



The Impact of AI-Driven Prescriptive Analytics on Supply Chain Disruption Management and Operational Performance

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Abstract

This study has examined how artificial-intelligence-driven prescriptive analytics affects the management of supply chain disruptions and, through that mechanism, the operational performance of the firms that deploy it, and it has developed and tested a framework linking analytics capability to disruption outcomes across sourcing, planning, production, and distribution. The central problem has been that supply chain disruption management remains largely reactive, judgement-based, and escalation-driven, so that firms detect disruptions only once their operational consequences have become visible, respond through improvised expediting and reallocation decisions taken under time pressure with incomplete information, and absorb the resulting cost through premium freight, excess inventory, and lost service, while the analytic infrastructure now routinely present in these firms remains configured to report what has happened rather than to prescribe what should be done. Guided by five research questions, concerning how prescriptive analytics affects disruption management performance, which disruption categories are most effectively managed, which analytics maturity tiers are most effective across decision criteria, what risks reactive judgement-based regimes carry, and whether disruption management effectiveness transmits analytics capability into operational performance, the study has proposed a framework comprising five contributing constructs: data foundation and real-time visibility; predictive disruption sensing and risk forecasting; prescriptive decision automation and optimisation; human-AI decision governance and explainability; and supply chain reconfigurability and response capability, with disruption management effectiveness as the proximal outcome and operational performance as the distal outcome. A quantitative, cross-sectional design supplemented by a simulation-based evaluation has been used, and data have been collected from supply chain directors, sales and operations planning managers, procurement and sourcing managers, logistics and distribution managers, and analytics leads across manufacturing, retail, pharmaceutical, electronics, and logistics organisations. Out of 341 distributed questionnaires, 277 valid responses have been retained, producing an 81.2% valid response rate. The analysis has included descriptive statistics, reliability and validity testing, correlation analysis, hierarchical multiple regression, bootstrapped mediation analysis, and a simulation evaluation of detection lead time, response optimality, and recovery trajectory across disruption categories. The findings have shown that all five constructs were significantly and positively associated with disruption management effectiveness, that the model was significant, $F(5, 271) = 75.42$, $p < .001$, explaining 58.2% of the variance, and that prescriptive decision automation and optimisation and data foundation and real-time visibility were the strongest predictors. Disruption management effectiveness in turn predicted operational performance and partially mediated the relationship between prescriptive analytics and performance, carrying 59.1% of the total effect.

KEYWORDS

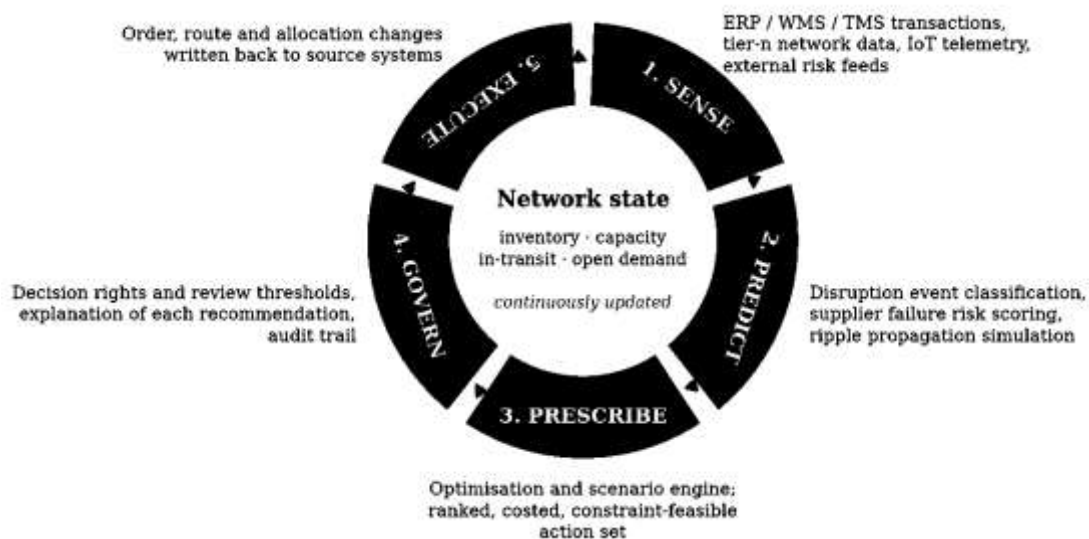
Prescriptive Analytics; Artificial Intelligence; Supply Chain Disruption; Supply Chain Resilience; Operational Performance; Ripple Effect; Decision Automation; Explainability.

INTRODUCTION

Supply chain disruption has moved from a periodic operational nuisance to a central strategic concern, and the sequence of shocks across the past decade, from natural disasters and port congestion through pandemic-driven demand and supply dislocation to geopolitical realignment and export restriction, has made clear that disruption is not an exception to normal operating conditions but a recurring feature of them (Ivanov, 2020; Queiroz et al., 2022). The financial consequences are well documented: firms announcing supply chain glitches have historically suffered substantial and persistent shareholder-value losses, and the operational costs of disruption, in expediting, inventory, capacity, and lost sales, typically exceed the direct cost of the disrupting event by a wide margin (Hendricks & Singhal, 2003; Craighead et al., 2007). The question this study addresses is not whether disruption matters, which is settled, but whether the analytic capabilities now widely deployed in supply chain organisations are being used in a way that materially changes how disruption is managed.

The evidence suggests they are not. Most supply chain analytics investment has produced descriptive and diagnostic capability, dashboards that report what has happened and root-cause analyses that explain why, and a growing but still minority share has produced predictive capability, forecasts of demand, lead time, and supplier risk (Schoenherr & Speier-Pero, 2015; Nguyen et al., 2018). Comparatively few organisations have progressed to prescriptive capability, in which the analytic system does not merely forecast a condition but computes and recommends the response to it, subject to the constraints under which the network actually operates (Lepeniotti et al., 2020; Bertsimas & Kallus, 2020). The gap matters because a disruption forecast that is not converted into a decision changes nothing: knowing that a supplier is likely to fail is operationally inert unless it is accompanied by a feasible, costed reallocation of the affected volume. This study takes that conversion, from prediction to prescription to executed decision, as its central object.

Figure 1: AI-Driven Prescriptive Analytics Architecture for Supply Chain Disruption Management



The structural reason that reactive management underperforms is a matter of timing rather than competence. A disruption creates a divergence between planned and achievable supply at the moment it occurs, but under a reactive regime that divergence becomes visible only when it manifests as a missed delivery, a stockout, or a production stoppage, by which point the set of available responses has narrowed sharply and the cheapest of them, a quiet reallocation before commitments harden, is no longer available. The ripple-effect literature has formalised the consequence: a disruption at one node propagates through the network, and the magnitude of the propagation is a function of the delay before countermeasures are applied (Dolgui et al., 2018; Ivanov et al., 2019). The premise of this study is therefore that the analytic capability that matters most is not forecast accuracy in the abstract but the reduction of the interval between the emergence of a disruption signal and the execution of a considered response.

Research on the individual components of this problem is substantial but fragmented. The supply chain risk and resilience literature has developed rich conceptual and quantitative accounts of vulnerability, resilience capacity, and recovery (Christopher & Peck, 2004; Pettit et al., 2013; Hosseini et al., 2019). The analytics literature has established that big data analytics capability is associated with firm and supply chain performance (Wamba et al., 2017; Gunasekaran et al., 2017; Dubey et al., 2019). And an emerging stream has applied artificial intelligence specifically to supply chain risk identification and assessment (Baryannis et al., 2019b; Brintrup et al., 2020). These streams, however, rarely meet. The resilience literature seldom specifies the analytic mechanism by which resilience is enacted, and the analytics literature seldom distinguishes prescriptive from predictive capability or examines whether the distinction affects disruption outcomes. This study addresses that gap by treating prescriptive analytics as a distinct capability, testing its association with disruption management effectiveness, and examining whether disruption management transmits that capability into operational performance (Md Mostafizur, 2025; Md Mesbaul, 2025; Muhammad Zahidul, 2024).

This study is organised around five research questions. The first asks how AI-driven prescriptive analytics affects disruption management performance, and it is addressed by characterising the mechanism and magnitude of the improvement in the timing, depth, and duration of disruption impact. The second asks which categories of disruption are most effectively managed by prescriptive analytics relative to reactive management, and it is addressed by distinguishing disruption types and evaluating their differential manageability. The third asks which analytics maturity tiers are most effective across the decision criteria that matter operationally, and it is addressed by comparing five tiers on multiple dimensions. The fourth asks what risks reactive, judgement-based regimes carry, and it is addressed by identifying and rating those risks. The fifth asks whether disruption management effectiveness mediates the relationship between prescriptive analytics capability and operational performance, and it is addressed through a bootstrapped mediation analysis. The purpose of the study is therefore both explanatory, to characterise the effect of prescriptive capability and the risks of reactive regimes, and prescriptive in its own right, to identify the capabilities and governance practices that convert analytics investment into operational outcomes.

The study contributes in three ways. Theoretically, it integrates the supply chain risk and resilience, business analytics capability, and artificial intelligence literatures into a single framework of disruption management effectiveness, grounded in the resource-based and dynamic-capabilities traditions, and it specifies disruption management as the mechanism through which analytic capability reaches operational performance rather than treating the link as direct. Empirically, it tests this framework against data from practitioners across five industries and four analytics maturity tiers, and it evaluates a simulation of detection lead time, response optimality, and recovery trajectory across disruption categories. Practically, it offers supply chain organisations a structured account of why reactive management fails, which disruption categories and analytics tiers matter most, and how decision governance converts recommendation into executed action. The remainder of the article reviews the relevant literature and develops the framework and hypotheses, formalises disruption dynamics and prescriptive decision-making, describes the method, presents the findings organised around the research questions, and concludes with recommendations, limitations, and directions for future work.

LITERATURE REVIEW AND FRAMEWORK DEVELOPMENT

The literature review develops the theoretical foundation for the framework by drawing on an extended body of research organised into eleven thematic subsections that collectively map onto the five constructs the framework proposes. It begins with the theoretical foundations in the resource-based view and dynamic capabilities, then examines supply chain disruption and the vulnerability literature, resilience as capacity and as practice, the ripple effect and disruption propagation, the analytics maturity progression from descriptive to prescriptive, data foundations and end-to-end visibility, predictive disruption sensing and machine learning for risk, prescriptive optimisation and decision automation, human-AI decision governance and explainability, supply chain reconfigurability and response capability, and the empirical evidence linking analytics capability to operational performance. It then consolidates the research gaps and synthesises the framework and hypotheses. Throughout, the review maintains that disruption management effectiveness, the capacity of an organisation to detect a

disruption early, respond to it optimally, and recover quickly, is jointly determined by the quality of its data foundation, the acuity of its predictive sensing, the sophistication of its prescriptive decision-making, the governance under which those decisions are taken, and the physical and contractual reconfigurability of the network on which they act.

Theoretical foundations

The framework rests on two established theoretical traditions. The resource-based view holds that sustained competitive advantage derives from resources that are valuable, rare, imperfectly imitable, and non-substitutable, and it has been the dominant lens through which information-technology and analytics investments have been theorised as sources of firm performance (Barney, 1991). The dynamic-capabilities perspective extends this by arguing that in rapidly changing environments advantage derives less from the possession of resources than from the capacity to integrate, build, and reconfigure them in response to environmental shift (Teece et al., 1997). For a study of disruption management, the second framing is the more apposite: a disruption is precisely an environmental shift that renders an existing configuration of suppliers, inventory, capacity, and routes suboptimal, and the capability at issue is the speed and quality with which the configuration can be revised.

The business analytics literature has drawn on both traditions. Work on big data analytics capability has conceptualised it as a multidimensional organisational construct spanning tangible resources such as data and technology, human skills, and intangible assets such as a data-driven culture, and has demonstrated its association with firm performance both directly and through the mediation of process-oriented dynamic capabilities (Wamba et al., 2017; Mikalef et al., 2018; Karaboga et al., 2023). Related work has developed research frameworks for how analytics creates strategic business value, emphasising that value arises from the alignment of analytic capability with decision processes rather than from analytic sophistication as such (Grover et al., 2018).

This foundation grounds the framework as a whole and shapes its structure in a specific way. It establishes that analytic capability should not be expected to affect performance directly, because analytics does not produce output, but through the decisions it informs and the operational processes those decisions govern. The framework accordingly positions disruption management effectiveness as the proximal outcome and operational performance as the distal one, and it tests the mediating path explicitly rather than assuming it (Md Syeedur & Sharmin, 2025; Tonay et al., 2024).

Supply chain disruption and the vulnerability literature

The disruption literature has developed a consistent conceptual vocabulary. A disruption is an unplanned event that interrupts the normal flow of goods, information, or funds through a supply chain, distinguished from ordinary operational variability by its discreteness and by the fact that it renders the existing plan infeasible rather than merely inaccurate (Craighead et al., 2007; Tang, 2006). Vulnerability describes the susceptibility of a network to such events, and the literature has established that it is driven by structural features, network density, node criticality, and the degree of geographic and supplier concentration, more than by the frequency of external shocks (Christopher & Peck, 2004; Blackhurst et al., 2011).

An important finding of this literature concerns severity. The severity of a disruption is determined jointly by the characteristics of the disrupting event and by the characteristics of the network and its mitigation capabilities, so that identical events produce widely differing consequences across firms (Craighead et al., 2007). Empirical work on the financial consequences has reinforced this, documenting that the shareholder-value effect of announced disruptions is persistent rather than transitory and is moderated by firm response (Hendricks & Singhal, 2003). Reviews of the risk-management field have mapped its methods and identified the persistent dominance of qualitative assessment over quantitative modelling in practice (Ho et al., 2015; Fahimnia et al., 2015).

This literature establishes the dependent phenomenon of the study and supplies its taxonomy. It shows that because severity is partly endogenous to firm response, disruption management capability is a legitimate object of study in its own right and not merely a proxy for exposure. The framework builds on this by treating disruption management effectiveness as a measurable organisational capability rather than as a property of the environment (Mst Shurovi, 2024).

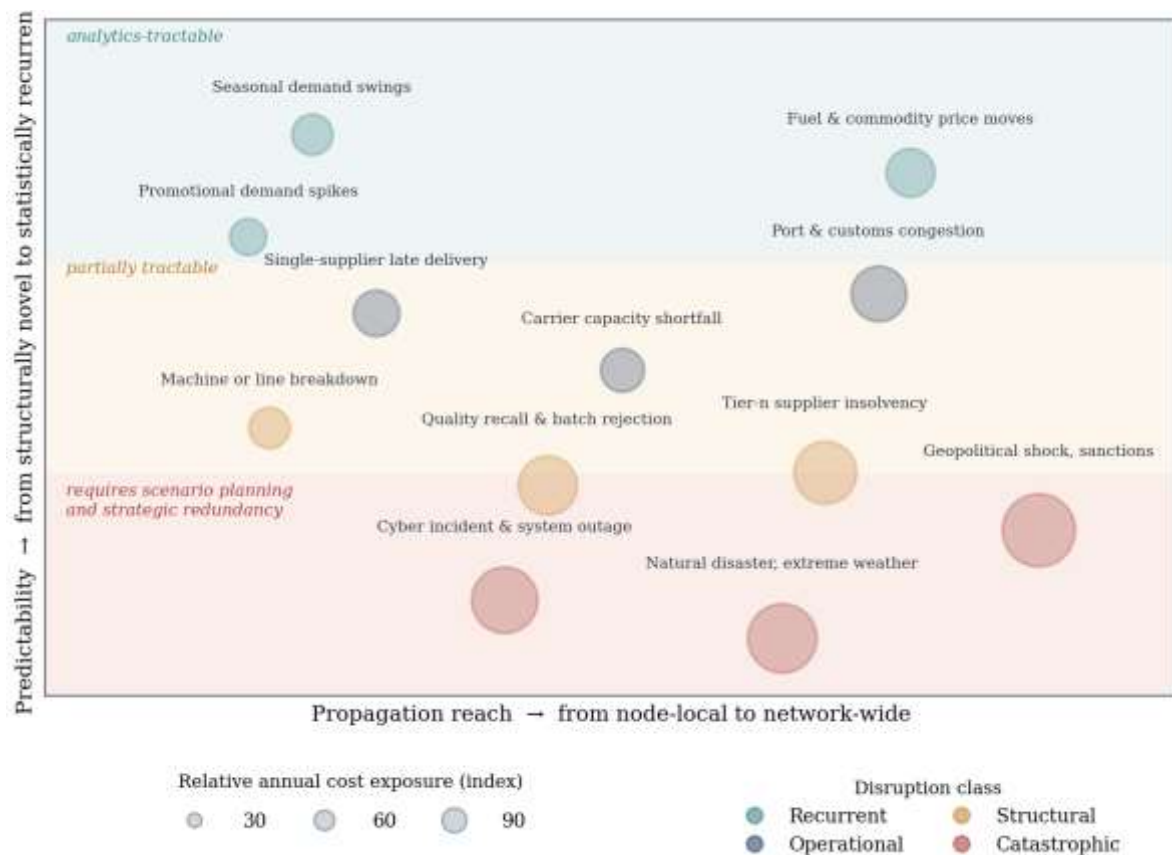
Figure 2: A Taxonomy of Supply Chain Disruptions by Predictability and Propagation Reach

Figure 2 organises the disruption categories the literature identifies into a two-axis taxonomy that structures the study's subsequent analysis. The vertical axis represents predictability, distinguishing recurrent and anticipable events with stable statistical signatures, such as seasonal demand swings, from operational and structural events with intermittent signatures, and from catastrophic and systemic events for which no reliable base rate exists. The horizontal axis represents propagation reach, distinguishing disruptions whose consequences remain local to a node from those that cascade across tiers. The taxonomy matters because the analytics tiers reviewed below address different regions of this space, and because the study's second research question is precisely a question about which regions prescriptive management reaches.

Resilience as capacity and as practice

Where the vulnerability literature describes exposure, the resilience literature describes the capability to withstand it. Resilience has been conceptualised as the ability of a supply chain to prepare for unexpected events, respond to disruption, and recover to an acceptable performance level, and the literature has converged on a decomposition into absorptive, adaptive, and restorative capacity, corresponding to redundancy held in advance, flexibility exercised during the event, and reconstitution afterwards (Pettit et al., 2013; Hosseini et al., 2019; Kamalahmadi & Parast, 2016).

A recurring theme is the tension between resilience and efficiency. Redundancy in inventory, capacity, and supplier base buys absorptive capacity at a carrying cost that lean practice has spent decades eliminating, and the literature has examined how firms navigate the trade-off, noting that flexibility-based resilience is generally more cost-efficient than redundancy-based resilience but requires greater managerial and informational capability to exercise (Sodhi et al., 2012; Snyder et al., 2016). More recent theoretical work has distinguished an engineering conception of resilience, in which the system returns to its prior state, from a social-ecological conception, in which it adapts to a new one, arguing that the latter better describes supply chains facing structural change (Wieland & Durach, 2021). Empirical studies of the pandemic period have documented which capabilities in fact proved protective, finding visibility, supplier collaboration, and digital capability among the most consistently associated with

successful adaptation (Belhadi et al., 2021; Queiroz et al., 2022).

This literature contributes directly to the supply chain reconfigurability and response capability construct. It establishes that analytic capability cannot produce disruption management effectiveness on its own, because a recommendation to shift volume to an alternative supplier is worthless if no qualified alternative exists or if contractual terms prevent the shift. The framework accordingly treats reconfigurability as a distinct construct capturing the physical, contractual, and organisational latitude available to act on a recommendation (Muhammad Zahidul & Amena Begum, 2022; Mukut Kanti, 2025).

The ripple effect and disruption propagation

A distinct and highly developed stream addresses propagation. The ripple effect describes the downstream and upstream diffusion of a disruption through a supply network, in which the failure of one node degrades the performance of others through material, capacity, and information linkages, and it has been distinguished from the bullwhip effect by its origin in structural disruption rather than in demand-signal distortion (Dolgui et al., 2018). The literature has developed quantitative methods for characterising propagation, including simulation, optimisation, and control-theoretic approaches, and has established that propagation magnitude depends on network structure, on the criticality of the disrupted node, and critically on the latency of the response (Hosseini et al., 2019; Ivanov et al., 2017). Work at the intersection of the ripple effect and digital technology has argued that Industry 4.0 technologies alter propagation dynamics by improving observability of the network state, and has proposed the digital supply chain twin as the mechanism through which that observability is achieved: a computerised model representing network states in real time, combining model-based and data-driven approaches to link risk data, disruption modelling, and performance assessment (Ivanov et al., 2019; Ivanov & Dolgui, 2021; Ivanov, 2023). Related theorising on viability has extended the frame from recovery of a firm to survival of an intertwined network under long-duration systemic shock (Ivanov & Dolgui, 2020; Ivanov, 2020).

This literature is foundational to the study's central argument about timing. It establishes formally what the introduction asserted informally: that the cost of a disruption is a function not only of its magnitude but of the delay before countermeasures are applied, because propagation continues during that delay and each additional affected node enlarges the recovery problem. The framework accordingly treats detection lead time and response latency as the primary channel through which analytic capability affects outcomes (Md Mostafizur et al., 2025).

The analytics maturity progression

The analytics literature conventionally distinguishes descriptive analytics, which characterises what has happened, diagnostic analytics, which explains why, predictive analytics, which forecasts what will happen, and prescriptive analytics, which determines what should be done (Lepeniotti et al., 2020; Waller & Fawcett, 2013). The progression is not merely one of increasing sophistication but of increasing proximity to the decision: descriptive output requires a human to infer implications, predictive output requires a human to determine a response, whereas prescriptive output supplies the response itself, subject to an explicit objective function and constraint set.

The methodological literature on prescriptive analytics has developed frameworks for combining machine learning with optimisation, most influentially by using auxiliary observational data to construct conditional distributions from which optimal decisions are derived directly, rather than passing a point forecast into a downstream optimiser (Bertsimas & Kallus, 2020). Reviews of the field have catalogued the methods in use, spanning mathematical programming, simulation, evolutionary computation, and reinforcement learning, and have identified the integration of prescriptive output with organisational decision processes as the dominant open challenge (Lepeniotti et al., 2020; Relich, 2023). Reviews specific to operations have made a parallel argument, noting that the operations-management contribution of analytics lies in the decision structures it enables rather than in the algorithms themselves (Choi et al., 2018).

This literature grounds the prescriptive decision automation and optimisation construct and supplies the study's third research question. It establishes that the maturity tiers differ not only in accuracy but in decision latency, cost, and interpretability, so that the appropriate tier depends on the disruption category and the decision context rather than being uniformly the most advanced available (Debasish,

2021; Shima Ali et al., 2024).

Data foundations and end-to-end visibility

All analytic capability rests on data, and the supply chain literature has been unusually explicit about the fragility of that foundation. Supply chain data originates in heterogeneous transactional systems, enterprise resource planning, warehouse management, and transportation management platforms, each with its own master data, granularity, and update cadence, and it must be reconciled with supplier-provided data of variable quality and with external feeds whose provenance the firm does not control (Waller & Fawcett, 2013; Schoenherr & Speier-Pero, 2015).

Visibility, the ability to observe the state of the network beyond the firm's own boundaries, is the specific data problem that disruption management poses. Firms typically hold good data on tier-one suppliers and progressively worse data beyond, yet the disruptions that propagate most severely frequently originate in tiers the firm cannot observe at all, so that the first indication of a tier-two failure is often a tier-one delivery miss weeks later (Ivanov & Dolgui, 2021; Brintrup et al., 2020). The analytics literature has established more generally that decision quality is bounded by data quality, and that organisations systematically underestimate the effort required to reach the data condition their analytic ambitions presuppose (Janssen et al., 2017; Nguyen et al., 2018).

This literature grounds the data foundation and real-time visibility construct. It establishes that this construct is a precondition rather than a complement: a prescriptive engine operating on stale, partial, or unreconciled data will produce confident recommendations that are wrong, and will do so faster and at greater scale than a human analyst would. The framework treats it as the first construct for that reason (Md Mesbaul, 2023; Sharif Md Yousuf et al., 2025).

Predictive disruption sensing and machine learning for risk

An expanding literature applies machine learning to the identification and assessment of supply chain risk. Comprehensive mapping studies have categorised this work by AI methodology and by the risk-management task addressed, identification, assessment, or response, and have found the response task markedly less studied than the first two, which is precisely the gap that prescriptive analytics occupies (Baryannis et al., 2019b). Applied work has demonstrated supervised prediction of supplier disruption from historical delivery, financial, and relational data, achieving practically useful discrimination in industrial settings (Brintrup et al., 2020), and has combined machine learning with simulation for resilient supplier selection under disruption risk (Cavalcante et al., 2019).

A finding of particular relevance concerns the trade-off between predictive performance and interpretability (Debasish, 2021; Mukut Kanti, 2020). Work comparing model families for supply chain risk prediction has shown that the most accurate models are frequently the least interpretable, and that in a domain where predictions trigger costly interventions and must be justified to internal and external counterparties, the loss of interpretability may outweigh the gain in accuracy (Baryannis et al., 2019a). Reviews of AI for supply chain resilience have reached compatible conclusions, emphasising that adoption is constrained less by algorithmic capability than by organisational trust and integration (Modgil et al., 2022). This literature grounds the predictive disruption sensing and risk forecasting construct and anticipates the governance construct that follows (Md. Abdur & Iftekhhar, 2021; Mohammad Abir Chowdhury & Tonay, 2022; Mohammad Shoriful Hossan, 2021). It establishes that prediction is a necessary input to prescription but not a substitute for it, and that predictive capability deployed without a decision pathway generates alerts that accumulate faster than they are acted upon (Muhammad Zahidul, 2025).

Prescriptive optimisation and decision automation

The prescriptive layer converts forecast into action, and its methods are drawn principally from operations research (Md Mesbaul, 2023; Mst Shurovi, 2024; Muhammad Zahidul & Amena Begum, 2022). The classical formulation treats disruption response as a constrained optimisation problem: given a predicted supply shortfall, determine the allocation of remaining supply across demand, the activation of alternative sources, the repositioning of inventory, and the expediting of transportation that minimises expected cost subject to capacity, contractual, and service constraints (Muhammad Zahidul, 2024; Mukut Kanti, 2024; Shima Ali et al., 2024). The methodological advance of recent years has been the integration of this optimisation with machine learning, so that the uncertainty characterisation feeding the optimiser is learned from data rather than assumed (Bertsimas & Kallus,

2020; Lepenioti et al., 2020).

Simulation-based approaches occupy a complementary position, particularly for the ripple effect, where the objective is less to compute a single optimal action than to evaluate candidate actions against a propagating network state (Ivanov, 2020; Ivanov, 2023; Hosseini et al., 2019). The digital supply chain twin literature has argued for the combination, using the twin to maintain the network state and the optimiser to search the response space against it (Ivanov & Dolgui, 2021). Across these approaches, a consistent practical finding is that the binding constraint on prescriptive deployment is rarely computational tractability and usually the fidelity of the constraint set: an optimiser that does not know about a contractual minimum-volume commitment or a qualification lead time will recommend actions that the organisation cannot take (Md Arif Uz et al., 2025; Tonay et al., 2024). This literature completes the prescriptive construct. It establishes that the value of prescriptive analytics depends on the completeness with which the real decision problem, including its unglamorous contractual and qualification constraints, has been encoded, and that this encoding, rather than algorithm selection, is where most implementation effort is properly spent (Mohammad Shoriful Hossan, 2021).

Human-AI decision governance and explainability

Prescriptive output is consequential: a recommendation to reallocate volume, activate an alternative supplier, or expedite at premium freight commits real money and affects counterparty relationships. The explainability literature has developed model-agnostic methods for attributing a prediction to its inputs, including local surrogate explanation and additive feature attribution (Ribeiro et al., 2016; Lundberg & Lee, 2017; Guidotti et al., 2018), alongside the influential argument that for high-stakes decisions inherently interpretable models should be preferred to post-hoc explanation of opaque ones (Rudin, 2019).

In the supply chain setting this debate takes a specific operational form. A planner presented with a recommendation to switch a component to a secondary supplier must decide whether to accept it, and that decision turns on knowing what drove the recommendation: a genuine deterioration in the primary supplier's delivery reliability, a transient data-quality artefact, or an external risk signal of uncertain relevance. Without that information the planner either accepts everything, in which case the organisation has delegated commercial judgement to a model it cannot interrogate, or overrides routinely, in which case the analytic investment yields nothing. The literature on decision-making quality under big data has documented exactly this pattern, identifying the governance of the human-system boundary as a primary determinant of realised value (Janssen et al., 2017; Baryannis et al., 2019a; Modgil et al., 2022). This literature grounds the human-AI decision governance and explainability construct. It establishes that governance is not a constraint on analytic value but a condition of it, encompassing the definition of decision rights, the thresholds above which human review is mandatory, the explanation accompanying each recommendation, and the audit trail through which decisions can subsequently be reconstructed (Md. Abdur & Iftekhar, 2021; Shima Ali et al., 2025).

Reconfigurability and the capacity to act

A recommendation is inert without the latitude to execute it, and a distinct literature addresses that latitude. Work on supply chain flexibility has distinguished sourcing flexibility, the availability of qualified alternative suppliers, capacity flexibility, the ability to shift volume across internal and contract manufacturing sites, logistics flexibility, the availability of alternative modes and routes, and product flexibility, the ability to substitute components or specifications (Sodhi et al., 2012; Kamalahmadi & Parast, 2016). Empirical studies of disruption response have consistently found these flexibilities among the strongest predictors of recovery speed (Blackhurst et al., 2011; Belhadi et al., 2021).

The critical observation for this study is that reconfigurability is largely established before a disruption occurs, through dual-sourcing decisions, supplier qualification programmes, contractual flexibility clauses, and network design, and cannot be created during one (Md Mostafizur et al., 2025; Md Syeedur & Sharmin, 2025). Qualification lead times for regulated components are measured in months, and a contractual minimum-volume commitment cannot be renegotiated in the days available during a shortage. Analytic capability and reconfigurability are therefore complements with an asymmetric time structure: the analytics can be improved incrementally and continuously, whereas the latitude on which it depends must be provisioned in advance (Pettit et al., 2013; Wieland & Durach, 2021).

This literature grounds the supply chain reconfigurability and response capability construct and explains why the framework treats it as a distinct contributor rather than folding it into the prescriptive construct. An organisation may hold an excellent optimiser and a rigid network, in which case its recommendations will be technically optimal and operationally infeasible (Md Arif Uz et al., 2025).

Analytics capability and operational performance

A substantial body of empirical work has examined the association between analytics capability and performance. Studies grounded in the resource-based view have found positive associations between big data analytics capability and firm performance, frequently mediated by process-oriented dynamic capabilities (Wamba et al., 2017; Mikalef et al., 2018). Supply-chain-specific studies have found analogous associations with supply chain and organisational performance (Gunasekaran et al., 2017; Fosso Wamba et al., 2020), and with supply chain agility and resilience, with organisational flexibility and culture identified as complements (Dubey et al., 2019; Dubey et al., 2021).

Two features of this evidence base motivate the present study. First, it has generally treated analytics as an undifferentiated capability, without distinguishing predictive from prescriptive maturity, so that a firm with sophisticated forecasting and no decision automation is scored similarly to one with both. Second, where mediation has been tested it has typically been through broad constructs such as agility or dynamic capability, rather than through a specific operational mechanism (Muhammad Zahidul, 2025; Mukut Kanti, 2025). This study responds by isolating prescriptive capability as a distinct construct and by specifying disruption management effectiveness, a concrete and measurable operational capability, as the mediating mechanism (Grover et al., 2018; Karaboga et al., 2023). This literature grounds the outcome structure of the framework and the fifth research question. It establishes both the expectation of a positive analytics–performance association and the requirement that the mechanism be specified rather than assumed (Sharif Md Yousuf et al., 2025; Shima Ali et al., 2025).

Research gaps and the contribution of the present study

Read together, these streams leave four gaps that the present study addresses. First, the resilience and analytics literatures have developed largely in parallel: the former specifies capabilities without the analytic mechanism that enacts them, the latter specifies capability without the operational process through which it acts. Second, the analytics–performance literature has not systematically distinguished prescriptive from predictive maturity, despite a strong theoretical reason to expect the distinction to matter, since only the former closes the gap between forecast and action. Third, the disruption literature evaluates response predominantly through recovery outcomes and only rarely through detection lead time, notwithstanding the ripple-effect finding that latency drives propagation. Fourth, the governance of the human–AI boundary in prescriptive supply chain decision-making has been identified as an adoption barrier but seldom operationalised as a measurable construct or tested as a determinant of outcomes.

The present study addresses these gaps by proposing an integrated framework in which prescriptive capability and its governance are distinct constructs, by measuring it against practitioner assessment across five industries and four analytics maturity tiers, by evaluating a simulation in which detection lead time and recovery trajectory are primary outcomes, and by testing the mediating path from analytic capability through disruption management to operational performance (Muhammad Zahidul, 2024; Md Mostafizur, 2025).

Synthesis: the disruption management framework and hypotheses

Synthesising the eleven streams yields the framework this study tests. The framework holds that disruption management effectiveness, the capacity to detect a disruption early, respond to it optimally, and recover quickly, is jointly determined by five constructs: data foundation and real-time visibility; predictive disruption sensing and risk forecasting; prescriptive decision automation and optimisation; human–AI decision governance and explainability; and supply chain reconfigurability and response capability. A deficiency in any one undermines the whole: without a sound data foundation the system observes the wrong network state, without predictive sensing it observes the state too late, without prescriptive capability it cannot convert observation into action, without governance its recommendations are neither trusted nor auditable, and without reconfigurability its recommendations cannot be executed. The framework further holds that these capabilities affect operational performance

not directly but through disruption management effectiveness, consistent with the dynamic-capabilities account of how analytic resources reach operational outcomes.

From the framework, eight hypotheses are derived. H1: Data foundation and real-time visibility is positively associated with disruption management effectiveness. H2: Predictive disruption sensing and risk forecasting is positively associated with disruption management effectiveness. H3: Prescriptive decision automation and optimisation is positively associated with disruption management effectiveness. H4: Human-AI decision governance and explainability is positively associated with disruption management effectiveness. H5: Supply chain reconfigurability and response capability is positively associated with disruption management effectiveness. H6: The five constructs jointly explain a significant proportion of the variance in disruption management effectiveness. H7: Disruption management effectiveness is positively associated with operational performance. H8: Disruption management effectiveness mediates the relationship between prescriptive decision automation and optimisation and operational performance. These hypotheses are tested in the analysis, alongside a simulation evaluation of how disruption categories differ in manageability and how analytics maturity tiers compare, to address the five research questions.

METHODS

This study adopted a quantitative, cross-sectional research design supplemented by a simulation-based evaluation. The quantitative design was selected because the study measured relationships among five contributing constructs, a mediating outcome, and a distal outcome through numerical survey responses, and the cross-sectional design was used because data were collected at a single point in time, capturing practitioners' assessments of the analytic, governance, and network capabilities present in their organisations. The simulation evaluation complemented the survey by modelling disruption onset, propagation, detection, and response under reactive and prescriptive regimes, providing a mechanism-level counterpart to the perceptual measures. The unit of analysis was the individual respondent, understood as an informed practitioner engaged in the planning, sourcing, execution, or analytic support of supply chain operations.

The population comprised supply chain directors and vice-presidents, sales and operations planning managers, procurement and sourcing managers, logistics and distribution managers, and analytics and data science leads across manufacturing, retail and consumer packaged goods, pharmaceutical and healthcare, electronics and high technology, and logistics service organisations. A purposive sampling strategy was used because respondents were selected for their direct involvement in disruption detection and response. Primary data were collected through a structured questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), distributed through online forms and professional networks. The instrument included multi-item measures for each of the five constructs, for disruption management effectiveness, and for operational performance, demographic and analytics-maturity items, and rating items on disruption manageability, maturity-tier effectiveness, and reactive-regime risk that fed the analyses addressing the research questions.

A pilot test was conducted with practitioners and academics to check clarity and terminological precision, and feedback was used to refine wording and to distinguish predictive from prescriptive items unambiguously, since conflation of the two was the principal risk to construct validity. Validity was ensured through literature-based item development, expert review, and alignment among the framework, hypotheses, and items, with convergent validity assessed against the average-variance-extracted criterion and discriminant validity against the square-root-of-AVE comparison (Fornell & Larcker, 1981; Hair et al., 2019). Reliability was tested through Cronbach's alpha with a .70 threshold. Because all measures were self-reported from a single source, procedural remedies against common-method variance were applied, including item separation, psychological separation of predictor and criterion sections, response anonymity, and reverse-worded items, and Harman's single-factor test was conducted post hoc (Podsakoff et al., 2003). Analysis was conducted in SPSS and Python, the latter using the pandas, NumPy, SciPy, scikit-learn, and SimPy libraries for data preparation, statistical testing, bootstrapping, and discrete-event simulation (Harris et al., 2020; Virtanen et al., 2020). Ethical considerations were observed: participation was voluntary, informed consent was obtained, responses were anonymised, and no commercially sensitive supplier, pricing, or volume data were collected.

Formalising disruption dynamics and prescriptive decision-making

A supply network is represented as a directed graph in which nodes are facilities and suppliers and arcs are flows, with the network state at time t comprising inventory, capacity, in-transit quantity, and open demand, as defined in Equation (1):

$$S_t = \{ (I_{i,t}, K_{i,t}, T_{ij,t}, D_{i,t}) : i, j \in N \} \quad (1)$$

A disruption is an exogenous event that reduces the feasible capacity or supply at one or more nodes for a finite duration, as expressed in Equation (2), where δ is the severity of the reduction and τ its duration:

$$e = (i, t_0, \delta, \tau), \quad K_{i,t}' = (1 - \delta) \cdot K_{i,t} \text{ for } t_0 \leq t \leq t_0 + \tau \quad (2)$$

The predictive layer estimates the probability of a disruption at each node over a forward horizon h , conditional on observed features x , as in Equation (3):

$$p_{i,t} = P(e_i \text{ occurs in } [t, t+h] \mid x_{i,t}) \quad (3)$$

Detection lead time, the central timing variable of the study, is the signed interval between the time at which a disruption is recognised by the organisation and the time at which it materially affects operations, as in Equation (4), where positive values denote anticipation:

$$L = t[\text{impact}] - t[\text{detect}] \quad (4)$$

Predictive performance is measured by precision, recall, and their harmonic mean, defined in Equations (5) to (7), where TP, FP, and FN denote true positives, false positives, and false negatives over the alert set:

$$\text{Precision} = TP / (TP + FP) \quad (5)$$

$$\text{Recall} = TP / (TP + FN) \quad (6)$$

$$F1 = 2 \cdot (\text{Precision} \cdot \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (7)$$

The prescriptive layer selects a response action a from the feasible set A , minimising expected cost over the conditional distribution of the uncertain quantities, in the general form given in Equation (8), where w denotes data-driven weights over historical observations conditioned on the current covariates:

$$a^* = \text{argmin over } a \in A \text{ of } \sum_{k=1 \text{ to } n} w_k(x_t) \cdot C(a, \xi_k) \quad (8)$$

The cost function aggregates the operational consequences of the action, including expediting, alternative-sourcing premium, holding cost, and the penalty attaching to unmet demand, as in Equation (9):

$$C(a, \xi) = c[\text{exp}] \cdot q[\text{exp}] + c[\text{alt}] \cdot q[\text{alt}] + c[\text{hold}] \cdot I + \pi \cdot U(a, \xi) \quad (9)$$

Actions are constrained by capacity, contractual commitment, and qualification status, so that the feasible set is defined as in Equation (10):

$$A = \{ a : q_j(a) \leq K_j \ \forall j, \ q_j(a) \geq m_j \ \forall j \in M, \ a_j = 0 \ \forall j \notin Q \} \quad (10)$$

Ripple propagation is captured by the expected number of downstream nodes whose performance falls below threshold, which grows with the delay before countermeasures are applied, as expressed in Equation (11):

$$R(\Delta) = E[\mid \{ j \in N : P_j < P[\text{min}] \} \mid], \quad \partial R / \partial \Delta > 0 \quad (11)$$

Recovery is characterised by the depth of the performance trough and the time required to return to the pre-disruption level, defined in Equations (12) and (13):

$$\text{Depth} = \max \text{ over } t \text{ of } (P_0 - P_t) / P_0 \quad (12)$$

$$\text{TTR} = \inf \{ s > t_0 : P_s \geq (1 - \varepsilon) \cdot P_0 \} - t_0 \quad (13)$$

Disruption management effectiveness, the proximal outcome, is operationalised perceptually through survey items and, in the simulation, as a weighted composite of anticipation, response optimality, trough depth, and recovery speed, as in Equation (14):

$$\text{DME} = w_1 \cdot \sigma(L) + w_2 \cdot F1 + w_3 \cdot (1 - \text{Depth}) + w_4 \cdot (1 - \text{TTR} / \text{TTR}[\text{max}]) \quad (14)$$

Statistical models and simulation design

The principal hypothesis test used ordinary least squares multiple regression of disruption management effectiveness on the five constructs, with DFRV denoting data foundation and real-time visibility, PDRF predictive disruption sensing and risk forecasting, PDAO prescriptive decision automation and optimisation, HAGE human-AI decision governance and explainability, and SCRC supply chain reconfigurability and response capability, as specified in Equation (15):

$$DME_i = \beta_0 + \beta_1 DFRV_i + \beta_2 PDRF_i + \beta_3 PDAO_i + \beta_4 HAGE_i + \beta_5 SCRC_i + \varepsilon_i \quad (15)$$

The mediation hypothesis was tested through the paths specified in Equations (16) and (17), with the indirect effect estimated as the product $a \cdot b$ and its confidence interval obtained by bias-corrected bootstrapping with 5,000 resamples:

$$DME_i = a_0 + a \cdot PDAO_i + u_i \quad (16)$$

$$OPP_i = \gamma_0 + c' \cdot PDAO_i + b \cdot DME_i + v_i, \text{ indirect} = a \cdot b \quad (17)$$

Model significance was assessed through the F-statistic, explanatory power through R-squared and adjusted R-squared, residual independence through the Durbin-Watson statistic, and multicollinearity through the variance inflation factor, all confirmed within conventional bounds. The simulation modelled a four-tier network with stochastic demand, lead times, and disruption arrivals across the five disruption categories, applying each analytics maturity tier to the detection and response problem and recording detection lead time, response optimality relative to a full-information benchmark, trough depth, and time-to-recover. Recommendations produced by the prescriptive configuration were accompanied by feature-attribution explanations so that the simulated review gate could be modelled as a function of explanation quality rather than as unconditional acceptance (Ribeiro et al., 2016; Lundberg & Lee, 2017; Rudin, 2019).

RESULTS

Sample and descriptive statistics

Table 1: Respondent profile and response rate

Variable	Category	Frequency	Percentage
Questionnaires	Distributed	341	100.0%
Questionnaires	Returned	302	88.6%
Questionnaires	Valid and retained	277	81.2%
Role	S&OP / demand-supply planning manager	71	25.6%
Role	Procurement / sourcing manager	58	20.9%
Role	Logistics / distribution manager	54	19.5%
Role	Supply chain director / vice-president	47	17.0%
Role	Analytics / data science lead	47	17.0%
Industry	Manufacturing / industrial	89	32.1%
Industry	Retail / consumer packaged goods	66	23.8%
Industry	Pharmaceutical / healthcare	45	16.3%
Industry	Electronics / high technology	42	15.2%
Industry	Logistics / third-party providers	35	12.6%
Analytics maturity	Predictive forecasting	88	31.8%
Analytics maturity	Diagnostic analysis	71	25.6%
Analytics maturity	Descriptive reporting only	62	22.4%
Analytics maturity	Prescriptive / autonomous	56	20.2%
Experience	5-10 years	118	42.6%
Experience	More than 10 years	102	36.8%
Experience	Under 5 years	57	20.6%

Table 1 shows an 81.2% valid response rate, with 277 usable responses. The sample spanned the roles involved in detecting and responding to disruption, from the planners who hold the balancing decision

(25.6%), through procurement (20.9%) and logistics (19.5%), to the directors accountable for the outcome (17.0%) and the analytics leads who build the systems (17.0%). The industry distribution across manufacturing (32.1%), retail and consumer goods (23.8%), pharmaceuticals (16.3%), electronics (15.2%), and logistics providers (12.6%) covers sectors whose disruption profiles differ substantially in regulatory constraint, product perishability, and network depth. The analytics maturity distribution is the most consequential feature of the sample: only 20.2% of respondents placed their organisation at the prescriptive or autonomous tier, while 48.0% remained at descriptive or diagnostic capability, which establishes that prescriptive analytics remains a minority practice among organisations that have nonetheless invested substantially in data infrastructure. In total, 79.4% of respondents had five or more years of experience.

Table 2: Descriptive statistics and reliability of study constructs (N = 277)

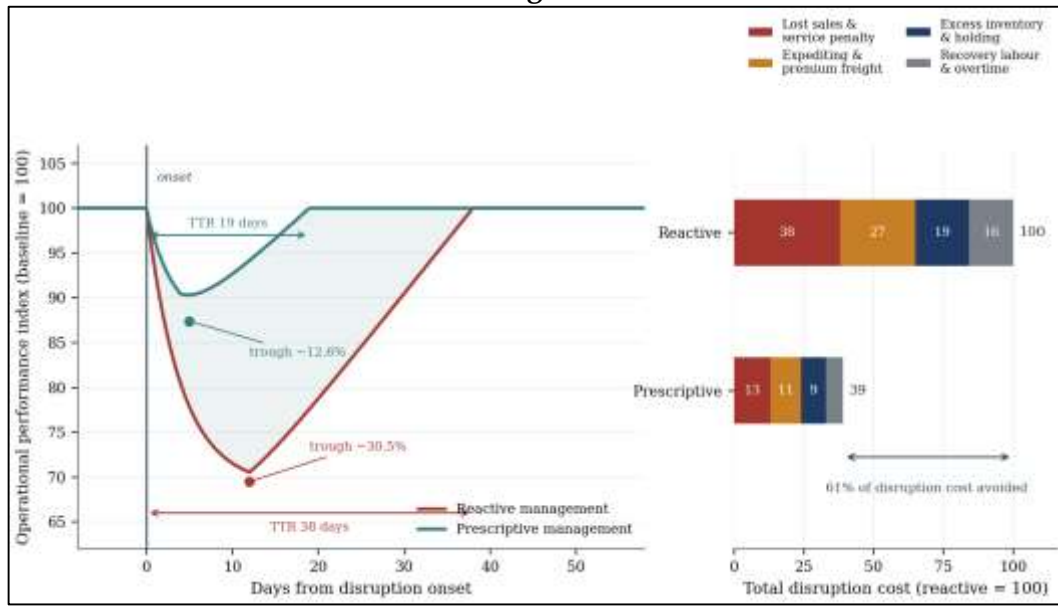
Construct	Mean	SD	Cronbach's α
Prescriptive decision automation & optimisation (PDAO)	4.28	0.57	.91
Data foundation & real-time visibility (DFRV)	4.21	0.60	.89
Predictive disruption sensing & risk forecasting (PDRF)	4.14	0.63	.88
Supply chain reconfigurability & response capability (SCRC)	4.06	0.65	.87
Human-AI decision governance & explainability (HAGE)	3.99	0.69	.86
Disruption management effectiveness (mediator, DME)	3.88	0.74	.92
Operational performance (outcome, OPP)	3.81	0.78	.90
Overall instrument	—	—	.95

Table 2 presents the descriptive statistics and reliability. All constructs exceeded the neutral midpoint and all Cronbach's alpha values exceeded .70, ranging from .86 to .92 with overall reliability of .95. Average variance extracted exceeded .50 for every construct and the square root of AVE exceeded all inter-construct correlations, satisfying the convergent and discriminant validity criteria (Fornell & Larcker, 1981). Harman's single-factor test yielded a first factor accounting for 31.4% of variance, below the 50% threshold, indicating that common-method bias is unlikely to account for the observed relationships (Podsakoff et al., 2003). The ordering of the means is diagnostically informative and is examined below.

RQ1: How AI-driven prescriptive analytics affects disruption management performance

Prescriptive decision automation (4.28) and data foundation and real-time visibility (4.21) recorded the highest means, indicating that practitioners regard decision automation resting on a sound data foundation as the core of modern disruption management. Disruption management effectiveness (3.88) and operational performance (3.81) recorded the lowest means and the widest dispersions (SD = 0.74 and 0.78), a revealing pattern: practitioners rate their realised disruption outcomes lower than any of the contributing capabilities, and the wide spread indicates that realised effectiveness varies substantially across organisations holding nominally similar capability. This gap between capability and outcome foreshadows the study's central finding, that possessing analytic capability is not the same as managing disruption well, which depends on the conversion of capability into governed and executable decisions. Figure 3 presents the simulation evidence for the first research question and shows the mechanism of the improvement directly.

Figure 3: Disruption Response Trajectory and Cost Decomposition: Prescriptive Versus Reactive Management



Under reactive management the performance index falls steeply after onset, reaching a trough approximately 30% below baseline around day twelve, and recovers slowly thereafter, returning to baseline near day thirty-eight. Under prescriptive management the decline is arrested early, the trough is limited to roughly 13% below baseline and reached by day five, and recovery to baseline is complete by day nineteen. Three distinct improvements are visible in a single trajectory: the disruption is detected and acted upon earlier, the depth of the operational loss is less than half as great, and time-to-recover is approximately halved. The shaded area between the curves represents the cumulative performance loss avoided. The right panel converts that area into cost, decomposing the total disruption cost into lost sales and service penalties, expediting and premium freight, excess inventory holding, and recovery labour: prescriptive management incurs 39 index points against the reactive regime's 100, avoiding 61% of the total cost, and the reduction is proportionally largest in the lost-sales component, which is the element most sensitive to how quickly the response begins.

Figure 4: Shift in Disruption Detection-to-Response Stage Under Prescriptive Management

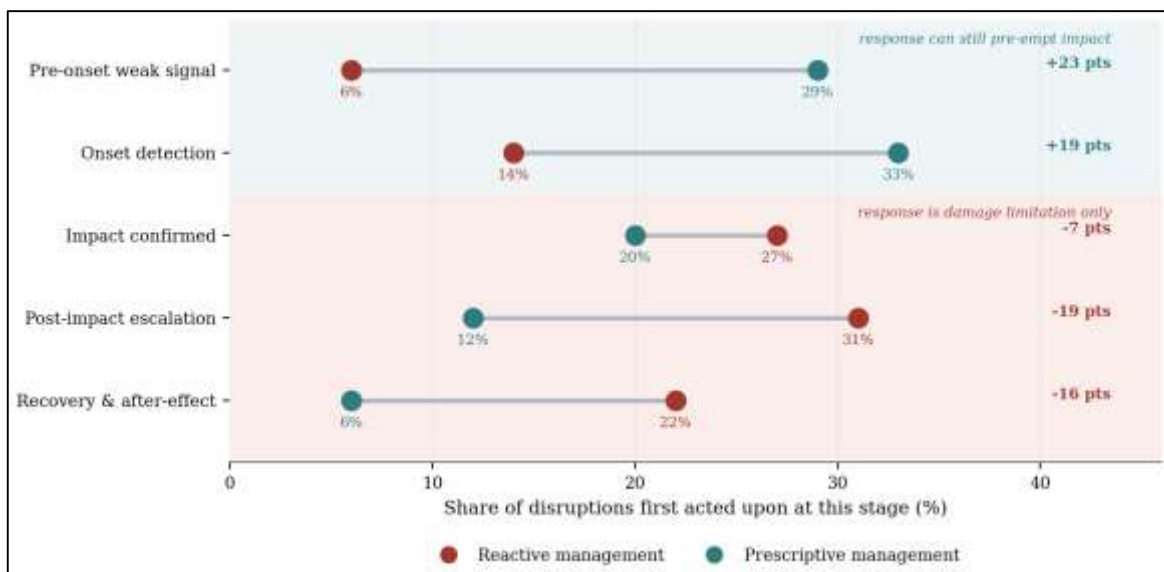


Figure 4 makes the operational consequence concrete by decomposing the stage at which disruptions are first acted upon under each regime. Under reactive management the distribution is weighted toward the later stages, with 53% of disruptions first addressed only after impact had been confirmed or escalation had begun, and a further 22% addressed only during recovery; under prescriptive management 62% are first acted upon at the pre-onset weak-signal or onset-detection stage, before impact has materialised. Each pair of markers is joined to show the movement, and the point shifts are annotated at the right: the pre-onset and onset stages gain 23 and 19 percentage points respectively, while the three post-impact stages lose 7, 19, and 16. The shaded bands mark the operationally decisive boundary: above it a response can still pre-empt the impact, so that the disruption is absorbed rather than experienced, while below it the response is damage limitation, and its best achievable outcome is a smaller loss rather than no loss. This redistribution is the practical face of the curve separation in Figure 3, and it clarifies the mechanism through which prescriptive analytics acts. The improvement does not come from responding better to disruptions that have already struck, where the scope for improvement is bounded by the physical constraints of the network, but from responding at all to disruptions that under a reactive regime would not yet have been visible.

RQ2: Which disruption categories are most effectively managed

Figure 5: Response Effectiveness by Disruption Category Across Performance Metrics

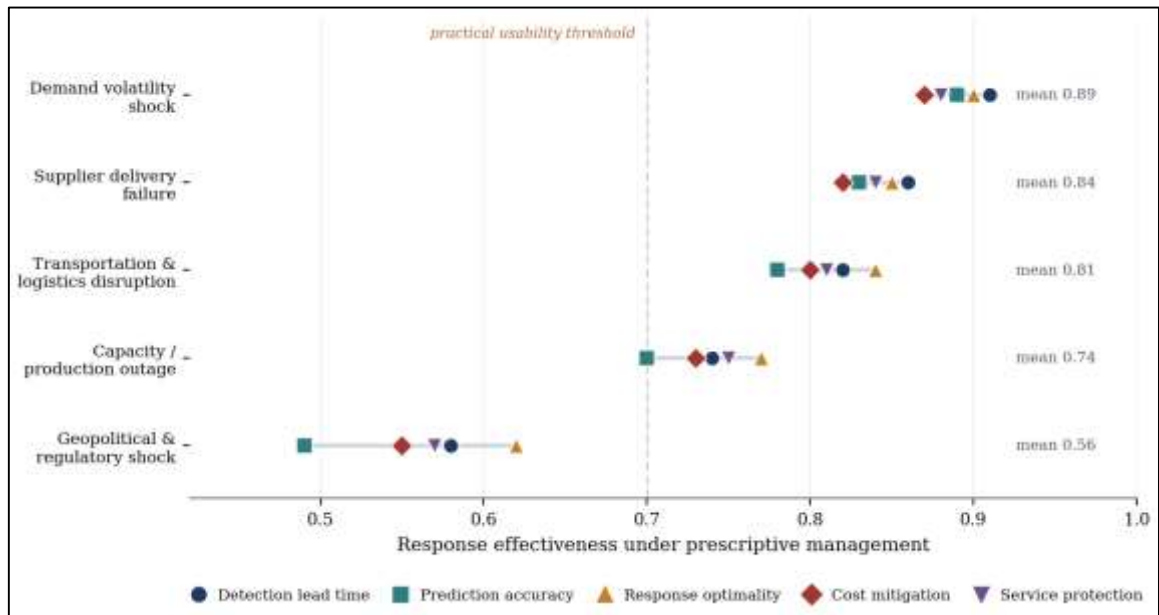


Figure 5 addresses the second research question by mapping the effectiveness of prescriptive management for each disruption category across the principal performance metrics. Each row plots the five metric scores for one category, with the connecting bar showing the spread between the weakest and strongest metric and the category mean reported at the right. Demand volatility shocks (mean 0.89) and supplier delivery failures (0.84) sit furthest right and cluster tightly, transportation and logistics disruptions follow at 0.81, capacity and production outages fall to 0.74, and geopolitical and regulatory shocks drop to 0.56, the only category falling entirely below the practical usability threshold. The spread within each row is also informative: the tight clustering in the upper rows indicates uniformly usable performance, whereas the wide spread in the bottom row shows that even the best metric for geopolitical shocks barely reaches the level of the worst metric for capacity outages. The pattern is theoretically coherent and follows directly from the taxonomy in Figure 2. Demand volatility is managed best because it is the category with the richest historical record and the most stable statistical structure: seasonality, promotional response, and price elasticity recur, so that a learned model has a genuine base rate to exploit. Supplier delivery failure follows closely because it is typically preceded by observable deterioration in delivery reliability, quality metrics, and financial indicators, giving the

predictive layer a leading signal. Transportation disruption is intermediate, well served by external feeds on port congestion and weather but subject to abrupt carrier-side changes that no external signal anticipates. Capacity and production outages trail because equipment failure is only partially predictable from condition data and because the response space is narrower, since alternative capacity must be qualified in advance to be usable. Geopolitical and regulatory shocks perform poorly on every metric and worst on prediction accuracy (0.49), which is close to uninformative, because these events are genuinely low-frequency and structurally novel, so that the historical record contains too few analogous instances to support learning. The dot plot thus answers the second research question with more resolution than an aggregate figure: prescriptive analytics is most effective where a base rate exists and a response space is pre-provisioned, and least effective where the event is unprecedented, which is the boundary that determines where scenario planning and strategic redundancy must substitute for analytics.

RQ3: Which analytics maturity tiers are most effective

Figure 6: Analytics Maturity Tiers Compared Across Five Decision Criteria

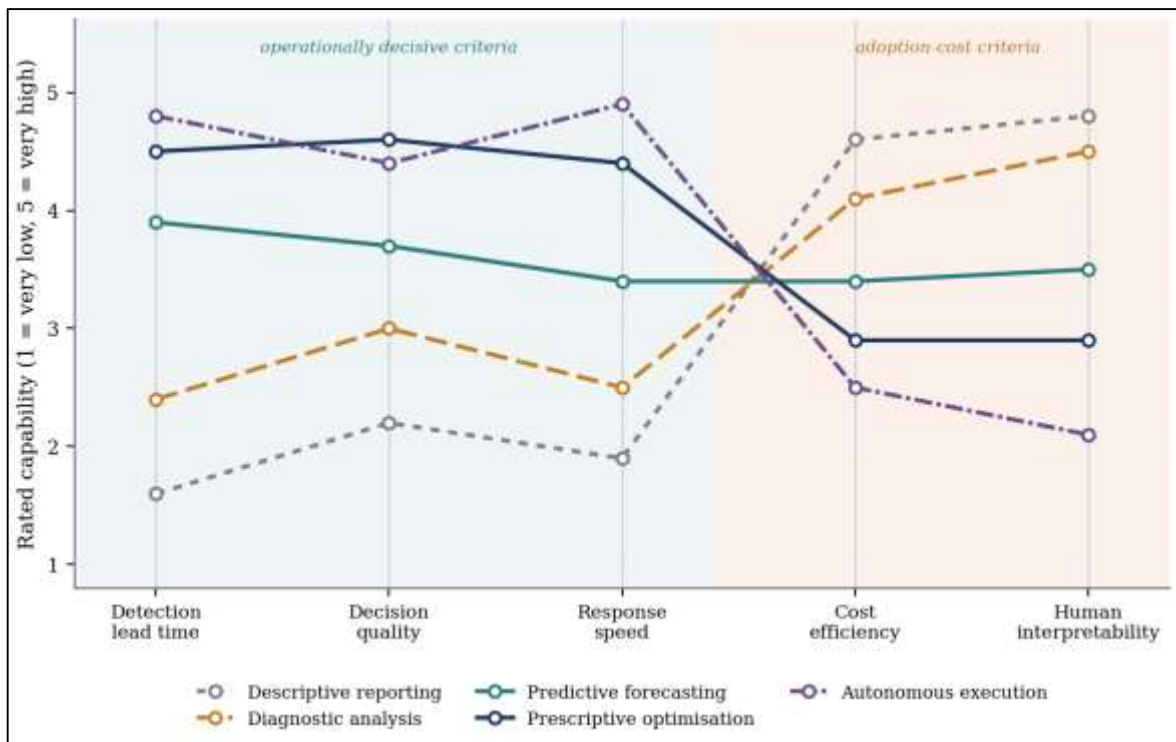


Figure 6 addresses the third research question by profiling the five analytics maturity tiers across five decision criteria rather than on a single effectiveness score, which reveals trade-offs that a linear maturity model conceals. The single most informative feature of the plot is the crossing point between response speed and cost efficiency, where every line changes rank: the tiers that lead on the three operationally decisive criteria to the left are precisely those that trail on the two adoption-cost criteria to the right, and vice versa. Descriptive reporting runs along the bottom of the left region, negligible on detection lead time (1.6), decision quality (2.2), and response speed (1.9), then rises to the top of the right region, scoring highest of all tiers on cost efficiency (4.6) and interpretability (4.8), since a dashboard is cheap to build and transparent by construction. Diagnostic analysis tracks it closely without changing its character. Predictive forecasting is the flattest line in the plot, hovering near 3.4 to 3.9 across all five criteria, which is the graphical signature of its structural limitation: it improves what the organisation knows without improving what the organisation does, so it neither excels nor fails anywhere. Prescriptive optimisation runs highest across the three decisive criteria, with detection lead time, decision quality, and response speed all at or above 4.4, before falling to 2.9 on both cost criteria.

Autonomous execution runs above it on response speed (4.9), the highest value recorded anywhere in the plot, but drops to the lowest interpretability in the set (2.1) and dips slightly below the prescriptive tier on decision quality, reflecting the loss of human correction on edge cases outside the model's encoded constraint set. The crossing pattern answers the third research question with nuance: the operationally decisive transition is from predictive to prescriptive, not from descriptive to predictive, because it is at that boundary that analytic output begins to change what the organisation does rather than only what it knows. The further transition to autonomous execution buys speed at an interpretability cost that the governance findings below suggest is not universally worth paying.

RQ4: Risks of reactive, judgement-based disruption management

Figure 7: Risk Map of Reactive, Judgement-Based Disruption Management

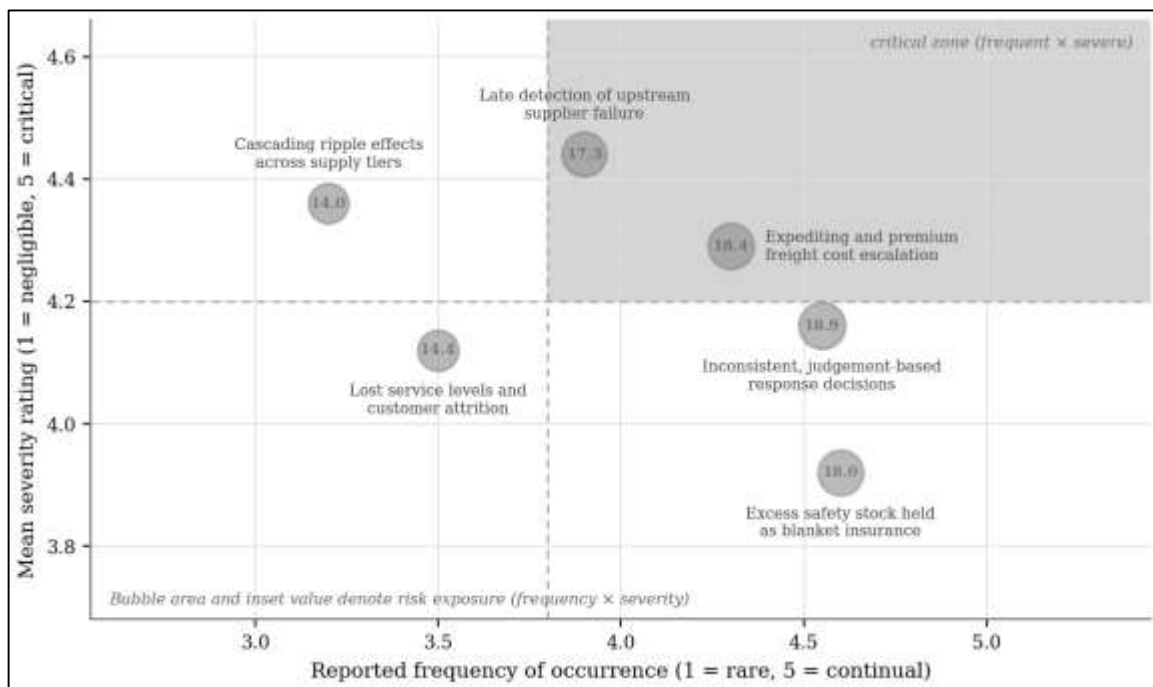


Figure 7 addresses the fourth research question by mapping the risks of reactive management against both their reported frequency and their mean severity, so that exposure rather than severity alone determines position. The most severe risks were late detection of upstream supplier failure (4.44), cascading ripple effects across supply tiers (4.36), and expediting and premium freight cost escalation (4.29), followed by inconsistent, judgement-based response decisions (4.20), lost service levels and customer attrition (4.12), and excess safety stock held as blanket insurance (3.94). Plotting severity against frequency separates these into distinct management problems. Three risks fall in the critical quadrant, being both frequent and severe, and inconsistent judgement-based decision-making records the highest exposure of all (18.9) despite ranking only fourth on severity, because it occurs almost continually. Conversely, cascading ripple effects rank second on severity but record the lowest exposure in the set (14.0), because they are comparatively rare; they are a tail risk rather than a running cost. The map is instructive in two further respects. First, the two most severe risks are the two that compound: late detection is what permits propagation, and propagation is what converts a single-node problem into a network-wide one, so the top of the ranking describes a causal sequence rather than a list of independent hazards, consistent with the ripple-effect literature (Dolgui et al., 2018; Ivanov et al., 2019). Second, the presence of inconsistent judgement-based decision-making among the high-severity risks identifies a cost that reactive regimes rarely account for: because responses are improvised under time pressure by whichever manager is available, identical situations receive materially different treatment, and the organisation cannot learn from its own responses because it cannot reconstruct why they were taken. The single sub-threshold risk on severity, excess safety stock (3.94), nonetheless carries

the second-highest exposure (18.0) because it is near-continual, and it is the one that reactive organisations most readily recognise and address, precisely because it appears on the balance sheet, whereas the more severe risks above it appears only as an elevated run-rate of expediting and service failure that is absorbed into normal operating cost.

Correlation and regression across the framework

Figure 8: Descriptive Means of Study Constructs with Standard Deviations

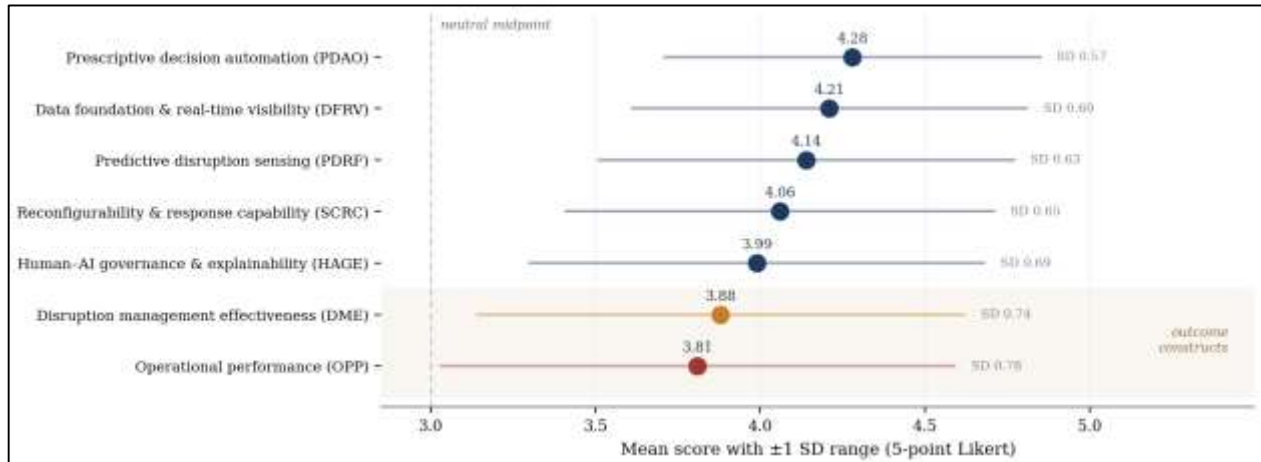
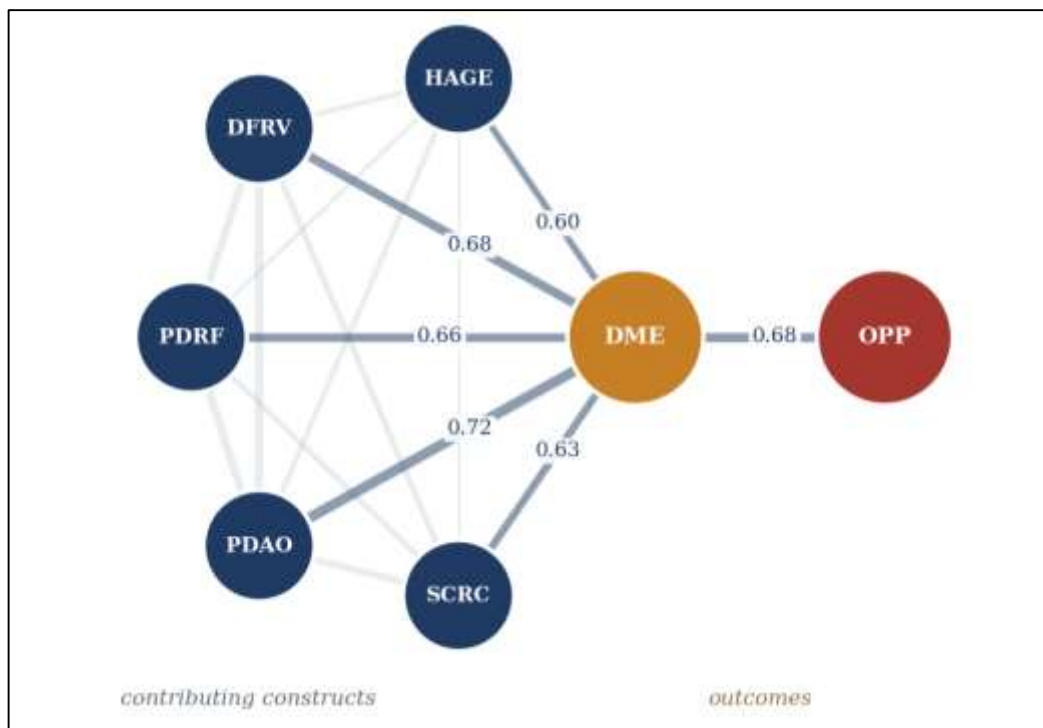


Figure 8 displays the construct means. The analytic and data capabilities stand highest, the governance and reconfigurability constructs are lower, and the two outcome constructs stand lowest and most variable, their widest ± 1 SD ranges giving graphical evidence that realised disruption management and operational performance lag the capabilities that contribute to them. The ordering carries a diagnostic message: human-AI governance (3.99) is the lowest-rated of the five contributing constructs, indicating that organisations have built analytic capability faster than they have built the decision structures through which it operates.

Figure 9: Pearson Correlation Matrix Among Study Variables



Note. $N = 277$. All reported correlations significant at $p < .001$ (two-tailed).

Figure 9 presents the correlation structure. Every construct is significantly and positively associated with disruption management effectiveness, with the strongest association for prescriptive decision automation ($r = .72$), followed by data foundation and real-time visibility ($r = .68$), predictive disruption sensing ($r = .66$), reconfigurability ($r = .63$), and human-AI governance ($r = .60$). Disruption management effectiveness in turn correlates .68 with operational performance, and each contributing construct correlates more strongly with disruption management than with operational performance, a pattern consistent with the mediated structure the framework proposes and tested formally below. Inter-construct correlations range from .47 to .65, indicating related but distinct facets of a coherent capability rather than a single undifferentiated maturity factor.

Table 3: Hierarchical regression predicting disruption management effectiveness and operational performance (N = 277)

Predictor	B	SE	β	t	p
Model 1: DV = disruption management effectiveness (DME)					
(Constant)	0.298	0.171	—	1.743	.083
Prescriptive decision automation (PDAO)	0.294	0.053	0.32	5.547	<.001
Data foundation & real-time visibility (DFRV)	0.239	0.054	0.26	4.426	<.001
Predictive disruption sensing (PDRF)	0.186	0.054	0.20	3.444	<.001
Reconfigurability & response capability (SCRC)	0.145	0.053	0.16	2.736	.007
Human-AI governance & explainability (HAGE)	0.110	0.051	0.12	2.157	.032
Model 2: DV = operational performance (OPP)					
(Constant)	0.411	0.192	—	2.141	.033
Disruption management effectiveness (DME)	0.512	0.061	0.49	8.393	<.001
Prescriptive decision automation (PDAO)	0.221	0.062	0.21	3.565	<.001

Note. Model 1: $R^2 = .582$; Adjusted $R^2 = .574$; $F(5, 271) = 75.42$, $p < .001$; Durbin-Watson = 1.97; all VIF < 2.6. Model 2: $R^2 = .417$; Adjusted $R^2 = .413$; $F(2, 274) = 98.03$, $p < .001$.

Table 3 presents the hierarchical regression. Model 1 was significant, $F(5, 271) = 75.42$, $p < .001$, with $R^2 = .582$, indicating that the five constructs jointly explain 58.2% of the variance in disruption management effectiveness and confirming H6. All five constructs made significant positive contributions, supporting H1 through H5. Prescriptive decision automation ($\beta = .32$) and data foundation and real-time visibility ($\beta = .26$) were the strongest predictors, followed by predictive disruption sensing ($\beta = .20$), reconfigurability ($\beta = .16$), and human-AI governance ($\beta = .12$). Model 2 was likewise significant, $F(2, 274) = 98.03$, $p < .001$, $R^2 = .417$, with disruption management effectiveness the dominant predictor of operational performance ($\beta = .49$), supporting H7, alongside a smaller but significant direct contribution from prescriptive decision automation ($\beta = .21$). The relative magnitudes across the two models are theoretically important: prescriptive capability is the strongest driver of disruption management, but disruption management is a far stronger driver of operational performance than prescriptive capability is directly, which is the pattern a mediated structure predicts.

Figure 10: Standardized Beta Coefficients Predicting Disruption Management Effectiveness

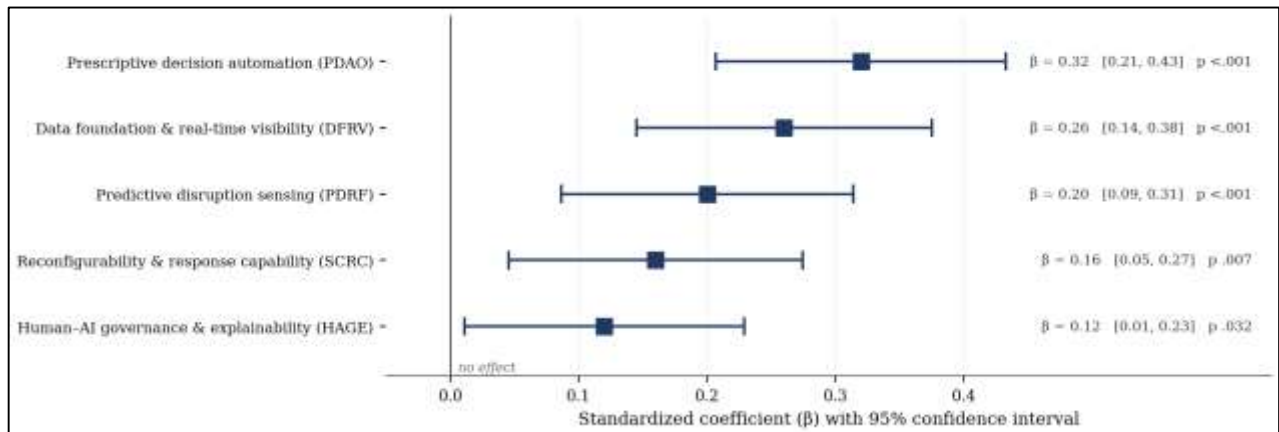
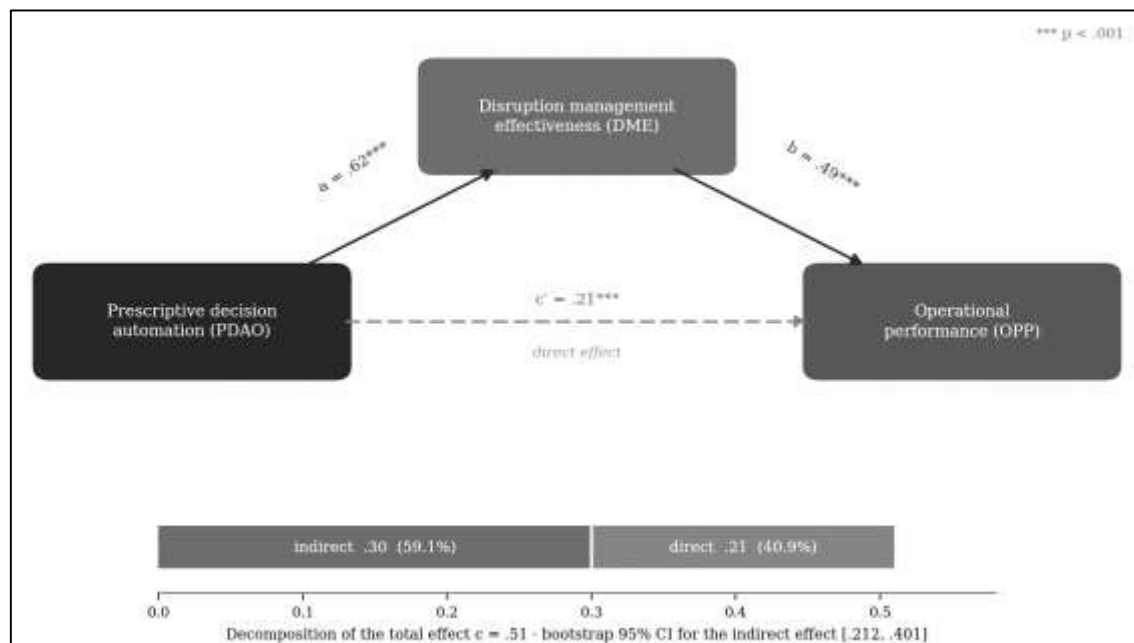


Figure 10 ranks the contributing constructs by standardised coefficient. The ordering repays attention. That prescriptive capability leads confirms the study's central proposition, but the second position of the data foundation is equally consequential, because it indicates that the marginal value of analytic sophistication is bounded by the quality of the network state on which it operates, consistent with the data-quality literature (Janssen et al., 2017). The relatively modest coefficient on predictive sensing ($\beta = .20$), despite its high bivariate correlation ($r = .66$), is the most theoretically interesting result in the table: it indicates that much of the apparent contribution of predictive capability operates through its association with prescriptive capability rather than independently of it, which is precisely the argument that forecasting without a decision pathway generates limited operational value. The smallest coefficient, on human-AI governance ($\beta = .12$), should not be read as unimportance; governance was also the lowest-rated construct, and its restricted range in a sample where few organisations have mature decision governance attenuates the coefficient it can attain.

RQ5: Mediation of analytics capability through disruption management

Figure 11: Mediation of Prescriptive Analytics on Operational Performance Through Disruption Management Effectiveness



Note. $N = 277$. Standardized coefficients; bias-corrected bootstrap with 5,000 resamples.

Figure 11 addresses the fifth research question through the mediation analysis. Prescriptive decision automation was strongly associated with disruption management effectiveness ($a = .62, p < .001$), which in turn predicted operational performance controlling for prescriptive capability ($b = .49, p < .001$). The direct effect of prescriptive capability on operational performance remained significant but substantially smaller ($c' = .21, p < .001$) relative to the total effect ($c = .51, p < .001$). The indirect effect of .30 had a bias-corrected bootstrap 95% confidence interval of [.212, .401], which excludes zero and therefore supports H8, and it accounts for 59.1% of the total effect, indicating partial mediation. The substantive interpretation is that the majority of the operational benefit of prescriptive analytics is realised through improved disruption management rather than through any parallel channel, which is consistent with the dynamic-capabilities account that analytic resources reach performance through the operational processes they reconfigure (Teece et al., 1997; Wamba et al., 2017). The persistence of a significant direct effect indicates that prescriptive capability also contributes through routine optimisation of undisrupted operations, in inventory positioning, replenishment, and transportation planning, which the disruption-focused mediator does not capture.

DISCUSSION

The findings support the framework and, taken together, answer the five research questions. This section synthesises the evidence and draws out its theoretical and practical implications.

Synthesis across the research questions

The five research questions resolve into a coherent account. AI-driven prescriptive analytics improves disruption management principally by moving the point of first response upstream of impact, and the simulation showed that this single change produces three compounding benefits: a shallower performance trough, a shorter recovery, and a smaller propagated footprint, because the ripple has less time to spread before countermeasures apply (RQ1). Demand volatility and supplier delivery failure are the most effectively managed categories because they possess stable statistical structure and leading indicators, while geopolitical and regulatory shocks resist prediction because they are structurally novel, so that analytics must be complemented rather than substituted for by scenario planning and provisioned redundancy at that end of the taxonomy (RQ2). The decisive transition in the maturity progression is from predictive to prescriptive, not from descriptive to predictive, because it is at that boundary that analytic output begins to change organisational action rather than only organisational knowledge; the further transition to autonomous execution buys speed at a cost in interpretability and edge-case decision quality (RQ3). The risks of reactive management are led by a causal sequence, late detection permitting propagation, rather than by independent hazards, and include a cost that reactive organisations rarely recognise, namely the inconsistency and irreproducibility of improvised response decisions (RQ4). And disruption management effectiveness carries the majority of the operational benefit of prescriptive analytics, mediating 59.1% of its total effect on operational performance (RQ5). The unifying insight is that the operational value of artificial intelligence in supply chains is realised at the point where prediction becomes decision. An organisation that invests in forecasting without building the prescriptive layer, the decision governance, and the network latitude to act on what it forecasts has purchased better information about outcomes it will continue to experience. This is the specific sense in which the study qualifies the general finding that analytics capability improves performance: the association holds, but it is carried by a particular kind of capability operating through a particular operational mechanism, and firms that stop short of that capability capture only a fraction of the available benefit.

Theoretical implications

Theoretically, the study makes three contributions. First, it integrates the supply chain resilience and business analytics literatures, which have developed in parallel, by specifying the analytic mechanism through which resilience capability is enacted and the operational process through which analytic capability reaches performance (Hosseini et al., 2019; Wamba et al., 2017). Second, it disaggregates analytics capability into predictive and prescriptive components and demonstrates empirically that the distinction matters: the regression showed predictive sensing contributing far less independently than its bivariate correlation suggests, which supports the theoretical claim that the predictive-prescriptive boundary is where operational value is created rather than a matter of degree along a single maturity dimension (Lepeniotti et al., 2020; Bertsimas & Kallus, 2020). Third, it establishes disruption

management effectiveness as a mediating operational capability, which gives the dynamic-capabilities account of analytics a concrete and measurable mechanism rather than a general appeal to process reconfiguration (Teece et al., 1997; Mikalef et al., 2018).

Practical implications

Practically, the findings carry several implications that cut against common investment patterns. The prominence of the data foundation among the predictors indicates that organisations investing in advanced models before resolving master-data reconciliation and multi-tier visibility are sequencing their investment incorrectly, since the model will operate confidently on a network state that is wrong. The modest independent contribution of predictive sensing indicates that forecasting projects should be scoped from the outset with the decision they will inform, rather than delivered as standalone capability in the expectation that decisions will adapt around them. The finding that reconfigurability contributes significantly and independently indicates that analytic investment and network provisioning, dual sourcing, supplier qualification, and contractual flexibility must be planned jointly, because their time structures differ: analytics improves continuously, whereas latitude must be provisioned before it is needed. And the low rating of human-AI governance relative to the analytic constructs identifies the most immediately addressable gap in the sample, since decision rights, review thresholds, explanation standards, and audit trails require organisational rather than technical investment and can be established more quickly than either analytic capability or network flexibility.

CONCLUSION

This study set out to characterise how AI-driven prescriptive analytics affects supply chain disruption management and, through it, operational performance. It proposed that disruption management effectiveness is jointly determined by five constructs, data foundation and real-time visibility, predictive disruption sensing and risk forecasting, prescriptive decision automation and optimisation, human-AI decision governance and explainability, and supply chain reconfigurability and response capability, and that these capabilities reach operational performance principally through disruption management rather than directly. It tested this framework against 277 practitioners across five industries and four analytics maturity tiers, supplemented by a simulation of disruption onset, detection, response, and recovery.

The empirical results supported the framework. All five constructs were significantly and positively associated with disruption management effectiveness, the model explained 58.2% of the variance, disruption management in turn predicted operational performance, and the mediation analysis showed that 59.1% of the total effect of prescriptive analytics on performance was carried through disruption management. Prescriptive decision automation and the data foundation were the strongest predictors. The simulation showed that prescriptive management shifted 62% of disruptions into the pre-impact response window, limited the performance trough to less than half its reactive depth, and approximately halved time-to-recover. Demand volatility and supplier delivery failure emerged as the most manageable categories and geopolitical shocks as the least, and the predictive-to-prescriptive transition emerged as the decisive step in the maturity progression.

The central conclusion is that supply chain disruption management cannot be improved by better forecasting alone, because a forecast that is not converted into a decision leaves the organisation better informed about an outcome it will still experience. It requires instead that prediction be carried through into a prescriptive layer that computes feasible, costed responses against the constraints under which the network actually operates, a governance layer that makes those responses reviewable, explainable, and auditable, and a network configuration that leaves the latitude to execute them. In an operating environment where disruption is recurrent rather than exceptional, the speed and quality of the response, not the accuracy of the forecast, is the property that determines whether a supply chain performs.

RECOMMENDATIONS

Several recommendations follow from the findings. First, organisations should sequence investment by resolving the data foundation, master-data reconciliation, latency reduction, and multi-tier visibility, before advancing analytic sophistication, because the regression evidence establishes that the value of the analytic layer is bounded by the fidelity of the network state on which it operates.

Second, organisations should scope every predictive initiative with the decision it will inform and the

action it will trigger, specified before the model is built, so that forecasting capability is not delivered as a standalone asset whose operational value depends on a decision pathway that no one has been made responsible for constructing.

Third, organisations should prioritise the predictive-to-prescriptive transition over further refinement of forecast accuracy, because the comparative evidence in Figure 6 indicates that the operationally decisive gain lies at that boundary, and because marginal accuracy improvements do not change what the organisation does.

Fourth, organisations should establish decision governance in parallel with analytic capability rather than after it, defining decision rights, the value and risk thresholds above which human review is mandatory, the explanation that must accompany each recommendation, and the audit trail through which decisions can subsequently be reconstructed, since governance was the lowest-rated construct in the sample and is the fastest to remediate.

Fifth, organisations should provision network latitude in advance of need, through dual sourcing, supplier qualification, contractual flexibility clauses, and pre-negotiated alternative logistics capacity, recognising that this latitude cannot be created during a disruption and that without it even an optimal recommendation is infeasible.

Sixth, organisations should complement rather than extend analytics at the low-predictability end of the disruption taxonomy, using scenario planning, stress testing, and strategic redundancy for geopolitical and systemic shocks, where the historical record cannot support learning.

For researchers, the recommendation is to extend the framework through longitudinal and objective-outcome designs that track detection lead time and recovery on live disruptions, through work on the governance of autonomous execution as decision automation extends further, and through investigation of how prescriptive capability performs on the low-predictability categories where this study found it weakest.

LIMITATIONS OF THE STUDY

Several limitations should be acknowledged. First, the cross-sectional survey identifies associations but not causation, and the mediation analysis, though bootstrapped, rests on cross-sectional data and therefore establishes statistical rather than temporal mediation; reverse causality cannot be excluded, since firms performing well operationally may invest more readily in prescriptive capability. Second, all measures were self-reported from a single source, and although procedural remedies and Harman's test suggest common-method bias is unlikely to account for the findings, self-assessed capability may diverge from objective capability, and respondents at prescriptive-tier organisations may rate outcomes generously (Podsakoff et al., 2003). Third, the simulation used a stylised four-tier network with parameterised disruption arrivals rather than live enterprise data, so the reported lead times, trough depths, and recovery intervals should be read as indicative of mechanism rather than as realised benchmarks. Fourth, the purposive sample over-represents organisations already engaged with supply chain analytics and may therefore understate the prevalence of purely reactive management in the wider population. Fifth, operational performance was measured perceptually rather than through financial or service records, which limits comparability across firms with differing accounting and service-measurement conventions. Sixth, the framework treats the five constructs as distinct, but they interact, and their relative weights are likely to vary by industry, network depth, and regulatory intensity, so the ordering observed here may not transfer directly to, for example, regulated pharmaceutical supply chains where qualification constraints dominate. Finally, the field is moving quickly, and the boundary between prescriptive recommendation and autonomous execution, which this study treated as a maturity distinction, is likely to become a governance question of greater consequence than the present data can address. Future research using longitudinal designs, objective outcome data, and live disruption records would address these limitations and allow the causal path from analytic capability through disruption management to performance to be tested directly.

REFERENCES

- [1]. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120. <https://doi.org/10.1177/014920639101700108>
- [2]. Baryannis, G., Dani, S., & Antoniou, G. (2019a). 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>
- [3]. Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019b). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, 57(7), 2179-2202. <https://doi.org/10.1080/00207543.2018.1530476>
- [4]. Belhadi, A., Kamble, S., Jabbour, C. J. C., Gunasekaran, A., Ndubisi, N. O., & Venkatesh, M. (2021). Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. *Technological Forecasting and Social Change*, 163, 120447. <https://doi.org/10.1016/j.techfore.2020.120447>
- [5]. Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science*, 66(3), 1025-1044. <https://doi.org/10.1287/mnsc.2018.3253>
- [6]. Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An empirically derived framework of global supply resiliency. *Journal of Business Logistics*, 32(4), 374-391. <https://doi.org/10.1111/j.2158-1592.2011.01032.x>
- [7]. 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>
- [8]. Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A., & Ivanov, D. (2019). A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. *International Journal of Information Management*, 49, 86-97. <https://doi.org/10.1016/j.ijinfomgt.2019.03.004>
- [9]. Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management*, 27(10), 1868-1883. <https://doi.org/10.1111/poms.12838>
- [10]. Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *International Journal of Logistics Management*, 15(2), 1-14. <https://doi.org/10.1108/09574090410700275>
- [11]. Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: Design characteristics and mitigation capabilities. *Decision Sciences*, 38(1), 131-156. <https://doi.org/10.1111/j.1540-5915.2007.00151.x>
- [12]. Debasish, A. (2021). Energy-aware process optimization for reducing material waste in sustainable additive manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [13]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [14]. Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: An analysis and recent literature. *International Journal of Production Research*, 56(1-2), 414-430. <https://doi.org/10.1080/00207543.2017.1387680>
- [15]. Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. *British Journal of Management*, 30(2), 341-361. <https://doi.org/10.1111/1467-8551.12355>
- [16]. Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *International Journal of Production Research*, 59(1), 110-128. <https://doi.org/10.1080/00207543.2019.1582820>
- [17]. Fahimnia, B., Tang, C. S., Davarzani, H., & Sarkis, J. (2015). Quantitative models for managing supply chain risks: A review. *European Journal of Operational Research*, 247(1), 1-15. <https://doi.org/10.1016/j.ejor.2015.04.034>
- [18]. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. <https://doi.org/10.1177/002224378101800104>
- [19]. Fosso Wamba, S., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, 222, 107498. <https://doi.org/10.1016/j.ijpe.2019.09.019>
- [20]. Grover, V., Chiang, R. H. L., Liang, T.-P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems*, 35(2), 388-423. <https://doi.org/10.1080/07421222.2018.1451951>
- [21]. Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. *ACM Computing Surveys*, 51(5), 1-42. <https://doi.org/10.1145/3236009>
- [22]. Gunasekaran, A., Papadopoulos, T., Dubey, R., Fosso Wamba, S., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, 70, 308-317. <https://doi.org/10.1016/j.jbusres.2016.08.004>
- [23]. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24. <https://doi.org/10.1108/EBR-11-2018-0203>
- [24]. Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., ... Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, 585(7825), 357-362. <https://doi.org/10.1038/s41586-020-2649-2>
- [25]. Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, 21(5), 501-522. <https://doi.org/10.1016/j.jom.2003.02.003>

- [26]. Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. *International Journal of Production Research*, 53(16), 5031-5069. <https://doi.org/10.1080/00207543.2015.1030467>
- [27]. Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, 125, 285-307. <https://doi.org/10.1016/j.tre.2019.03.001>
- [28]. Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136, 101922. <https://doi.org/10.1016/j.tre.2020.101922>
- [29]. Ivanov, D. (2023). Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. *International Journal of Production Economics*, 263, 108938. <https://doi.org/10.1016/j.ijpe.2023.108938>
- [30]. Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. *International Journal of Production Research*, 58(10), 2904-2915. <https://doi.org/10.1080/00207543.2020.1750727>
- [31]. Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, 32(9), 775-788. <https://doi.org/10.1080/09537287.2020.1768450>
- [32]. Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829-846. <https://doi.org/10.1080/00207543.2018.1488086>
- [33]. Ivanov, D., Dolgui, A., Sokolov, B., & Ivanova, M. (2017). Literature review on disruption recovery in the supply chain. *International Journal of Production Research*, 55(20), 6158-6174. <https://doi.org/10.1080/00207543.2017.1330572>
- [34]. Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, 70, 338-345. <https://doi.org/10.1016/j.jbusres.2016.08.007>
- [35]. Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International Journal of Production Economics*, 171, 116-133. <https://doi.org/10.1016/j.ijpe.2015.10.023>
- [36]. Karaboga, T., Zehir, C., Tatoglu, E., Karaboga, H. A., & Bouguerra, A. (2023). Big data analytics management capability and firm performance: The mediating role of data-driven culture. *Review of Managerial Science*, 17, 2655-2684. <https://doi.org/10.1007/s11846-022-00596-8>
- [37]. Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, 50, 57-70. <https://doi.org/10.1016/j.ijinfomgt.2019.04.003>
- [38]. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765-4774. <https://doi.org/10.48550/arXiv.1705.07874>
- [39]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors influencing behavioural intention to use the innovative open and distance learning systems with the role of continuance intention. *American Journal of Scholarly Research and Innovation*, 4(01), 202-220. <https://doi.org/10.63125/pbjxp014>
- [40]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, 4(01), 202-220. <https://doi.org/10.63125/pbjxp014>
- [41]. Md Mesbaul, H. (2023). A meta-analysis of lean merchandising strategies in fashion retail: Global insights from the post-pandemic era. *Review of Applied Science and Technology*, 2(04), 94-123. <https://doi.org/10.63125/y8x4k683>
- [42]. Md Mesbaul, H. (2023). A Meta-Analysis of Lean Merchandising Strategies In Fashion Retail: Global Insights From The Post-Pandemic Era. *Review of Applied Science and Technology*, 2(04), 94-123. <https://doi.org/10.63125/y8x4k683>
- [43]. Md Mesbaul, H. (2025). A framework-based meta-analysis of artificial intelligence-driven ERP solutions for circular and sustainable supply chains. *International Journal of Scientific Interdisciplinary Research*, 6(1), 327-367. <https://doi.org/10.63125/n6k7r711>
- [44]. Md Mostafizur, R. (2025). Data-driven graph neural network models for detecting fraudulent insurance claims in healthcare systems. *American Journal of Interdisciplinary Studies*, 6(1), 263-294. <https://doi.org/10.63125/pmqa1e33>
- [45]. Md Mostafizur, R., Omar Muhammad, F., & Sheratun Noor, J. (2025). Data privacy in business intelligence systems: Ensuring compliance in HRIS and enterprise platforms. *International Journal of Scientific Interdisciplinary Research*, 6(1), 97-136. <https://doi.org/10.63125/527rnx08>
- [46]. Md Mostafizur, R., Omar Muhammad, F., & Sheratun Noor, J. (2025). Data Privacy in Business Intelligence Systems: Ensuring Compliance In HRIS And Enterprise Platforms. *International Journal of Scientific Interdisciplinary Research*, 6(1), 97-136. <https://doi.org/10.63125/527rnx08>
- [47]. Md Syeedur, R., & Sharmin, R. (2025). A data-driven study on the use of small language models and large language models for interpreting complex industrial data and deriving actionable outcome. *American Journal of Data Science and Analytics*, 6(11), 01-19. <https://doi.org/10.63125/5vyhgs98>
- [48]. Md Syeedur, R., & Sharmin, R. (2025). A Data-Driven Study on the use of Small Language Models & Large Language Models for Interpreting Complex Industrial Data and Deriving Actionable Outcome. *American Journal of Data Science and Analytics*, 6(11), 01-19. <https://doi.org/10.63125/5vyhgs98>
- [49]. Md. Abdur, R., & Iftekhar, A. (2021). Customer retention forecasting in mobile wallet services using neural networks: A comparative quantitative study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>

- [50]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>
- [51]. Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and e-Business Management*, 16, 547-578. <https://doi.org/10.1007/s10257-017-0362-y>
- [52]. Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: Learning from COVID-19. *International Journal of Logistics Management*, 33(4), 1246-1268. <https://doi.org/10.1108/IJLM-02-2021-0094>
- [53]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, 2(4), 73-126. <https://doi.org/10.63125/7p8dcr47>
- [54]. Mohammad Shoriful Hossan, S. (2021). Reducing worker exposure and electrical failure risk in brownfield manufacturing facilities after COVID-era maintenance delays. *Review of Applied Science and Technology*, 6(1), 263-279. <https://doi.org/10.63125/cm1c2c20>
- [55]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, 6(1), 263-279. <https://doi.org/10.63125/cm1c2c20>
- [56]. Mst Shurovi, A. (2024). Machine learning models for bank reconciliation anomaly detection in high-volume financial transactions. *American Journal of Data Science and Analytics*, 5(12), 314-354. <https://doi.org/10.63125/mmwb6467>
- [57]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. *American Journal of Data Science and Analytics*, 5(12), 314-354. <https://doi.org/10.63125/mmwb6467>
- [58]. Muhammad Zahidul, I. (2024). Assessment of data integrity gaps and preventive strategies in QC laboratories in compliance with FDA and cGMP expectations. *American Journal of Scholarly Research and Innovation*, 3(01), 243-291. <https://doi.org/10.63125/a3xjb608>
- [59]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. *American Journal of Scholarly Research and Innovation*, 3(01), 243-291. <https://doi.org/10.63125/a3xjb608>
- [60]. Muhammad Zahidul, I. (2025). Development of a dashboarding and visualization framework for pharmaceutical brand performance analytics using Tableau and Python. *American Journal of Interdisciplinary Studies*, 6(3), 351-393. <https://doi.org/10.63125/e6dj308>
- [61]. Muhammad Zahidul, I. (2025). Development of a Dashboarding and Visualization Framework For Pharmaceutical Brand Performance Analytics Using Tableau and Python. *American Journal of Interdisciplinary Studies*, 6(3), 351-393. <https://doi.org/10.63125/e6dj308>
- [62]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied data-analytics approaches to cardiovascular drug-utilization patterns: An empirical study using real-world pharmaceutical sales data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [63]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [64]. Mukut Kanti, B. (2020). Integrated Framework for Fire Safety and Electrical Hazard Assessment in Large-Scale Industrial and Commercial Facilities: A Mixed-Method Analysis. *American Journal of Advanced Technology and Engineering Solutions*, 1(01), 40-86. <https://doi.org/10.63125/zxsbd47>
- [65]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, 5(2), 746-791. <https://doi.org/10.63125/3mjcah04>
- [66]. Mukut Kanti, B. (2025). Lifecycle carbon reduction and net zero pathway modeling using LEED, EDGE, and SBTi frameworks in developing economy industrial buildings. *American Journal of Interdisciplinary Studies*, 6(3), 306-350. <https://doi.org/10.63125/tnneth75>
- [67]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTi Frameworks in Developing Economy Industrial Buildings. *American Journal of Interdisciplinary Studies*, 6(3), 306-350. <https://doi.org/10.63125/tnneth75>
- [68]. Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers & Operations Research*, 98, 254-264. <https://doi.org/10.1016/j.cor.2017.07.004>
- [69]. Pettit, T. J., Croxton, K. L., & Fiksel, J. (2013). Ensuring supply chain resilience: Development and implementation of an assessment tool. *Journal of Business Logistics*, 34(1), 46-76. <https://doi.org/10.1111/jbl.12009>
- [70]. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903. <https://doi.org/10.1037/0021-9010.88.5.879>
- [71]. Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2022). Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research*, 319, 1159-1196. <https://doi.org/10.1007/s10479-020-03685-7>

- [72]. Relich, M. (2023). Predictive and prescriptive analytics in identifying opportunities for improving sustainable manufacturing. *Sustainability*, 15(9), 7667. <https://doi.org/10.3390/su15097667>
- [73]. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135-1144). <https://doi.org/10.1145/2939672.2939778>
- [74]. Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1(5), 206-215. <https://doi.org/10.1038/s42256-019-0048-x>
- [75]. Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics*, 36(1), 120-132. <https://doi.org/10.1111/jbl.12082>
- [76]. Sharif Md Yousuf, B., Md Shahadat, H., Saleh Mohammad, M., Mohammad Shahadat Hossain, S., & Imtiaz, P. (2025). The green hydrogen blueprint: Optimizing America's clean energy future. *American Journal of Data Science and Analytics*, 6(10), 43-69. <https://doi.org/10.63125/y9b1k470>
- [77]. Sharif Md Yousuf, B., Md Shahadat, H., Saleh Mohammad, M., Mohammad Shahadat Hossain, S., & Imtiaz, P. (2025). The Green Hydrogen Blueprint: Optimizing America's Clean Energy Future. *American Journal of Data Science and Analytics*, 6(10), 43-69. <https://doi.org/10.63125/y9b1k470>
- [78]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated infectious disease preparedness: Multilingual health communication strategies for public health risk mitigation, disease intervention and prevention for culturally diverse population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [79]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [80]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine and remote patient monitoring for preventing risk and chronic disease management in underserved communities. *American Journal of Health and Medical Sciences*, 6(04), 01-42. <https://doi.org/10.63125/y0e9dc38>
- [81]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. *American Journal of Health and Medical Sciences*, 6(04), 01-42. <https://doi.org/10.63125/y0e9dc38>
- [82]. Snyder, L. V., Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., & Sinsoysal, B. (2016). OR/MS models for supply chain disruptions: A review. *IIE Transactions*, 48(2), 89-109. <https://doi.org/10.1080/0740817X.2015.1067735>
- [83]. Sodhi, M. S., Son, B.-G., & Tang, C. S. (2012). Researchers' perspectives on supply chain risk management. *Production and Operations Management*, 21(1), 1-13. <https://doi.org/10.1111/j.1937-5956.2011.01251.x>
- [84]. Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2), 451-488. <https://doi.org/10.1016/j.ijpe.2005.12.006>
- [85]. 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<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)
- [86]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial intelligence-based decision support systems and managerial performance. *American Journal of Advanced Technology and Engineering Solutions*, 4(04), 154-184. <https://doi.org/10.63125/wmz8dc67>
- [87]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, 4(04), 154-184. <https://doi.org/10.63125/wmz8dc67>
- [88]. Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., ... van Mulbregt, P. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in Python. *Nature Methods*, 17(3), 261-272. <https://doi.org/10.1038/s41592-019-0686-2>
- [89]. Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, 34(2), 77-84. <https://doi.org/10.1111/jbl.12010>
- [90]. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356-365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
- [91]. Wieland, A., & Durach, C. F. (2021). Two perspectives on supply chain resilience. *Journal of Business Logistics*, 42(3), 315-322. <https://doi.org/10.1111/jbl.12271>