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AI-Driven Order Optimization and Stock Planning Systems: Strategic Decision-Making Beyond Traditional Sales Forecasting

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Abstract - Order optimization and stock planning have traditionally been treated as operational planning activities centered on sales forecasting accuracy and inventory balancing. While forecasting remains an important input, growing market volatility, demand uncertainty, and capital constraints have exposed the limitations of forecast-centric planning models. In complex commercial environments, order and inventory decisions increasingly function as strategic choices that directly influence profitability, risk exposure, and organizational agility. This paper examines how AI-driven order optimization and stock planning systems transform decision-making beyond traditional sales forecasting. From a business management perspective, the study argues that artificial intelligence shifts planning logic from prediction-focused models toward integrated, optimization-based decision systems. Rather than asking what demand will be, AI-enabled systems evaluate how ordering and stocking decisions should be configured under uncertainty, given multiple objectives and constraints. The paper conceptualizes AI-driven planning systems as strategic decision architectures that combine real-time data, optimization logic, and adaptive learning. It analyzes how these systems enable managers to balance competing priorities such as service levels, working capital efficiency, and operational risk. In doing so, AI-driven order optimization and stock planning move from reactive adjustment toward proactive and continuous decision governance. Building on management and decision systems literature, the study proposes a strategic decision-making framework that clarifies the roles of AI-driven optimization, managerial judgment, and governance mechanisms in order and inventory planning. The framework emphasizes that managerial value is created not through automation alone, but through deliberate design of decision rules, oversight structures, and accountability. The paper contributes to business management research by reframing order optimization and stock planning as strategic decision domains rather than technical forecasting exercises. For practitioners, it offers guidance on how to institutionalize AI-driven planning systems as scalable and governable capabilities that support long-term performance under uncertainty. The findings suggest that organizations that treat order and inventory decisions as strategic, AI-enabled choices are better positioned to achieve resilience, efficiency, and sustained competitive advantage.

Keywords - AI-Driven Decision Systems, Order Optimization, Stock Planning and Inventory Management, Strategic Decision-Making, Business Management

I. INTRODUCTION

Order optimization and stock planning decisions sit at the intersection of operational execution and strategic management. These decisions determine how organizations allocate capital, manage risk, and respond to uncertainty across their commercial operations. Traditionally, order quantities and inventory levels have been derived from sales forecasts, with planning accuracy evaluated primarily through forecast error metrics. While this approach provided structure in relatively stable environments, it is increasingly misaligned with the realities of contemporary markets.

Commercial environments today are characterized by volatile demand, fragmented channels, supply disruptions, and heightened cost pressures. In such conditions, accurate forecasting alone is insufficient to ensure effective decision-making. Managers are no longer simply tasked with predicting demand; they must determine how to configure ordering and stocking decisions in ways that balance service levels, working capital efficiency, and risk exposure under uncertainty. This shift elevates order optimization and stock planning from technical planning tasks to strategic decision problems.

The limitations of forecast-centric planning are especially evident when forecasts are treated as deterministic inputs rather than probabilistic signals. Traditional planning models often assume that forecast accuracy translates directly into better performance outcomes. In practice, even highly accurate forecasts can lead to suboptimal decisions if they are not integrated into broader optimization logic that considers constraints, trade-offs, and managerial priorities. As a result, organizations may experience excessive inventory, frequent stockouts, or inefficient capital utilization despite improvements in forecasting techniques.

AI-driven decision systems offer an alternative approach to order optimization and stock planning. Rather than focusing exclusively on predicting future demand, these systems evaluate decision options by incorporating multiple objectives and constraints simultaneously. AI-enabled optimization models assess how different ordering and stocking configurations perform under varying conditions, enabling managers to choose strategies that are robust rather than merely precise. This shift reflects a broader transformation in managerial decision-making from prediction-oriented planning toward optimization-oriented governance.

From a business management perspective, the adoption of AI-driven order optimization and stock planning systems raises important questions about decision authority, accountability, and strategic control. When optimization logic is embedded in algorithms, how should managers define objectives and acceptable risk levels? How can organizations ensure that AI-driven recommendations align with long-term strategy rather than short-term efficiency gains? These questions highlight that AI-driven planning systems are not neutral tools; they encode managerial intent and shape organizational behavior.

Existing research on inventory management and operations planning has largely emphasized mathematical optimization, forecasting accuracy, and computational efficiency. While these contributions are valuable, they often understate the managerial implications of shifting from forecast-based planning to AI-driven decision systems. There is limited conceptual guidance on how managers should design, govern, and evaluate AI-enabled order and stock planning as strategic capabilities.

This paper addresses this gap by examining AI-driven order optimization and stock planning systems through a business management lens. It argues that the strategic value of these systems lies not in automation or predictive accuracy alone, but in their ability to support structured decision-making under uncertainty. The analysis reframes order and inventory planning as a domain of strategic choice shaped by managerial objectives, governance mechanisms, and accountability structures.

The objectives of this study are threefold. First, it seeks to clarify the limitations of traditional sales forecasting and inventory planning models in volatile commercial environments. Second, it analyzes how AI-driven decision systems transform order optimization and stock planning by integrating optimization, adaptation, and real-time data. Third, it proposes a strategic decision-making framework that articulates the roles of AI, managerial judgment, and governance in sustaining performance and resilience.

By positioning order optimization and stock planning as strategic decision systems, this paper contributes to business management literature on decision-making, operations governance, and AI-enabled management. For practitioners, it offers a foundation for leveraging AI-driven planning systems as instruments of strategic control rather than operational automation. Ultimately, the paper contends that organizations that move beyond forecast-centric planning toward AI-driven decision governance are better equipped to navigate uncertainty and achieve sustainable performance.

II. ORDER OPTIMIZATION AND STOCK PLANNING AS STRATEGIC MANAGEMENT DOMAINS

Order optimization and stock planning have traditionally been framed as operational planning activities focused on execution efficiency. In many organizations, these decisions are delegated to supply chain or operations functions and evaluated primarily through cost-based metrics such as inventory turnover or service level attainment. From a business management perspective, however, this framing underestimates the strategic significance of ordering and stocking decisions and their direct impact on organizational performance.

At their core, order and stock decisions determine how financial resources are committed under uncertainty. Inventory represents one of the largest uses of working capital in many commercial organizations, while ordering decisions shape exposure to demand volatility, supply disruptions, and price fluctuations. As such, decisions regarding when, how much, and what to order are inseparable from broader strategic considerations related to risk tolerance, growth priorities, and capital efficiency.

A defining feature of order optimization and stock planning as strategic domains is trade-off intensity. Managers must continuously balance competing objectives, including service level reliability, inventory carrying costs, obsolescence risk, and responsiveness to market changes. These trade-offs are not purely technical; they reflect strategic choices about customer value propositions and competitive positioning. For example, prioritizing high service levels may support market differentiation but requires greater capital commitment and risk acceptance.

Order and inventory decisions are also characterized by intertemporal effects. Choices made today influence future flexibility and performance. Excess inventory may constrain future investment options, while insufficient stock can damage customer relationships and brand credibility. These long-term consequences elevate order optimization beyond short-term efficiency considerations and into the realm of strategic decision-making.

Another strategic dimension arises from organizational coordination. Order and stock planning decisions sit at the intersection of sales, operations, finance, and procurement. Misalignment among these functions can lead to conflicting priorities, such as sales-driven overordering or finance-driven understocking. Effective strategic management of order and inventory planning therefore requires governance mechanisms that align functional objectives with enterprise-wide strategy.

Uncertainty further reinforces the strategic nature of these decisions. Demand variability, supply disruptions, and macroeconomic shocks introduce risk that cannot be eliminated through forecasting alone. Managers must decide how much uncertainty the organization is willing to absorb and how risk should be distributed across inventory buffers, supplier contracts, and ordering policies. These decisions reflect strategic posture rather than operational calculation.

From this perspective, treating order optimization and stock planning as purely operational tasks obscures their role in shaping organizational resilience and competitive advantage. Strategic management of these domains involves defining acceptable risk levels, prioritizing performance objectives, and establishing decision rules that guide behavior across the organization. AI-driven decision systems, discussed in subsequent sections, provide new mechanisms for operationalizing these strategic choices at scale.

In summary, order optimization and stock planning constitute strategic management domains characterized by capital commitment, trade-off intensity, intertemporal impact, cross-functional coordination, and uncertainty. Recognizing their strategic nature clarifies why traditional forecasting-centered approaches are insufficient and sets the foundation for examining the limitations of conventional sales forecasting and inventory planning models, addressed in the following section.

III.LIMITATIONS OF TRADITIONAL SALES FORECASTING AND INVENTORY PLANNING MODELS

Traditional sales forecasting and inventory planning models have long served as the analytical backbone of ordering and stocking decisions. By estimating future demand and translating these estimates into replenishment quantities, such models provide a structured basis for planning. However, as commercial environments have become more volatile and complex, the limitations of forecast-centric approaches have become increasingly evident, particularly from a strategic management perspective.

A primary limitation lies in the assumption of forecast centrality. Traditional models implicitly treat demand forecasts as the dominant input to planning decisions, with ordering and stocking policies derived mechanically from predicted demand levels. This logic assumes that improving forecast accuracy will automatically improve decision quality. In practice, even modest forecast errors can propagate into large inventory imbalances when decisions are not explicitly optimized for uncertainty, constraints, and strategic priorities.

Another critical limitation is the static treatment of uncertainty. Forecast-based models often represent uncertainty through safety stock buffers calculated using historical variance. While this approach provides a basic risk cushion, it fails to account for dynamic changes in demand patterns, supply reliability, or market conditions. As a result, safety stock levels may be either insufficient during periods of heightened volatility or excessive during periods of stability, leading to inefficient capital allocation.

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Traditional planning models also struggle with multi-objective trade-offs. Forecast-driven approaches typically prioritize service level attainment or cost minimization in isolation. Strategic decisions, however, require balancing multiple objectives simultaneously, such as working capital efficiency, responsiveness, and risk exposure. When models are not designed to explicitly evaluate these trade-offs, managers are forced to make ad hoc adjustments that undermine analytical consistency.

A further limitation concerns organizational decision dynamics. Forecast outputs are often treated as authoritative inputs in planning discussions, even when underlying assumptions are uncertain or outdated. This reliance can discourage managerial judgment and reduce adaptability. Conversely, when managers override forecasts without structured guidance, planning becomes fragmented and inconsistent. In both cases, the absence of an integrated decision framework weakens strategic control.

Traditional inventory planning models are also constrained by their reactive orientation. Adjustments are typically made after discrepancies between forecast and actual demand are observed. This lag reduces the organization's ability to anticipate and mitigate emerging risks. In environments where demand shifts rapidly, reactive adjustments may arrive too late to prevent stockouts, excess inventory, or service disruptions.

Finally, forecast-centric models offer limited governance transparency. While they generate numerical outputs, they rarely make explicit the decision logic linking forecasts to ordering policies. Managers may accept or reject recommendations without a clear understanding of how trade-offs were evaluated. This opacity complicates accountability and learning, as it becomes difficult to assess whether outcomes resulted from forecasting errors, planning assumptions, or execution decisions.

In summary, traditional sales forecasting and inventory planning models are constrained by forecast centrality, static uncertainty treatment, limited trade-off evaluation, reactive orientation, and weak governance transparency. These limitations highlight the need for decision systems that move beyond prediction toward integrated optimization and adaptation. The following section examines how AI-driven decision systems address these shortcomings by reframing order and inventory planning as strategic decision processes rather than forecasting exercises.

IV. AI-DRIVEN DECISION SYSTEMS IN ORDER AND INVENTORY MANAGEMENT

AI-driven decision systems represent a fundamental shift in how order optimization and inventory planning are conceptualized and executed. Rather than treating forecasting as the core decision input, these systems integrate prediction, optimization, and adaptation into a unified decision architecture. From a managerial perspective, their primary contribution lies in restructuring how uncertainty, constraints, and strategic objectives are translated into actionable decisions.

At the heart of AI-driven decision systems is the move from predictive orientation to prescriptive and adaptive logic. Predictive models estimate what may happen; prescriptive models evaluate what should be done given multiple possible futures. In order and inventory management, this distinction is critical. Managers are less concerned with a single demand estimate than with how different ordering and stocking configurations perform across a range of demand scenarios. AI-driven systems operationalize this perspective by evaluating decisions under uncertainty rather than optimizing against point forecasts.

These systems also enable explicit multi-objective optimization. Order and inventory decisions rarely pursue a single goal. Service levels, working capital efficiency, holding costs, obsolescence risk, and supply reliability must all be considered simultaneously. AI-driven optimization frameworks allow managers to encode priorities and trade-offs directly into decision logic. As a result, decisions reflect strategic intent rather than implicit assumptions embedded in traditional planning formulas.

Another defining characteristic of AI-driven decision systems is their capacity for continuous adaptation. Unlike static planning models, AI-enabled systems learn from realized outcomes and update decision logic as conditions evolve. Changes in demand volatility, supplier performance, or cost structures

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can be incorporated into future recommendations without requiring wholesale redesign of planning processes. This adaptability supports resilience in environments where uncertainty is persistent rather than episodic.

From a governance standpoint, AI-driven decision systems enhance decision transparency and traceability. By making optimization objectives, constraints, and assumptions explicit, these systems provide managers with clearer insight into how recommendations are generated. This transparency supports accountability by enabling evaluation of decision quality rather than relying solely on outcome-based assessment. Managers can distinguish between unfavorable outcomes driven by external shocks and those resulting from suboptimal decision logic.

AI-driven systems also reshape managerial involvement in order and inventory planning. Managers move from manual calculation and exception handling toward defining decision boundaries, acceptable risk levels, and performance priorities. Their role becomes one of decision architecture design and oversight rather than direct execution. This shift allows managerial expertise to scale across a large number of operational decisions.

However, the effectiveness of AI-driven decision systems depends on deliberate managerial design. Poorly specified objectives or constraints can produce recommendations that are technically optimal but strategically misaligned. Managers must therefore treat system configuration as a strategic activity, revisiting assumptions and priorities as organizational goals evolve.

In summary, AI-driven decision systems transform order and inventory management by shifting the focus from forecast accuracy to decision robustness, from static planning to adaptive optimization, and from manual oversight to governance through design. These capabilities provide the foundation for more sophisticated order optimization models, examined in the following section, which explores how AI-based approaches reshape ordering decisions in practice.

V.AI-BASED ORDER OPTIMIZATION MODELS

Order optimization models determine when, how much, and under what conditions organizations commit resources to procurement and production decisions. Traditionally, these models relied on deterministic rules derived from forecasts, reorder points, or fixed replenishment cycles. AI-based order optimization models depart from this logic by treating ordering decisions as dynamic choices evaluated across multiple objectives and uncertain outcomes.

A key feature of AI-based order optimization is the explicit representation of decision alternatives. Rather than calculating a single “optimal” order quantity, these models evaluate a range of feasible options under varying demand, supply, and cost scenarios. This approach enables managers to assess robustness—how well an ordering strategy performs across uncertainty—rather than relying on precision under assumed conditions.

AI-based models also incorporate temporal optimization. Ordering decisions affect not only immediate inventory levels but also future flexibility, supplier relationships, and cost exposure. By considering ordering decisions over multiple periods, AI-driven systems capture intertemporal trade-offs that traditional single-period models often ignore. This capability supports more coherent long-term planning aligned with strategic priorities.

Another important dimension is the integration of constraints and risk considerations. AI-based optimization models can incorporate supplier capacity limits, lead-time variability, contractual obligations, and risk thresholds directly into decision logic. Managers can specify acceptable risk levels or service guarantees, ensuring that recommendations reflect organizational risk appetite rather than purely cost-minimizing logic.

From a managerial perspective, AI-based order optimization enhances decision consistency and scalability. Similar ordering situations are evaluated using the same criteria, reducing variability caused by individual judgment differences. At the same time, models can adapt recommendations based on contextual factors, balancing consistency with flexibility. This scalability allows managers to influence a large number of decisions through system design rather than manual oversight.

AI-based models also support scenario exploration.

Managers can examine how recommended ordering strategies change under alternative assumptions, such as shifts in demand volatility or supplier reliability. This exploratory capability strengthens strategic understanding and enables more informed governance of ordering policies.

However, the effectiveness of AI-based order optimization depends on managerial involvement in defining objectives and constraints. Overly narrow optimization criteria may produce recommendations that conflict with broader strategic goals, while overly broad criteria may dilute decision clarity. Managers must therefore actively calibrate model parameters to ensure alignment with organizational priorities.

In summary, AI-based order optimization models transform ordering decisions by enabling robust, multi-period, and risk-aware evaluation of alternatives. Their value lies not in automating procurement, but in supporting strategic decision-making under uncertainty. The next section examines how AI-enabled stock planning and inventory optimization extend these principles to inventory management decisions.

VI.AI-ENABLED STOCK PLANNING AND INVENTORY OPTIMIZATION

Stock planning decisions translate ordering strategies into sustained operational readiness. They determine how much uncertainty an organization absorbs through inventory buffers, how capital is allocated over time, and how service commitments are honored across fluctuating demand conditions. In traditional settings, stock planning relied on static safety stock formulas and fixed service level targets. AI-enabled inventory optimization reframes these choices as dynamic, context-sensitive decisions embedded within broader strategic objectives.

A defining contribution of AI-enabled stock planning is the shift from static buffers to dynamic inventory policies. Rather than maintaining fixed safety stock levels based on historical variance, AI-driven systems adjust inventory targets in response to evolving demand patterns, lead-time reliability, and cost structures. This adaptability allows organizations to reduce excess inventory during stable periods while preserving resilience during volatility.

AI-enabled stock planning also enhances risk-sensitive decision-making. Inventory decisions inherently involve trade-offs between service reliability and capital efficiency. By modeling demand uncertainty probabilistically and evaluating outcomes across scenarios, AI-driven systems make risk explicit. Managers can specify acceptable service level ranges or downside risk thresholds, ensuring that inventory policies reflect strategic risk appetite rather than implicit assumptions.

Another important advancement lies in segmented inventory strategies. AI-enabled systems can differentiate stock policies across products, customers, or channels based on value contribution, demand variability, and lifecycle stage. This segmentation supports more nuanced inventory governance than uniform policies, aligning stock investment with strategic priorities such as growth markets or key accounts.

From a governance perspective, AI-enabled inventory optimization improves traceability and accountability. Decisions regarding safety stock adjustments or inventory rebalancing are grounded in explicit optimization logic rather than ad hoc judgment. Managers can review the rationale behind inventory recommendations, facilitating evaluation and learning. This transparency strengthens confidence in inventory decisions and supports cross-functional alignment.

AI-enabled stock planning also interacts closely with financial management. Inventory levels influence working capital, cash flow, and return on invested capital. By integrating financial constraints into optimization logic, AI-driven systems enable managers to evaluate inventory decisions in terms of their broader financial impact. This integration elevates stock planning from operational tuning to strategic capital allocation.

Despite these advantages, AI-enabled stock planning requires careful managerial calibration. Overemphasis on cost efficiency may compromise service reliability, while excessive risk aversion can inflate inventory. Managers must therefore periodically review optimization objectives and constraints to ensure alignment with changing strategic conditions.

In summary, AI-enabled stock planning transforms inventory management by introducing dynamic, risk-aware, and segmented decision logic. These capabilities support strategic control over inventory investment while preserving operational resilience. The following section examines how order optimization and stock planning systems interact when integrated into unified AI-driven planning architectures.

VII. INTEGRATION OF ORDER OPTIMIZATION AND STOCK PLANNING SYSTEMS

Order optimization and stock planning decisions are deeply interdependent. Ordering policies determine inventory inflows, while stock planning policies shape the buffer requirements that guide ordering behavior. When these decisions are managed through separate models or organizational silos, inconsistencies often arise, leading to excess inventory, service disruptions, or inefficient capital use. AI-driven planning systems address this challenge by integrating order optimization and stock planning into a unified decision architecture.

Integrated systems evaluate ordering and stocking decisions jointly rather than sequentially. Instead of first forecasting demand, then calculating order quantities, and finally adjusting safety stock, AI-driven systems assess how alternative ordering strategies affect inventory risk and service performance over time. This joint evaluation enables managers to identify decision configurations that balance short-term responsiveness with long-term stability.

Integration also enables continuous feedback between order execution and inventory outcomes. Realized demand, supplier performance, and inventory movements are fed back into the system, allowing decision logic to adapt dynamically. This feedback loop reduces the lag between planning assumptions and operational reality, improving decision robustness under changing conditions.

From a managerial perspective, integrated planning systems support end-to-end visibility. Managers can trace how strategic priorities—such as service differentiation or capital efficiency—are translated into ordering and stocking policies across the organization. This visibility strengthens governance by aligning functional decisions with enterprise-level objectives.

In summary, integrating order optimization and stock planning systems transforms planning from a fragmented process into a cohesive strategic capability. This integration provides the foundation for higher-level managerial control, discussed in the following section.

VIII. MANAGERIAL IMPLICATIONS FOR STRATEGIC DECISION-MAKING

The adoption of AI-driven order and inventory planning systems reshapes managerial roles and decision authority. Managers move from approving individual orders or inventory adjustments toward designing the decision logic that governs these actions. Strategic decision-making increasingly occurs through the definition of objectives, constraints, and risk thresholds embedded within AI systems.

This shift elevates managerial influence by allowing strategic intent to scale across numerous operational decisions. However, it also demands new competencies, including systems thinking, risk assessment, and governance design. Managers must balance trust in AI-driven recommendations with contextual judgment, ensuring that strategic priorities are preserved even as decision execution becomes more automated.

IX. GOVERNANCE, RISK, AND ACCOUNTABILITY IN AI-DRIVEN PLANNING SYSTEMS

AI-driven planning systems amplify both value creation and risk. Errors in decision logic or data inputs can propagate across the organization. Effective governance therefore requires clear accountability structures, transparency in optimization logic, and escalation mechanisms for high-impact decisions.

Accountability remains human-centered: managers are responsible for defining decision rules, monitoring outcomes, and intervening when necessary. Governance frameworks must ensure that AI-driven decisions are auditable, explainable, and aligned with ethical and strategic standards.

X. A STRATEGIC DECISION FRAMEWORK

FOR AI-DRIVEN ORDER AND STOCK PLANNING

This paper proposes a strategic decision framework that integrates AI-driven optimization with managerial oversight. The framework comprises four layers: data integrity, optimization logic, governance controls, and managerial accountability. Together, these layers ensure that AI-driven planning systems function as strategic assets rather than operational tools.

The framework emphasizes that sustained performance depends on continuous calibration of decision logic in response to evolving conditions. Managers act as stewards of the decision system, guiding adaptation while preserving strategic coherence.

XI.FUTURE DIRECTIONS OF AI-DRIVEN PLANNING SYSTEMS

Future developments in AI-driven planning systems are likely to include greater autonomy, enhanced explainability, and real-time adaptation. These advances will further blur the boundary between planning and execution, increasing the importance of governance design and ethical oversight. Research opportunities remain in understanding how different governance configurations influence resilience and performance.

XII.CONCLUSION

This paper examined how AI-driven order optimization and stock planning systems transform strategic decision-making beyond traditional sales forecasting. By reframing planning as a strategic governance challenge, the study demonstrated that AI-driven systems enable robust, adaptive, and accountable decision-making under uncertainty.

The findings highlight that the strategic value of AI in order and inventory planning lies not in predictive accuracy alone, but in its ability to support structured decision governance. Organizations that treat AI-driven planning systems as strategic decision architectures are better positioned to achieve resilience, efficiency, and sustained competitive advantage.

REFERENCES

[1] Silver, E. A., Pyke, D. F., & Thomas, D. J. (2017). *Inventory and Production Management in Supply Chains* (4th ed.). CRC Press.
[2] Chopra, S., & Meindl, P. (2022). *Supply Chain Management: Strategy, Planning, and Operation* (8th ed.). Pearson Education.
[3] Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2008). *Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies* (3rd ed.). McGraw-Hill.
[4] Silver, E. A., & Peterson, R. (1985). *Decision Systems for Inventory Management and Production Planning*. Wiley.
[5] Zipkin, P. (2000). *Foundations of Inventory Management*. McGraw-Hill.
[6] Hopp, W. J., & Spearman, M. L. (2011). *Factory Physics* (3rd ed.). Waveland Press.
[7] Fildes, R., Ma, S., & Kolassa, S. (2019). Retail forecasting: Research and practice. *International Journal of Forecasting*, 35(1), 1–9.
[8] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and machine learning forecasting methods: Concerns and ways forward. *PLOS ONE*, 13(3), e0194889.
[9] Davenport, T. H., & Harris, J. G. (2007). *Competing on Analytics: The New Science of Winning*. Harvard Business School Press.
[10] Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
[11] Simon, H. A. (1997). *Administrative Behavior: A Study of Decision-Making Processes in Administrative Organizations* (4th ed.). Free Press.
[12] Power, D. J. (2002). *Decision Support Systems: Concepts and Resources for Managers*. Quorum Books.
[13] Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 61(4), 66–83.
[14] Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210.
[15] Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586.

[16] Snyder, L. V., & Shen, Z.-J. M. (2019). *Fundamentals of Supply Chain Theory* (2nd ed.). Wiley.
[17] Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1), 333–372.
[18] Kroll, J. A., Huey, J., Barocas, S., et al. (2017). Accountable algorithms. *University of Pennsylvania Law Review*, 165(3), 633–705.