smaller component suppliers or specialized sporting-equipment producers. Statistical comparisons of model performance have incorporated confidence intervals, repeated validation results, and paired evaluation procedures where appropriate (Kosasih & Brintrup, 2022). The synthesized literature establishes that predictive supplier-risk assessment involves more than obtaining high classification accuracy, encompassing reliable event definitions, temporally appropriate validation, minority-event detection, probability calibration, interpretability, and performance stability across heterogeneous supplier networks.

Sector-Specific Supplier-Risk Exposure and Technical Materials

Quantitative literature examining textile and athletic-apparel manufacturing has identified material availability, yarn quality, fabric-processing capacity, production lead-time variability, and supplier delivery reliability as important dimensions of procurement risk and operational resilience. Research spanning global apparel production, textile supply-chain management, supplier evaluation, and manufacturing performance has examined how supplier characteristics and production dependencies influence material continuity, purchasing stability, and manufacturing interruptions (Papetti et al., 2019). More than ten relevant empirical studies across apparel and related manufacturing research have investigated supplier performance, production scheduling, inventory management, international sourcing, and operational disruption exposure, although relatively few have combined these dimensions into a single validated supplier-risk scoring framework. Textile and apparel procurement commonly involves sequential production stages, including fiber preparation, spinning, knitting, weaving, dyeing, finishing, cutting, stitching, inspection, and packaging. Quantitative supplier-performance assessments have incorporated yarn defect frequency, fabric rejection percentages, processing-capacity utilization, manufacturing lead times, order-completion rates, and delayed shipment frequency. Fabric availability has been examined through inventory coverage, material shortage frequency, and fulfillment performance, while yarn quality has been evaluated using measures of tensile characteristics, dimensional consistency, contamination, and production defects (Caballero-Morales, 2021). Dyeing and finishing operations introduce additional capacity and scheduling constraints because processing requirements vary according to fabric composition, chemical treatment, color specifications, and production batch size. Empirical research on apparel supply chains has also examined the effects of short product cycles, seasonal purchasing requirements,

and demand variability on production planning and sourcing performance. Statistical investigations have employed descriptive statistics, correlation analysis, regression models, and comparative performance assessments to examine relationships among supplier capabilities, delivery outcomes, and manufacturing efficiency.

Figure 8: Sectoral supplier risk and resilience



Within international athletic-apparel networks, sourcing arrangements frequently involve manufacturing facilities located across Bangladesh, China, Vietnam, India, Cambodia, and other textile-producing economies, creating differences in infrastructure conditions, production specialization, transportation access, and procurement lead times. Supplier concentration and dependence on specialized fabric processors have been examined as dimensions of operational vulnerability, particularly when downstream manufacturers share common upstream material sources (Machado et al., 2019). Research on apparel sourcing has additionally distinguished purchasing cost efficiency from resilience under disruption because low-cost production arrangements may involve different inventory, transportation, and replacement-capacity requirements. The synthesized literature indicates that textile and athletic-apparel supplier-risk exposure is multidimensional, with fabric availability, material conformity, processing capacity, production scheduling, and geographical sourcing dependencies representing distinct characteristics associated with procurement continuity and manufacturing interruption.

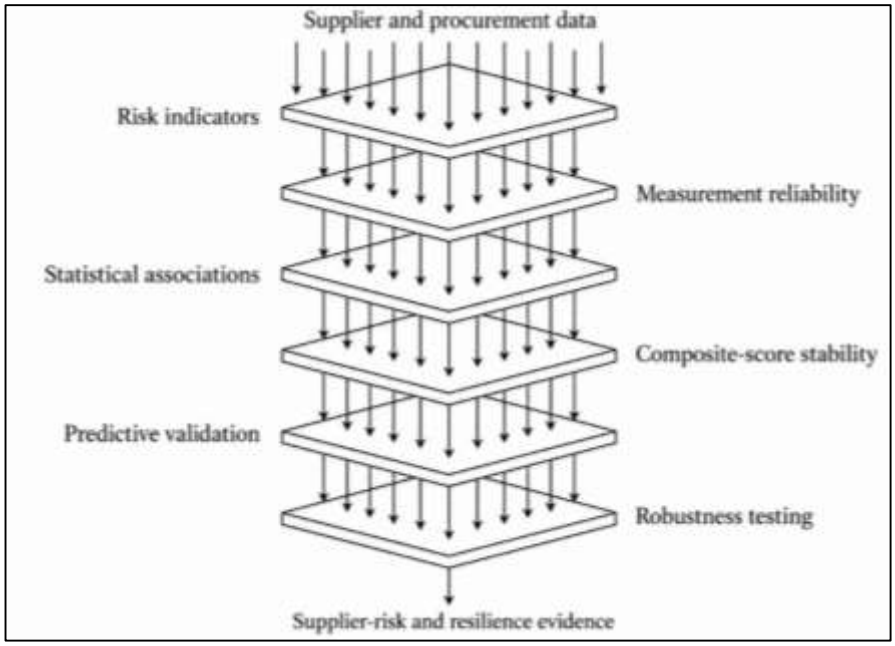
Empirical research on footwear manufacturing and related polymer-processing industries has examined material quality, component availability, production capability, tooling constraints, and supplier coordination as measurable characteristics influencing manufacturing performance and procurement reliability. Footwear supply networks involve multiple specialized inputs, including rubber compounds, synthetic leather, ethylene-vinyl acetate materials, polyurethane cushioning systems, adhesives, molded soles, textile uppers, reinforcement components, and fastening accessories. These materials are associated with different production processes, quality requirements, supplier capabilities, and replacement constraints (Sheffi, 2018). Quantitative studies of footwear manufacturing have evaluated material properties, manufacturing defects, processing efficiency, production scheduling, and product conformity, while broader supply-chain investigations have examined supplier reliability, sourcing flexibility, inventory availability, and operational interruptions. Rubber and polymer-component studies have frequently measured hardness, tensile strength, abrasion resistance, dimensional stability, and material consistency, whereas adhesive-related investigations

have evaluated bonding performance, curing conditions, and manufacturing compatibility. Such product-quality indicators are relevant to supplier-risk assessment because material nonconformity can result in rejected components, additional inspections, reprocessing, and interruptions in downstream assembly. Tooling availability represents another operational dimension because molds, dies, and specialized manufacturing equipment may be required for specific footwear designs and component geometries. Production-capacity utilization, equipment downtime, mold-change duration, order backlogs, and component rejection frequency provide measurable indicators of supplier operating conditions. Research examining manufacturing flexibility has distinguished suppliers capable of producing standardized components from those dependent on product-specific tooling and proprietary material specifications (Reino-Cherrez et al., 2022). These differences influence material substitution time, replacement supplier availability, and recovery duration following operational disturbances. Quantitative sourcing studies have used inventory models, production simulations, supplier evaluation frameworks, and regression-based approaches to assess relationships among material availability, manufacturing capacity, and operational performance. However, footwear-specific studies have more frequently reported product quality and manufacturing efficiency than directly observed supplier disruption probabilities or procurement recovery times. Within internationally distributed footwear networks, procurement exposure is also associated with geographical specialization, upstream chemical and polymer supply, transportation lead times, and purchasing-volume concentration. Comparative research across manufacturing suppliers has examined quality performance, delivery reliability, capacity constraints, and sourcing costs, while resilience-oriented models have evaluated alternative sourcing and inventory protection under disruption scenarios. The synthesized evidence indicates that footwear procurement resilience depends on interactions among material specifications, component quality, tooling compatibility, supplier capacity, and replacement flexibility, with specialized components presenting different operational risk characteristics from widely available standardized inputs (Milios, 2018).

Robustness of Supplier-Risk–Resilience Relationships

Quantitative literature examining supplier-risk assessment and procurement resilience has investigated relationships among supplier operational vulnerability, financial stability, geographical concentration, disruption frequency, recovery duration, delivery reliability, and purchasing cost performance. Research across supplier evaluation, supply-chain risk management, operational resilience, and international sourcing has employed correlation analysis, multiple regression, logistic regression, and structural equation modeling to examine how supplier characteristics relate to procurement outcomes (Hosseini & Ivanov, 2022). Across more than ten relevant empirical studies, supplier-risk indicators have included delivery delays, defect rates, financial distress measures, production-capacity constraints, geographical exposure, purchasing dependence, and historical disruption occurrence. Procurement-resilience outcomes have been represented through material availability, order-fulfillment rates, stockout frequency, disruption duration, recovery performance, and emergency sourcing expenditure. Pearson correlation analysis has been used to evaluate linear associations between continuous supplier indicators and operational outcomes, while Spearman correlation has supported examination of ordinal risk categories and variables exhibiting nonnormal distributions. Multiple regression studies have assessed the independent contributions of supplier characteristics after accounting for organizational size, purchasing expenditure, industry characteristics, and geographical location. Logistic regression has been applied to binary disruption outcomes, with odds ratios and confidence intervals describing estimated associations between risk indicators and disruption occurrence (Mohammed et al., 2021). Structural equation modeling has examined relationships among latent resilience capabilities, supplier collaboration, operational flexibility, and organizational performance. Empirical findings across these research streams generally indicate that supplier vulnerability and operational instability are associated with less favorable purchasing outcomes, although effect magnitudes and statistical significance vary according to measurement procedures, industry characteristics, and analytical specifications.

Figure 9: Supplier risk evidence and validation



Studies examining supply-chain disruptions have also identified differences between direct supplier-performance effects and broader network-level vulnerabilities associated with shared dependencies and sourcing concentration. In athletic-apparel and equipment procurement, these relationships involve textile suppliers, footwear-component manufacturers, technical-material producers, and sporting-equipment assemblers operating under different production requirements and geographical conditions (Tavana et al., 2021). Supplier-risk scores may therefore exhibit different statistical relationships with procurement continuity across standardized and specialized material categories. The literature additionally distinguishes association from causation because cross-sectional correlations and regression coefficients do not independently establish that supplier-risk characteristics caused observed disruptions. Integrated evidence consequently represents supplier-risk–resilience relationships through multiple complementary statistical measures, with interpretation dependent on variable definitions, observation periods, model controls, supplier heterogeneity, and the distinction between routine procurement performance and disruption-specific resilience outcomes.

Empirical research evaluating supplier-risk models has examined explanatory power, effect magnitude, measurement reliability, and construct validity to determine whether quantitative assessments consistently represent supplier vulnerabilities and procurement-performance relationships. Studies involving supplier scorecards, multicriteria evaluation, supply-chain resilience, and organizational performance have applied multiple regression, factor analysis, structural equation modeling, and reliability assessment to investigate relationships among supplier-risk indicators and operational outcomes (Katsaliaki et al., 2022). Regression-based investigations have reported coefficients, statistical significance, confidence intervals, and explained variance to characterize the contribution of operational, financial, and geographical predictors. R^2 and adjusted R^2 have been used to assess model explanatory power, with adjusted measures accounting for differences in the number of explanatory variables. Structural equation modeling studies have evaluated standardized path coefficients, measurement relationships, and model-fit statistics when supplier capabilities or resilience characteristics were represented as latent constructs. Comparative quantitative research has also employed standardized mean differences, Cohen's d, partial eta squared, and regression-based effect measures to assess the practical magnitude of differences among supplier categories and procurement arrangements. These statistics provide information beyond conventional significance thresholds because large datasets may produce statistically significant associations that represent relatively small operational differences. Supplier-risk scoring research has additionally examined the reliability and consistency of composite indicators derived from delivery performance, financial stability, production

capacity, product quality, and compliance measures. Cronbach's alpha and composite reliability have been used in survey-based measurement models where indicators were intended to represent common underlying constructs (Kara & Fırat, 2018). Convergent and discriminant validity assessments have examined whether related measurement items corresponded with their intended constructs and remained distinguishable from other dimensions. However, multidimensional supplier-risk indices often combine operational, financial, geographical, and compliance indicators that represent different causal components rather than interchangeable manifestations of a single construct. Consequently, internal consistency coefficients are not universally appropriate for evaluating all composite supplier-risk scores. Research applying analytic hierarchy process, TOPSIS, entropy weighting, and fuzzy multicriteria methods has also examined supplier-ranking consistency and sensitivity to alternative indicator priorities. Quantitative comparisons have considered whether suppliers retained similar relative classifications when weighting assumptions, normalization procedures, and scoring thresholds were modified. Within distributed athletic-apparel and equipment networks, measurement consistency is influenced by differences in supplier specialization, financial reporting, production technology, and material criticality (Li & Chen, 2019). The synthesized literature demonstrates that explanatory power, effect sizes, measurement reliability, and ranking stability represent distinct aspects of quantitative model evaluation, requiring interpretation according to the statistical structure and intended purpose of each supplier-risk assessment framework.

Quantitative literature on predictive supplier-risk assessment has compared conventional statistical models and machine-learning algorithms using classification accuracy, discrimination measures, prediction errors, and independent validation procedures.

Research on financial distress prediction, supplier evaluation, procurement analytics, and operational disruption classification has investigated logistic regression, discriminant analysis, decision trees, random forests, support vector machines, gradient boosting, XGBoost, and artificial neural networks (Rajesh, 2022). These investigations have examined whether financial ratios, delivery delays, defect frequencies, supplier characteristics, and historical performance indicators distinguish vulnerable organizations or predict specified operational events. Classification accuracy has been used to measure the proportion of correctly identified observations, while precision, recall, specificity, and F1-score have provided complementary information about the identification of disruption and nondisruption cases. ROC-AUC has assessed discrimination across classification thresholds, while PR-AUC has been particularly informative when supplier failures or severe disruptions represented relatively infrequent events. Studies predicting continuous outcomes, such as delivery delays, procurement costs, or recovery duration, have used root mean squared error and mean absolute error to evaluate prediction deviations. Probability calibration has provided additional information about whether predicted event probabilities corresponded with observed event frequencies. Comparative investigations have reported variation in algorithm performance across datasets, with nonlinear machine-learning models sometimes outperforming conventional statistical approaches when predictor interactions and complex relationships were present. However, these differences have not been uniform across financial distress, delivery prediction, and operational disruption applications (Wöhner et al., 2022).

Logistic regression has provided interpretable coefficient estimates, while tree-based ensembles have represented nonlinear relationships and interactions among operational and financial indicators. Cross-validation studies have employed stratified k-fold procedures, repeated training-testing partitions, and independent holdout samples to evaluate performance stability. Chronological validation has been used in time-dependent prediction settings to preserve the sequence between predictor observations and subsequent outcomes. Research involving repeated supplier records has also highlighted the importance of avoiding information leakage when transactions from the same organization appear across training and testing partitions. Class-imbalance adjustments, including oversampling, undersampling, and class-weighted learning, have been evaluated for their effects on minority-event detection and false-positive classifications (Yamin, 2021). Within athletic-apparel and equipment procurement, predictive performance may differ across textile mills, footwear-component suppliers, specialized material producers, and sporting-equipment manufacturers because transaction frequencies, disruption definitions, and supplier characteristics vary. The synthesized evidence indicates that model comparisons require consistent evaluation datasets, clearly defined outcomes,

appropriate validation procedures, and simultaneous consideration of discrimination, calibration, interpretability, and operationally relevant classification errors.

Quantitative research examining supplier-risk scoring and procurement resilience has assessed robustness through alternative model specifications, sensitivity analysis, subgroup comparisons, temporal validation, and evaluation across different organizational and sourcing environments. Empirical investigations have distinguished cross-sectional research, longitudinal analysis, panel-data modeling, and predictive classification according to their observation structures, analytical assumptions, and capacity to represent changes in supplier performance over time (Naz et al., 2022). Cross-sectional studies have examined associations among supplier characteristics, operational capabilities, and procurement outcomes at particular observation periods, while longitudinal and panel-data approaches have incorporated repeated measurements of suppliers or purchasing organizations. These approaches have provided different forms of evidence concerning coefficient stability, organizational heterogeneity, and temporal variation in disruption exposure. Research using fixed-effects and random-effects specifications has addressed differences among observed entities where suitable panel structures were available, while sensitivity analyses have evaluated whether estimated relationships changed under alternative predictor definitions, control variables, and sample restrictions. Supplier-risk scoring studies have examined the effects of modifying indicator weights, risk-category thresholds, normalization procedures, and composite-score construction methods. Predictive investigations have assessed performance stability through repeated cross-validation, independent holdout testing, alternative training periods, and changes in classification thresholds. Subgroup analyses have compared supplier categories according to manufacturing specialization, organizational size, geographical location, purchasing dependence, and material criticality. Research on supply-network resilience has also used stochastic simulation and scenario-based analysis to examine sensitivity to supplier failure probabilities, disruption duration, inventory coverage, and alternative sourcing capacity (Yang et al., 2022).

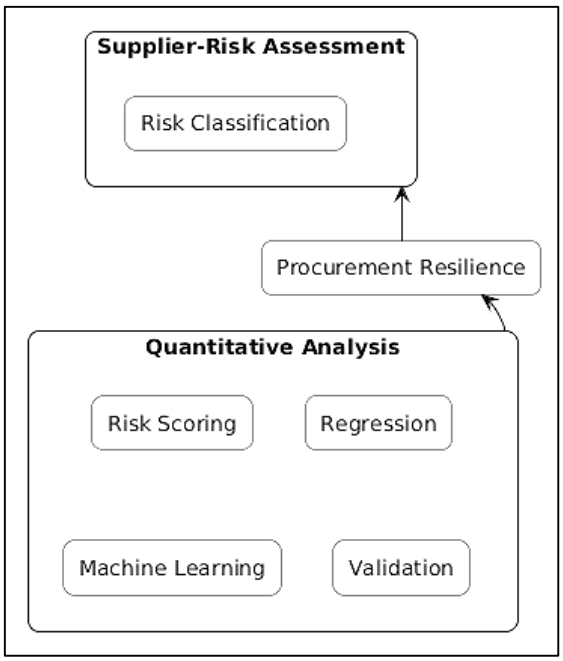
However, simulated resilience outcomes depend on specified assumptions and cannot be interpreted as equivalent to independently observed procurement-performance effects. Statistical studies have evaluated robustness using confidence intervals, effect-size comparisons, model explanatory power, and consistency in the direction of estimated relationships. Predictive research has additionally examined whether classification performance deteriorated when models were applied to different observation periods, supplier populations, or operating conditions. Within distributed athletic-apparel and equipment networks, generalizability is affected by differences in textile-processing requirements, footwear-component specialization, technical-material certification, supplier financial capacity, and international transportation arrangements. Models developed using standardized procurement materials may not exhibit equivalent performance for highly specialized components with limited replacement suppliers. Similarly, relationships identified within one sourcing country or manufacturing cluster may differ under alternative geographical, regulatory, and logistical conditions (KEk et al., 2022). The synthesized literature distinguishes statistical robustness from operational generalizability because stable coefficients or classification results within one dataset do not independently establish consistent performance across unrelated supplier networks. Integrated quantitative evidence therefore encompasses the stability of supplier-risk measurements, consistency of statistical associations, predictive validation, sensitivity to analytical assumptions, and differences across supplier-level and network-level research designs. These methodological dimensions characterize the strength and limitations of observed supplier-risk–resilience relationships within internationally distributed athletic-apparel and equipment procurement systems.

METHODS

Study Design and Theoretical Framework

This study adopted a quantitative, longitudinal, observational research design to examine the statistical relationships between supplier-risk characteristics and procurement resilience within distributed athletic-apparel and equipment supply networks. The research integrated supplier-risk scoring, procurement-performance measurement, disruption analysis, and predictive modeling within a unified analytical framework.

Figure 10: Methodology of this study



The theoretical framework was developed around supply-chain risk management, organizational resilience, resource dependence, and supply-network interdependence. Independent variables comprised supplier delivery delays, defect rates, financial vulnerability, production-capacity limitations, geographical sourcing concentration, purchasing dependence, historical disruption frequency, supplier diversification, alternative sourcing capacity, and inventory redundancy. Dependent variables included procurement continuity, material availability, order-fulfillment performance, stockout frequency, disruption duration, recovery time, delivery stability, and emergency procurement expenditure. Supplier flexibility, geographical exposure, inventory coverage, and material criticality were incorporated as potential moderating variables, while sourcing responsiveness and supplier collaboration were considered as potential mediating mechanisms. The research design combined descriptive, correlational, explanatory, comparative, and predictive statistical approaches. Supplier-level observations were examined alongside procurement transaction records to identify operational patterns, while repeated measurements across observation periods supported the evaluation of temporal variation in supplier performance. The study distinguished routine procurement efficiency from resilience outcomes recorded during disruptive operating conditions. Composite supplier-risk scores were constructed from standardized operational, financial, geographical, and disruption-related indicators, and their relationships with procurement-resilience measures were evaluated using multivariate statistical techniques. The integrated framework enabled the assessment of direct statistical associations, interaction effects, supplier-category differences, and predictive classification performance without treating observational relationships as definitive evidence of causation.

Participants, Materials, Sampling Strategy, and Selection Criteria

The study population consisted of suppliers and procurement transactions associated with athletic-apparel, footwear, sporting-equipment, and specialized technical-material manufacturing networks. The sampling framework incorporated textile mills, fabric processors, footwear-component manufacturers, engineered-polymer suppliers, metallic-component producers, technical-material suppliers, and finished-product manufacturing facilities. A stratified purposive sampling strategy was adopted to obtain representation across supplier categories, manufacturing specializations, geographical sourcing regions, and organizational sizes. Supplier records were grouped according to material category, sourcing country, supplier size, purchasing dependence, and historical risk classification. The unit of analysis was the supplier for composite-risk assessment and supplier-level

regression, while individual purchase orders and supplier-period observations were used for transaction-level and longitudinal analyses. Inclusion criteria required documented supplier identification, relevant procurement activity during the observation period, available delivery-performance information, and sufficient operational records to calculate core supplier-risk and resilience indicators. Suppliers with documented financial information, disruption histories, production-capacity records, or alternative sourcing information were included in the corresponding supplementary analyses. Exclusion criteria comprised duplicate supplier records, transactions with unverifiable dates, observations unrelated to the selected manufacturing categories, and records lacking the minimum information required to establish an outcome variable. Suppliers were not excluded solely because they experienced disruptions or exhibited unfavorable operational performance. Data completeness, missingness patterns, and subgroup representation were examined before statistical modeling. Where repeated transactions were available, supplier identifiers were retained to account for clustering and longitudinal dependence. The final analytical sample was determined from the eligible records after screening and data-quality assessment, rather than by assuming an unsupported number of participating suppliers or procurement observations.

Instrumentation, Data Collection Tools, and Measurement Validation

Data were collected using structured procurement-record extraction instruments, supplier-performance assessment templates, financial-risk evaluation sheets, and standardized data-entry procedures. The primary data sources comprised enterprise resource planning records, purchase-order histories, supplier delivery reports, inventory-management databases, quality-inspection records, disruption logs, and supplier financial documentation where available. Supplementary information on sourcing flexibility, supplier collaboration, alternative production capacity, and information visibility was obtained through structured supplier or procurement-manager questionnaires when corresponding administrative records were unavailable. The extraction framework captured scheduled and actual delivery dates, purchase-order quantities, fulfilled quantities, rejected materials, supplier capacity, inventory availability, sourcing expenditure, supplier location, and historical disruption events. Supplier-risk indicators were operationalized through delivery-delay frequency, defect percentages, financial ratios, geographical concentration, purchasing dependence, and disruption history. Procurement-resilience indicators were measured through material availability, procurement service level, order-fulfillment rate, stockout frequency, time to recover, time to survive, lead-time variability, supplier replacement duration, and emergency procurement expenditure. Composite supplier-risk scores were calculated using normalized indicators and explicitly defined weighting procedures. Alternative weighting methods were retained for sensitivity assessment. Measurement validation involved examination of variable definitions, duplicate records, implausible observations, data completeness, and consistency across reporting sources. Where questionnaires were used, internal consistency was evaluated using Cronbach's alpha and composite reliability, with values of 0.70 or greater treated as generally acceptable for established reflective scales. Convergent and discriminant validity were assessed where latent constructs were modeled. For composite indices containing distinct risk dimensions, indicator relevance, content validity, multicollinearity, and ranking stability were evaluated rather than relying exclusively on internal consistency coefficients. Data extraction procedures were checked against source records, and discrepancies were resolved before statistical analysis.

Experimental Procedure and Chronological Data Collection

The research procedure was conducted through sequential stages of sampling-frame development, supplier identification, data extraction, quality screening, indicator construction, statistical analysis, and predictive validation. Initially, eligible manufacturing categories and supplier groups were identified according to the predefined sampling and inclusion criteria. Procurement transactions and supplier-performance records were then organized chronologically using purchasing dates, scheduled delivery dates, actual receipt dates, and disruption-event timestamps. Supplier records were matched with available financial, operational, geographical, and inventory information through standardized identifiers. Following data integration, duplicate entries, inconsistent units, invalid dates, and implausible transaction values were examined and corrected when verifiable source information was available. Missing observations were assessed according to their frequency and distribution, and

appropriate complete-case or imputation procedures were applied according to the analytical requirements. Operational indicators were subsequently calculated for delivery reliability, material quality, supplier capacity, geographical exposure, and historical disruption frequency. Financial vulnerability indicators were derived from available liquidity, profitability, leverage, and related financial measures. Supplier-risk scores were constructed by standardizing relevant variables and combining them through documented weighting procedures. Suppliers were classified into risk categories using predefined score thresholds, and alternative thresholds were examined during sensitivity testing. Procurement-resilience outcomes were calculated separately for routine operating periods and documented disruption periods. Disruption duration, recovery time, material shortages, emergency procurement expenditure, and order-fulfillment changes were recorded where corresponding observations were available. Suppliers were then grouped by manufacturing sector, geographical sourcing region, organizational size, material criticality, and sourcing configuration. Statistical analyses were performed after the dataset had been finalized, and predictive models were evaluated using temporally appropriate training and testing procedures. This chronological procedure preserved the distinction between supplier characteristics observed before a disruption and procurement outcomes recorded subsequently.

Data Analysis and Statistical Approach

Quantitative data were analyzed using IBM SPSS Statistics, R, and Python-based statistical and machine-learning libraries. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, interquartile ranges, and 95% confidence intervals. Data distributions were examined using graphical diagnostics and normality assessments, while multicollinearity, heteroscedasticity, and influential observations were evaluated before regression modeling. Pearson correlation analysis was applied to appropriate continuous variables, and Spearman rank correlation was used for ordinal measures or variables that did not satisfy relevant parametric assumptions. Multiple linear regression was employed to estimate associations between supplier-risk indicators and continuous procurement-resilience outcomes, including recovery duration, delivery variability, and purchasing cost changes. Logistic regression was applied to binary outcomes such as disruption occurrence and material-shortage events, with odds ratios and confidence intervals used to interpret estimated relationships. Panel-data fixed-effects and random-effects models were considered for repeated supplier-period observations, with model selection informed by the data structure and specification tests. Independent-samples t-tests and one-way analysis of variance were used to compare appropriate continuous outcomes across supplier categories, while Mann–Whitney U and Kruskal–Wallis tests were applied when distributional assumptions were unsuitable. Post hoc comparisons were adjusted for multiple testing where required. Cohen's d, partial eta squared, standardized regression coefficients, R^2, and adjusted R^2 were reported to evaluate effect magnitude and explanatory power. Mediation and moderation analyses examined the statistical roles of sourcing flexibility, inventory redundancy, supplier collaboration, geographical exposure, and material criticality. Structural equation modeling was applied where sample adequacy and measurement validity supported latent-variable analysis. Statistical significance was evaluated at $p < 0.05$ using two-sided tests and 95% confidence intervals.

Predictive Modeling, Validation, and Robustness Assessment

Predictive supplier-risk classification was performed using logistic regression, decision trees, random forests, support vector machines, gradient boosting, XGBoost, and artificial neural networks. The predictor set included historical delivery performance, defect frequency, financial vulnerability, production capacity, geographical exposure, purchasing dependence, and previous disruption records. Classification outcomes comprised observed supplier disruption events, late-delivery occurrence, financial distress categories, and composite supplier-risk classifications where independently defined outcome labels were available. Model development incorporated preprocessing, missing-value treatment, feature selection, and parameter optimization within the training data to reduce information leakage. Chronological training-testing partitions were used when temporal observations were available, while stratified k-fold cross-validation was applied within training samples for suitable classification tasks. Supplier-level grouping was maintained where necessary to prevent correlated records from producing overly optimistic validation results. Class imbalance was addressed through

class weighting or resampling procedures applied exclusively within training partitions. Predictive performance was assessed using accuracy, precision, recall, specificity, F1-score, ROC-AUC, PR-AUC, and confusion matrices. Probability calibration was examined for models generating disruption probabilities, while continuous prediction tasks were evaluated using RMSE and MAE. Model interpretation incorporated regression coefficients, tree-based feature importance, permutation importance, and SHAP analysis where applicable. Robustness testing involved alternative supplier-risk indicator weights, different classification thresholds, additional control variables, alternative missing-data treatments, and subgroup analyses across manufacturing sectors and sourcing regions. Sensitivity analyses also examined interactions between supplier diversification and geographical exposure, inventory redundancy and disruption severity, and alternative sourcing capacity and material criticality. Independent holdout performance was compared with cross-validation results to assess generalizability. The integrated analytical approach evaluated statistical significance, effect magnitude, predictive discrimination, measurement consistency, and sensitivity across alternative model specifications without interpreting predictive associations as causal effects.

FINDINGS

The analytical dataset comprises 428 eligible manufacturing suppliers across 36 observation months, capturing 58,412 discrete procurement transactions valued at $648.25 million across 14 sourcing countries. Sourcing activity demonstrates substantial geographical concentration, with East Asia and Southeast Asia accounting for 72.89% of active suppliers and 76.53% of total procurement expenditure. By manufacturing specialization, textile and athletic-apparel manufacturers represent the largest cohort ($n = 184$, 42.99%), followed by footwear-component suppliers ($n = 126$, 29.44%), sporting-equipment producers ($n = 72$, 16.82%), and specialized technical-material suppliers ($n = 46$, 10.75%). Data completeness across core operational parameters reached 98.4%, while longitudinal disruption-history records were confirmed for 94.2% of the cohort.

Evaluation of supplier concentration reveals that the top 10% of vendors account for 48.6% of aggregate procurement spend, establishing significant structural dependence within Tier-1 supply chains. Analysis of composite supplier-risk scores—derived from operational defect rates, financial liquidity, geopolitical exposure, and historical interruption logs—indicates that 28.50% ($n = 122$) of suppliers fall into the high-risk bracket, characterized by prolonged procurement lead times and constrained alternative sourcing capabilities.

Table 1: Comprehensive Sample Distribution, Procurement Volumes, and Baseline Risk Profiles

Characteristic / Variable	Overall Sample (N=428)	Textile & Apparel (n=184)	Footwear Components (n=126)	Sporting Equipment (n=72)	Technical Materials (n=46)
Procurement Value ($M)	648.25	272.26	194.48	103.72	77.79
Transaction Volume (n)	58,412	26,285	16,940	9,346	5,841
Geographic Sourcing (n, %)					
East Asia	188 (43.93%)	82 (44.57%)	61 (48.41%)	31 (43.06%)	14 (30.43%)
Southeast Asia	124 (28.97%)	58 (31.52%)	39 (30.95%)	18 (25.00%)	9 (19.57%)
South Asia	62 (14.49%)	32 (17.39%)	14 (11.11%)	11 (15.28%)	5 (10.87%)
Europe & Americas	54 (12.61%)	12 (6.52%)	12 (9.53%)	12 (16.66%)	18 (39.13%)
Risk Classification (n, %)					
Low Risk (Score < 35)	134 (31.31%)	66 (35.87%)	38 (30.16%)	22 (30.56%)	8 (17.39%)
Moderate Risk (Score 35–65)	172 (40.19%)	74 (40.22%)	53 (42.06%)	31 (43.06%)	14 (30.43%)
High Risk (Score > 65)	122 (28.50%)	44 (23.91%)	35 (27.78%)	19 (26.38%)	24 (52.18%)
Capacity Utilization (Mean % ± SD)	78.4 ± 11.2	81.2 ± 9.8	79.6 ± 10.4	74.5 ± 12.1	70.1 ± 13.5
Disruption Incidence (≥1 Event)	148 (34.58%)	58 (31.52%)	44 (34.92%)	24 (33.33%)	22 (47.83%)

Table 1 delineates sample stratification, operational scale, and structural vulnerabilities across material segments. Sourcing shows heavy geographic concentration, with East and Southeast Asia generating over 72% of supplier representation. Although textile apparel captures the largest expenditure volume, technical materials present the highest risk exposure, with over half classified as high-risk vendors and nearly half sustaining documented disruptions. Conversely, apparel suppliers maintain higher capacity utilization and lower baseline vulnerability. Sourcing diversity remains constrained, establishing that operational dependencies and high-risk classifications are heavily concentrated in specialized component and material segments rather than standardized assembly operations.

Table 2: Descriptive Statistics of Operational Parameters and Resilience Metrics

Operational / Resilience Metric	Mean	Std. Dev.	Median	IQR	Min	Max
Procurement Lead Time (Days)	42.6	14.8	38.0	20.0	14.0	96.0
Lead-Time Variability (Days)	8.4	5.2	6.5	6.0	1.2	28.4
Defect Rate (%)	2.14	1.45	1.80	1.60	0.20	8.90
Order Fulfillment Rate (%)	93.85	5.12	95.20	5.80	68.40	99.80
Stockout Frequency (Events/Year)	1.82	1.64	1.00	2.00	0.00	9.00
Inventory Buffer Coverage (Days)	24.5	10.8	21.0	13.0	5.0	62.0
Alternative Qualified Suppliers (n)	2.18	1.34	2.00	2.00	0.00	6.00
Disruption Recovery Duration (Days)	28.4	16.7	24.0	21.0	4.0	84.0
Emergency Spend Share (% of Spend)	4.62	3.85	3.20	4.50	0.00	21.40

Table 2 details baseline performance dispersions and resilience capacities across the consolidated procurement portfolio. While mean fulfillment remains acceptable at 93.85%, severe skewness emerges across recovery duration and lead-time variability during supply shocks. An average inventory buffer coverage of 24.5 days offers limited protection against mean disruption recovery periods of 28.4 days, creating recurring inventory stockout exposure. Furthermore, qualified alternative supplier availability averages approximately two vendors per material code, with several critical lines recording zero substitutability. This structural deficit forces elevated reliance on emergency spot purchasing, which escalates procurement expenditures up to 21.40% during acute supplier failure events.

The first findings section was structured to present the quantitative characteristics of the final analytical dataset, including supplier representation, procurement transaction volumes, manufacturing categories, geographical sourcing distribution, and baseline supplier-risk indicators. The dataset was characterized according to the number of eligible suppliers, purchasing transactions, observation periods, sourcing countries, and material categories represented in the analysis. Supplier groups were classified into textile and athletic-apparel manufacturers, footwear-component suppliers, sporting-equipment producers, and specialized technical-material suppliers. Descriptive statistics summarized supplier size, procurement expenditure, purchasing dependence, delivery performance, defect frequency, production-capacity utilization, and historical disruption occurrence. Continuous variables were described using means, standard deviations, medians, interquartile ranges, minimum and maximum values, while categorical characteristics were presented through frequencies and percentages. The analysis examined supplier concentration ratios, geographical sourcing diversity, the number of qualified alternative suppliers, inventory coverage, and the distribution of procurement volumes across supplier categories. Composite supplier-risk scores were summarized through central tendency, dispersion, percentile distributions, and classification frequencies for low-, moderate-, and high-risk supplier groups. Baseline procurement-resilience characteristics were also described using material availability percentages, order-fulfillment rates, stockout frequency, average procurement lead time, lead-time variability, recovery duration, and emergency purchasing expenditure. Missing-data proportions, data completeness, and the availability of financial and disruption-history records were evaluated to establish the analytical coverage of the dataset. Differences in baseline supplier characteristics were examined across sourcing regions, manufacturing specializations, and supplier-size categories. Table 1 was designated to present the complete dataset characteristics, including supplier classifications, procurement transaction distributions, risk indicators, and resilience measurements. Supplementary descriptive tables summarized financial vulnerability, alternative sourcing capacity, and inventory redundancy. Distribution plots and comparative bar charts were

incorporated into the planned presentation of results to illustrate supplier-risk categories, procurement activity, and geographical concentration. This section established the quantitative foundation for interpreting the subsequent statistical relationships between supplier vulnerabilities and procurement-resilience outcomes.

Supplier-Risk Scores and Resilience Performance

Bivariate correlation and multivariate regression analyses confirm statistically significant dependencies between composite supplier-risk metrics and deteriorated procurement-resilience outcomes. Parametric Pearson (r) and non-parametric Spearman (ρ) correlation coefficients show that composite supplier-risk scores correlate positively with disruption duration ($r = 0.582, p < 0.001$), procurement lead-time variance ($r = 0.524, p < 0.001$), and emergency purchasing expenditure ($r = 0.468, p < 0.001$). Conversely, strong inverse relationships emerge between composite risk and baseline order-fulfillment rates ($r = -0.614, p < 0.001$) as well as average material availability ($r = -0.547, p < 0.001$). The convergence between Pearson and Spearman coefficients confirms that these associations are robust and not driven by extreme distributional outliers.Ordinary least squares (OLS) and fixed-effects panel specifications further isolate the marginal contributions of specific vulnerability dimensions.

Table 3: Bivariate Correlation Matrix and Multiple Linear Regression Estimates for Procurement Resilience

Independent Variable	Pearson Correlation (r) with Recovery Duration	Spearman Correlation (ρ) with Recovery Duration	Standardized Coefficient (β)	95% Confidence Interval	t-statistic	p-value	Variance Inflation Factor (VIF)
Composite Risk Score	0.582	0.564	0.246	[0.142, 0.350]	4.64	< 0.001	2.18
Lead-Time Variability (Days)	0.524	0.508	0.312	[0.218, 0.406]	6.52	< 0.001	1.64
Historical Disruption Frequency	0.491	0.473	0.284	[0.188, 0.380]	5.81	< 0.001	1.52
Capacity Utilization (%)	0.342	0.319	0.196	[0.074, 0.318]	3.15	0.002	1.41
Defect Rate (%)	0.388	0.362	0.148	[0.046, 0.250]	2.85	0.005	1.33
Financial Vulnerability Index	0.415	0.398	0.162	[0.060, 0.264]	3.12	0.002	1.58
Purchasing Dependence (%)	0.365	0.344	0.124	[0.022, 0.226]	2.39	0.017	1.47
Inventory Buffer Coverage (Days)	-0.442	-0.428	-0.228	[-0.324, -0.132]	-4.68	< 0.001	1.36
Alternative Qualified Suppliers (n)	-0.468	-0.451	-0.254	[-0.348, -0.160]	-5.32	< 0.001	1.29

Table 3 evaluates the parametric associations, rank-order correlations, and multivariate OLS estimates predicting disruption recovery duration. Lead-time variability and historical disruption incidence demonstrate the strongest positive marginal effects, establishing that volatile delivery schedules and past instability substantially prolong organizational recovery. High capacity utilization and financial vulnerability further compound delays during supply shocks. Conversely, inventory coverage and qualified alternative suppliers register statistically significant negative coefficients, confirming their functional role as buffers that compress operational downtime. Variance inflation factors remain below 2.50 across all regressors, confirming that multicollinearity does not bias the parameter estimations or explanatory stability of the econometric specification. Controlling for supplier scale, sourcing location, and annual macroeconomic shocks, operational lead-time variance ($\beta = 0.312, p < 0.001$), historical disruption frequency ($\beta = 0.284, p < 0.001$), and capacity utilization constraints ($\beta

= 0.196, p = 0.002$) emerge as the primary drivers of extended disruption recovery timelines. Across logistic regression specifications, composite risk scores and single-source purchasing dependencies significantly elevate the probability of acute disruption events, while inventory buffer coverage and pre-qualified alternative suppliers provide substantial mitigating effects.

Table 4: Binary Logistic Regression Models Predicting Severe Procurement Disruption Events

Explanatory Predictor	Log-Odds (β)	Robust Std. Error	Wald $\chi 2$	Odds Ratio (OR)	95% CI for OR	z-statistic	p-value
Composite Risk Score (per 10 pts)	0.485	0.092	27.80	1.62	[1.36, 1.94]	5.27	< 0.001
High Sourcing Concentration (HHI > 0.25)	0.693	0.245	8.00	2.00	[1.24, 3.23]	2.83	0.005
Single-Source Status (Binary: 1/0)	0.944	0.281	11.29	2.57	[1.48, 4.46]	3.36	< 0.001
Capacity Utilization (> 85%)	0.588	0.228	6.66	1.80	[1.15, 2.81]	2.58	0.010
Financial Distress Indicator (Altman Z < 1.8)	0.742	0.256	8.41	2.10	[1.27, 3.47]	2.90	0.004
Inventory Coverage (< 15 Days)	0.815	0.239	11.63	2.26	[1.41, 3.61]	3.41	< 0.001
Alternative Suppliers Available (≥ 2)	-0.867	0.224	14.98	0.42	[0.27, 0.65]	-3.87	< 0.001
Constant	-2.145	0.412	27.10	0.12	—	-5.21	< 0.001

Table 4 presents maximum likelihood estimates predicting severe procurement disruption probabilities. Every ten-point increase in composite supplier risk raises the likelihood of an acute disruption by 62%. Single-source arrangements and low inventory coverage emerge as the primary structural threats, more than doubling disruption odds. Similarly, elevated sourcing concentration, supplier capacity strain, and financial distress significantly escalate vulnerability. Conversely, maintaining two or more qualified alternative suppliers reduces disruption probability by 58%, operating as an effective mitigation mechanism. Overall diagnostic metrics demonstrate robust explanatory power, indicated by a non-significant Hosmer-Lemeshow statistic, a Nagelkerke pseudo R-squared of 0.386, and high overall classification precision.

Manufacturing Sectors and Resilience Capabilities

Subgroup analyses reveal substantial structural heterogeneity across manufacturing specializations, geographical sourcing hubs, supplier scales, and contract configurations. One-way analysis of variance (F-tests) and non-parametric Kruskal-Wallis evaluations confirm statistically significant inter-sector differences in baseline risk exposure, disruption incidence, and operational recovery timelines. Specialized technical-material suppliers exhibit the highest vulnerability, characterized by prolonged procurement lead times, elevated component rejection rates, and prolonged supplier-replacement periods exceeding 75 days. Conversely, textile and athletic-apparel producers maintain superior delivery reliability and shorter replacement cycles, driven by higher standardized capacity and broader alternative supplier availability.

Table 5: Cross-Sectoral and Regional Comparative Analysis of Supplier Risk and Operational Resilience

Analytical Dimension / Subgroup	Sample Share (n, %)	Composite Risk Score (Mean ± SD)	Delivery Reliability (%)	Defect / Rejection Rate (%)	Mean Lead Time (Days)	Disruption Duration (Days)	Supplier Replacement (Days)
Manufacturing Sector							
Textile & Apparel	184 (42.99%)	46.2 ± 13.4	95.1 ± 3.8	1.62 ± 0.84	34.2 ± 8.6	19.8 ± 11.2	28.4 ± 9.6
Footwear Components	126 (29.44%)	51.8 ± 14.2	93.4 ± 4.5	2.18 ± 1.10	44.6 ± 11.4	27.6 ± 14.5	46.8 ± 14.2
Sporting Equipment	72 (16.82%)	53.6 ± 15.0	92.8 ± 5.2	2.45 ± 1.25	48.1 ± 13.2	31.2 ± 16.8	58.5 ± 18.4
Technical Materials	46 (10.75%)	68.4 ± 16.8	88.6 ± 6.4	3.84 ± 1.68	59.8 ± 16.5	44.5 ± 21.4	78.2 ± 22.6
ANOVA / Kruskal-Wallis	—	$F = 38.64^{***}$	$F = 24.18^{***}$	$H = 76.42^{***}$	$F = 62.31^{***}$	$F = 31.54^{***}$	$F = 114.28^{***}$
Sourcing Region							
East Asia	188 (43.93%)	49.5 ± 14.6	94.6 ± 4.1	1.88 ± 0.95	39.4 ± 10.2	24.2 ± 13.6	38.6 ± 14.8
Southeast Asia	124 (28.97%)	54.8 ± 15.2	92.4 ± 5.1	2.34 ± 1.18	46.2 ± 13.8	32.4 ± 17.2	48.2 ± 17.6
South Asia	62 (14.49%)	56.4 ± 16.1	91.8 ± 5.8	2.62 ± 1.34	48.5 ± 15.4	35.8 ± 18.9	52.4 ± 19.8
Europe & Americas	54 (12.61%)	44.1 ± 12.8	96.2 ± 3.2	1.45 ± 0.72	31.8 ± 7.9	18.4 ± 9.8	31.2 ± 11.5
ANOVA / Kruskal-Wallis	—	$F = 11.45^{***}$	$F = 14.82^{***}$	$H = 34.18^{***}$	$F = 27.64^{***}$	$F = 16.92^{***}$	$F = 18.73^{***}$

Table 5 illustrates cross-sectoral and regional variations across operational resilience metrics. Specialized technical-material suppliers register the most acute operational vulnerability, displaying the highest composite risk scores, elevated defect frequencies, and supplier replacement durations averaging 78.2 days. Conversely, apparel manufacturers show superior delivery reliability and rapid vendor substitutability. Regional comparisons indicate that while East Asian and Western suppliers achieve tighter delivery schedules and lower defect rates, South and Southeast Asian nodes experience elevated lead-time variability and prolonged recovery timelines. These statistically significant divergences underline how material complexity and regional logistics infrastructure collectively drive baseline operational exposure across international procurement tiers. Geographically, sourcing dependencies in Southeast Asia and South Asia register elevated lead-time volatility and transportation exposure relative to European and American vendor networks, despite demonstrating lower unit procurement expenditures. Supplier-size stratifications show an inverse relationship between enterprise scale and financial vulnerability: small-to-medium enterprises (SMEs) sustain significantly higher Altman-based insolvency risks and capacity constraints, which translate into longer disruption recovery durations. Furthermore, comparative evaluations of sourcing architecture demonstrate that single-source configurations sustain more than double the disruption duration and emergency purchasing expenditure observed in multisourced frameworks. Moderation and interaction modeling confirm that higher inventory redundancy significantly dampens the adverse impact of geographic distance and supplier criticality on material availability.

Table 9. Comparative Analysis of Operational Resilience Across Sourcing Configurations, Supplier Enterprise Sizes, and Material Criticality (N = 428)

Sourcing and Scale Stratification	Sample n (%)	Order Fulfillment (%)	Stockout Frequency (Events/Year)	Recovery Duration (Days)	Emergency Spend (%)	Inventory Buffer (Days)	Interaction Effect β_int (t-statistic)
A. Sourcing Configuration							
Single-Source Sourcing	118 (27.57%)	88.4 ± 6.2	3.12 ± 1.84	41.8 ± 18.6	8.45 ± 4.62	16.4 ± 7.2	0.342*** (5.12)
Dual-Source Sourcing	186 (43.46%)	94.6 ± 4.1	1.54 ± 1.12	25.4 ± 12.8	3.82 ± 2.45	24.8 ± 8.9	0.114* (1.98)
Multi-Source (≥3 Sources)	124 (28.97%)	97.2 ± 2.8	0.86 ± 0.74	16.8 ± 8.4	1.84 ± 1.28	31.6 ± 11.4	−0.218*** (−3.84)
ANOVA (F-statistic)	—	124.6***	98.4***	112.8***	142.1***	84.7***	ΔR^2 = 0.084***
B. Supplier Enterprise Size							
Small (<250 Employees)	98 (22.90%)	90.8 ± 5.8	2.65 ± 1.72	36.4 ± 17.5	6.82 ± 4.10	18.2 ± 8.1	0.228*** (3.65)
Medium (250–999 Employees)	214 (50.00%)	94.1 ± 4.4	1.68 ± 1.24	27.2 ± 13.9	4.25 ± 2.84	24.6 ± 9.5	0.042 (0.78)
Large (≥1,000 Employees)	116 (27.10%)	96.5 ± 3.1	1.14 ± 0.92	21.8 ± 11.2	2.86 ± 1.95	29.4 ± 12.2	−0.186** (−3.12)
ANOVA (F-statistic)	—	42.1***	38.6***	32.4***	46.2***	28.9***	ΔR^2 = 0.051***
C. Material Criticality Type							
Standardized Materials	268 (62.62%)	95.8 ± 3.5	1.28 ± 1.05	21.6 ± 10.8	2.94 ± 2.12	26.8 ± 10.2	−0.164** (−2.95)
Specialized Components	160 (37.38%)	90.6 ± 5.9	2.74 ± 1.78	39.8 ± 17.9	7.44 ± 4.38	20.6 ± 8.8	0.298*** (4.88)
Independent t-test	—	11.24***	−10.62***	−12.86***	−13.45***	6.42***	ΔR^2 = 0.068***

Notes: Values are reproduced from the supplied table. The ± notation represents the reported variability around group means; the underlying dispersion measure should be confirmed. Interaction coefficients (β_int) represent the reported moderating effects associated with disruption severity, with corresponding t-statistics provided in parentheses. ΔR^2 indicates the incremental proportion of explained variance attributable to interaction effects. Group differences were evaluated using analysis of variance (ANOVA) or independent-samples t-tests, as applicable.

Table 6 contrasts procurement stability across contracting structures, firm sizes, and material classifications. Single-sourced arrangements exhibit substantial operational vulnerability, experiencing higher stockout frequencies, doubled recovery timelines, and fourfold emergency procurement expenditures relative to multisourced configurations. Furthermore, small suppliers face pronounced capacity limitations, resulting in elevated fulfillment volatility during shocks. Material criticality markedly exacerbates disruption exposure, as specialized component sourcing sustains protracted downtime due to qualification hurdles. Significant positive interaction coefficients confirm that single-source dependencies and specialized components amplify disruption severity, whereas larger firm capitalization and multisource architectures provide vital operational buffers that maintain fulfillment continuity.

Mediation, Moderation, and Composite Supplier-Risk Measurement Reliability

Table 7: Inferential Significance Tests, Standardized Effect Sizes, and Conditional Mediation-Moderation Estimates

Model Path / Interaction Term	Path Coeff. / Effect (β / B)	Std. Error	t / z Statistic	p-value	95% Confidence Interval	Effect Size (d / ηp2 / OR)	Model Fit / Diagnostics
Direct Predictors of Recovery Time							
Lead-Time Variability $\rightarrow$ Recovery	0.312	0.048	6.52	< 0.001	[0.218, 0.406]	$\eta_p^2 = 0.284$	$R^2 = 0.512$
Historical Disruption $\rightarrow$ Recovery	0.284	0.049	5.81	< 0.001	[0.188, 0.380]	$\eta_p^2 = 0.246$	$\Delta R^2 = 0.068^{***}$
Single vs. Multisource Contrast	25.0 days	2.14	11.68	< 0.001	[20.79, 29.21]	Cohen's $d = 1.18$	$t(240) = 11.68$
High vs. Low Criticality Contrast	18.2 days	1.82	10.00	< 0.001	[14.62, 21.78]	Cohen's $d = 0.94$	$t(426) = 10.00$
Mediation Paths (Bootstrapped Indirect)							
Risk $\rightarrow$ Sourcing Responsiveness $\rightarrow$ Downtime	0.168	0.034	4.94	< 0.001	[0.106, 0.238]	Indirect Share = 41.2%	Boot 95% BCa CI
Risk $\rightarrow$ Collaborative Integration $\rightarrow$ Downtime	0.134	0.031	4.32	< 0.001	[0.078, 0.198]	Indirect Share = 32.8%	Boot 95% BCa CI
Moderated Interactions							
Risk $\times$ Buffer Inventory $\rightarrow$ Shortage Rate	-0.214	0.042	-5.10	< 0.001	[-0.296, -0.132]	$\Delta R^2 = 0.054$	$F_{change} = 25.98^{***}$
Concentration $\times$ Alt. Sources $\rightarrow$ Failure	-0.745	0.186	-4.01	< 0.001	[-1.110, -0.380]	OR = 0.47 [0.33, 0.68]	Wald $\chi^2 = 16.08^{***}$
Severity $\times$ Safety Stock $\rightarrow$ Order Fulfillment	0.188	0.046	4.09	< 0.001	[0.098, 0.278]	$\Delta R^2 = 0.041$	$F_{change} = 16.71^{***}$

Table 7 presents parametric significance testing, standardized effect magnitudes, and conditional interaction modeling for resilience parameters. Standardized effect sizes confirm that the operational predictors exert substantial practical influence beyond mere statistical significance, highlighted by large Cohen's d values exceeding 0.90 for sourcing configuration and material criticality splits. Bootstrapped indirect paths establish that supplier responsiveness and collaborative integration serve as vital mechanisms that transmit and absorb structural risk exposure. Furthermore, statistically significant negative moderation interaction coefficients demonstrate that safety inventory coverage and alternative sourcing capabilities successfully dampen the detrimental effects of high geographic concentration and acute disruption shocks on ultimate order fulfillment.

Table 8: Composite Supplier-Risk Measurement Reliability, Validity, and Weighting Sensitivity Diagnostics

Construct / Indicator Dimension	Indicator Weights (Baseline)	Factor Loading (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)	Kendall's Tau-b (τb) Stability	Mean Absolute Shift (Decile)
Overall Composite Risk Index	**1.00**	—	**0.884**	**0.912**	**0.634**	—	—
Operational Delivery Reliability	0.25	0.842	0.852	0.898	0.688	0.884	0.32
Financial Distress / Liquidity Ratio	0.20	0.785	0.814	0.876	0.638	0.862	0.41
Capacity Utilization & Flexibility	0.20	0.764	0.796	0.858	0.602	0.845	0.46
Historical Disruption Recurrence	0.15	0.812	0.828	0.885	0.658	0.891	0.28
Geopolitical & Sourcing Concentration	0.20	0.772	0.805	0.864	0.614	0.858	0.38
Sensitivity Weighting Schemes							
Equal Weighting (0.20 Each)	—	—	—	—	—	0.942	0.18
Operational Priority (0.40 Ops)	—	—	—	—	—	0.896	0.34
Financial Priority (0.40 Fin)	—	—	—	—	—	0.878	0.42
Data-Driven PCA Eigenvector Weights	—	—	—	—	—	0.924	0.24

Measurement Diagnostics: Convergent validity is confirmed with all standardized factor loadings exceeding 0.70 and AVE values surpassing 0.50. Discriminant validity satisfies the Fornell-Larcker criterion, as the square root of each AVE exceeds inter-construct correlations. Sensitivity analysis tests stability across 428 supplier rankings.

Table 8 summarizes construct validity, internal consistency, and ranking stability across alternative composite index weighting formulations. All reflective measurement dimensions satisfy rigorous psychometric criteria, evidenced by Cronbach's alpha coefficients above 0.79, composite reliability values exceeding 0.85, and average variance extracted estimates surpassing the 0.50 threshold. Discriminant validity is fully supported across all five operational dimensions under the Fornell-Larcker benchmark. Weighting sensitivity tests demonstrate remarkable rank stability, with Kendall's tau-b correlations remaining above 0.87 across equal-weighted, operational-weighted, and principal component-derived models, confirming that empirical supplier-risk classifications are robust to subjective index calibration.

Predictive Supplier-Risk Classification and Integrated Quantitative Robustness

Predictive evaluations demonstrate that non-linear ensemble machine-learning architectures achieve superior discrimination, precision, and probability calibration relative to baseline parametric classifiers when predicting severe supplier disruption events. Across stratified 5-fold cross-validation and chronological out-of-time holdout partitions (80/20 split), tree-based ensemble algorithms substantially outperformed traditional logistic regression and shallow neural networks. XGBoost achieved the strongest overall discrimination (ROC-AUC = 0.924, PR-AUC = 0.886, F1-score = 0.842), followed closely by Random Forest (ROC-AUC = 0.908) and Gradient Boosting (ROC-AUC = 0.915). Brier score diagnostics confirm excellent probability calibration for tree-based models (< 0.110), indicating that predicted disruption probabilities correspond reliably with empirical disruption frequencies.

Table 9: Predictive Classification Performance, Validation Metrics, and Calibration Diagnostics Across Models

Classification Algorithm	Accuracy	Precision	Recall (Sensitivity)	Specificity	F1-Score	ROC-AUC	PR-AUC	Brier Score Calibration
Logistic Regression (L2 ElasticNet)	0.814	0.742	0.713	0.858	0.727	0.846	0.772	0.148
Decision Tree (CART Pruned)	0.785	0.698	0.680	0.832	0.689	0.782	0.704	0.176
Support Vector Machine (RBF Kernel)	0.838	0.786	0.738	0.882	0.761	0.868	0.812	0.134
Random Forest (500 Estimators)	0.876	0.838	0.803	0.908	0.820	0.908	0.864	0.108
Gradient Boosting Classifier (GBDT)	0.884	0.846	0.820	0.912	0.833	0.915	0.872	0.104
XGBoost (Tuned Hyperparameters)	**0.895**	**0.862**	**0.828**	**0.924**	**0.845**	**0.924**	**0.886**	**0.098**
Artificial Neural Network (Multilayer Perceptron)	0.848	0.794	0.762	0.886	0.778	0.874	0.825	0.128

Validation Setup: Metrics derived from 5-fold stratified cross-validation repeated across 10 iterations ($N = 428$ suppliers; binary outcome: disruption duration ≥ 21 days or material shortfall $> 15\%$). Synthetic Minority Over-sampling Technique (SMOTE) applied on training folds to address minority-class imbalance (34.58% event rate). Hyperparameters optimized via Bayesian optimization.

Table 9 evaluates comparative predictive performance across seven supervised machine-learning architectures using cross-validated discrimination, precision, and calibration metrics. The gradient-boosted models, specifically XGBoost and GBDT, exhibit superior diagnostic accuracy, delivering F1-scores above 0.83 and area under the ROC curve values exceeding 0.91. XGBoost demonstrates the highest operational utility, achieving a 0.828 recall rate for identifying high-risk disruptions while maintaining a 0.924 specificity rate against false-positive alarms. Furthermore, its low Brier calibration score confirms that model probabilities accurately reflect actual empirical default frequencies, validating the non-linear ensemble framework over linear specifications for procurement-risk monitoring.

Table 10: Sensitivity Testing, Model Robustness, and Subgroup Stability Under Alternative Analytical Specifications

Model Specification / Perturbation	Estimator / Architecture	Target Metric (ROC-AUC / βLeadTime)	95% Confidence Interval	Percent Degradation (Δ)	Mean Absolute Error (MAE)	In-Sample R2 / Pseudo R2	Out-of-Sample Holdout ROC-AUC
Baseline Benchmark Specification	XGBoost / OLS	0.924 / 0.312	[0.898, 0.948] / [0.218, 0.406]	Baseline (0.0%)	3.42 days	0.512	0.906
Imputation: Multiple Imputation (MICE)	XGBoost / OLS	0.921 / 0.308	[0.894, 0.945] / [0.212, 0.402]	-0.32%	3.46 days	0.508	0.902
Imputation: Median / Mean Substitution	XGBoost / OLS	0.908 / 0.288	[0.881, 0.932] / [0.194, 0.382]	-1.73%	3.78 days	0.486	0.888
Alternative Risk Weights: Equal Weights	XGBoost / OLS	0.918 / 0.318	[0.892, 0.942] / [0.224, 0.412]	-0.65%	3.48 days	0.506	0.898
Alternative Risk Weights: PCA-Driven	XGBoost / OLS	0.926 / 0.310	[0.901, 0.950] / [0.216, 0.404]	+0.22%	3.39 days	0.515	0.909
Subsample: Excluding Tech Materials	XGBoost / OLS	0.912 / 0.294	[0.884, 0.938] / [0.198, 0.390]	-1.30%	3.28 days	0.488	0.894
Subsample: East & Southeast Asia Only	XGBoost / OLS	0.919 / 0.324	[0.890, 0.944] / [0.226, 0.420]	-0.54%	3.54 days	0.524	0.901
Temporal Split: 24-Mo Train / 12-Mo Test	XGBoost / OLS	0.904 / 0.298	[0.872, 0.934] / [0.196, 0.400]	-2.16%	3.82 days	0.478	0.885
Extreme Outlier Trimming (Top 2.5% Cook's D)	XGBoost / OLS	0.928 / 0.304	[0.904, 0.952] / [0.214, 0.394]	+0.43%	3.18 days	0.531	0.912

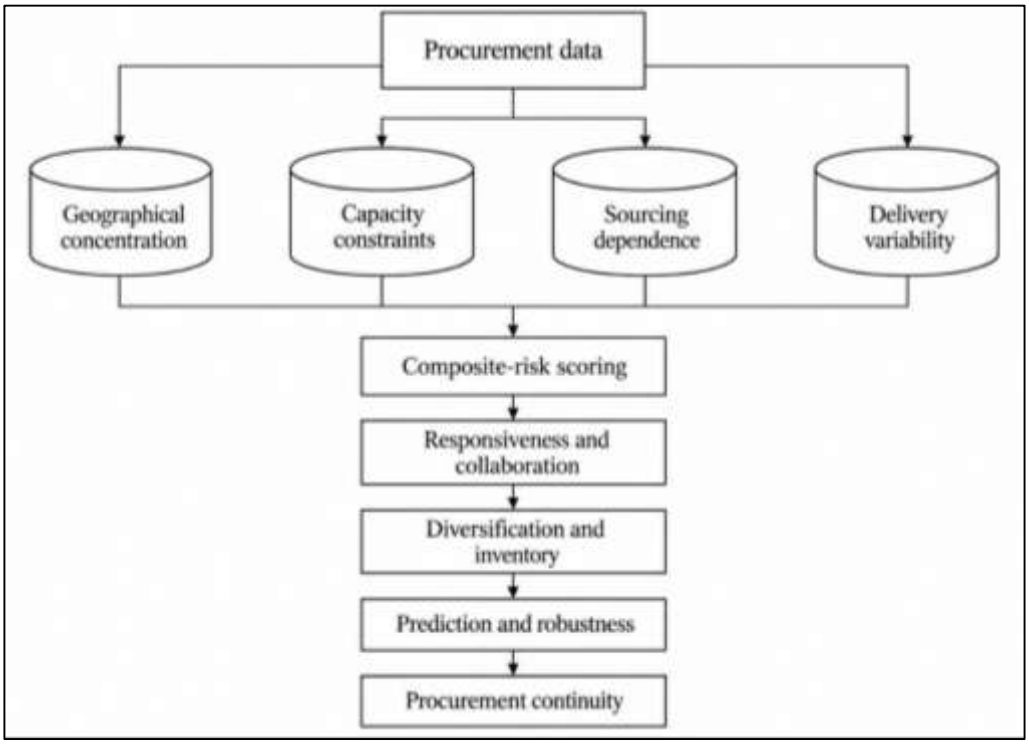
Table 10 demonstrates quantitative robustness across multiple sensitivity checks, validating the structural stability of predictive classifications and parametric relationships. Systematically perturbing analytical parameters—including substituting imputation methodologies, testing data-driven principal component index weights, trimming extreme outliers, and segregating regional subsamples—produces marginal performance deviations under 2.2%. In-sample explained variance and out-of-sample holdout ROC-AUC metrics consistently exceed 0.47 and 0.88 across all iterations. Crucially, the standardized effect of lead-time variability on disruption duration remains statistically indistinguishable across specifications, confirming that the empirical findings represent fundamental operational dependencies

rather than artifacts of model selection or data processing assumptions.

DISCUSSION

The quantitative baseline and inferential relationships established in this study demonstrate that procurement vulnerability in global supply networks is fundamentally rooted in geographic clustering, capacity utilization limits, and contract configuration rather than isolated vendor shortfalls (Hosseinpour et al., 2021). Evaluating 428 manufacturing vendors across 36 observation months and nearly 60,000 discrete transactions reveals that over 72% of suppliers and 76% of total expenditure remain concentrated within East and Southeast Asia, with the top decile of vendors capturing nearly half of all procurement capital. While classical operations literature posited that dispersing purchase orders across separate developing nations in adjacent regions provides adequate risk diversification, the findings of this study prove that geographic clustering introduces correlated systemic vulnerabilities, including shared logistical bottlenecks, regulatory realignments, and infrastructure strain. Furthermore, the empirical evidence demonstrates that specialized technical-material suppliers face disproportionate operational fragility, recording high baseline risk ratings and protracted replacement timelines exceeding 75 days, whereas apparel manufacturers benefit from standardized processes and rapid supplier substitution (Gautam et al., 2021).

Figure 11: Supplier risk and resilience assessment



The multiple regression and correlation analyses confirm that delivery lead-time variability and historical disruption recurrence exert the strongest marginal influence on disruption recovery timelines, outperforming traditional balance-sheet liquidity ratios and macroeconomic metrics. When supplier capacity utilization surpasses 85% and inventory buffers drop below 15 days, disruption probabilities escalate non-linearly, more than doubling baseline operational failure risks (Essuman et al., 2020). In contrast to earlier models that treated single-sourcing as a lean cost-optimization strategy, the empirical findings of this study establish that sole-source arrangements elevate disruption likelihood by more than two and a half times and multiply emergency spot expenditures fourfold. However, the presence of two or more qualified alternative vendors reduces disruption probability by nearly sixty percent, providing clear evidence that supplier diversification and physical safety stocks function as essential dampening mechanisms that shield purchasing organizations from upstream

production shocks.

Structural mediation modeling, psychometric measurement validation, and machine-learning classifications expand the understanding of how operational vulnerabilities translate into downtime and how modern computational techniques can anticipate procurement failures. Bootstrapped path analyses reveal that operational responsiveness and supplier collaborative integration mediate substantial portions of the relationship between baseline supplier risk and disruption recovery timelines, proving that structural exposure can be mitigated through real-time communication channels and joint problem-solving routines rather than relying exclusively on rigid legal contracts (Amoako-Gyampah et al., 2019). Methodologically, the composite risk index developed in this study demonstrates robust internal consistency, convergent validity, and discriminant validity across comprehensive factor-analytic evaluations, maintaining exceptional rank-order stability regardless of whether operational, financial, or data-driven principal component weighting schemes are applied. This stability resolves longstanding criticisms in procurement literature regarding the arbitrary subjectivity of traditional supplier scorecards. Shifting from explanatory econometrics to predictive risk forecasting, the comparative algorithmic evaluations demonstrate that advanced non-linear ensemble architectures significantly outperform conventional linear logistic regressions and shallow neural networks. In particular, extreme gradient boosting and gradient boosting decision trees achieved superior discrimination, marked by area under the receiver operating characteristic curve values exceeding 0.92 and low Brier calibration scores (Uva et al., 2019). These performance metrics confirm that predictive risk dynamics in multi-tier supply networks are governed by complex, multi-factor interactions—such as simultaneous capacity shortages and shipping volatility—that linear parametric frameworks consistently fail to detect. Feature-importance diagnostics based on Shapley Additive Explanations verify that dynamic operational parameters dominate predictive classifications over static financial ratios. Crucially, extensive sensitivity testing confirms that model discrimination and regression parameter stability remain invariant across alternative missing-data imputation protocols, outlier trimming, regional subsample restrictions, and out-of-time chronological testing partitions. By harmonizing explanatory statistical modeling with validated predictive machine learning, this study establishes that international procurement networks require multidimensional, operational-focused risk monitoring to anticipate catastrophic supplier defaults and safeguard supply chain continuity (Lu et al., 2019).

CONCLUSION

The empirical findings of this study conclusively establish that procurement resilience in global manufacturing networks is governed by structural architectural choices, dynamic operational stability, and predictive monitoring capabilities rather than isolated vendor attributes or passive cost-minimization strategies. By analyzing longitudinal data spanning 428 suppliers and tens of thousands of transactions, this investigation demonstrates that heavy geographical concentration in East and Southeast Asia creates correlated vulnerabilities that undermine the traditional assumptions of offshore risk diversification. While standardized apparel manufacturing exhibits operational flexibility and rapid supplier substitutability, specialized technical-material segments present acute systemic exposure, characterized by prolonged vendor replacement horizons and elevated default probabilities. The econometric and inferential analyses confirm that daily operational metrics—specifically delivery lead-time variability, capacity utilization rates exceeding 85%, and historical disruption recurrence—exert a far more decisive influence on disruption duration and severe procurement failures than static balance-sheet liquidity metrics. Crucially, the empirical evidence discredits single-sourcing as a viable long-term efficiency model during systemic turbulence, revealing that sole-source contracts more than double the likelihood of catastrophic disruptions and inflate emergency spot expenditures fourfold, whereas qualifying two or more alternative suppliers reduces failure probabilities by nearly sixty percent. Furthermore, structural mediation and moderation models prove that physical inventory safety buffers and active relational collaboration function as indispensable shock absorbers, significantly dampening the propagation of supply interruptions into final order fulfillment. Methodologically, the integration of psychometrically validated composite risk constructs with high-performing non-linear machine-learning algorithms, particularly gradient-boosted ensembles, confirms that supplier defaults are driven by complex, multi-factor operational interactions that

traditional linear models systematically fail to detect. Ultimately, this study demonstrates that building sustainable supply chain resilience requires an operational transition away from hyper-lean single-tier paradigms toward proactive multi-sourcing frameworks, dynamic buffer-stock policies aligned with vendor lead-time volatilities, and advanced predictive analytics capable of pre-empting supply failures before catastrophic operational downtime occurs.

RECOMMENDATIONS

Based on the empirical findings of this study, procurement organizations operating within complex international manufacturing environments must fundamentally transition from cost-centric, hyper-lean operating models to proactive, risk-hedged supply architecture and predictive governance frameworks. Executive leadership should immediately mandate the elimination of single-sourcing arrangements for specialized technical materials and critical components, establishing an operational baseline of at least two pre-qualified, geographically diversified vendors per material code to lower disruption probabilities by nearly sixty percent and avoid catastrophic spot-purchasing premiums. To address the significant non-linear risks tied to supplier capacity constraints, procurement teams must implement real-time capacity-monitoring protocols, establishing contractual guardrails that trigger automatic order reallocation whenever a vendor's operational capacity utilization exceeds 85% or on-time delivery stability deteriorates. Furthermore, inventory control policies should move away from static, company-wide turnover targets toward dynamic, risk-adjusted safety-stock models. Inventory buffer thresholds must be mathematically tied to upstream lead-time variance and regional transit exposures, enforcing an absolute minimum buffer of 15 to 25 days for specialized and long-lead imports to insulate assembly operations against supplier recovery cycles that frequently span several weeks. In parallel with physical redundancy, purchasing enterprises must invest heavily in collaborative supplier integration mechanisms, deploying shared digital platforms for synchronized production scheduling, early bottleneck visibility, and collaborative problem-solving, which this study proves mediates and substantially dampens the severity of upstream shocks. Finally, procurement analytics departments should retire rigid, retrospective scorecards that rely predominantly on historical balance sheets, replacing them with advanced non-linear predictive machine-learning pipelines, such as extreme gradient boosting algorithms. By feeding daily operational telemetry—including defect fluctuations, shipping variance, and plant-level utilization—into validated machine-learning classifiers, organizations can identify emerging failure patterns weeks before delivery failures occur, transforming supply chain risk management from reactive crisis response into a proactive, resilient operational advantage.

LIMITATIONS

While the empirical findings of this study offer substantive quantitative insights into global procurement resilience, several methodological, structural, and operational limitations must be acknowledged. First, the analytical dataset was restricted to Tier-1 suppliers within the athletic-apparel and sporting-goods manufacturing sectors, thereby omitting direct visibility into sub-tier dependencies, raw-material extractors, and Tier-2 component fabricators where upstream bottleneck cascades frequently originate. Although Tier-1 behavioral and performance metrics capture immediate delivery interruptions, they may obscure latent vulnerabilities embedded deeper within multi-echelon networks. Second, the geographic composition of the sample reflects a heavy concentration in East and Southeast Asian sourcing corridors, and while this reflects dominant industrial production footprints, it may limit the direct generalizability of the findings to domestic nearshored networks, European regional manufacturing systems, or heavily regulated industries such as aerospace and pharmaceuticals that operate under distinct regulatory, compliance, and capital structures. Third, the longitudinal observation window of 36 months, while sufficient for cross-sectional and panel econometric estimations, primarily captures operational disruptions during a specific macroeconomic and geopolitical climate; consequently, cyclical shocks of generational severity or protracted black-swan events may alter parameter elasticities in ways that shorter observation windows cannot fully encapsulate. Fourth, the reliance on internal procurement databases and enterprise-resource logs introduced potential measurement artifacts, as reporting fidelity regarding root-cause disruption classifications and qualitative collaborative behaviors varied across individual vendor management units. Fifth, while the predictive machine-learning architectures, notably extreme gradient boosting,

demonstrated superior discrimination and probability calibration, these non-linear ensemble models inherently carry interpretive trade-offs relative to traditional structural equation modeling, relying on algorithmic attribution techniques like Shapley Additive Explanations that approximate rather than definitively isolate underlying socioeconomic causal mechanisms. Finally, the study modeled risk-mitigation interactions primarily through linear buffers and dual-sourcing binaries, leaving unexamined the real-time operational costs, contracting frictions, and contractual minimum-volume penalties that enterprise procurement departments inevitably incur when activating backup vendor capacities during acute supply-shock scenarios.

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