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From Reactive to Proactive Supply Chain Planning: The Role of Intelligent Automation

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Abstract: Supply chains are increasingly exposed to volatility, uncertainty, complexity, and ambiguity, rendering traditional reactive planning approaches inadequate for sustaining operational performance and resilience. While intelligent automation has been widely promoted as a transformative force in supply chain management, empirical evidence explaining how it enables a shift from reactive to proactive planning remains fragmented. This study addresses this gap by developing and testing a simulation-based primary research model that examines the performance implications of intelligent automation enabled proactive supply chain planning. Drawing on dynamic capabilities theory and resilience perspectives, the study constructs a scenario-based simulation framework comparing reactive planning systems with proactive planning architectures supported by predictive analytics, machine learning driven forecasting, and automated decision execution. Primary data are generated through repeated simulation runs under varying demand volatility and disruption scenarios. The results demonstrate that proactive planning systems consistently outperform reactive counterparts in terms of forecasting accuracy, lead-time stability, and disruption recovery speed. The findings further indicate that intelligent automation enhances sensing, seizing, and reconfiguring capabilities, enabling anticipatory decision-making rather than ex post corrective actions. By providing simulation-based evidence, this study contributes to supply chain theory by clarifying the mechanisms through which intelligent automation drives proactive planning and resilience. From a managerial perspective, the results offer actionable insights into sequencing automation investments and aligning digital capabilities with planning processes. The study advances the literature by positioning intelligent automation not merely as an efficiency tool, but as a strategic enabler of proactive and adaptive supply chain planning.

Keywords: Intelligent Automation; Proactive Supply Chain Planning; Simulation Modeling; Dynamic Capabilities; Supply Chain Resilience

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1. Introduction

Global supply chains are operating in an environment characterized by persistent volatility, heightened uncertainty, structural complexity, and frequent disruptions. Demand shocks, geopolitical instability, climate-induced events, and rapid technological change have collectively exposed the limitations of conventional supply chain planning approaches. Many organizations continue to rely on reactive planning systems that respond to deviations only after disruptions materialize, often resulting in delayed decisions, cost escalation, and reduced service levels **(Ahmed et al., 2017).** The COVID-19 pandemic, semiconductor shortages, and logistics bottlenecks have further demonstrated that ex post corrective actions are insufficient for maintaining performance in highly turbulent environments **(Ivanov, 2020; Queiroz et al., 2022).**

Reactive supply chain planning is largely built on historical data, periodic forecasting cycles, and manual decision adjustments. While such systems may perform adequately in stable conditions, they lack the capability to anticipate emerging risks or adapt dynamically to rapid environmental changes. As a result, reactive planning often amplifies variability across the supply chain, leading to phenomena such as demand distortion, excessive safety stock, and prolonged recovery times following disruptions **(Choi et al., 2020).** These limitations have prompted scholars and practitioners to call for a fundamental shift toward proactive planning paradigms that emphasize anticipation, early warning, and continuous reconfiguration of planning decisions.

Advances associated with Industry 4.0 have created new opportunities to enable this transition. Intelligent automation, encompassing predictive analytics, machine learning, and automated execution mechanisms, allows supply chains to process large volumes of real-time data and generate forward-looking insights. Unlike traditional automation, which focuses primarily on efficiency and task substitution, intelligent automation supports cognitive functions such as pattern recognition, prediction, and adaptive decision-making **(Wamba et al., 2017; Frank et al., 2019).** These capabilities are particularly relevant for supply chain planning, where timely anticipation of demand shifts and disruptions is critical for sustaining performance and resilience.

Despite growing interest in intelligent automation, existing research remains fragmented in two important ways. First, much of the literature treats intelligent automation as a set of isolated technologies rather than as an integrated planning capability. Studies often examine predictive analytics, machine learning, or automation tools independently, without explaining how they jointly enable a proactive planning logic **(Bag et al., 2022).** Second, empirical evidence demonstrating the causal performance implications of proactive planning remains limited. Survey-based studies dominate the field, relying heavily on perceptual measures and cross-sectional data, which constrain causal inference and obscure dynamic system behavior under disruption scenarios **(Jum'a et al., 2021).** In response to these limitations, this study adopts a simulation-based primary research approach to examine how intelligent automation enables the transition from reactive to proactive supply chain planning. Simulation modeling is particularly suitable for this purpose because it allows systematic comparison of alternative planning architectures under controlled yet realistic conditions, including varying demand volatility and disruption intensity **(Ivanov & Dolgui, 2020).** By generating primary data through repeated simulation runs, the study avoids common biases associated with perceptual data and enables direct observation of performance dynamics over time.

The study is theoretically grounded in dynamic capabilities theory, which emphasizes an organization's ability to sense changes, seize opportunities, and reconfigure resources in response to environmental turbulence **(Teece, 2007).** Proactive supply chain planning is conceptualized as a manifestation of dynamic capabilities, supported by intelligent automation that enhances sensing through predictive analytics, seizing through anticipatory decision rules, and reconfiguring through automated execution. In addition, resilience theory provides a complementary lens for assessing the capacity of proactive planning systems to absorb shocks and recover rapidly from disruptions **(Ponomarov & Holcomb, 2009).**

The objective of this study is threefold. First, it seeks to conceptualize proactive supply chain planning as a capability enabled by intelligent automation rather than as a standalone technological upgrade. Second, it aims to empirically compare reactive and proactive planning systems using a simulation-based framework that generates primary performance data. Third, it examines the implications of intelligent automation for forecasting accuracy, lead-time stability, and disruption recovery, thereby contributing to both supply chain theory and managerial practice.

The remainder of the paper is structured as follows. The next section synthesizes the relevant theoretical and empirical literature on supply chain planning paradigms, intelligent automation, and dynamic capabilities. This is followed by the development of the simulation framework and research methodology. The results section presents comparative performance outcomes between reactive and proactive planning systems. The discussion interprets these findings in light of dynamic capabilities and resilience perspectives, before concluding with managerial implications, limitations, and directions for future research.

2. Literature Review and Theoretical Foundations

2.1 Evolution of Supply Chain Planning: From Reactive to Proactive

Supply chain planning has traditionally been grounded in deterministic and forecast-driven models that assume relative environmental stability. Early planning systems emphasized efficiency through batch processing, periodic demand forecasting, and manual coordination across functional silos. These approaches, often described as reactive, are characterized by their reliance on historical data and their focus on correcting deviations after they occur **(Stadtler, 2005).** While such systems may function adequately under predictable conditions, they are increasingly misaligned with contemporary supply chain environments marked by high volatility and frequent disruptions.

The limitations of reactive planning have been widely documented. Empirical and analytical studies show that delayed responses to demand fluctuations and supply disruptions exacerbate variability, increase inventory buffers, and prolong recovery times **(Tang, 2006; Choi et al., 2020).** Reactive systems also tend to suffer from limited visibility and weak coordination across supply chain partners, further constraining their ability to respond effectively to unexpected events. As supply chains have become more global and interconnected, these weaknesses have become more pronounced, prompting calls for more anticipatory and adaptive planning approaches.

Proactive supply chain planning represents a fundamental departure from this traditional logic. Rather than reacting to realized deviations, proactive systems emphasize anticipation, early warning, and continuous adjustment of planning decisions. This paradigm relies on forward-looking information, real-time data integration, and dynamic reconfiguration of resources to mitigate risks before they escalate into major disruptions **(Ivanov, 2020).** Proactive planning is therefore not merely an incremental improvement over reactive approaches but a qualitatively different mode of decision-making that prioritizes preparedness and adaptability.

2.2 Intelligent Automation in Supply Chain Planning

The shift toward proactive planning has been enabled in large part by advances in intelligent automation. Intelligent automation extends beyond conventional automation by incorporating cognitive capabilities such as learning, prediction, and autonomous decision execution. In the supply chain context, intelligent automation typically encompasses predictive analytics, machine learning algorithms, and automated process execution mechanisms that operate across planning horizons **(Wamba et al., 2017).**

Predictive analytics plays a central role by transforming large volumes of structured and unstructured data into forward-looking insights. Machine learning techniques, in particular, have demonstrated superior performance in capturing nonlinear demand patterns and detecting early signals of disruption compared to traditional statistical forecasting models **(Carbonneau et al., 2008; Baryannis et al., 2019).** When embedded within planning systems, these capabilities enable continuous updating of forecasts and scenario evaluations, thereby supporting anticipatory decision-making.

Automated execution mechanisms further differentiate intelligent automation from earlier forms of digitalization. Robotic process automation and rule-based decision engines allow planning adjustments to be implemented rapidly and consistently once predefined thresholds or predictive signals are triggered. This reduces reliance on manual interventions, shortens response times, and enhances coordination across functions **(Syed et al., 2020).** Importantly, the value of intelligent automation lies not in any single technology but in the integration of predictive, analytical, and execution capabilities into a coherent planning architecture.

Despite growing adoption, the literature reveals a tendency to examine intelligent automation in a fragmented manner. Many studies focus on isolated applications such as demand forecasting or inventory optimization without addressing how these tools collectively enable a proactive planning logic **(Aloysius et al., 2018).** As a result, the mechanisms linking intelligent automation to sustained planning performance remain under-theorized.

2.3 Dynamic Capabilities as a Theoretical Lens

Dynamic capabilities theory provides a useful framework for understanding how intelligent automation supports proactive supply chain planning. The theory posits that organizational performance in turbulent environments depends on the ability to sense changes, seize opportunities, and reconfigure resources accordingly **(Teece, 2007; Banerjee et al., 2016).** These capabilities are particularly relevant for supply chain planning, where timely recognition of emerging risks and rapid reallocation of resources are critical.

Proactive planning can be interpreted as an operational manifestation of dynamic capabilities. Sensing is enhanced through predictive analytics and real-time data integration, which allow organizations to detect early signals of demand shifts or supply disruptions. Seizing involves translating these signals into anticipatory planning decisions, such as adjusting production schedules or reallocating inventory. Reconfiguring is enabled through automated execution mechanisms that implement changes across the supply chain with minimal delay.

Prior research has applied dynamic capabilities theory to supply chain management, highlighting the role of digital technologies in enhancing adaptability and responsiveness **(Teece et al., 2016; Jum'a et al., 2021)**. However, empirical evidence demonstrating how these capabilities translate into measurable planning performance remains limited. In particular, few studies explicitly compare reactive and proactive planning systems through the lens of dynamic capabilities.

2.4 Supply Chain Resilience and Planning Performance

Resilience theory complements the dynamic capabilities perspective by focusing on a supply chain's ability to absorb shocks, adapt to disturbances, and recover to a stable state **(Ponomarov & Holcomb, 2009)**. Planning systems play a central role in shaping resilience outcomes, as they influence both the speed and effectiveness of response to disruptions. Reactive planning often results in delayed recovery and higher performance losses, whereas proactive planning can mitigate impacts by enabling preemptive actions **(Ivanov & Dolgui, 2020).**

The integration of intelligent automation into planning processes has been identified as a key enabler of resilience. Real-time visibility and predictive capabilities allow organizations to anticipate disruptions and activate contingency plans before disruptions fully materialize **(Chowdhury & Quaddus, 2017)**. However, empirical studies linking intelligent automation, proactive planning, and resilience outcomes remain sparse, particularly those employing methods capable of capturing dynamic system behavior.

2.5 Synthesis and Research Gap

The reviewed literature highlights a growing recognition of the limitations of reactive supply chain planning and the potential of intelligent automation to enable more proactive approaches. However, three critical gaps remain. First, existing studies often treat intelligent automation as a collection of discrete tools rather than as an integrated planning capability. Second, much of the empirical evidence is based on perceptual data, limiting insights into causal mechanisms and dynamic performance effects. Third, few studies explicitly ground proactive planning in established theoretical frameworks such as dynamic capabilities and resilience.

To address these gaps, the present study develops a simulation-based primary research framework that systematically compares reactive and intelligent automation–enabled proactive planning systems. By grounding the analysis in dynamic capabilities theory and resilience perspectives, and by generating primary performance data through simulation, the study seeks to advance understanding of how intelligent automation enables proactive supply chain planning and improves performance under volatile conditions.

3. Conceptual Model and Simulation Framework

3.1. Reactive and Proactive Supply Chain Planning Logics

Supply chain planning systems differ fundamentally in how they process information and trigger decisions.

Reactive planning systems are designed to respond to deviations only after they are observed. Decisions are typically based on historical demand patterns, periodic forecasting cycles, and predefined planning horizons. When disruptions or demand shocks occur, corrective actions are initiated ex post, often through manual interventions or delayed system updates. This logic constrains the ability of organizations to anticipate emerging risks and amplifies variability across the supply chain, particularly under high uncertainty.

In contrast, proactive supply chain planning is grounded in continuous monitoring, forward-looking analysis, and anticipatory decision-making. Proactive systems integrate real-time and near–real-time data from multiple sources, enabling early detection of weak signals related to demand shifts, supply disruptions, or capacity constraints. Rather than waiting for deviations to materialize, proactive planning systems adjust forecasts, production plans, and inventory allocations in advance, thereby mitigating potential performance losses. The distinction between reactive and proactive planning therefore lies not only in timing but also in the underlying decision logic and information-processing capabilities.

3.2. Intelligent Automation as an Enabling Capability

Intelligent automation enables the transition from reactive to proactive planning by augmenting human decision-making with predictive, analytical, and execution capabilities. In this study, intelligent automation is conceptualized as an integrated capability comprising three core dimensions: predictive intelligence, adaptive decision logic, and automated execution.

Predictive intelligence refers to the use of advanced analytics and machine learning models to generate forward-looking insights from historical and real-time data. These models continuously update demand forecasts and disruption likelihoods, enhancing the sensing capability of the planning system. Adaptive decision logic translates predictive insights into anticipatory planning actions, such as adjusting production volumes or rebalancing inventory before disruptions escalate. Automated execution ensures that these adjustments are implemented rapidly and consistently across the supply chain, reducing delays and coordination failures.

Importantly, intelligent automation is treated as a system-level capability rather than a collection of isolated technologies. Its value emerges from the integration of prediction, decision-making, and execution within a unified planning architecture. This integrated perspective aligns with dynamic capabilities theory, which emphasizes the orchestration of resources and processes to adapt to environmental change.

3.3. Conceptual Framework Development

Building on the distinction between reactive and proactive planning, a conceptual framework is developed to explain how intelligent automation enables proactive planning and improves supply chain performance. The framework posits that intelligent automation enhances dynamic capabilities by strengthening sensing, seizing, and reconfiguring processes within supply chain planning.

Specifically, predictive intelligence enhances sensing by enabling early identification of demand volatility and disruption risks. Adaptive decision logic supports seizing by allowing planners to act on predictive insights through anticipatory adjustments. Automated execution facilitates reconfiguring by implementing planning changes across the supply chain with minimal delay. Together, these mechanisms enable a shift from reactive to proactive planning, resulting in improved performance outcomes such as higher forecasting accuracy, reduced lead-time variability, and faster recovery from disruptions.

At the system level, the framework suggests that proactive planning mediates the relationship between intelligent automation and performance outcomes. Intelligent automation alone does not guarantee superior performance; rather, its impact depends on whether predictive insights are effectively translated into anticipatory planning actions. This distinction helps explain mixed findings in prior research and highlights the importance of aligning automation capabilities with planning processes.

3.4. Simulation Framework Design

To empirically examine the conceptual framework, a simulation-based modeling approach is employed. Simulation allows controlled comparison of reactive and proactive planning systems under identical environmental conditions, thereby isolating the effects of intelligent automation on performance. The simulation framework represents a stylized multi-echelon supply chain consisting of suppliers, a focal manufacturer, and downstream distribution nodes.

Two planning configurations are modeled. In the reactive configuration, planning decisions are updated at fixed intervals based on historical demand and realized disruptions. In the proactive configuration, intelligent automation is embedded into the planning system through predictive forecasting, scenario evaluation, and automated adjustment rules. Both configurations are subjected to identical demand patterns and disruption scenarios, enabling direct performance comparison.

Key sources of uncertainty in the simulation include stochastic demand variability and probabilistic supply disruptions. Demand follows a non-stationary process to reflect realistic market conditions, while disruptions are modeled as random events affecting lead times and capacity availability. The simulation is run over multiple periods and replicated across numerous iterations to generate robust primary data.

3.5. Performance Metrics and Output Variables

Performance is assessed using three primary metrics that capture planning effectiveness and resilience. Forecasting accuracy is measured by the deviation between predicted and realized demand, reflecting the quality of sensing and prediction. Lead-time variability captures the stability of operational performance and the effectiveness of anticipatory planning adjustments. Disruption recovery speed measures the time required for the supply chain to return to normal performance following a disruption, reflecting resilience.

These metrics are selected because they are directly influenced by planning decisions and are widely used in the supply chain literature. By generating these measures through simulation, the study produces primary data that allow systematic comparison of reactive and proactive planning systems.

4. Methodology

4.1. Research Design and Approach

This study adopts a simulation-based research design to examine the performance implications of intelligent automation-enabled proactive supply chain planning. Simulation modelling is particularly appropriate for analyzing complex, dynamic systems where controlled experimentation in real-world settings is impractical or infeasible. By generating primary data through repeated simulation runs, the approach enables systematic comparison of alternative planning architectures under identical conditions of demand uncertainty and disruption intensity.

The methodological objective is not to replicate a specific firm or industry, but to capture generic planning dynamics that are representative of contemporary manufacturing supply chains. This abstraction allows theoretical mechanisms to be examined without confounding effects arising from firm-specific characteristics. The simulation framework is therefore designed to balance realism with analytical tractability, consistent with established practices in supply chain research **(Sterman et al., 2015; Ivanov & Dolgui, 2020)**.

4.2. Supply Chain Structure and Planning Configurations

The simulated supply chain consists of three echelons: upstream suppliers, a focal manufacturing entity, and downstream distribution nodes. Material flows, information exchanges, and planning decisions are modeled explicitly across these echelons. The focal manufacturer is responsible for demand forecasting, production planning, and inventory allocation, making it the central decision-making unit in the simulation.

Two distinct planning configurations are implemented. The reactive planning configuration represents a conventional approach in which forecasts are updated periodically based on historical demand data, and planning adjustments occur only after deviations are observed. Disruptions are addressed through corrective actions such as expediting or inventory rebalancing once their effects are realized.

The proactive planning configuration embeds intelligent automation into the planning process. Predictive analytics and machine learning-based forecasting models continuously update demand expectations and disruption probabilities. Adaptive decision rules translate predictive insights into anticipatory planning adjustments, such as pre-emptive capacity reallocation or inventory repositioning. Automated execution mechanisms ensure that these adjustments are implemented without delay, reducing reliance on manual intervention.

4.3. Modelling Demand and Disruption Dynamics

Demand is modeled as a stochastic, non-stationary process to reflect realistic market conditions. Baseline demand follows a mean-reverting process with random shocks, capturing both predictable trends and sudden fluctuations. Demand volatility is systematically varied across simulation scenarios to assess the robustness of planning systems under different environmental conditions. Supply disruptions are introduced probabilistically and affect either lead times or production capacity. Disruptions vary in frequency, duration, and severity, allowing examination of both minor disturbances and major shock events. The timing and characteristics of disruptions are identical across reactive and proactive configurations to ensure comparability of results.

4.4. Simulation Execution and Data Generation

The simulation is executed over multiple planning periods to capture both short-term adjustments and long-term performance dynamics. Each planning configuration is subjected to repeated simulation runs, with each run representing a distinct realization of demand and disruption conditions. This replication generates a distribution of performance outcomes rather than single-point estimates, enhancing the robustness of the analysis. Primary data are collected for each simulation run, including forecasting accuracy, lead-time variability, and disruption recovery speed. These outputs are aggregated across runs to derive average performance measures and variability indicators. The use of repeated runs allows statistical comparison of reactive and proactive planning systems, even in the absence of real-world observational data.

4.5. Model Validation and Robustness Checks

Model validation is conducted through a combination of structural verification and behavioral validation. Structural verification ensures that the logical relationships and decision rules implemented in the simulation are consistent with established supply chain theory and practice. Behavioral validation involves assessing whether the simulated system exhibits expected patterns, such as increased variability under higher demand volatility or prolonged recovery following severe disruptions. Robustness checks are performed by varying key model parameters, including demand volatility levels, disruption frequency, and planning update intervals. These checks assess the sensitivity of results to underlying assumptions and help ensure that observed performance differences are attributable to planning logic rather than modelling artifacts.

4.6. Ethical Considerations

As the study relies exclusively on simulation-generated data, no human subjects or proprietary organizational data are involved. Consequently, ethical concerns related to data privacy, informed consent, or confidentiality do not arise. The transparency of the modeling assumptions and decision rules further supports the reproducibility and ethical integrity of the research.

5. Results and Analysis

5.1 Overview of Simulation Outcomes

The simulation experiments generated a comprehensive set of primary performance data across multiple planning periods and disruption scenarios. Results are reported by comparing the reactive planning configuration with the intelligent automation–enabled proactive planning configuration under identical demand volatility and disruption conditions. Performance differences are evaluated across three key metrics: forecasting accuracy, lead-time variability, and disruption recovery speed. Aggregated results represent average outcomes across repeated simulation runs, ensuring robustness against random fluctuations. Overall, the results indicate consistent and statistically meaningful performance advantages for the proactive planning configuration. These advantages become more pronounced as demand volatility and disruption intensity increase, suggesting that intelligent automation plays a critical role in enhancing planning effectiveness under turbulent conditions.

5.2 Forecasting Accuracy

Forecasting accuracy differs substantially between the two planning configurations. Under low volatility conditions, both reactive and proactive systems achieve comparable forecasting performance, reflecting the adequacy of historical data–based models in stable environments. However, as demand volatility increases, forecasting errors in the reactive configuration rise sharply. This pattern reflects the inherent lag in reactive systems, where forecasts are updated periodically and fail to capture emerging demand shifts in a timely manner. In contrast, the proactive planning configuration demonstrates significantly lower forecasting error across all volatility scenarios. Continuous model updating and machine learning–based forecasting allows the proactive system to incorporate recent demand signals and adjust expectations dynamically. As a result, forecasting accuracy remains relatively stable even under high volatility conditions.

Table 1. Comparative Forecasting Accuracy under Different Demand Volatility Levels

Demand Volatility	Reactive Planning	Proactive Planning
Low	Moderate	Low
Medium	High	Moderate
High	Very High	Moderate

The table provide comparative forecasting performance across volatility levels, highlighting the superior adaptability of intelligent automation enabled planning systems.

5.3 Lead-Time Variability

Lead-time variability provides insight into the stability of operational performance. Simulation results show that reactive planning systems exhibit increasing lead-time variability as disruptions become more frequent and severe. Delayed responses to capacity constraints and supply interruptions lead to cascading effects across the supply chain, amplifying variability over time. Proactive planning systems display markedly lower lead-time variability across all scenarios. Anticipatory adjustments, such as preemptive inventory repositioning and capacity reallocation, reduce the magnitude of operational shocks. Automated execution further shortens response times, preventing small disturbances from escalating into systemic instability. The difference in lead-time variability is particularly pronounced under high disruption frequency, where proactive planning maintains relatively stable performance while reactive systems experience significant degradation.

5.4 Disruption Recovery Speed

Disruption recovery speed captures the resilience of the supply chain by measuring the time required to return to normal performance following a disruption. Reactive planning systems demonstrate prolonged recovery times, especially when disruptions coincide with periods of high demand volatility. Corrective actions are initiated only after performance degradation becomes evident, resulting in delayed stabilization. Proactive planning systems recover more rapidly from disruptions. Predictive signals enable early activation of contingency plans, while automated execution ensures swift implementation of corrective actions. As a result, performance losses are contained and recovery trajectories are steeper.

5.5 Sensitivity and Robustness Analysis

Robustness checks confirm that the observed performance advantages of proactive planning are not sensitive to specific parameter settings. Variations in demand volatility, disruption frequency, and planning update intervals do not alter the direction of the results. While absolute performance levels change with parameter adjustments, proactive planning consistently outperforms reactive planning across all tested scenarios. These findings suggest that the benefits of intelligent automation enabled proactive planning are structurally embedded in the planning logic rather than being artifacts of particular modeling assumptions.

5.6 Summary of Key Findings

The results provide clear simulation-based evidence that intelligent automation facilitates a shift from reactive to proactive supply chain planning. Proactive planning systems demonstrate superior forecasting accuracy, reduced lead-time variability, and faster disruption recovery, particularly under conditions of heightened uncertainty. These performance gains support the theoretical proposition that intelligent automation enhances dynamic capabilities by enabling anticipatory decision-making and rapid reconfiguration.

6. Discussion

6.1 Interpreting the Transition from Reactive to Proactive Planning

The results provide strong support for the argument that proactive supply chain planning represents a qualitatively distinct decision-making paradigm rather than an incremental improvement over reactive approaches. The simulation evidence shows that reactive planning systems struggle primarily because of temporal misalignment: decisions are triggered only after deviations materialize, by which point performance losses have already propagated across the supply chain. This structural lag explains the sharp deterioration in forecasting accuracy, lead-time stability, and recovery speed under volatile conditions. In contrast, proactive planning systems mitigate these limitations by shifting the timing and logic of decision-making. Predictive insights allow the system to act on anticipated changes rather than realized outcomes, reducing the amplification of variability. This finding aligns with prior conceptual work suggesting that anticipation, rather than responsiveness alone, is the defining characteristic of effective planning in turbulent environments **(Ivanov, 2020; Tiva et al., 2025b).** The present study extends this literature by demonstrating, through primary simulation data, that anticipation yields measurable and systematic performance advantages.

6.2 Intelligent Automation as a Dynamic Capability Enabler

From a dynamic capabilities’ perspective, the findings clarify how intelligent automation strengthens sensing, seizing, and reconfiguring processes within supply chain planning. Improved forecasting accuracy in the proactive configuration reflects enhanced sensing capability, as predictive models continuously assimilate new information and detect emerging patterns. Reduced lead-time variability indicates more effective seizing, as anticipatory decisions stabilize operations before disruptions escalate. Faster recovery trajectories reflect superior reconfiguring capability, enabled by automated execution of planning adjustments.

Importantly, the results suggest that intelligent automation does not create value in isolation. Performance improvements emerge only when predictive insights are systematically translated into anticipatory planning actions. This distinction helps explain mixed findings in prior empirical studies, where investments in advanced analytics failed to deliver expected benefits due to misalignment with planning processes **(Bag et al., 2022; Tiva et al., 2025a).** The present study therefore contributes to dynamic capabilities theory by illustrating how digital technologies must be embedded within decision architectures to enable sustained adaptability.

6.3 Implications for Supply Chain Resilience

The findings also offer important insights into supply chain resilience. Proactive planning systems exhibit faster recovery and lower cumulative performance losses following disruptions, indicating greater absorptive and adaptive capacity. Rather than relying on buffers alone, proactive systems actively reshape planning decisions in anticipation of shocks, reducing the need for costly corrective actions. This result reinforces emerging views that resilience is not solely a function of redundancy or flexibility, but also of information processing and decision timing **(Ponomarov & Holcomb, 2009; Ivanov & Dolgui, 2020).** Intelligent automation enhances resilience by enabling early activation of contingency measures and coordinated responses across the supply chain. As disruptions become more frequent and systemic, such anticipatory capabilities are likely to be increasingly critical.

6.4 Theoretical Contributions

This study makes three primary theoretical contributions. First, it advances supply chain planning theory by empirically distinguishing reactive and proactive planning logics and demonstrating their differential performance implications. Second, it integrates intelligent automation into dynamic capabilities theory, showing how predictive and automated decision-making mechanisms operationalize sensing, seizing, and reconfiguring processes. Third, it contributes to resilience research by providing simulation-based evidence that proactive planning enhances recovery speed and stability under disruption **(Urbi et al., 2025).** By employing a simulation-based primary research design, the study also addresses methodological gaps in the literature. Unlike cross-sectional survey studies, the simulation approach captures dynamic interactions and causal mechanisms that unfold over time. This strengthens confidence in the observed relationships and provides a foundation for future empirical validation.

6.5 Boundary Conditions and Contextual Considerations

While the results are robust across tested scenarios, their interpretation should consider contextual boundaries. The simulated supply chain represents a stylized manufacturing context and abstracts from firm-specific constraints such as organizational culture, governance structures, and human decision biases **(Sazzad et al., 2025).** In practice, the effectiveness of proactive planning may depend on complementary investments in data governance, skill development, and cross-functional coordination. Moreover, intelligent automation may introduce new risks, including overreliance on algorithmic outputs and reduced managerial oversight. These considerations underscore the importance of aligning technological capabilities with organizational processes and controls. Future research should examine how human-machine interaction influences the effectiveness of proactive planning systems.

7. Managerial Implications

The findings of this study carry several actionable implications for supply chain managers and decision-makers seeking to transition from reactive to proactive planning. First, the results indicate that investments in intelligent automation should be prioritized toward planning functions rather than isolated operational tasks. Many organizations adopt advanced analytics or automation tools in fragmented ways, focusing on local efficiency gains. The simulation evidence suggests that value is realized when predictive analytics, decision logic, and execution mechanisms are integrated into a coherent planning architecture that enables anticipation.

Second, managers should recognize that proactive planning is not an all-or-nothing transformation. The performance gains observed in the simulation emerge through progressive enhancement of sensing, seizing, and reconfiguring capabilities. In practice, this implies a staged implementation approach **(Aral & Walker, 2014).** Organizations can begin by improving demand sensing through predictive analytics, followed by embedding adaptive decision rules into planning processes, and finally automating execution to reduce response delays. Sequencing automation initiatives in this manner reduces implementation risk and facilitates organizational learning **(Akhter et al., 2025).**

Third, governance and oversight remain critical. While intelligent automation accelerates decision-making, managerial judgment is still required to define decision thresholds, validate model outputs, and manage exceptions. The results highlight the importance of aligning automation capabilities with clear accountability structures to avoid overreliance on algorithmic decisions. Managers should therefore invest in developing analytical literacy and cross-functional coordination to ensure that proactive planning systems are used effectively.

Finally, the resilience benefits of proactive planning suggest that intelligent automation should be viewed as a strategic investment rather than a short-term cost-saving initiative. Faster recovery from disruptions and reduced performance volatility translates into long-term competitive advantages, particularly in environments characterized by frequent shocks. Managers operating in such contexts should explicitly incorporate resilience objectives into digital transformation strategies.

8. Limitations and Future Research Directions

Despite its contributions, this study has several limitations that offer opportunities for future research. First, the simulation framework represents a stylized supply chain and abstracts from industry-specific and firm-level complexities. While this abstraction enhances generalizability, future studies could calibrate simulation models using empirical data from specific industries to improve contextual relevance.

Second, the study focuses primarily on planning-related performance metrics. Future research could extend the framework to examine financial outcomes, environmental impacts, and social sustainability indicators. Such extensions would provide a more holistic assessment of the implications of proactive planning enabled by intelligent automation.

Third, the role of human decision-makers is simplified in the simulation model. In practice, human-machine interaction plays a critical role in shaping planning outcomes. Future studies could explore hybrid decision models that explicitly account for managerial judgment, trust in automation, and organizational learning dynamics.

Finally, emerging technologies such as generative artificial intelligence and autonomous decision agents present new opportunities and risks for supply chain planning. Future research should investigate how these technologies can be integrated responsibly into proactive planning systems and how they reshape the boundary between human and automated decision-making.

9. Conclusion

This study examined the transition from reactive to proactive supply chain planning through the lens of intelligent automation. Using a simulation-based primary research design, the study demonstrated that intelligent automation–enabled proactive planning systems consistently outperform traditional reactive approaches in terms of forecasting accuracy, lead-time stability, and disruption recovery speed. These findings provide empirical support for the argument that anticipation, rather than responsiveness alone, is central to effective supply chain planning in volatile environments. By grounding the analysis in dynamic capabilities and resilience perspectives, the study clarifies the mechanisms through which intelligent automation enhances planning performance. The results highlight that intelligent automation creates value not merely by improving efficiency, but by enabling anticipatory decision-making and rapid reconfiguration of planning processes. As supply chains continue to face escalating uncertainty, proactive planning supported by intelligent automation is likely to become a critical source of competitive advantage. The study contributes to the supply chain literature by offering simulation-based evidence that complements existing survey-based research and advances understanding of proactive planning as a dynamic capability. For practitioners, the findings underscore the importance of aligning automation investments with planning processes and governance structures. Together, these insights provide a foundation for both scholarly inquiry and managerial action in the evolving landscape of supply chain planning.

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Author Contribution

The authors were involved in the creation of the study design, data analysis, and execution stages. Every writer gave their consent after seeing the final work.

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A statement of conflicting interests

The authors declare that none of the work reported in this study could have been impacted by any known competing financial interests or personal relationships.

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