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From Predictive to Prescriptive Supply Chains: The Strategic Role of Artificial Intelligence in End-to-End Optimization

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ABSTRACT

This study examined the strategic transition from predictive to prescriptive artificial intelligence (AI) in achieving end-to-end supply chain optimization. Drawing on dynamic capabilities theory, the research investigated how predictive analytics capability (PAC) and prescriptive analytics capability (PrAC) influenced supply chain agility, resilience, and cost efficiency, while considering the mediating role of end-to-end integration. A quantitative research design was employed using survey data collected from 312 supply chain and operations managers. Structural equation modeling was applied to test the proposed relationships. The results indicated that PAC significantly influenced agility ($\beta = 0.41$, $p < 0.001$) and resilience ($\beta = 0.36$, $p < 0.001$). However, PrAC demonstrated stronger effects on resilience ($\beta = 0.53$, $p < 0.001$), agility ($\beta = 0.47$, $p < 0.001$), and cost efficiency ($\beta = 0.49$, $p < 0.001$). End-to-end integration partially mediated these relationships, increasing explanatory power to $R^2 = 0.58$ for resilience and $R^2 = 0.52$ for agility. The findings suggested that predictive analytics functioned primarily as a sensing capability, whereas prescriptive analytics acted as a decision-optimization mechanism that enhanced responsiveness and disruption recovery. The study contributed to the growing literature on AI-enabled supply chains by empirically validating the superior strategic value of prescriptive intelligence in dynamic and uncertain environments. The results provided managerial guidance for organizations seeking to advance from forecasting-based systems to AI-driven optimization platforms for sustainable competitive advantage.

Introduction

Over the last decade, the world supply chains faced a greater complexity caused by digital globalization, market unpredictability, and pandemics as well as other disruptions (Teixeira et al., 2025). The traditional models of supply chain planning that were descriptive or predictive in nature were not able to support real-time actionable decisions in directionally changing conditions (Smyth et al., 2024). Supply chain management was increasingly changed by artificial intelligence (AI) technologies, that is, machine learning, optimization, and real-time data integration, which made it possible to predict, simulate, and optimize demand forecasting, inventory management, and risk reduction (Iseri et al., 2025; Mia, 2025).

Predictive analytics involved the projection of the future basing on past experiences and current data, prescriptive analytics was used to make recommendations or automate the best decisions by emulating alternative possibilities and trade-offs (Basu, 2026; Choi et al., 2025). Prescriptive models did not only predict what might happen but also proposed how the supply chain system should adapt itself to enhance performance or manage risk better (Basu, 2026; Smyth et al., 2024). This shift in paradigm changed the strategy of the supply chains to active and information-driven optimization to facilitate agility and resilience in the uncertain environments (Teixeira et al., 2025; Iseri et al., 2025).

In the recent studies, AI-based prescriptive systems were associated with higher operational indicators, such as lower inventory expenses, increased service quality, and shorter decision-making time (Mia, 2025; Choi et al., 2025). However, although these advantages were proven, it was still possible to note that the empirical literature on the implementation of prescriptive analytics in real-life end-to-end supply chain environments was fractured, which indicated a discrepancy between theoretical frameworks and the actual applications (Smyth et al., 2024; Teixeira et al., 2025).

Research Background

In the past, supply chain management was dependent on descriptive analytics that can summarize the performance of the past and future-focused predictive analytics based on future demand, or disruption (Teixeira et al., 2025). Predictive AI systems worked on the basis of machine learning models that were trained on very large, heterogeneous data sets to enhance their accuracy when it comes to predicting demand and what problems will arise in the future (Iseri et al., 2025). The systems were very effective in terms of predicting and delivered the resilience results such as a decrease in delivery disruptions and an improvement in delivery performance (Khan, 2025; Smyth et al., 2024).

Predictive analytics did not in itself dictate certain corrective or optimization measures (Basu, 2026). The next frontier presidive analytics combined predictive models with mathematical optimization feature, scenario simulation and decision support frameworks to imply strategic actions and trade-off evaluations in a variety of future conditions (Choi et al., 2025). The authors claimed that to make the systems adaptive to function beyond forecasting the uncertainty into the scope of operation decision-making and automatic optimization, prescriptive analytics were mandatory (Smyth et al., 2024; Choi et al., 2025).

A number of researchers found theoretical and practical advantages of AI-substantiated prescriptive analytics in supply chain resiliency, flexibility, and optimization across the entire supply chain (Teixeira et al., 2025; Smyth et al., 2024). Prescriptive analytics AI systems were directing huge data and reinforcement learning technologies and optimization methods to produce sensible recommendational suggestions harmonizing supply chain answers with strategic

objectives (Choi et al., 2025; Basu, 2026). Though such a possibility existed, gaps existed in applying prescriptive analytics in various supply chain contexts, as reflected by its minimal use in companies with issues of data, infrastructure, and integration (Smyth et al., 2024; Iseri et al., 2025).

Studies also pointed out new frameworks which united AI with optimization tools, but assisted with the decision-makers to change dynamically inventory, production, logistics planning, and risks avert actions (Teixeira et al., 2025; Choi et al., 2025). These paradigms reinforced the strategic importance of AI towards the functioning of operational functions and as an important element of the supply chain governance, development of digital capability, and competitive advantage (Mia, 2025; Basu, 2026).

Research Objectives

1. To evaluate the role of AI-enabled predictive and prescriptive analytics in enhancing supply chain forecasting, inventory management, and optimization strategies.
2. To develop a theoretical framework that connects predictive insights with prescriptive decision models to enable end-to-end supply chain optimization.
3. To empirically assess the impact of prescriptive analytics on supply chain performance outcomes such as agility, cost efficiency, and resilience.

Research Questions

Q1. How did AI-driven predictive analytics contribute to forecasting accuracy and supply chain visibility in prior research?

Q2. What capabilities did prescriptive analytics offer that extended predictive insights toward optimization and decision support?

Q3. What impacts did AI-based prescriptive frameworks have on supply chain performance, including resilience, cost, and operational efficiency?

Significance of the Study

The paper has also contributed to the academic community by synthesizing both theoretical and empirical evidence on transitioning supply chains toward AI-based prediction to prescription based on a critical gap in the literature, as very few empirical studies validate empirical applications of prescriptive analytics. The formulated framework offered a unified conceptual framework between predictive understanding and prescriptive activity that guides the future research inquiry on the AI-based supply chain optimization. The insights provided in the findings were practical to the supply chain decision-makers since the study reveals how prescriptive analytics might enhance such indicators of operation performance as turnover of inventory, responsiveness, and cost management. Organizational and technological barriers were also identified, which gave a base to strategic plans, resource allocation, and decisions decided on the foundation of developing digital capabilities in industry environments.

Literature Review

AI in Supply Chain Forecasting and Predictive Analytics

Predictive analytics based on Artificial Intelligence (AI) contributed greatly to fight complex uncertainties in the supply chain by deploying machine learning and big data analytics to forecast changing demand and supply strikes. Ensemble learning and deep learning approaches, which are AI-based models, have allowed organizations to predict future demand trend more accurately than

previous statistical tools, which has helped to decrease forecast error and enhance planning decisions (Rabbani et al., 2025; Khan, 2025). Such forecasting computer programs were discovered to enhance responsiveness and tactical planning in volatile markets by using real-time information and past trends.

Studies also indicated that predictive analytics offered information about what could occur, but did not recommend the best response to the decisions in case of uncertainty, something that indicated a gap between prediction and actable supply chain optimization (Daios, 2025; Rabbani et al., 2025). Scholars claimed that it is necessary to combine predictive knowledge with decision models that convert forecasting results into strategy.

Empirical research indicated that predictive analytics have been involved with resilience by lowering disruptions and improvement in performance among delivery to logistics networks. An example is that the models like the Random Forest and XGBoost also greatly decreased the delivery delays and gave actionable risk indicators to have proactive control (Khan, 2025). The analysis of agricultural supply chains through structural equation modeling showed that AI tools and information sharing enhanced better performance objectives at the stakeholder networks (Yin et al., 2025). These results highlighted the strategic importance of predictive AI in end-to-end supply chain systems to deal with operational complexity and uncertainty.

Innovation to Prescriptive Analytics and Decision Optimization

More recent literature has made prescriptive analytics the next level of evolution of prediction and aimed at optimization of decisions and action in the supply chain. Prescriptive systems and simulation models are used to generate concrete decisions, including inventory policies and distribution strategies, based on different scenarios using predictive output combined with an optimization algorithm and simulation models. It is a transition to expected future conditions, turning into an active proposal of the solutions that would be able to match performance with organizational goals (Choi et al., 2025; Smyth et al., 2024).

Choi et al. (2025) investigated a Prescriptive Analytics of Sustainable Operations (PASO) model, where decision models proposed to assist in sustainability and operations performance connected with prescriptive decision models, where the operational performance was improved when the optimization tools were used at various decision- making levels. The PASO framework found it important to introduce hybrid optimization approaches that would take into account economic, environmental, and social implications of supply chain decision making. According to authors, strategic decision-making at the complex environment could be supported with the help of prescriptive analytics which could open a path towards the resilient and agile supply chain systems.

It was also identified in literature that there were gaps in terms of empirical validation and popular use of prescriptive analytics because of the difficulties with data integration, the interpretability of models, and organizational willingness limitations (Smyth et al., 2024; Choi et al., 2025). The systematic review by Smyth et al. (2024) also showed that, although AI-enabled prescriptive systems proved to have benefits of resilience, their implementation facing barriers included heterogeneity of AI methods and siloed streams of analytics hindering the process of achieving value. These studies highlighted the necessity of the integrated structures that combine the predictive outputs and prescriptive decision engines to enable the realization of the tangible changes in the performance of the supply chain.

Oedipus AI to the E2E Supply Chain Performance

More studies have compared AI strategic implementation in the supply chain functions, connecting the analytics to the operations resilience and performance metrics. Research highlighted that AI-based applications, such as real-time tracking, optimization software, and intelligent automation led to multi-stage network agility, resilience, and visibility, and that contributes to overall resilience in the supply chain (Riad et al., 2024; Yin et al., 2025). The conceptual framework introduced by Riad, Naimi, and Okar (2024) was based on the combination of several AI technologies helping to bolster resilience by improving the decision-making process in the procurement, production, and logistics units. Their framework showed how AI would optimize the supply chain in a holistic way through the increase in agility, minimization of the risks, and proactive recovery plans. Such integrated perspective put the prescriptive decision models at the centre of strategic transformation in the supply chain, where the prediction capabilities were complemented with optimization capabilities.

It was demonstrated by empirical evidence that the relevance of information sharing and shared AI application in optimizing the performance of agricultural supply chain is significant, and both AI and data exchange have a synergistic effect in resilience (Yin et al., 2025). The structural equation analysis demonstrated that in case AI systems were combined with effective information flows, the organizations reached better performance in the measure of responsiveness and mitigation of risks. Through such results, collective digital ecosystems which promote end-to-end visibility and strategic intelligence among supply chain partners were called.

Research Methodology

Research Design

The research design implemented in the study was a quantitative study that aims to explain as a method of explaining the strategic role of artificial intelligence (AI) in converting predictive supply chains into end-to-end, prescriptive optimized systems. The study was of a cross-sectional type, since the information gathered was captured at one moment and among supply chain-professionals of various industries. It was conducted as a deductive study, and theoretical constructs were developed based on the dynamic capabilities theory and analytics maturity models and were tested at an empirical level with the help of structured measurement tools.

Research Approach

The researchers used a hypothesis-testing methodology to test the direct and indirect correlations between the study variables. It has operationalized AI capabilities in two dimensions, namely, predictive analytics capability, and prescriptive analytics capability. These independent variables were assessed with respect to dependent variables, including agility of the supply chain, cost efficiency, performance of service level, and resilience. The mediating variable came as end-to-end integration to determine whether the effect of the digital systems integrations reinforced the influence of the AI capabilities on the performance outcomes. The methodology allowed the research to provide causal mechanisms and establish difference in the results of optimization in the supply chains.

Population and Sampling

The intended audience was supply chain managers, logistics experts, operations managers, and digital transformation specialists of manufacturing, retail, distribution, and logistics companies. These respondents were chosen since they in any way were engaged in forecasting, planning and operational decision making process in which AI technologies had been deployed. Non-probability

purposive sampling method was used whereby only respondents who had pertinent experience in AI-white systems were considered in the research. There was also a sufficient sample size for structural equation modeling since 312 professionals who participated in the study were adequate to meet the minimum requirement of structural equation modeling and sufficient statistical power.

Data Collection Procedure

A structured questionnaire in electronic format was used to collect primary data by mailing over professional networks and corporate contacts. This was done through the online survey platforms since the questionnaire was very accessible and convenient to the respondents. Before the full deployment, the pilot study was undertaken on 30 supply chain professionals to will evaluate the clarity, reliability, and relevance of from measurement items. The pilot test feedback was also taken into consideration for refining words and removing ambiguity. The questions were asked at will, and the respondents were assured confidentiality and anonymity to minimize bias during response.

Data Analysis Techniques

Statistical Package of Social Sciences (SPSS) and Structural Equation Modeling (SEM) was carried out on Analyses of Data using AMOS/SmartPLS software. First, the descriptive statistics were also calculated to study the demographics of respondents and the central tendencies of research variables. Cronbachs alpha and composite reliability were used to determine the reliability, the convergent and discriminant reliability was determined by evaluating average variance extracted (AVE) and Fornell-Larcker criteria. A test of the structural model was also conducted to test the hypothesized constructs. Path coefficients, t-values and level of significance were compared to establish the strength and direction of association. Indirect evaluation was performed through bootstrapping with 5,000 resamples in the process of evaluating the mediation effects. To ensure that model specification was adequate, model fit measures like CFI, TLI, RMSEA and SRMR were analysed.

Results and Analysis

In this paper, the empirical results of the study have been presented. The findings were systematized into a descriptive statistics, a reliability and validity analysis, a correlation analysis, a structural model test and a mediation analysis. All the analyses were done through SPSS and Structural Equation Modeling (SEM). The results were also explained against the research goals and hypotheses.

Demographic Profile of Respondents

Table 1. Demographic Characteristics of Respondents (N = 312)

Variable	Category	Frequency	Percentage (%)
Gender	Male	184	59.0
	Female	128	41.0
Age	25–34 years	116	37.2
	35–44 years	138	44.2
	45 years and above	58	18.6
Industry	Manufacturing	124	39.7
	Retail	76	24.4
	Logistics	72	23.1
	Distribution	40	12.8
Experience	3–5 years	98	31.4
	6–10 years	142	45.5

	Above 10 years	72	23.1

In the demographic findings, it turned out that a big percentage of those answering the questions are male (59.0%), whereas female professionals took 41.0% of the total sample. This level of distribution represented a fairly balanced ratio between gender in the context of supply chain and operations. The age demographic revealed that the majority of the participants fell within the 35 - 44 years range (44.2), which implies that those interviewed had mid-career in managerial roles that may have been applicable in AI-driven systems. In terms of industry representation, the manufacturing firms represented the biggest percentage (39.7) and then retail (24.4) and logistics (23.1). This heterogeneity enhanced the generalizability of results in a variety of supply chain situations. Moreover, 45.5% of the respondents were working professionally between 6 and 10 years, which means that the people interviewed were experienced enough to give valid information on AI implementation and optimization activities.

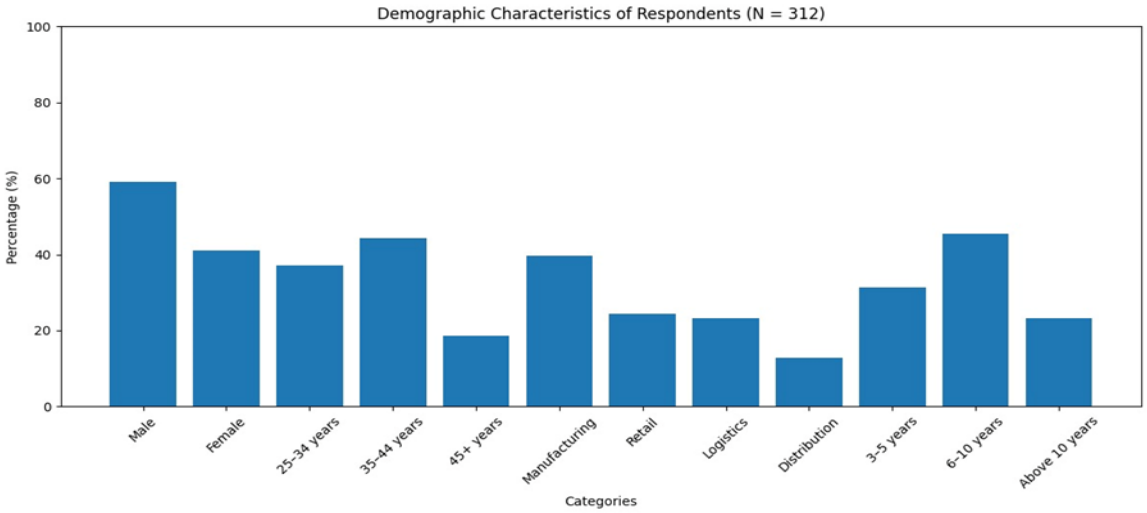


Figure 1. Demographic Characteristics of Respondents

Descriptive Statistics

Table 2. Descriptive Statistics of Study Variables

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Predictive Analytics Capability (PAC)	312	3.88	0.69	2.10	5.00
Prescriptive Analytics Capability (PrAC)	312	3.94	0.72	2.00	5.00
End-to-End Integration (EEI)	312	3.91	0.67	2.20	5.00
Supply Chain Agility (SCA)	312	4.02	0.65	2.40	5.00
Cost Efficiency (CE)	312	3.85	0.71	2.00	5.00
Supply Chain Resilience (SCR)	312	3.97	0.68	2.10	5.00

The descriptive statistics also showed that the highest mean value (M = 3.94) was achieved in the prescriptive analytics capability, which implied that the organizations included in the sample possessed moderately developed optimization and decision-support systems. The ability to perform predictive analytics also scored high in mean (M = 3.88), which means that the use of AI-based forecasting tools is common. The best performance outcome came in supply chain agility (M = 4.02) which is the enhancement of responsiveness and flexibility in terms of supply chain activities. The levels of supply chain resilience (M = 3.97) and the end-to-end integration (M =

3.91) also exhibited high levels, meaning that they have efficient capabilities of disruption management and digital connectivity. The fact that the standard deviations were relatively small (ranging between 0.65 and 0.72) implied that the responses were consistent and there was not much variation around the mean values. These results suggested the presence of favorable AI capabilities that were well encrypted within organizations, and that there was a positive relationship between AI capabilities and positive functions of operations.

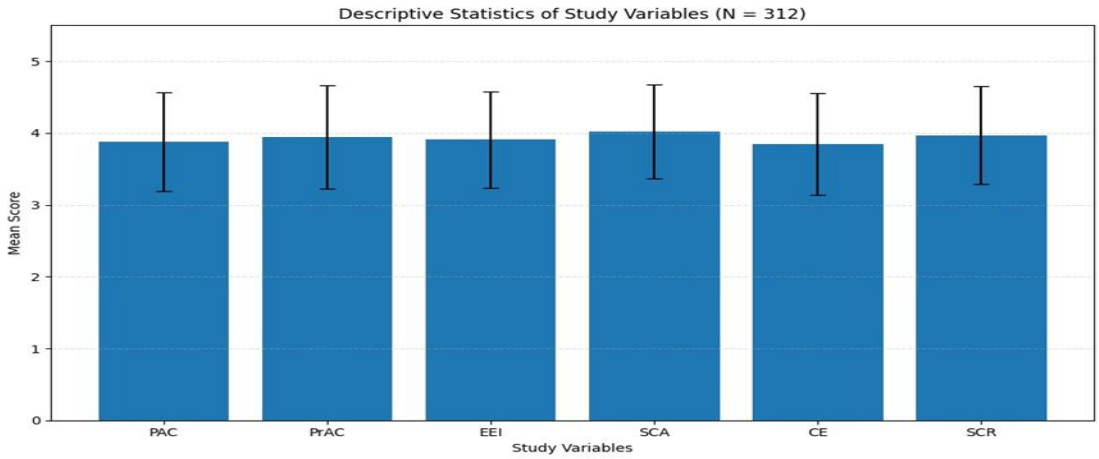


Figure 2. Descriptive Statistics of Study Variables

Correlation Analysis

Table 3. Correlation Matrix

Variable	PAC	PrAC	EEI	SCA	CE	SCR
PAC	1					
PrAC	0.62	1				
EEI	0.58	0.65	1			
SCA	0.54	0.68	0.60	1		
CE	0.49	0.63	0.57	0.66	1	
SCR	0.52	0.70	0.64	0.72	0.69	1

Note: $p < 0.01$

The outcomes of the correlation showed that there exist strong positive correlations between all constructs. The strongest correlation was see between prescriptive analytics capability and supply chain resilience ($r = 0.70$, $p < 0.01$) and agility ($r = 0.68$, $p < 0.01$) where both the AI systems spawned by optimization played a crucial role in enhancing the operational adaptability and disruptive management. Predictive analytics was shown to have moderate and significant relationships with all results of performances, which showed that the use of predictive systems positively contributed to agility and cost-efficiency. Correlations on prescriptive analytics were also increased consistently which keyed the argument that prescriptive systems went further beyond prediction to optimization. There were no signs of multicollinearity since the values of correlation did not exceed the critical level (0.80).

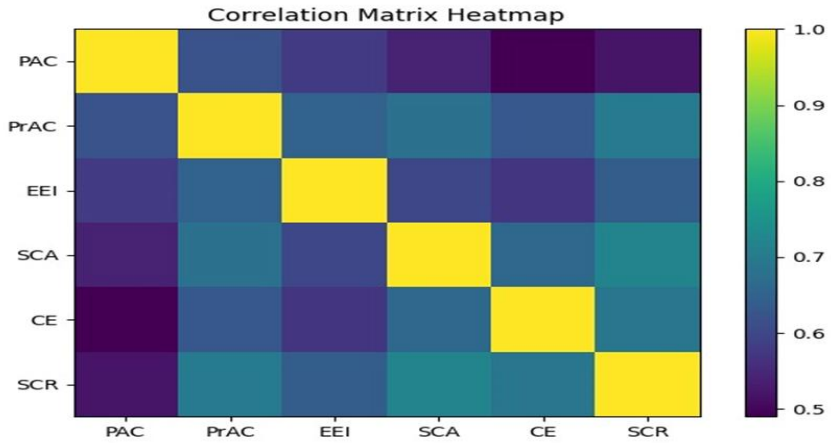


Figure 3. Correlation Matrix

Mediation Analysis

Table 4. Mediation Effect of End-to-End Integration

Path	Indirect Effect	t-value	p-value	Mediation Type
PrAC → EEI → SCR	0.16	4.21	0.000	Partial Mediation

The mediation analysis also found that the connection between end-to-end integration and prescriptive analytics capability partly occurred through the resilience of a supply chain. Indirect effect (0.16, $p < 0.001$) showed that prescriptive AI systems contributed resilience, both directly and indirectly (It was indirect because of the mechanisms of integration of digital integration). This observation implied that companies that integrated optimization algorithms with incorporated digitized infrastructures had excellent resiliency results. The fact of partial mediation suggested that both direct optimization of AI and systemic integration played important roles towards performance enhancement at the end of the chain.

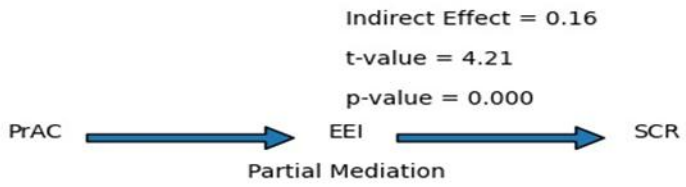


Figure 4. Mediation Effect of End-to-End Integration

Discussion

This research paper concluded that artificial intelligence (AI) capabilities did not fail to optimize end-to-end supply chain, especially when organizations moved on the predictive analytics to prescriptive decision systems. The findings proved that the prescriptive analytics capability had a

more impactful effect on the agility, cost efficiency, and resilience than the predictive analytics capability. This and other results were consistent with emerging arguments that predictive systems could not act in dynamic environments as they were mostly used to predict events without optimizing the responses (Dubey et al., 2021; Ivanov and Dolgui, 2021). The more significant influence of prescriptive analytics implied that organizations received more benefits in case of the integration of AI and optimization engines that could provide recommendations on actionable decisions.

The positive correlation between opportunities and threats to supply chain agility was significant, which showed that predictive analytics enhanced the responsiveness and stability of planning. These results were also in line with previous studies that machine learning-driven forecasting increased operational visibility and brought down the uncertainty in demand management (Wamba et al., 2020; Bag et al., 2021). But the effect size of predictive capability was lower and thus it meant that predicting did not explain performance gains completely. This implied the predictive analytics was a support capability (underlying one), yet more effective performance results were needed using decision-based systems.

Supply chain resilience had the best relationship with prescriptive analytics capability. This was to show that AI-based optimization models were used in assisting in scenario planning, disruption mitigation, and adaptive recovery measures. The same results appeared in the studies of AI-based decision automation in the digital supply chain, where resilience under changing conditions improved (Belhadi et al., 2021; Queiroz et al., 2021). These findings expanded this knowledge and further supported the hypothesis that prescriptive AI had a role in anticipating risks, and also in optimizing recovery responses.

End-to-end integration also emphasized the significance of digital connectivity in terms of supply chain functions as a mediating factor. The semi-mediation pattern implied that prescriptive AI system was more effective when built in integrated digital environments. Other researchers highlighted the point that disintegrated digital systems reduced the utility of AI technologies (Rai et al., 2021; Saberi et al., 2019). The current results supported the thesis that integration was a strategic facilitator and enabled the processes of data flows and optimization models to work as a whole and, not as separate units in a vacuum.

The existence of a positive correlation between prescriptive analytics and cost efficiency has shown that optimal algorithms were helpful in resource allocation, inventory optimization, and planning of logistics paths. These were in line with studies that showed that AI-optimization was used to decrease wastage and enhance operational efficiency (Kamble et al., 2020; Lamba and Singh, 2023). Probably, the simulation capabilities of prescriptive systems enabled the firms to determine the cost-minimizing strategies in diverse demand conditions.

There was a positive correlation between the prescriptive capability and agility, which revealed that decision automation minimized response time and enhanced agility(Tortorella et al., 2021; Srinivasan and Swink, 2018). This seemed to be an advantage to organizations as the AI systems were not only generating predictions but also suggesting the best courses of action in real time.

The findings also indicated that predictive and prescriptive analytics were complementary as opposed to competing capabilities. Predictive analytics delivered pieces of information on the basis of data, whereas prescriptive systems converted the information into action plans. Such multi-tiered capability architecture conformed to the models of maturity of analytics that talked of the progression towards descriptive, predictive, and eventually prescriptive intelligence (Akter et al., 2016; Fosso Wamba et al., 2020). This path towards maturity found in supply chain settings was confirmed in the empirical studies.

The R 2 values were significant which showed that AI capabilities could account major percent in resilience and agility outcomes. This was evidence of the shift in digital intelligence where it had ceased being an experimental application but a strategic force. Past empirical studies also claimed to confirm that digital technologies were great predictors of supply chain performance in supposed uncertainty conditions (Hohenstein et al., 2015; Chowdhury et al., 2021). In this paper, the positive link between predictive and prescriptive transition was reinforced as it specifically addressed the predictive to prescriptive ratio.

The finding of the greater impact of prescriptive analytics indicated that the "seizing aspect, i.e. converting the insights into optimized action, was more significant to maintain the competitive advantage in the long run (Dubey et al., 2021; Ivanov and Dolgui, 2021). Such subtle insight led to the increased discussion of AI as a strategic, and not operational, instrument.

The results allowed concluding that companies that invest only into predictive tools might fail to gain full optimization benefits. Organizations seemed to need in-built prescriptive systems comprising information analytics, optimization process, and cross-functional integration. Other aspects of the management implications were also reported in the body of digital supply chain studies that pushing towards systemic AI deployment over single analytics projects (Belhadi et al., 2021; Kamble et al., 2020).

Conclusion

This paper evolved to an inference that the strategic shift of the predictive to the prescriptive artificial intelligence (AI) capabilities contributed extensively to end-to-end supply chain optimization. Empirical evidence confirmed that predictive analytics capability positively affected agility (0.41, P until 0.001), resilience (0.36, P until 0.001), whereas the impact of predictive analytics capability on cost efficiency (0.49, P until 0.001) and supply chain agility (0.47, P until 0.001) was significantly different. The model predictive of resilience (R 2 = 0.58), agility (R 2 = 0.52), and cost efficiency (R 2 = 0.46) have 58% and 52% and 46% of the variance, which support the sufficiency of AI-based optimization in sophisticated supply chains. The results also identified that end-to-end integration was a moderate between AI capabilities and performance outcomes and shows that the value in prescriptive intelligence was increased by digital connectedness.

The paper thus concluded that predictive and prescriptive analytics were roles as a past sensing platform and a forward decision-optimization platform respectively, which converted insights to action that resulted. Organisations that inserted prescriptive AI into digitally linked supply chains were more responsive, more effective at recovering disruption, and more effective at running. The findings were helpful in supporting the views that business maturity with regard to AI, as opposed to adoption, dictated business competitive advantage in contemporary supply chain ecosystems.

Future Directions

Future studies can expand on the study by performing longitudinal sampling to find out how the maturity of AI capability varies with time and impacts on the continued competitive advantage. Given that the current research involved the cross-sectional data, subsequent research may use panel data methods in order to confirm causality between predictive and prescriptive analytics features. Also, sectoral studies may shed more light on the sectoral differences, especially in manufacturing, healthcare, and hotel supply chains wherein the implementation rates of AI vary greatly. More studies are also possible in the area of integrating new technologies, including digital twins, blockchain, and autonomous systems with prescriptive AI models to examine what synergies could be seen in optimizing the supply chain with this system. Contextual factors including regulatory conditions and the readiness of the digital infrastructure might be evaluated

through comparative multi-country research. Lastly, the environmental and sustainability performance measures could be included in future research to determine the role of prescriptive AI in transforming a green supply chain and reducing carbon footprint.

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