Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 3, 2026

EVALUATING THE IMPACT OF PREDICTIVE ANALYTICS ON LOGISTICS EFFICIENCY AND OPERATIONAL RISK MANAGEMENT IN DIGITALLY TRANSFORMED SUPPLY CHAINS

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DOI: https://doi.org/10.5281/zenodo.24278884

Keywords
Digital transformation; predictive analytics; supply chain management; logistics efficiency; operational risk management; artificial intelligence; supply chain resilience.

Article History
Received: 07 January 2026
Accepted: 17 March 2026
Published: 31 March 2026

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Abstract
The practice of sharing children's photos and private information online is known as "sharenting," and this study investigates how Pakistani parents view and handle these ethical and privacy issues. Twelve in-depth interviews with socially engaged Pakistani parents of young children were subjected to a thematic analysis in NVivo 15 using an interpretive qualitative method. The results demonstrate that parents use sharenting primarily to celebrate milestones, preserve memories, uphold family ties, and obtain social validation; however, privacy and child safety concerns influence their choices. Image abuse, AI-based manipulation, identity theft, digital kidnapping, regular tracking, unfavorable online interactions, and long-term digital footprint risks were all noted by participants. What parents share and with whom is also influenced by cultural and religious values, such as modesty (haya), fear of the evil eye (Nazar), and family honor (izzat). In response, parents use private WhatsApp groups, audience restrictions, face masking, location avoidance, privacy settings, and increasing their children's participation in consent as they get older. However, families are primarily dependent on self-regulation due to a lack of knowledge about children's digital rights and perceived weaknesses in Pakistan's institutional and legal framework.

1. INTRODUCTION

Supply chains coordinate procurement, production, inventory, transportation, warehousing and distribution across organisations and geographic locations. Global sourcing, shorter delivery expectations, demand volatility and interconnected supplier networks have increased the complexity of these activities. Traditional approaches based on periodic reporting and historical averages remain useful, but they can be slow to identify emerging disruptions or changing demand patterns.

Digital transformation offers organisations opportunities to connect operational processes through enterprise resource planning (ERP), cloud computing, IoT devices, tracking systems and analytics platforms. Wang et al. (2016) distinguish descriptive analytics, which explains past performance; predictive analytics, which estimates future outcomes; and prescriptive analytics, which supports the selection of actions. Their work highlights the importance of progressing from isolated functional applications towards integrated supply chain analytics.

Predictive analytics applies statistical models and machine-learning methods to estimate future demand, delivery times, equipment failures, supplier performance and disruption risks. These estimates can inform inventory replenishment, transportation scheduling, warehouse capacity and contingency planning. However, prediction is not equivalent to prevention: a forecast creates value only when an organisation has the authority, resources and processes to act on it.

Empirical studies provide evidence for the broader relevance of digital and analytical capabilities. He et al. (2024) examined 40,321 firm-year observations from Chinese A-share listed companies over 2007–2022 and reported a positive, statistically significant association between digital transformation and supply chain efficiency. Wei et al. (2022), using 159 matched questionnaires, reported positive direct and indirect relationships between big data analytics use and supply chain performance, with lean and agile strategies acting as mediating mechanisms. Dubey et al. (2019) analysed 173 usable responses and identified a positive relationship between big data analytics capability and supply chain agility.

Despite this evidence, the literature often examines digital transformation, forecasting performance, logistics efficiency and resilience as related but separate topics. This creates a need for an integrated framework that distinguishes predictive model performance from the operational outcomes and risk responses that may follow.

1.1 Research problem, aim and objectives

Research problem: Although digital technologies and predictive analytics are increasingly used in supply chain management, the pathways through which predictive capability contributes to measurable logistics efficiency and operational risk-management capability require further integrated investigation.

The aim is to develop and evaluate an evidence-based framework explaining the role of predictive analytics in logistics efficiency and operational risk management within digitally transformed supply chains.

The objectives are to:

Q1 examine predictive analytics applications across supply chain operations?

Q2 identify its proposed relationships with logistics efficiency?

Q3 examine its contribution to operational risk identification and response?

Q4 assess the enabling roles of data quality, digital integration and organisational readiness?

Q5 specify measurable indicators and hypotheses for future empirical testing?

Research questions: How is predictive analytics capability associated with logistics efficiency? How can predictive models support operational risk identification and response? How do data quality and digital integration influence model reliability? Which organisational capabilities help convert predictive information into operational action?

1.2 Research gap and contribution

Prior research establishes links between digital transformation, analytics capability, supply chain performance and resilience. Nevertheless, the evidence is distributed across different levels of analysis: firm-level digital transformation, survey-based analytics capability, model-level forecasting performance and literature reviews of resilience. These outcomes are not interchangeable. In particular, improved forecast accuracy does not necessarily demonstrate lower logistics costs, fewer disruptions or faster recovery. This article addresses the conceptual gap by bringing predictive capability, logistics indicators and risk-management processes into one framework, while keeping published findings separate from proposed measurements and hypotheses.

The contribution is fourfold: it integrates logistics efficiency and operational risk management; distinguishes model-level metrics from operational outcomes; provides a measurable framework for future quantitative testing; and uses the resource-based view and dynamic capabilities theory to explain how digital resources may be converted into responsive operational capabilities.

2. Literature Review

2.1 Digital transformation in supply chain operations

Digital transformation involves embedding digital technologies in organisational structures, processes and decisions. In supply chains, it can connect

suppliers, manufacturers, logistics providers, warehouses and customers through shared information systems. Wang et al. (2016) describe the progression from descriptive to predictive and prescriptive analytics. Toorajipour et al. (2021), in a systematic review of AI in supply chain management, identify applications across logistics, production, marketing and wider supply chain functions.

Digital infrastructure can improve visibility and coordination, but adoption alone does not guarantee integration. Separate ERP, warehouse-management and transportation-management systems may continue to create information silos. He et al. (2024) provide evidence of a positive association between broader digital transformation and supply chain efficiency, but their analysis does not isolate the effect of predictive analytics from other digital technologies.

2.2 Predictive analytics and logistics efficiency

Predictive analytics can support demand forecasting, inventory replenishment, estimated arrival-time prediction, route planning, warehouse workload forecasting and predictive maintenance. Forecasts can reduce uncertainty in operational planning, but performance should be evaluated at two levels: the accuracy of the prediction and the operational result of the decision made using that prediction.

Pietukhov et al. (2023) examined a hybrid forecasting approach combining logistic regression and neural networks in a large supply chain organisation. Their investigation involved 30 organisational teams and reported a 17% improvement in accuracy and a 13% improvement in F1 score compared with a baseline that did not incorporate process-improvement information. These are model-performance improvements reported by that study; they are not reductions in delivery delays or costs, and should not be generalised to all organisations.

Wei et al. (2022) provide complementary organisational evidence. Their findings suggest that analytics use relates to supply chain performance both directly and indirectly through lean and agile strategies. This indicates that analytical information creates value through operational practices, not through software adoption alone.

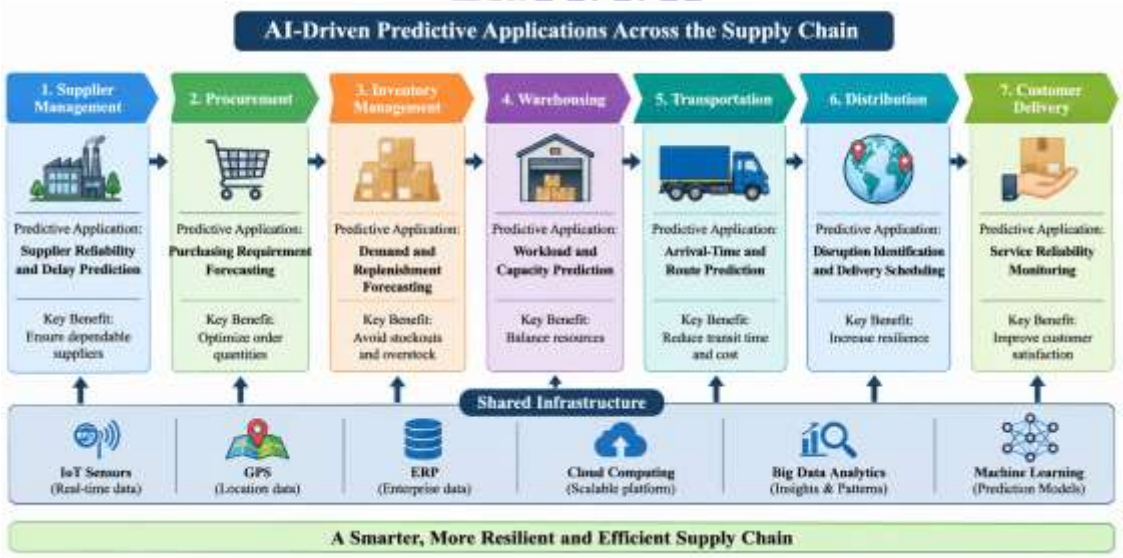


Figure 1. Predictive analytics applications across supply chain operations

2.3 Predictive analytics and operational risk management

Operational risks include supplier failure, transportation disruption, inventory shortages, equipment breakdown, information-system interruption and unexpected demand changes. Predictive systems can monitor leading indicators, identify anomalies and estimate the likelihood or impact of potential events. Emrouznejad et al. (2023) review supply chain risk management

research and identify environmental, organisational and network-related risk sources, emphasising the importance of cooperation and information sharing.

Ivanov and Dolgui (2021) discuss the digital supply chain twin as a means of representing supply chain structures and processes in a digital environment. Such representations can help organisations examine disruption scenarios and compare possible responses. Smyth et al. (2024) reviewed AI and prescriptive analytics for supply chain resilience. Their search retrieved 5,293 records and selected 76 primary studies. The calculated inclusion proportion is 1.44%; this is a screening statistic, not an adoption rate or an effect estimate.

Predictive risk models have limitations. Rare events may be poorly represented in historical data, while geopolitical, environmental or technological changes can make past patterns less informative. False alerts can also create unnecessary intervention costs. Predictive outputs should therefore be treated as decision support, combined with human oversight, scenario planning and contingency procedures.



Figure 2. Predictive analytics process for operational risk management

2.4 Organisational barriers and enabling conditions

Data quality affects model reliability: missing, duplicated, delayed or inconsistent records can undermine forecasts. Digital integration matters because operational information is often distributed across ERP, warehouse, procurement and transportation systems. Organisational readiness also matters because employees need analytical skills, decision rights and clear escalation procedures.

Dubey et al. (2019), using 173 usable organisational responses, found a positive association between big data analytics capability and supply chain agility. Organisational flexibility strengthened the relationship between analytics capability and agility, although the same moderating effect was not identified for competitive advantage. This reinforces the need to consider organisational conditions alongside technical capability.

2.5 Comparative evidence from previous studies

Table 1. Comparative quantitative evidence reported in previous research

Study	Design / evidence base	Published quantitative result	Interpretation
He et al. (2024)	Chinese A-share listed companies, 2007–2022	40,321 firm-year observations; coefficients 0.0316 and 0.0378; $p < .01$	Positive association between digital transformation and the study's supply chain-efficiency measure; coefficients are not percentage changes.
Wei et al. (2022)	Organisational survey	159 matched questionnaires	Positive direct and indirect relationships between analytics use and supply chain performance; effect-size percentage not stated here.
Dubey et al. (2019)	Organisational survey	173 usable responses	Positive relationship between analytics capability and supply chain agility; no percentage effect reported here.
Pietukhov et al. (2023)	Forecasting investigation in one large supply chain organisation	30 teams; accuracy improved by 17%; F1 score improved by 13%	Reported relative improvements against the study's baseline; not logistics cost or delay reductions.
Smyth et al. (2024)	Systematic literature review	5,293 records retrieved; 76 primary studies included; 1.44% calculated inclusion proportion	Review-screening proportion, calculated as 76 ÷ 5,293 × 100; not a supply chain performance rate.
Emrouznejad et al. (2023)	Content-analysis-based review	No pooled sample percentage reported in the article summary used here	Identifies risk categories and research themes rather than a common operational effect size.

3. Theoretical and Conceptual Framework

3.1 Resource-based view

The resource-based view argues that valuable organisational resources can support sustained competitive advantage (Barney, 1991). In digital supply chains, relevant resources include integrated information systems, operational databases, analytical technologies, skilled employees and data-governance routines. Predictive analytics can be understood as a capability created by combining these technological and human resources.

3.2 Dynamic capabilities theory

Dynamic capabilities theory explains how organisations sense opportunities and threats, seize opportunities and reconfigure resources as conditions change (Teece, 2007). Predictive analytics can strengthen sensing by identifying emerging demand shifts or disruption signals. It can support seizing through decisions about procurement, inventory and transportation. It can support reconfiguration when organisations change routes, allocate inventory differently or qualify alternative suppliers.

3.3 Proposed conceptual model and hypotheses

The proposed model treats digital transformation as the technological foundation and predictive analytics capability as the central organisational capability. Logistics efficiency and operational risk-management capability are separate outcomes. Data quality and digital integration are expected to support prediction reliability, while organisational readiness is expected to influence whether predictive insights are translated into action.

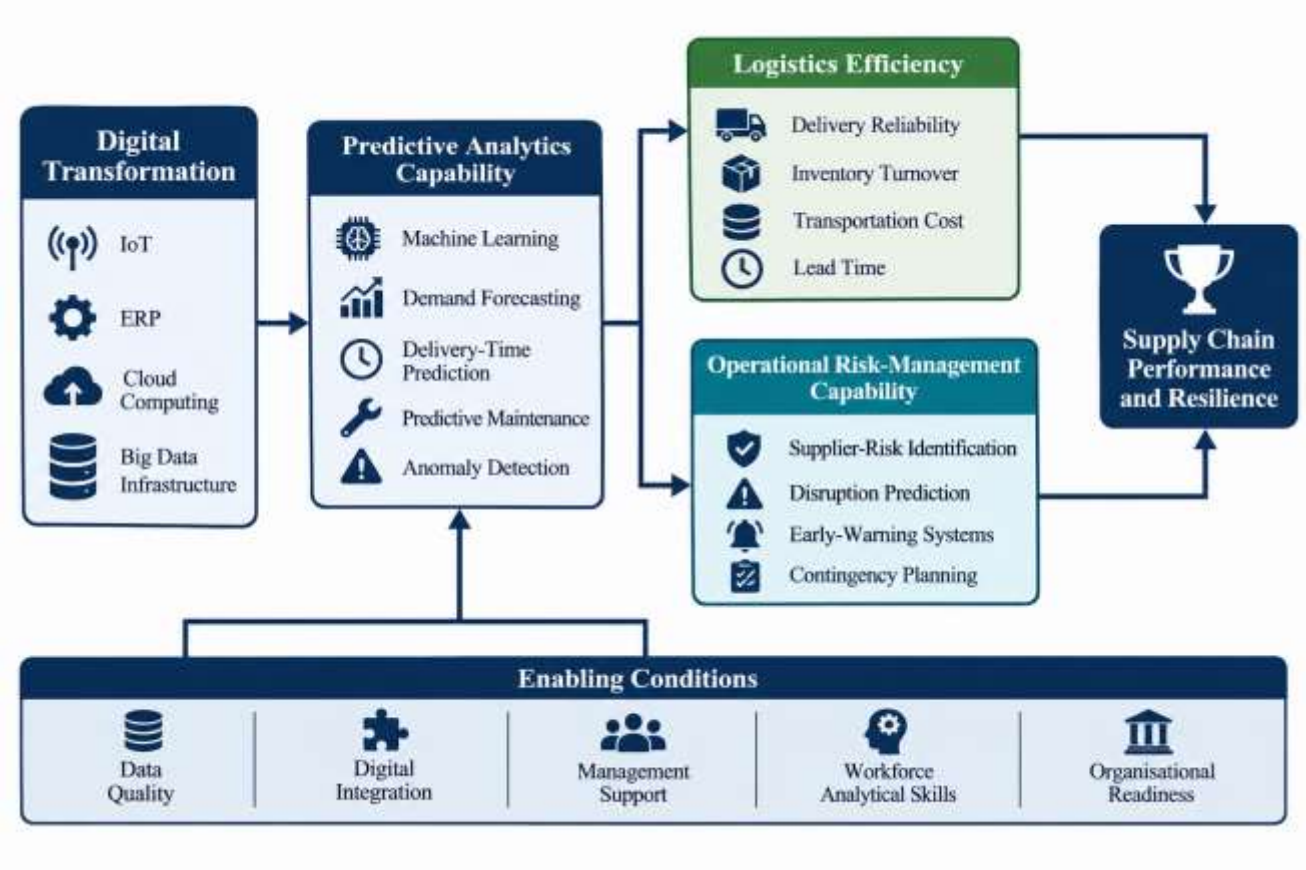


Figure 3. Integrated conceptual framework .

The diagram should show digital transformation (IoT, ERP, cloud computing and big data infrastructure) feeding predictive analytics capability (machine learning, demand forecasting, delivery-time prediction and anomaly detection). Predictive analytics should connect to two distinct outcomes: logistics efficiency and operational risk-management capability. Both outcomes may contribute to supply chain performance and resilience. Data quality, digital integration, management support, workforce analytical skills and organisational readiness should be shown as enabling conditions.

The following hypotheses are proposed for future empirical testing:

H1: Predictive analytics capability is positively associated with logistics efficiency.

H2: Predictive analytics capability is positively associated with operational risk-management capability.
H3: Digital integration is positively associated with predictive analytics effectiveness.
H4: Data quality is positively associated with predictive model reliability.
H5: Organisational readiness is positively associated with effective predictive analytics implementation.
H6: Predictive analytics capability is positively associated with supply chain resilience.
H7: Organisational readiness positively moderates the relationship between predictive analytics capability and logistics efficiency.

4. Proposed Research Methodology

4.1 Research design and population

A quantitative explanatory design is proposed. The target population comprises organisations engaged in manufacturing, retail distribution, transportation, warehousing and third-party logistics. Potential respondents include supply chain managers, logistics managers, procurement officers, warehouse managers, transportation coordinators and data-analytics specialists. The study has not yet been conducted; therefore, no original sample size, response rate or empirical result is claimed.

Purposive sampling can identify organisations with established digital information systems. Stratified sampling across industry, organisation size and logistics function may then improve coverage. The final sample size should be determined by an a priori statistical power analysis based on the planned number of predictors, anticipated effect size, significance level and desired statistical power. The sample size should not be selected by copying the sample sizes of earlier studies.

4.2 Data collection and measurement

Primary data may be collected through a structured questionnaire using validated multi-item scales for predictive analytics capability, digital integration, data quality, organisational readiness and risk-management capability. Where organisations permit access, secondary operational records should be collected for forecasting errors, delivery performance, inventory movement, transport expenditure, supplier reliability and incident response. Survey perceptions and objective operational records should be analysed separately where their measurement levels differ.

Table 2. Proposed variables and operational measurement plan

Construct / variable	Operational indicator	Measurement / unit	Proposed data source
Predictive analytics capability	Use of forecasting, anomaly detection and predictive decision support	Multi-item Likert scale; report scale mean and reliability	Questionnaire; system-use records
Forecast accuracy	Absolute forecast error relative to actual demand	MAPE (%) or WAPE (%)	Forecasting records
Delivery reliability	Orders delivered by agreed due date	On-time delivery rate (%)	Transportation / order records
Inventory efficiency	Cost of goods sold relative to average inventory	Inventory turnover (times per period)	Inventory and finance records
Stockout incidence	Product-location-periods with at least one stockout	Stockout incidence (%)	Inventory records
Transportation efficiency	Transportation expenditure divided by completed deliveries	Currency per delivery	Transport and finance records
Supplier reliability	Supplier deliveries received on or before agreed date	Supplier on-time delivery rate (%)	Procurement records
Operational disruption	Recorded disruption events over a defined exposure	Count or rate per 100 operating periods;	Incident-management records

	period	denominator specified	
Risk responsiveness	Elapsed time between actionable warning and response	Hours or days	Alert and incident logs
Organisational readiness	Management support, employee skills and decision authority	Multi-item Likert scale	Questionnaire

These are proposed measures, not observed results. The unit of analysis and denominator must be fixed before data collection. Survey scales should be piloted and checked for content validity, internal consistency and construct validity.

4.3 Data preparation and statistical analysis

The analysis should begin with data screening, descriptive statistics, missing-data assessment and outlier checks. Internal consistency may be assessed using Cronbach's alpha and/or composite reliability, while construct validity may be examined through confirmatory factor analysis where sample size and model structure permit. Correlations can describe bivariate associations but should not be interpreted as causal evidence.

Multiple regression may be used for observed composite variables. Structural equation modelling may be appropriate where constructs are latent and the sample supports the measurement and structural models. The analysis should report coefficients, standard errors, confidence intervals, p-values, model fit where relevant and effect sizes. Control variables may include organisation size, industry, firm age, supply chain complexity and digital maturity, subject to theoretical justification and data availability. Robustness checks should include alternative operationalisations and, where possible, out-of-sample predictive validation.

4.4 Equations and measurement definitions

The following equations present the original measurement and analytical expressions in editable Microsoft Word mathematical format. Additional equations address the methodological issues identified in the review.

Equation 1. Mean Absolute Percentage Error (MAPE)

$$MAPE=\frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right|$$

A_t is actual demand, F_t is forecast demand and n is the number of observations. MAPE is undefined when actual demand is zero and may become unstable when actual values are very small.

Equation 2. Mean Absolute Error (MAE)

$$MAE=\frac{1}{n}\sum_{t=1}^{n}|A_t-F_t|$$

MAE is the average absolute difference between actual and forecast values, expressed in the original unit.

Equation 3. Root Mean Square Error (RMSE)

$$RMSE=\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t-F_t)^2}$$

RMSE penalises larger errors more heavily because the errors are squared before averaging.

Equation 4. Inventory turnover ratio

$$ITR=\frac{\text{Cost of Goods Sold}}{\text{Average Inventory}}$$

Average inventory should be valued consistently with cost of goods sold and calculated over the same reporting period.

Equation 5. On-time delivery rate

$$OTD=\frac{\text{Orders Delivered On Time}}{\text{Total Delivered Orders}}\times 100$$

For consistent measurement, define the denominator as orders due for delivery in the measurement period; state how partial deliveries and customer-requested date changes are treated.

Equation 6. Stockout frequency

$$SF=\frac{\text{Number of Stockout Events}}{\text{Total Inventory Periods}}\times 100$$

The original expression is retained. In an empirical study, define inventory periods explicitly (for example, product-location-days). If events can occur

repeatedly within one period, use stockout incidence periods rather than event counts to avoid rates above 100%.

Equation 7. Operational risk exposure

$$RE_i = P_i \times I_i$$

RE_i is the risk exposure for event i, P_i is estimated probability and I_i is financial or operational impact. If ordinal scales are used, the product is a prioritisation score rather than a monetary loss estimate.

Equation 8. Proposed predictive analytics regression model

$$LE_i = \beta_0 + \beta_1 PAC_i + \beta_2 DT_i + \beta_3 DQ_i + \beta_4 OR_i + \varepsilon_i$$

LE is logistics efficiency; PAC is predictive analytics capability; DT is digital transformation; DQ is data quality; OR is organisational readiness; β terms are coefficients; and ε is the error term.

Equation 9. Operational risk-management model

$$ORM_i = \alpha_0 + \alpha_1 PAC_i + \alpha_2 DI_i + \alpha_3 DQ_i + \alpha_4 OR_i + \mu_i$$

ORM is operational risk-management capability; DI is digital integration; and μ is the error term.

Additional Equation 10. Weighted Absolute Percentage Error (WAPE) — recommended where actual demand can be zero in individual periods:

Equation 10. WAPE

$$WAPE = \frac{\sum_{t=1}^{n} |A_t - F_t|}{\sum_{t=1}^{n} |A_t|} \times 100$$

WAPE avoids division by zero at individual time points, although it is undefined if total actual demand across the entire evaluation period is zero.

Additional Equation 11. Moderation model for H7:

Equation 11. Organisational-readiness moderation model

$$LE_i = \beta_0 + \beta_1 PAC_i + \beta_2 OR_i + \beta_3 (PAC_i \times OR_i) + \beta_4 DT_i + \beta_5 DQ_i + \varepsilon_i$$

The interaction coefficient β_3 tests whether organisational readiness changes the association between predictive analytics capability and logistics efficiency. Centre or standardise continuous predictors where appropriate to aid interpretation.

4.5 Ethical considerations

Organisational permission and informed consent should be obtained before collecting primary data. Commercially sensitive information should be anonymised, securely stored and accessed only by authorised researchers. The study should comply with institutional ethics requirements and applicable data-protection rules. Reports should avoid disclosing identifiable supplier, customer or employee information.

5. Published Quantitative Evidence and Proposed Empirical Tests

Because this article does not analyse an original dataset, this section reports findings from previous studies and identifies how a future study could test related relationships. Published coefficients and percentages are not presented as results of the proposed research.

5.1 Digital transformation and supply chain efficiency

He et al. (2024) analysed 40,321 firm-year observations from Chinese A-share listed companies between 2007 and 2022. The manuscript reports baseline regression coefficients of 0.0316 without control variables and 0.0378 after control variables, both statistically significant at $p < .01$. The reported Cragg–Donald Wald F statistic was 28.598. The dependent variable was operationalised using the study's supply chain-efficiency measure, including inventory-turnover-days information. These coefficients must not be described as percentage improvements in logistics performance or as effects of predictive analytics alone.

Table 3. Quantitative results reported by He et al. (2024)

Reported measure	Published value	Correct interpretation
Observation period	2007–2022	Longitudinal period examined
Firm-year observations	40,321	Number of observations, not number of distinct firms
Coefficient without controls	0.0316	Regression coefficient for the study's operationalised measure
Coefficient with controls	0.0378	Regression coefficient after inclusion of controls

Statistical significance	$p < .01$	Reported statistical significance level
Cragg–Donald Wald F statistic	28.598	Instrument-strength diagnostic reported in the study
Alternative digitalisation indicator	76 digital-related terms	Alternative operationalisation reported by the study

The original article also notes a PLOS ONE editorial notice dated 10 September 2026 concerning two retracted works in the reference list of He et al. (2024), while stating that those references were not crucial to the article's conclusions. This qualification should remain disclosed when citing the study. The result supports a relationship between digital transformation and the study's supply chain-efficiency measure; it does not isolate predictive analytics as the cause.

5.2 Forecasting performance evidence

Pietukhov et al. (2023) reported a hybrid forecasting approach using logistic regression and neural networks, with process-improvement information incorporated into the model. The study involved 30 teams in a large supply chain organisation and reported 17% higher accuracy and 13% higher F1 score compared with its baseline. The article does not provide grounds for treating these as percentage-point increases or as direct reductions in operating costs.

Table 4. Published percentage improvements in predictive model performance

Indicator	Published result	What the percentage means	What it does not establish
Forecasting accuracy	17% improvement	Relative improvement reported against the study's baseline	Not a 17-percentage-point increase unless the source explicitly defines it that way; not a 17% cost reduction
F1 score	13% improvement	Relative improvement reported against the study's baseline	Not a 13-percentage-point increase; not a 13% reduction in disruptions
Teams in investigation	30 teams	Study's organisational team count	Not a generalisable population sample for all supply chains

5.3 Organisational analytics evidence

Wei et al. (2022) used 159 matched questionnaires and reported positive direct and indirect relationships between big data analytics use and supply chain performance, with lean and agile supply chain strategies mediating the relationship. Dubey et al. (2019) used 173 usable responses and reported a positive relationship between analytics capability and supply chain agility. Organisational flexibility moderated the relationship between analytics capability and agility, but the same moderating effect was not found for the relationship with competitive advantage.

Table 5. Survey evidence and reported findings

Study	Usable evidence	Reported relationship	Percentage / effect-size information
Wei et al. (2022)	159 matched questionnaires	Analytics use positively related to supply chain performance directly and indirectly through lean and agile strategies	A percentage effect is not reported in the evidence summarised here
Dubey et al. (2019)	173 usable responses	Analytics capability positively related to supply chain agility; organisational flexibility moderated this relationship	A percentage effect is not reported in the evidence summarised here

Systematic review evidence

Smyth et al. (2024) retrieved 5,293 records and included 76 primary studies in their systematic review of AI and prescriptive analytics for supply chain resilience. The inclusion proportion is calculated below from the published counts.

Calculation. Review inclusion proportion

$$\frac{76}{5{,}293} \times 100 = 1.44\%$$

This percentage describes the proportion of retrieved records included in the review, not the proportion of firms adopting AI or the effectiveness of predictive analytics.

Table 6. Evidence counts and calculated percentage

Evidence measure	Count / percentage	Status	Interpretation
Records retrieved	5,293	Published count	Initial search yield
Primary studies included	76	Published count	Studies retained for synthesis
Inclusion proportion	1.44%	Calculated from published counts	76 divided by 5,293, multiplied by 100; rounded to two decimal places

5.5 Proposed empirical results framework

The future study should report actual values only after data collection and analysis. The following table is deliberately populated with the indicators, units and reporting fields required; it does not fabricate numerical findings. The 'result to be estimated' column identifies the statistic that the researcher must calculate from the dataset.

Table 7. Reporting template for the future original study

Outcome / predictor	Required statistic	Unit	Result to be estimated from collected data
Forecasting performance	MAPE, WAPE, MAE and RMSE	%, original demand unit	Model-specific values using a held-out test dataset
Delivery reliability	On-time delivery rate	%	Observed percentage of eligible orders delivered on time
Inventory efficiency	Inventory turnover	Times per period	Cost of goods sold divided by average inventory
Stockout incidence	Stockout incidence rate	%	Product-location-periods with stockout divided by eligible product-location-periods
Risk responsiveness	Median warning-to-response time	Hours / days	Observed median elapsed time from alert to recorded response
Predictive analytics capability	Scale mean, reliability and regression coefficient	Scale points / coefficient	Validated construct score and estimated association with logistics outcomes
H7 moderation	Interaction coefficient and confidence interval	Coefficient / 95% CI	Estimated PAC × organisational-readiness interaction

This reporting structure ensures that tables are not left as empty shells while preserving research integrity: actual performance percentages must come from the future organisation-level dataset, not be invented or borrowed from unrelated studies.

6. Discussion

The reviewed evidence supports the relevance of digital transformation and analytics capabilities to supply chain operations, but it does not justify treating every reported association as evidence that predictive analytics directly improves every logistics outcome. He et al. (2024) report a statistically

significant association between digital transformation and supply chain efficiency. Their study concerns a broad digital-transformation measure, so it should be interpreted as contextual evidence rather than a direct estimate of predictive analytics effectiveness.

Wei et al. (2022) help explain how analytics can relate to performance through lean and agile strategies. This finding is consistent with the argument that predictive information becomes valuable when embedded in planning, coordination and resource allocation. Dubey et al. (2019) further suggest that organisational flexibility affects the conversion of analytics capability into supply chain agility. The proposed framework therefore treats organisational readiness as more than a background characteristic.

Pietukhov et al. (2023) provide model-level evidence: their hybrid approach improved reported accuracy by 17% and F1 score by 13%. These gains demonstrate potential improvements in predictive classification or forecasting performance, but do not by themselves establish that organisations reduced transport costs, stockouts or delivery delays. Future research should measure both model performance and downstream operational outcomes.

Risk management requires a similar distinction. Predictive analytics may identify a supplier delay or abnormal transport pattern earlier, but actual resilience depends on the availability of alternative suppliers, inventory buffers, route flexibility and decision authority. Digital twins and scenario analysis can help assess responses, but the quality of the representation and underlying data remains important.

The resource-based view explains why data, systems and analytical expertise may form valuable organisational resources. Dynamic capabilities theory explains how those resources can be used to sense threats, seize response opportunities and reconfigure operations. Together, these theories support the proposition that predictive analytics is an organisational capability rather than simply a software purchase.

7. Managerial and Practical Implications

7.1 Managerial implications

Managers should evaluate analytics investments through operational outcomes rather than the number of digital tools deployed. Implementation should begin with clearly defined use cases, data ownership, quality standards and escalation procedures. Predictive alerts should be connected to decisions such as replenishment, route changes, supplier review or maintenance scheduling.

7.2 Operational implications

Table 8. Operational applications and measurable performance indicators

Supply chain function	Predictive application	Performance indicator	Desired direction (not a claimed result)
Demand planning	Demand forecasting	MAPE / WAPE / MAE	Lower forecast error
Inventory	Replenishment and stockout prediction	Stockout incidence; inventory turnover	Fewer stockouts with appropriate inventory balance
Transportation	Estimated arrival-time prediction and route planning	On-time delivery rate; cost per delivery	Higher delivery reliability and controlled cost
Fleet management	Predictive maintenance	Unplanned downtime; maintenance cost	Lower unplanned downtime
Procurement	Supplier-delay and reliability prediction	Supplier on-time delivery rate	Higher supplier reliability
Warehousing	Workload and capacity forecasting	Order processing time; labour utilisation	More balanced capacity and processing
Distribution	Disruption prediction and delivery scheduling	Disruption rate; response time	Earlier detection and more effective response

Risk management	Early-warning and anomaly detection	Detection lead time; warning precision	Earlier actionable warnings with manageable false alerts

7.3 Risk, governance and workforce implications

Predictive alerts should trigger assessment rather than automatic action. Human oversight is required because models can produce false positives, miss novel events or reproduce biases in historical data. Organisations should establish data-sharing agreements, cybersecurity controls, access restrictions, model monitoring and procedures for reviewing model drift. Workforce training is necessary so employees understand model outputs, uncertainty and escalation thresholds.

8. Limitations and Future Research

This article is an evidence-based conceptual review and proposed research framework, not an original empirical study. Its hypotheses remain untested. The studies reviewed use different research designs, samples and outcome measures, so their results cannot be pooled into a single effect estimate. Some evidence is geographically concentrated, including studies of Chinese organisations, and may not generalise to supply chains in other institutional and economic settings. Predictive analytics also covers different model families and use cases, whose performance depends on the dataset, forecasting horizon and operational context.

Future research should use longitudinal organisational records to test whether improved model performance translates into changes in inventory turnover, delivery reliability, transportation expenditure, stockout incidence and disruption response. Studies should compare statistical and machine-learning methods using consistent train-validation-test procedures and out-of-sample evaluation. Research should also examine model drift, cybersecurity, explainability, data-sharing constraints and the costs of false alerts. Multi-industry and cross-country studies would help assess the generalisability of the proposed framework.

9. Conclusion

Digital transformation is changing procurement, inventory, transportation, warehousing and distribution. Predictive analytics offers a way to use historical and current information to anticipate operational requirements and potential disruptions. The literature reviewed here reports positive relationships between digital transformation, analytics capabilities and supply chain performance, as well as improvements in forecasting-model performance in a specific organisational investigation. These findings must be interpreted according to their study designs and measures.

The central contribution of this article is an integrated framework connecting predictive analytics capability with logistics efficiency and operational risk-management capability. It distinguishes prediction accuracy from operational performance and emphasises the roles of data quality, digital integration, organisational readiness and managerial response. Predictive analytics should therefore be understood as an organisational capability whose value depends on converting forecasts into timely, appropriate and measurable operational decisions.

REFERENCES

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Dubey, R., Gunasekaran, A., & Childe, S. J. (2019). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. Management Decision, 57(8), 2092–2112. https://doi.org/10.1108/MD-01-2018-0119

Emrouznejad, A., Abbasi, S., & Sıcakyüz, Ç. (2023). Supply chain risk management: A content analysis-based review of existing and emerging topics. Supply Chain Analytics, 3, Article 100031. https://doi.org/10.1016/j.sca.2023.100031

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., 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

He, J., Fan, M., & Fan, Y. (2024). Digital transformation and supply chain efficiency improvement: An empirical study from A-share listed companies in China. PLOS ONE, 19(4), Article e0302133. https://doi.org/10.1371/journal.pone.0302133

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

Pietukhov, R., Ahtamad, M., Faraji-Niri, M., & El-Said, T. (2023). A hybrid forecasting model with logistic regression and neural networks for improving key performance indicators in supply chains. Supply Chain Analytics, 4, Article 100041. https://doi.org/10.1016/j.sca.2023.100041

PLOS ONE Editors. (2026). Editorial note: Digital transformation and supply chain efficiency improvement: An empirical study from A-share listed companies in China. PLOS ONE, 21(9), Article e0357932. https://doi.org/10.1371/journal.pone.0357932

Smyth, C., Dennehy, D., Fosso Wamba, S., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: A systematic literature review and research agenda. International Journal of Production Research, 62(23), 8537–8561. https://doi.org/10.1080/00207543.2024.2341415

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. Journal of Business Research, 122, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009

Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014

Wei, S., Yin, J., & Chen, W. (2022). How big data analytics use improves supply chain performance: Considering the role of supply chain and information system strategies. The International Journal of Logistics Management, 33(2), 620–643. https://doi.org/10.1108/IJLM-06-2020-0255