

UAI JOURNAL OF ECONOMICS, BUSINESS AND MANAGEMENT

(UAIJEBM)



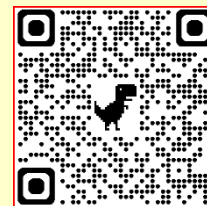
Abbreviated Key Title: UAI J Econ Bus Manag.

ISSN: 3049-2777 (Online)

Journal Homepage: <https://uaipublisher.com/>

Volume- 2 Issue- 4 (July – August) 2026

Frequency: Bimonthly



AI-Enabled Predictive Analytics and Supply Chain Disruption Response Performance in Logistics Firms: Moderating Role of Data Governance Maturity

VO MINH VINH¹, NGUYEN HO LINH SAN² and NGUYEN NGOC BAO LAM³

¹ Faculty of Management and Economics, Tomas Bata university, Czech Republic.

² Phan Châu Trinh High School, Da Nang, Vietnam

³ Viet Anh School 3, Ho Chi Minh, Vietnam

Corresponding Author: Vo Minh Vinh

ABSTRACT

This study examines the links among AI enabled predictive analytics capability, real time logistics data integration, and supply chain disruption response performance in emerging market logistics firms while evaluating the moderating influence of data governance maturity. Drawing on organizational information processing theory and dynamic capabilities theory, it frames disruption response performance as the result of organizational capabilities that convert predictive intelligence and current integrated logistics information into timely, coordinated, and effective actions. Data governance maturity serves as a boundary condition that shapes whether integrated logistics data can be turned into stronger disruption responses. A quantitative cross sectional design gathered responses through a five point Likert scale questionnaire from 385 Vietnamese professionals knowledgeable about logistics operations, supply chain management, AI analytics, information technology, risk management, or data governance. IBM SPSS version 26 supported reliability assessment, exploratory factor analysis, and multiple linear regression, while Hayes' Process Macro Model 1 examined the moderating effect. The findings show that AI enabled predictive analytics capability ($\beta = 0.588$) and real time logistics data integration ($\beta = 0.415$) significantly improve supply chain disruption response performance. Predictive analytics capability yields the stronger direct effect, underscoring the importance of anticipating disruption signals and operational consequences. Data governance maturity further reinforces the positive association between real time logistics data integration and disruption response performance through a significant interaction coefficient of 0.311. The results reveal that digital connectivity alone cannot guarantee effective disruption responses. Emerging market logistics firms must pair predictive analytics and current integrated data with clear ownership, standardized quality controls, secure access, continuous monitoring, and operational authority to act.

KEY WORDS: supply chain disruption response performance; AI enabled predictive analytics capability; real time logistics data integration; data governance maturity; emerging market logistics firms.

1. INTRODUCTION

Supply chain disruption response performance describes a firm's capacity to sense disruptive events, align swift decisions, reshape resources, and maintain essential logistics services amid disruption. This construct remains narrower than broad supply chain resilience since it centers on the speed, precision, and operational value of post disruption actions. The issue grows pressing as logistics operators confront ever more linked shocks from geopolitical strife, pandemics, severe weather, port bottlenecks, and demand swings. While awareness of disruption holds clear worth, it alone fails to yield strong responses unless paired with resource reconfiguration and solid risk management systems (Ambulkar et al., 2015). Digitalization may boost visibility, communication, and response strength, yet its gains differ across resilience phases and hinge on how organizations adapt (Zhao et al., 2023). The challenge proves especially acute in emerging markets, where scattered logistics networks, uneven digital systems, scarce analytical skill, and institutional flux often slow coordinated moves. Findings from one emerging economy show that integration, agility, and reconfiguration stand as core resilience drivers (Yamin, 2021). Hence the need to study predictive analytics and real time data integration remains high, even as one notes that flawed, hard to reach, or weakly governed data can speed poor choices instead of lifting disruption response performance.

Earlier studies have largely approached disruption response through wider notions such as resilience, responsiveness, and firm level performance. Munir et al. (2022) reported that data analytics bolsters anticipation and improvisation, which together foster resilience and responsiveness amid sudden shocks. Yet their findings drew on Pakistani manufacturers during the pandemic and stopped short of isolating response performance inside logistics operations. Mukherjee et al. (2024) demonstrated that artificial intelligence aids resilience strategies and outcomes among Indian firms, though the expansive artificial intelligence measure masked the unique role of predictive analytics. Newer work suggests digital technologies lift resilience via supply chain integration, while the focus stays fixed on manufacturing rather than logistics service providers (Cui et al., 2022). Khan et al. (2026) additionally showed that data governance lifts supply chain resilience through Industry 4.0 capabilities, yet they treated governance as a precursor instead of a boundary condition. As a result, current research leans on cross sectional views, crisis bound samples, broad resilience measures, and single country manufacturing settings. Few studies clarify whether real time logistics data truly yields stronger disruption responses across varying governance levels. The present paper seeks to close this gap by assessing the distinct impacts of predictive analytics capability and real time logistics data integration on disruption response performance and by checking whether data governance maturity amplifies the worth of integrated information among logistics firms in emerging markets.

Accordingly, this study is guided by the following three research questions:

- 1) To what extent does AI enabled predictive analytics capability influence supply chain disruption response performance in emerging market logistics firms?
- 2) How does real time logistics data integration affect supply chain disruption response performance in emerging market logistics firms?

- 3) How does data governance maturity moderate the relationship between real time logistics data integration and supply chain disruption response performance?

This study, therefore, seeks to test the direct impact of AI enabled predictive analytics capability on supply chain disruption response performance. A further aim is to explore whether real time logistics data integration heightens visibility, coordination, and response speed when disruptions strike. Another goal is to determine whether data governance maturity amplifies the role of integrated logistics information in shaping disruption response performance. The scholarly contribution rests on weaving predictive intelligence, information integration, and governance conditions into one coherent frame. Through separating disruption response performance from wider resilience ideas and focusing on logistics firms in emerging markets, the work yields sharper contextual insight into the conditions under which digital capabilities support prompt and effective reactions to supply chain disruptions.

2. LITERATURE REVIEW

2.1. Supply Chain Disruption Response Performance

Supply chain disruption response performance refers to the extent to which a business can rapidly identify an incident, coordinate appropriate actions, reallocate resources, and maintain essential flows of products, information, and services while the event is unfolding. This definition is grounded in the response dimension of supply chain resilience, encompassing timely decision-making, communication, flexibility, and resource mobilization following the detection of a disruption (Chowdhury & Quaddus, 2017). Conceptually, this element differs from preparedness (which occurs prior to a disruption) and recovery (which relates to the subsequent restoration of operations). Its significance lies in the ability to translate risk-related information into effective action, thereby mitigating service delays, financial losses, customer dissatisfaction, and the propagation of the disruption. Studies indicate that disruptions can inflict substantial damage on sales, costs, and operational continuity, making the quality of the response a central performance concern rather than merely a defensive capability (Katsaliaki et al., 2022). This issue is particularly critical for logistics enterprises in emerging markets. Their networks frequently contend with chronic infrastructure deterioration, institutional uncertainty, uncoordinated collaboration, and resource constraints. These conditions give rise to interconnected risks, where addressing one problem may shift vulnerability to another part of the system (Tukamuhabwa et al., 2017). Although digital technology can enhance visibility and coordination, logistics service providers often face network complexity, resource constraints, organizational resistance, and implementation challenges (Cichosz et al., 2020). Consequently, response performance depends not only on the availability of technology but also on reliable information, coordinated decision-making, and agile operational capabilities.

2.2. Critical Analysis of Theoretical Frameworks

2.2.1. Organizational Information Processing Theory

Organizational information processing theory, developed by Jay Galbraith, accounts for how organizations shape structures and information systems to fit their information needs amid uncertainty. Galbraith (1974) maintained that uncertainty widens the gap between the information an organization holds and the information it requires to perform tasks well. As environmental complexity grows, firms must either lower their information demands or raise their ability to gather, interpret, share, and apply information. Tushman &

Nadler (1978) later extended this view by treating organizations as information processing systems whose success hinges on the fit among environmental uncertainty, task features, organizational setups, and information processing capacity. This reasoning fits emerging market logistics firms especially well, since disruptions generate incomplete, fast changing, and widely scattered information about suppliers, transport routes, inventories, infrastructure, customer demand, and regulations. Within the same logic, AI enabled predictive analytics capability enlarges information processing capacity by assembling large data sets, detecting risk patterns, estimating future disruption probabilities, and issuing early warnings. It thereby lessens uncertainty by turning scattered observations into forward looking insight. Empirical findings show that big data analytics capability advances supply chain integration and operational flexibility through stronger processing of complex information and better coordination of activities (Yu et al., 2021a). Yet, prediction alone does not guarantee an effective response. Information must reach the right decision makers and operational partners quickly enough to allow route changes, resource shifts, inventory substitutions, and service recovery. Real time logistics data integration therefore serves as an information processing mechanism that links internal systems with carriers, suppliers, warehouses, customers, and external sources. Integrated information cuts latency and lets managers form a shared picture of disruption conditions. Srinivasan & Swink (2018) demonstrated that analytics yields greater operational value when visibility and flexibility support the handling of supply chain information. In parallel, information processing capability and digital supply chain arrangements have been shown to strengthen risk management and resilience by heightening disruption orientation and visibility (Rashid et al., 2024). Organizational information processing theory further clarifies the proposed moderating role of data governance maturity. Integration can raise the volume and speed of data without improving its accuracy, consistency, accessibility, or interpretability. Mature governance sets ownership, definitions, quality standards, access rules, validation procedures, and accountability across logistics information flows. Thus, it raises the reliability of integrated data and aids the conversion of information into coordinated action. Yu et al. (2021b) found that a data driven culture and information processing capability are vital for turning analytics into integrated supply chain practices. Recent evidence likewise indicates that internal control quality and information transparency amplify the resilience benefits of information processing capability (Zhao et al., 2026). Organizational information processing theory, therefore, supplies the main account of why predictive intelligence and integrated logistics data should improve supply chain disruption response performance and why the impact of integration rests on data governance maturity.

The framework rests on the premise that disruptions heighten information uncertainty and that emerging market logistics firms vary in their ability to handle this uncertainty. It holds that AI enabled predictive analytics capability sharpens the reading of future risks, while real time logistics data integration raises information availability and coordination. It also holds that integrated data delivers greater response value when data governance maturity secures accuracy, consistency, accessibility, security, and organizational accountability among the logistics actors involved.

2.2.2. *The Dynamic Capabilities Theory*

Dynamic capabilities theory was shaped by David Teece, Gary Pisano, and Amy Shuen to show how firms secure adaptation and competitive advantage amid fast shifting conditions. Teece et al.

(1997) described dynamic capabilities as the organizational capacities to integrate, build, and reconfigure internal and external competences when the environment changes. Later refinements arranged these capacities around sensing opportunities and threats, seizing fitting courses of action, and transforming or reconfiguring resources (Teece, 2007). This lens suits the explanation of supply chain disruption response performance because effective response demands more than ownership of technology, information, or physical assets. Firms must detect shifting conditions, choose suitable interventions, and redeploy resources before harm spreads through the logistics network. Inside this research frame, AI enabled predictive analytics capability aids sensing by spotting weak signals, forecasting transport delays, revealing demand anomalies, and assessing the probability and possible effects of disruptions. It turns data into anticipatory knowledge that lets logistics firms move before threats fully appear. Artificial intelligence capability stands as an organizational capacity to select, orchestrate, and apply technological and human resources rather than the mere purchase of an artificial intelligence tool (Mikalef & Gupta, 2021). That distinction backs treating predictive analytics as a capability whose worth grows through routines, expertise, infrastructure, and managerial application. Real time logistics data integration advances sensing and seizing by supplying continuous visibility across shipments, inventories, routes, suppliers, and customer needs. It allows decision makers to weigh response options and align actions across organizational lines. Its effect on supply chain disruption response performance appears when firms apply integrated information to reroute transport, replace suppliers, reorder priorities, assign capacity, and convey service updates. Therefore, Dynamic capabilities theory frames disruption response as deliberate resource orchestration rather than an automatic technological result. Studies indicate that analytics improves anticipation and improvisation, which then foster supply chain resilience and responsiveness amid sudden disruptions (Munir et al., 2022). Digital transformation likewise entails continuous strategic renewal in which firms reshape structures, collaboration, and culture around new technologies (Warner & Wäger, 2019). Data governance maturity reinforces this process by setting the decision rights, duties, standards, and controls needed to mobilize logistics data with confidence. When governance maturity is high, integrated data becomes a reliable organizational asset that managers can draw on to seize response options and reconfigure operations. Governance further unifies data definitions across partners, lowers disagreements over information quality, and makes clear who may authorize data based actions. As a result, the moderating effect captures differences in firms' capacity to orchestrate integrated information rather than differences in data availability alone. This reading aligns with findings that data governance bolsters supply chain resilience through structural, procedural, and relational practices that support digital technologies (Khan et al., 2026). Therefore, Dynamic capabilities complements organizational information processing theory by clarifying how firms convert processed information into adaptive decisions, coordinated interventions, and operational reconfiguration during supply chain disruptions.

The framework assumes that disruption settings are volatile enough to call for ongoing sensing, seizing, and resource reconfiguration. It assumes that AI enabled predictive analytics capability heightens threat sensing and that real time logistics data integration aids swift selection and execution of response actions. It further assumes that data governance maturity enhances the orchestration of integrated information resources, enabling logistics firms to turn timely data into coordinated operational shifts and stronger disruption response

performance.

2.3. The Impact of AI-Enabled Predictive Analytics Capability

AI-enabled predictive analytics capability denotes a firm's organizational capacity to blend AI methods, suitable data, analytical systems, and human skill in order to detect patterns, project future supply chain states, and convert probability based forecasts into practical logistics choices. It goes beyond simply owning forecasting tools, since true capability involves data gathering, model building, sense making, organizational learning, and regular use against operational issues (Baryannis et al., 2019; Brintrup et al., 2020; Mikalef & Gupta, 2021). Baryannis et al. (2019) note that AI assists supply chain risk management via identification, assessment, prediction, and response planning. Brintrup et al. (2020) also show that machine learning can examine past delivery data to anticipate supplier disruptions ahead of ordinary monitoring systems. Theoretically, organizational information processing theory casts AI enabled predictive analytics capability as an information processing device that shrinks the difference between the information needed for disruption choices and the information presently on hand. Predictive analytics enlarges a firm's ability to handle complex and uncertain information, which in turn aids supply chain integration, flexibility, and joint decision making (Yu et al., 2021). Dynamic capabilities theory further reads predictive analytics as a sensing capacity by which firms notice faint signals, judge rising threats, and ready adaptive moves (Teece, 2007; Warner & Wäger, 2019). Its strategic value therefore rests on shifting disruption management from after the fact explanation toward forward looking decision making. From a positivist stance, AI enabled predictive analytics capability can be handled as an observable organizational construct assessed through forecasting accuracy, risk spotting speed, analytical integration, and decision support quality (Mikalef & Gupta, 2021). A critical realist reading sees these indicators as observable results produced by deeper processes that include data quality, staff expertise, managerial judgment, and cross organizational coordination (Wynn & Williams, 2012; Zachariadis et al., 2013). Pragmatism judges the capability by whether predictive insights enable workable responses under real logistics limits rather than by whether an algorithm simply reaches statistical precision (Goldkuhl, 2012).

When AI enabled predictive analytics capability is advanced, logistics firms gain the means to spot demand anomalies, supplier decline, route congestion, weather risks, and capacity shortfalls sooner. Earlier detection lengthens the window for weighing options, obtaining replacement capacity, shifting shipments, revising inventories, and informing customers. As a result, the capability ought to raise supply chain disruption response performance through faster decisions, more accurate resource allocation, and steadier logistics services. Support for a robust positive link is considerable. Belhadi et al. (2024) reported that AI based innovation markedly lifts supply chain resilience and performance under environmental dynamism. Likewise, Dubey et al. (2022) showed that AI enabled big data analytics capability builds agility, resilience, and performance in humanitarian supply chains. In an emerging market context, Bag et al. (2022) found that predictive analytics bolsters resilience via better visibility in South African mining supply networks facing extreme weather. These results imply that predictive capability holds particular worth where infrastructure uncertainty and scattered market information render traditional planning unstable.

Even so, the relationship is not always robust. Culot et al. (2024) observe that empirical AI studies often focus on technical promise while organizational gains rest on complementary data, skills, processes, and implementation maturity. Fresh causal findings further reveal that AI development notably lifts resilience in skill intensive industries yet yields no significant impact in labor intensive ones, pointing to a neutral result where absorptive capacity and digital bases stay limited (Cheng et al., 2026). Prediction may, thus, fall short of improving response when data remain incomplete, models echo past bias, alerts go untrusted, or firms lack the means to carry out suggested actions. The critical realist view makes plain that AI acts as an enabling mechanism whose influence appears only once organizational and contextual conditions bring it into play. Despite such contingency, the theoretical pathways and gathered evidence uphold the anticipated positive direction. Accordingly:

H1: AI-enabled predictive analytics capability has a positive impact on supply chain disruption response performance in emerging market logistics firms.

2.4. The Impact of Real Time Logistics Data Integration

Real time logistics data integration denotes an organizational capacity to continually gather, standardize, link, and share present information about shipments, inventories, orders, transport capacity, suppliers, and external risks across internal units and supply chain partners, thus creating a common operational view that supports joint decision making. This conception joins technological system linkage with deliberate information exchange because connected platforms cannot aid logistics choices when data stay unreachable, mismatched, or separated by organizational boundaries (Lyu et al., 2022). It also stresses promptness since digitalized supply chains build resilience partly by raising the speed, visibility, and efficiency of information flow and its conversion into response actions (Zhao et al., 2023). Consequently, real time logistics data integration reaches beyond mere data presence or digital technology uptake. It demands interoperable systems, shared data meanings, partner connections, and routines that supply decision ready information as disruption conditions evolve.

Organizational information processing theory accounts for its value by arguing that environmental uncertainty raises the volume and quality of information firms need for sound coordination. Real time logistics data integration enlarges information processing capacity by cutting scattered observations and letting managers examine demand shifts, shipment positions, supplier limits, and transport options at the same time. Dynamic capabilities theory further frames this capability as a foundation for sensing disruption cues, selecting alternative logistics paths, and rearranging resources. Findings show that information technology system integration bolsters information sharing, while dynamic capability carries its effect onward to supply chain efficiency and flexibility (Lyu et al., 2022). Digitalization likewise lifts absorptive, response, and recovery capacities, though these capacities matter differently across disruption phases (Zhao et al., 2023). From a positivist angle, real time logistics data integration can be captured through observable measures such as data promptness, system interoperability, information reach, update frequency, and partner exchange. A critical realist view holds that these measures are outward signs of deeper processes that include partner trust, semantic alignment, staff skill, managerial power, and governance strength. Those processes decide whether integrated data produce coordinated moves rather than extra informational clutter. A pragmatic stance judges the capability by whether it permits practical rerouting, rescheduling, supplier replacement, inventory shifts, and customer updates under genuine operational limits

(Goldkuhl, 2012; Zachariadis et al., 2013).

Greater real time logistics data integration ought to raise supply chain disruption response performance by narrowing the gap between disruption recognition and operational action. Shared up to date information lets logistics firms locate affected shipments, gauge cascading effects, and arrange alternative capacity before service breakdowns grow worse. Zhao et al. (2023) offer solid support that supply chain digitalization lifts response capacity and performance through better information and communication efficiency. Dubey et al. (2023) likewise demonstrate that digital adaptability fosters digital agility and supply chain resilience, reinforcing the claim that linked information assets enable swift adjustment. This pathway carries special weight for emerging market logistics firms because institutional uncertainty, uneven infrastructure, scattered partner systems, and thin resource reserves can enlarge the harm caused by late or uneven information. Government effectiveness further shapes the resilience gains that digital capabilities yield, showing that organizational integration functions inside a wider institutional setting (Dubey et al., 2023).

Even so, the link should not be read as automatically strong in every firm. Wu et al. (2025) show that resource oriented digital technologies aid resilience through action oriented technologies and their joint use. This implies that integrated data may produce only a moderate or indirect influence when firms lack decision power, analytical skill, process flexibility, or partner collaboration. Lyu et al. (2022) also find that dynamic capability partly carries the contribution of information integration to process ambidexterity. Philosophically, this conditional pattern rejects technological determinism because data connectivity generates response potential rather than assured performance. When integration pairs with trustworthy data, aligned routines, and authority to act, however, it should heighten the speed, precision, and effectiveness of disruption responses. The following hypothesis is consequently advanced:

H2: Real time logistics data integration has a positive impact on supply chain disruption response performance in emerging market logistics firms.

2.5. The Moderating Role of Data Governance Maturity

Data governance maturity denotes the degree to which a firm has advanced from informal and scattered data management toward steadily institutionalized structures, decision rights, policies, responsibilities, standards, monitoring processes, and accountability arrangements that guide data across its full lifecycle. Data governance itself involves the exercise of organizational authority and control over data management so as to raise data value while lowering related costs and risks (Abraham et al., 2019). The maturity aspect therefore signals not merely the presence of governance policies but whether those policies are clearly set out, uniformly applied, routinely checked, and steadily refined. Mature governance ordinarily specifies data ownership, access rights, quality benchmarks, metadata needs, security duties, and steps for settling data inconsistencies. This capability holds particular weight in digitally linked supply chains because data sharing capacity, technical support, and data security form core pillars of sound supply chain data governance (Liu et al., 2025).

Organizational information processing theory frames data governance maturity as a device that raises the reliability and clarity of information used for disruption choices. Real time logistics data integration lifts the volume and pace of available information, yet greater information processing capacity yields scant benefit when records prove inaccurate, repeated, mismatched, or poorly

safeguarded. Hazen et al. (2014) stress that supply chain analytics and managerial choices remain only as trustworthy as the data beneath them. Mature governance tackles this issue by setting shared definitions, validation steps, ownership duties, and escalation paths that turn integrated logistics data into credible decision inputs. Dynamic capabilities theory further casts data governance maturity as an enabling capacity that underpins sensing, seizing, and reconfiguration. Governance does not itself redirect shipments or assign emergency capacity. Rather, it fortifies the informational base through which managers detect disruptions and align adaptive moves. From a positivist stance, data governance maturity can be measured through observable markers that cover formal policies, data ownership, decision rights, quality controls, metadata handling, security practices, compliance checks, and ongoing refinement (Abraham et al., 2019). A critical realist stance sees these markers as outward signs of deeper causal processes that include organizational accountability, managerial dedication, partner trust, professional skill, and authority distribution (Wynn & Williams, 2012; Zachariadis et al., 2013). As a result, two firms may hold similar written governance policies yet reach different results because organizational actors read, enforce, and apply those policies in distinct ways. From a pragmatic stance, data governance maturity ought to be judged by whether governance arrangements yield trusted, reachable, and usable information that aids real logistics choices rather than by whether firms merely display formal procedural adherence (Goldkuhl, 2012). This philosophical contrast keeps data governance maturity from being reduced to the amount of governance paperwork and instead treats it as an enacted organizational capacity that delivers reliable decision support.

Data governance maturity ought to positively moderate the link between real time logistics data integration and supply chain disruption response performance. When governance maturity stands high, integrated shipment, inventory, capacity, and supplier data are more likely to prove accurate, consistent, reachable, secure, and traceable. Managers can then gauge disruption severity, weigh response options, and align partners with higher confidence. Information governance can release organizational value from growing data resources when decision rights and accountability structures fit information needs (Tallon et al., 2013). Joshi et al. (2022) likewise show that mature governance process capacities lift technological performance, which then feeds into business performance. Applied to logistics disruption response, this logic indicates that governance turns data connectivity into dependable operational insight.

The reinforcing effect carries special relevance for emerging market logistics firms, where scattered information systems, uneven digital capacities, uneven partner standards, and institutional uncertainty can lower trust in shared data. Mature governance sets common rules across organizational lines and helps firms decide which data sources should steer urgent choices. Liu et al. (2025) demonstrate that supply chain data governance rests on linked technological, organizational, security, and sharing mechanisms rather than isolated controls. Consequently, governance maturity should heighten the gains from real time integration by lessening ambiguity and stopping conflicting information from slowing coordinated responses.

Thus, stronger governance does not imply maximum centralization or control. Overly rigid approval steps may slow information access and erode the speed edge that real time integration creates. Tallon et al. (2013) note that information governance effectiveness hinges on matching governance arrangements to organizational needs, while Joshi et al. (2022) show that governance value works through

technological capacity and differs across strategic settings. Data governance maturity should therefore heighten disruption response when it pairs control with operational flexibility. Therefore, the following hypothesis is advanced:

H3: Data governance maturity positively moderates the relationship between real time logistics data integration and supply chain disruption response performance in emerging market logistics firms.

Building on established theoretical foundations, this study extends the existing body of knowledge through the conceptual framework illustrated in Figure 1:

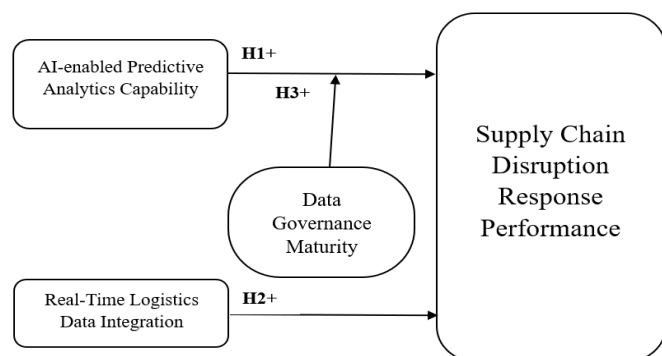


Figure 1: The Paper Conceptual Framework

3. METHODS

3.1. Sampling Strategy

This study employed a quantitative cross sectional design to investigate how AI enabled predictive analytics capability and real time logistics data integration shape supply chain disruption response performance while examining the moderating influence of data governance maturity. Vietnam was chosen because logistics firms there increasingly apply AI, transport management systems, internet connected devices, cloud platforms, and real time tracking tools while contending with infrastructure constraints, institutional uncertainty, and recurring supply chain interruptions. The quantitative method enabled hypothesis testing and estimation of direct and interaction effects from standardized survey answers. The cross sectional approach recorded organizational views of analytics capability, logistics data integration, governance maturity, and disruption response performance at one moment in time (Bryman, 2016).

Individual organizational members formed the unit of analysis. Purposive sampling focused on respondents who held adequate knowledge of logistics information systems and disruption management. Eligible participants were at least 18 years of age, worked for a logistics firm active in Vietnam, and possessed experience in logistics operations, supply chain management, transportation, warehousing, procurement, data analytics, information technology, risk management, or governance. Respondents comprised senior managers, middle managers, logistics and supply chain professionals, data analysts, information technology specialists, warehouse and transportation supervisors, and risk or compliance staff. Participants were drawn from firms of varying sizes, logistics sectors, regions, and degrees of digital maturity to broaden sample diversity.

Data collection relied on a structured self administered questionnaire adapted from prior research. AI enabled predictive analytics capability measured the organizational capacity to combine AI techniques, relevant data, analytical infrastructure, and employee

expertise so as to forecast disruptions and convert predictions into logistics actions (Dubey et al., 2019; Mikalef & Gupta, 2021). Real time logistics data integration assessed the capacity to continually capture, standardize, link, and share current shipment, inventory, capacity, supplier, and risk information across internal functions and supply chain partners (Lyu et al., 2022; Zhao et al., 2023). Data governance maturity examined the formalization and ongoing refinement of data ownership, quality standards, access rights, metadata, security, accountability, and monitoring arrangements (Abraham et al., 2019; Joshi et al., 2022). Supply chain disruption response performance evaluated the speed, accuracy, coordination, flexibility, and effectiveness with which firms detected disruptions, carried out corrective actions, sustained logistics services, and limited operational effects (Ambulkar et al., 2015; Zhao et al., 2023).

All items employed a five point Likert scale that ran from 1 for strongly disagree to 5 for strongly agree. Academic specialists in logistics, AI, analytics, governance, and quantitative methods examined the questionnaire for clarity and content suitability. Logistics managers and technology professionals then verified its practical usefulness. Translation and back translation secured conceptual equivalence between the English and Vietnamese versions. The questionnaire was circulated through universities, professional logistics associations, business networks, organizational contacts, and digital channels. Participation stayed voluntary and anonymous. Screening questions and attention checks helped maintain response quality. After incomplete, duplicate, patterned, unusually rapid, and disengaged responses were excluded, 385 valid questionnaires remained for analysis.

3.2. Data analysis

Data analysis used IBM SPSS version 26 and Hayes' Process Macro. Descriptive statistics outlined respondents' roles, experience, firm size, logistics sector, geographic location, and technological familiarity. Cronbach's alpha evaluated scale reliability, with coefficients of at least 0.70 and corrected item total correlations above 0.30 signalling acceptable internal consistency (Tavakol & Dennick, 2011). Exploratory factor analysis applied principal component extraction and Varimax rotation. Items were kept when factor loadings surpassed 0.50 without troublesome cross loadings (Hair et al., 2009). Multiple linear regression examined the direct effects of AI enabled predictive analytics capability and real time logistics data integration on supply chain disruption response performance under a significance threshold below 0.05. Finally, Hayes' Process Model 1 assessed whether data governance maturity intensified the link between real time logistics data integration and supply chain disruption response performance (Hayes, 2022).

4. RESULTS

4.1. Descriptive Statistical Analysis

The sample reflected logistics firms operating across the principal economic regions of Vietnam. In particular, 44.2% of respondents were employed by firms in Southern Vietnam, 31.9% worked in Northern Vietnam, and 23.9% were based in Central Vietnam. Concerning organizational roles, middle or functional managers formed the largest share at 24.9%, followed by owners, directors, or senior managers at 22.1%. Logistics or supply chain professionals made up 20.5%, while data analytics or information technology specialists comprised 17.4%. Risk, compliance, or data governance professionals accounted for the remaining 15.1%. With respect to organizational size, firms employing 50 to 249 people constituted

the biggest group at 33.5%, followed by organizations with 250 to 999 employees at 30.1%. Large firms employing at least 1,000 people represented 20.3%, whereas firms with fewer than 50 employees made up 16.1%. In addition, 37.7% of participants indicated high familiarity with their firms' analytics, logistics data, governance, and disruption response practices. Another 21.0% reported very high familiarity, while 30.9% described moderate familiarity. Only 10.4% showed limited familiarity. Altogether, the sample spanned varied organizational settings, and most respondents held adequate professional knowledge to assess the study constructs.

4.2. Reliability analysis

Table 1 summarizes the measurement items employed to assess the study constructs. Four items were used for each construct and were adapted from established academic sources to maintain theoretical consistency and capture its principal dimensions. Respondents evaluated every item using a five point Likert scale, where 1 indicated strongly disagree and 5 indicated strongly agree.

Table 1: Measurement Items

Code	Survey item	Theoretical source
AI enabled predictive analytics capability		
AEPAC1	Our organization has access to relevant and sufficiently detailed data for developing AI based logistics forecasts.	Dubey et al. (2019) and Mikalef & Gupta (2021)
AEPAC2	Our organization possesses the analytical infrastructure required to develop and operate AI based predictive models.	Mikalef and Gupta (2021)
AEPAC3	Our employees possess the expertise needed to interpret AI generated forecasts concerning logistics conditions.	Dubey et al. (2019) and Mikalef & Gupta (2021)
AEPAC4	Our AI analytical applications generate forecasts of potential disruptions and future logistics conditions.	Dubey et al. (2019) and Zhao et al. (2023)
Real time logistics data integration		
RTLDI1	Current shipment information is integrated across the relevant functions within our organization.	Lyu et al. (2022) and Zhao et al. (2023)
RTLDI2	Inventory, order, and transportation data are updated promptly within our shared information systems.	Lyu et al. (2022) and Zhao et al. (2023)
RTLDI3	Our information systems	Lyu et al. (2022)

	exchange current logistics data with relevant supply chain partners in compatible formats.	
RTLDI4	Authorized employees can access consistent and current logistics information through connected organizational systems.	Lyu et al. (2022) and Zhao et al. (2023)
Data governance maturity		
DGM1	Our organization consistently applies formal policies governing the access, protection, and use of logistics data.	Abraham et al. (2019) and Tallon et al. (2013)
DGM2	Data ownership and accountability responsibilities are clearly assigned within our organization.	Abraham et al. (2019) and Joshi et al. (2022)
DGM3	The quality of logistics data is regularly monitored using standardized procedures.	Hazen et al. (2014) and Liu et al. (2025)
DGM4	Our organization regularly reviews and improves its data governance procedures.	Abraham et al. (2019) and Joshi et al. (2022)
Supply chain disruption response performance		
SCDRP1	Our organization responds rapidly when unexpected supply chain disruptions occur.	Ambulkar et al. (2015) and Zhao et al. (2023)
SCDRP2	Our organization effectively coordinates corrective actions across relevant functions and supply chain partners during disruptions.	Chowdhury & Quaddus (2017) and Zhao et al. (2023)
SCDRP3	Our organization maintains essential logistics services while responding to supply chain disruptions.	Ambulkar et al. (2015) and Chowdhury and Quaddus (2017)
SCDRP4	Our organization restores affected logistics operations within an acceptable period following a disruption.	Ambulkar et al. (2015) and Chowdhury & Quaddus (2017)

Table 2: Reliability analysis of “Supply chain disruption response performance”.

Reliability Statistics				
Cronbach's Alpha		N of Items		
.815		4		
Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SCDRP1	10.472	4.986	0.568	0.789
SCDRP2	10.391	4.713	0.671	0.750
SCDRP3	10.446	4.824	0.632	0.766
SCDRP4	10.368	4.557	0.716	0.726

Source: (The authors, 2026)

As presented in Table 2, all four items showed corrected item total correlation values from 0.568 to 0.716, well above the recommended threshold of 0.30. The complete scale attained a Cronbach's alpha of 0.815, exceeding the minimum acceptable level of 0.70 and thereby confirming strong internal consistency. In addition, the Cronbach's alpha figures calculated after removing each item individually spanned from 0.726 to 0.789, and every one of these remained below the overall alpha. Such results demonstrate that deleting any item would lower the scale's reliability. Consequently, SCDRP1 to SCDRP4 made meaningful contributions to the measurement of supply chain disruption response performance and were kept for later analyses. Parallel reliability levels likewise appeared among the other measurement scales employed in the study (Hair et al., 2009; Tavakol & Dennick, 2011).

4.3. Exploratory factor analysis (EFA)

Table 3: Factor Loading Matrix.

Rotated Component Matrix ^a							
Component with loading factors							
1		2		3		4	
SCDRP1	0.738	AEPAC1	0.771	RTLDI1	0.765	DGM1	0.746
SCDRP2	0.780	AEPAC2	0.824	RTLDI2	0.809	DGM2	0.791
SCDRP3	0.816	AEPAC3	0.754	RTLDI3	0.788	DGM3	0.832
SCDRP4	0.795	AEPAC4	0.713	RTLDI4	0.720	DGM4	0.768
Extraction Method: Principal Component Analysis.							
Rotation Method: Varimax with Kaiser Normalization.							
a. Rotation converged in 7 iterations.							

Source: (The authors, 2026)

Table 3 displays the exploratory factor analysis outcomes and reveals four separate factors that stand for supply chain disruption response performance, AI-enabled predictive analytics capability, real time logistics data integration, and data governance maturity. Each of the 16 measurement items loaded firmly onto its designated factor, producing coefficients from 0.713 to 0.832 that clearly surpassed the 0.50 threshold recommended by Hair et al. (2009). The Varimax rotation reached convergence after six iterations and thereby confirmed a stable factor solution. As a result no items required removal, and the complete set of 16 indicators remained available for later statistical work. Collectively these results supply adequate support for the proposed four factor structure together with the construct validity of the measurement model.

4.4. Multiple linear regression model

Table 4: Coefficients^a.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Constant	0.417	0.139		3.000	0.003
AEPAC	0.536	0.027	0.588	19.852	0.000
RTLDI	0.392	0.030	0.415	13.067	0.000
a. Dependent Variable: SCDRP					

Source: (The authors, 2026)

Where AEPAC represents the mean of AEPAC1 to AEPAC4, RTLDI represents the mean of RTLDI1 to RTLDI4, and SCDRP represents the mean of SCDRP1 to SCDRP4.

As shown in Table 4, the significance values for the relationships between AI enabled predictive analytics capability and supply chain

disruption response performance and between real time logistics data integration and supply chain disruption response performance were both below 0.001, which is substantially lower than the 0.05 threshold. AI enabled predictive analytics capability had a significant positive effect on supply chain disruption response performance, with $\beta = 0.588$, $t = 19.852$, and $p < 0.001$. Real time logistics data integration also exerted a significant positive effect,

with $\beta = 0.415$, $t = 13.067$, and $p < 0.001$. These findings provide strong empirical support for accepting H1 and H2.

4.5. Moderator analysis

Table 5: Results analysis of “Data governance maturity”.

Model: 1 Y: SCDRP X: RTLDI W: DGM Sample size: 385

OUTCOME VARIABLE: SCDRP				Model Summary		
R	R-sq	MSE	F	dl1	dl2	p
.725	.526	0.218	140.932	3.000	381.000	.000

Model						
	Coeff.	SE	t	p	LLCI	ULCI
Constant	0.362	0.105	3.448	0.000	0.156	0.568
RTLDI	0.423	0.036	11.750	0.000	0.352	0.494
DGM	0.555	0.039	14.231	0.000	0.478	0.632
Int_1	0.311	0.034	9.147	0.000	0.244	0.378

Source: (The authors, 2026)

Where DGM was calculated as the mean score of items DGM1 to DGM4.

The positive interaction coefficient of $B = 0.311$ indicates that greater data governance maturity amplifies the beneficial influence of real time logistics data integration on supply chain disruption response performance among emerging market logistics firms. While real time logistics data integration supplies up to date and interconnected details on shipments, inventory, transport capacity, suppliers, and operational risks, its value for disruption response performance increases when organizations possess mature data governance practices. Clearly defined data ownership, standardized quality controls, formal access rules, uniform data definitions, security measures, and ongoing monitoring enable logistics managers to assess the integrated information with greater confidence and deploy it more suitably amid disruptions. As a result, firms that have reached advanced data governance maturity convert integrated logistics data into swifter, better coordinated, more accurate, and more effective disruption responses. In addition, the confidence interval for the interaction term, which stretches from $LLCI = 0.244$ to $ULCI = 0.378$, does not contain zero and thereby affirms both the significance and the reliability of this positive moderating influence. In short, the findings establish data governance maturity as a critical boundary condition that heightens the positive contribution of real time logistics data integration to supply chain disruption response performance in emerging market logistics firms. Therefore, H3 receives empirical support.

5. DISCUSSION

5.1. Result Summary

AI enabled predictive analytics capability and real time logistics data integration both produce significant positive effects on supply chain disruption response performance in emerging market logistics firms, as shown by the standardized regression coefficients of 0.588 and 0.415. These outcomes reveal that predictive disruption insights combined with current and integrated logistics information enable managers to detect emerging threats, evaluate operational impacts, coordinate response options, and carry out timely corrective measures. Meanwhile, data governance maturity acts as a significant

positive moderator that heightens the relationship between real time logistics data integration and supply chain disruption response performance, verified by the interaction coefficient of 0.311 and the confidence interval extending from 0.244 to 0.378. The pattern implies that integrated logistics data delivers greater response gains when backed by clearly assigned ownership, standardized quality controls, consistent data definitions, formal access procedures, security safeguards, and continuous monitoring. Altogether the empirical evidence upholds all three hypotheses and validates the theoretical framework linking AI enabled predictive analytics capability, real time logistics data integration, data governance maturity, and supply chain disruption response performance. With respect to the research questions, the first result shows that AI enabled predictive analytics capability markedly improves disruption response performance. The second establishes that real time logistics data integration likewise yields a significant positive effect, even though its standardized coefficient remains lower than that of AI enabled predictive analytics capability. The third demonstrates that higher data governance maturity substantially intensifies the positive contribution of real time logistics data integration to disruption response performance.

Collectively these findings suggest that emerging market logistics firms gain the greatest advantage when they pair anticipatory AI analytics with current integrated logistics data and mature governance arrangements. Enhancing disruption response performance thus requires firms to bolster predictive analytical resources, sustain timely information exchange, set reliable data standards, assign clear accountability, monitor data quality, and keep trusted logistics information readily available for coordinated decisions during disruptions.

5.2. Theoretical Implications

The empirical findings strongly support H1 because AI enabled predictive analytics capability significantly enhances supply chain disruption response performance with $\beta = 0.588$. This outcome aligns closely with Dubey et al. (2019), who maintain that predictive analytics converts extensive operational data into valuable supply chain intelligence, and with Mikalef & Gupta (2021), who define AI capability as the organizational capacity to mobilize technological, human, and data resources. At the same time, the study only partially accepts technologically deterministic views that more

advanced algorithms automatically yield stronger disruption responses. Wu et al. (2025) show that digital resources generate resilience through action oriented technologies and coordinated organizational deployment. The relatively strong coefficient therefore suggests that predictive value stems from combining forecasting models with relevant data, employee expertise, interpretation routines, and operational authority rather than simply obtaining AI software. Theoretically, this research extends dynamic capabilities theory by framing AI enabled predictive analytics capability as an organizational sensing mechanism that detects weak disruption signals before operational effects escalate. It also develops organizational information processing theory by illustrating that predictive analytics lowers uncertainty via anticipatory information processing, which clarifies why data volume or technological sophistication alone fails to ensure effective disruption responses.

The results likewise strongly support H2 since real time logistics data integration positively influences supply chain disruption response performance with $\beta = 0.415$. This finding agrees with Zhao et al. (2023), who illustrate that supply chain digitalization improves response capability through better information and communication efficiency. It further backs Lyu et al. (2022), whose work shows that system integration promotes information sharing, flexibility, and coordinated resource allocation. Yet the smaller coefficient compared with AI enabled predictive analytics capability questions the idea that increased connectivity necessarily creates superior disruption responses. The study partly concurs with Wu et al. (2025), who argue that digital resources build resilience only when converted into coordinated organizational actions, and with Lyu et al. (2022), who position dynamic capability as a linking mechanism between integration and process outcomes. Consequently, integration produces informational visibility but cannot by itself secure timely intervention when data remain inconsistent or decision authority stays fragmented. Theoretically, the research advances organizational information processing theory by treating real time logistics data integration as a cross organizational processing capacity that lessens information fragmentation and temporal delay. It also distinguishes information availability from effective information utilization, thereby rejecting purely technology centered accounts of disruption response performance.

Finally, the empirical evidence supports H3 as data governance maturity positively moderates the link between real time logistics data integration and supply chain disruption response performance, with an interaction coefficient of 0.311 and a confidence interval from 0.244 to 0.378. This outcome strongly agrees with Abraham et al. (2019), who regard data governance as authority and control that raise data value while reducing risk, and with Hazen et al. (2014), who stress that supply chain decisions are only as reliable as their underlying data. It also aligns with Liu et al. (2025), who present data quality, security, sharing capability, and technical support as linked governance foundations. Still, the study does not favor viewing governance maturity as maximum centralization or procedural control. Tallon et al. (2013) highlight the need for alignment between governance arrangements and information requirements, while Joshi et al. (2022) demonstrate that governance influences business outcomes through technological performance. Governance that slows access could thus weaken real time responsiveness. Theoretically, this study positions data governance maturity as a boundary condition inside organizational information processing theory, clarifying when integrated data turn into credible operational intelligence. It thereby reframes governance from a compliance tool into a capability that guides the transformation of

connected logistics information into coordinated disruption responses.

5.3. Practical Implications

The support for H1, reflected in $\beta = 0.588$, shows that emerging market logistics firms ought to build AI enabled predictive analytics as a genuine organizational capability instead of regarding it merely as software purchase. Managers need to link forecasting tools with relevant disruption data, analytical infrastructure, staff expertise, and operational decision routines. Mikalef & Gupta (2021) illustrate that AI value rests on the coordinated use of technological, human, and organizational resources, while Dubey et al. (2019) stress the role of analytical capability together with a supportive data culture. Firms should therefore form multidisciplinary disruption intelligence teams that include logistics managers, data analysts, information technology specialists, and risk professionals. These teams ought to review forecast accuracy, false alerts, model uncertainty, and the practical usefulness of predictions on a regular basis. Predictive warnings should further connect to predefined response procedures that cover alternative routes, substitute carriers, emergency inventory, and customer communication. Still, managers must refrain from fully automating disruption decisions because predictions remain probabilistic. Human validation stays essential whenever infrastructure limits, informal logistics networks, or unforeseen institutional shifts lower the usefulness of historical data.

The support for H2, with $\beta = 0.415$, demonstrates that logistics firms should bring together current shipment, inventory, order, capacity, supplier, and external risk information across internal units and supply chain partners. Managers ought to favor interoperable transport management, warehouse management, enterprise resource planning, and tracking systems rather than running isolated digital platforms. Lyu et al. (2022) indicate that information technology integration fosters information sharing and process flexibility, while Zhao et al. (2023) show that digitalization improves disruption response through higher information and communication efficiency. Firms should create common data definitions, shared dashboards, standardized exchange formats, and event based alerts that give authorized staff a unified operational view. Integration efforts should first target disruption critical data and high risk routes or partners, especially when financial and technological resources remain constrained. Yet connectivity alone must not be equated with responsiveness. Wu et al. (2025) reveal that digital resources produce resilience only after they turn into coordinated action. Firms must therefore allocate decision authority and practice escalation procedures so that staff can transform integrated information into prompt rerouting, rescheduling, capacity reallocation, and customer notification.

The positive moderation result for H3, represented by $B = 0.311$, reveals that firms extract greater response benefits from real time logistics data integration when data governance maturity stands high. Managers should assign clear data ownership, set quality standards, control access, document metadata, track inconsistencies, and design procedures for correcting unreliable records. Abraham et al. (2019) note that data governance ought to raise data value while managing data related costs and risks, whereas Hazen et al. (2014) warn that supply chain analytics stay only as dependable as the underlying data. Logistics firms should appoint data stewards across transportation, warehousing, procurement, information technology, and risk functions and employ governance dashboards to track completeness, accuracy, timeliness, and consistency. Governance rules should also apply to data supplied by carriers, suppliers, platforms, and customs intermediaries. Even so, excessive approval

layers might slow emergency information access. Governance should therefore balance control with operational flexibility through predefined access rights and rapid escalation protocols. As Joshi et al. (2022) observe, governance generates business value through effective technological performance rather than through procedural formalization alone.

5.4. Limitations

This study has several limitations. Its cross sectional design captures organizational perceptions at one point in time and therefore cannot establish how analytics, integration, governance, and disruption response capabilities evolve. Purposive sampling and reliance on 385 respondents from Vietnamese logistics firms may limit generalizability to other emerging markets with different institutional and infrastructural conditions. Although respondents possessed relevant professional knowledge, self reported measures may introduce social desirability, recall, and common method biases. The use of individual informants to evaluate organizational capabilities may not fully capture differences across departments or supply chain partners. Furthermore, the model examines only two technological antecedents and one governance moderator. It does not incorporate disruption severity, firm size, environmental turbulence, partner trust, digital skills, or infrastructure quality, which may influence response performance.

5.5. Future Research Directions

Future research should employ longitudinal designs to examine whether improvements in predictive analytics, data integration, and governance maturity produce sustained changes in disruption response performance. Multicountry studies could compare logistics firms across emerging markets and determine whether institutional quality, digital infrastructure, and regulatory environments alter the proposed relationships. Researchers should collect data from multiple respondents within each firm and combine survey responses with objective indicators such as detection time, recovery duration, delivery continuity, forecast accuracy, and disruption related cost. Qualitative case studies could clarify how managers interpret AI forecasts and resolve conflicts between rapid information access and governance controls. Future models could also examine analytical competence, organizational agility, partner trust, and disruption severity as mediators or moderators. Comparative research may determine whether data governance produces nonlinear effects when excessive formalization begins to restrict operational flexibility.

5.6. Conclusion

This study demonstrates that AI enabled predictive analytics capability and real time logistics data integration significantly enhance supply chain disruption response performance in emerging market logistics firms. AI enabled predictive analytics capability produces the stronger direct effect, indicating that anticipatory intelligence is particularly valuable for recognizing emerging threats and preparing adaptive responses. Real time logistics data integration also improves performance by providing current and connected operational information. Importantly, data governance maturity strengthens the contribution of logistics data integration by improving the quality, consistency, security, and accountability of shared information. All three hypotheses are therefore supported. By integrating organizational information processing theory and dynamic capabilities theory, the study explains how firms sense disruption signals, process operational information, and coordinate responses. Its central conclusion is that digital connectivity generates its greatest value when combined with predictive capability, trusted

data, flexible governance, and organizational authority to act.

REFERENCE

1. Abraham, R., Schneider, J., & Vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management*, 49, 424–438. <https://doi.org/10.1016/j.ijinfomgt.2019.07.008>
2. Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management*, 33(1), 111–122. <https://doi.org/10.1016/j.jom.2014.11.002>
3. Bag, S., Rahman, M. S., Srivastava, G., Chan, H. L., & Bryde, D. J. (2022). The role of big data and predictive analytics in developing a resilient supply chain network in the South African mining industry against extreme weather events. *International Journal of Production Economics*, 251, 108541. <https://doi.org/10.1016/j.ijspe.2022.108541>
4. Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. *Future Generation Computer Systems*, 101, 993–1004. <https://doi.org/10.1016/j.future.2019.07.059>
5. Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. *Annals of Operations Research*, 333(2), 627–652. <https://doi.org/10.1007/s10479-021-03956-x>
6. Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., & McFarlane, D. (2020). Supply chain data analytics for predicting supplier disruptions: A case study in complex asset manufacturing. *International Journal of Production Research*, 58(11), 3330–3341. <https://doi.org/10.1080/00207543.2019.1685705>
7. Bryman, A. (2016). *Social research methods*. Oxford University Press.
8. Cheng, G., & Zhang, H. (2026). The impact of China's artificial intelligence pilot policies on enterprise supply chain resilience. *Scientific Reports*, 16(1), 5382. <https://doi.org/10.1038/s41598-025-32003-z>
9. Chowdhury, M. M. H., & Quaddus, M. (2017). Supply chain resilience: Conceptualization and scale development using dynamic capability theory. *International Journal of Production Economics*, 188, 185–204. <https://doi.org/10.1016/j.ijspe.2017.03.020>
10. Cichosz, M., Wallenburg, C. M., & Knemeyer, A. M. (2020). Digital transformation at logistics service providers: Barriers, success factors and leading practices. *The International Journal of Logistics Management*, 31(2), 209–238. <https://doi.org/10.1108/IJLM-08-2019-0229>
11. Cui, L., Gao, M., Dai, J., & Mou, J. (2022). Improving supply chain collaboration through operational excellence approaches: An IoT perspective. *Industrial Management & Data Systems*, 122(3), 565–591. <https://doi.org/10.1108/IJMD-01-2020-0016>
12. Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and

- research directions. *Computers in Industry*, 162, 104132. <https://doi.org/10.1016/j.compind.2024.104132>
13. Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. *International Journal of Production Economics*, 250, 108618. <https://doi.org/10.1016/j.ijpe.2022.108618>
 14. Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., & Papadopoulos, T. (2023). Dynamic digital capabilities and supply chain resilience: The role of government effectiveness. *International Journal of Production Economics*, 258, 108790. <https://doi.org/10.1016/j.ijpe.2023.108790>
 15. Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28–36. <https://doi.org/10.1287/inte.4.3.28>
 16. Goldkuhl, G. (2012). Pragmatism vs interpretivism in qualitative information systems research. *European Journal of Information Systems*, 21(2), 135–146. <https://doi.org/10.1057/ejis.2011.54>
 17. Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). *Multivariate data analysis* (7th ed.). Prentice Hall.
 18. Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). Guilford Press.
 19. Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, 154, 72–80. <https://doi.org/10.1016/j.ijpe.2014.04.018>
 20. Joshi, A., Benitez, J., Huygh, T., Ruiz, L., & De Haes, S. (2022). Impact of IT governance process capability on business performance: Theory and empirical evidence. *Decision Support Systems*, 153, 113668. <https://doi.org/10.1016/j.dss.2021.113668>
 21. Katsaliaki, K., Galetsi, P., & Kumar, S. (2022). Supply chain disruptions and resilience: A major review and future research agenda. *Annals of Operations Research*, 319(1), 965–1002. <https://doi.org/10.1007/s10479-020-03912-1>
 22. Khan, M. R., Keoy, K. H., Lim, A. F., Basu, S., Lee, V. H., & Ooi, K. B. (2026). Data governance and Industry 4.0 for optimizing supply chain resilience. *Industrial Management & Data Systems*, 126(8), 2386–2412. <https://doi.org/10.1108/IMDS-04-2025-0534>
 23. Liu, Y., Wei, J., & Wang, X. (2025). Supply chain data governance optimization based on fuzzy DEMATEL-ISM. *SAGE Open*, 15(3), 21582440251353118. <https://doi.org/10.1177/21582440251353118>
 24. Lyu, T., Guo, Y., & Lin, H. (2022). Understanding green supply chain information integration on supply chain process ambidexterity: The mediator of dynamic ability and the moderator of leaders' networking ability. *Frontiers in Psychology*, 13, 1088077. <https://doi.org/10.3389/fpsyg.2022.1088077>
 25. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2021.103434>
 26. Mukherjee, S., Baral, M. M., Nagariya, R., Chittipaka, V., & Pal, S. K. (2024). Artificial intelligence-based supply chain resilience for improving firm performance in emerging markets. *Journal of Global Operations and Strategic Sourcing*, 17(3), 516–540. <https://doi.org/10.1108/JGOSS-06-2022-0049>
 27. Munir, M., Jajja, M. S. S., & Chatha, K. A. (2022). Capabilities for enhancing supply chain resilience and responsiveness in the COVID-19 pandemic: Exploring the role of improvisation, anticipation, and data analytics capabilities. *International Journal of Operations & Production Management*, 42(10), 1576–1604. <https://doi.org/10.1108/IJOPM-11-2021-0677>
 28. Rashid, A., Rasheed, R., Ngah, A. H., Pradeepa Jayaratne, M. D. R., Rahi, S., & Tunio, M. N. (2024). Role of information processing and digital supply chain in supply chain resilience through supply chain risk management. *Journal of Global Operations and Strategic Sourcing*, 17(2), 429–447. <https://doi.org/10.1108/JGOSS-12-2023-0106>
 29. Shrestha, N. (2020). Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistics*, 8(2), 39–42. <https://doi.org/10.12691/ajams-8-2-1>
 30. Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, 27(10), 1849–1867. <https://doi.org/10.1111/poms.12746>
 31. Tallon, P. P., Ramirez, R. V., & Short, J. E. (2013). The information artifact in IT governance: Toward a theory of information governance. *Journal of Management Information Systems*, 30(3), 141–178. <https://doi.org/10.2753/MIS0742-1222300306>
 32. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2, 53–55. <https://doi.org/10.5116/ijme.4dfb.8dfd>
 33. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>
 34. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z)
 35. Tukamuhabwa, B., Stevenson, M., & Busby, J. (2017). Supply chain resilience in a developing country context: A case study on the interconnectedness of threats, strategies and outcomes. *Supply Chain Management: An International Journal*, 22(6), 486–505. <https://doi.org/10.1108/SCM-02-2017-0059>
 36. Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *Academy of Management Review*, 3(3), 613–624. <https://doi.org/10.5465/amr.1978.4305791>
 37. Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326–349. <https://doi.org/10.1016/j.lrp.2018.12.001>

38. Wu, L., Zhang, Z., Huang, J., Su, I. H., & Tian, S. (2025). Digital technologies and supply chain resilience: A resource-action-performance perspective. *Information Systems Frontiers*, 27(5), 2137–2158. <https://doi.org/10.1007/s10796-025-10595-1>
39. Wynn Jr, D., & Williams, C. K. (2012). Principles for conducting critical realist case study research in information systems1. *MIS Quarterly*, 36(3), 787–809. <https://doi.org/10.2307/41703481>
40. Yamin, M. A. (2021). Investigating the drivers of supply chain resilience in the wake of the COVID-19 pandemic: Empirical evidence from an emerging economy. *Sustainability*, 13(21), 11939. <https://doi.org/10.3390/su132111939>
41. Yu, W., Wong, C. Y., Chavez, R., & Jacobs, M. A. (2021). Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *International Journal of Production Economics*, 236, 108135. <https://doi.org/10.1016/j.ijpe.2021.108135>
42. Yu, W., Zhao, G., Liu, Q., & Song, Y. (2021). Role of big data analytics capability in developing integrated hospital supply chains and operational flexibility: An organizational information processing theory perspective. *Technological Forecasting and Social Change*, 163, 120417. <https://doi.org/10.1016/j.techfore.2020.120417>
43. Zachariadis, M., Scott, S., & Barrett, M. (2013). Methodological implications of critical realism for mixed-methods research. *MIS Quarterly*, 37(3), 855–879. <https://doi.org/10.25300/MISQ/2013/37.3.09>
44. Zhao, N., Hong, J., & Lau, K. H. (2023). Impact of supply chain digitalization on supply chain resilience and performance: A multi-mediation model. *International Journal of Production Economics*, 259, 108817. <https://doi.org/10.1016/j.ijpe.2023.108817>
45. Zhao, Y., Song, Z., & Pei, L. (2026). Information processing capability and supply chain resilience: External environment and internal control perspectives. *Chinese Management Studies*, 20(3), 730–745. <https://doi.org/10.1108/CMS-11-2024-0925>