# Theoretical Perspectives on Intelligent Order Promising: Bridging ERP and AI-Driven Supply Chain Planning

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## ABSTRACT

Order Promising (OP) has emerged as a critical capability in modern supply chains, serving as the interface between customer demand and supply chain execution. Traditionally, OP has relied on rule-based Available-to-Promise (ATP) and Capable-to-Promise (CTP) models embedded in Enterprise Resource Planning (ERP) systems. However, the increasing complexity of global supply chains, demand volatility, and the rise of digital commerce have exposed the limitations of static promise mechanisms. This paper develops a theoretical framework for Intelligent Order Promising (IOP) that integrates ERP systems with advanced planning platforms, artificial intelligence (AI), and predictive analytics. The study examines OP not only as a logistics execution tool but also as a strategic lever for customer experience, profitability, and resilience. The framework conceptualizes IOP as a dynamic decision-making layer that balances promise reliability, supply chain efficiency, and customer-centricity. The paper contributes to the literature by positioning IOP as the bridge between transactional systems (ERP) and cognitive supply chain planning, highlighting directions for future research in digital and sustainable supply chains.

## General Terms

Order Promising; Supply Chain Management; Decision Support Systems; Optimization; Supply Chain Visibility; Artificial Intelligence; Resilient Supply Chains

## 1. INTRODUCTION

Order Promising (OP) has emerged as one of the most critical capabilities in contemporary supply chains, functioning as the direct interface between the customer and the firm's internal planning and execution systems. The promise of an order – whether it is delivery within two days for an e-commerce retailer or a six-month lead time for a semiconductor manufacturer – represents a contractual and psychological commitment that directly influences customer trust, satisfaction, and retention. In supply chain theory, OP has traditionally been understood through and mechanisms, where customer orders are matched against inventory availability, production capacity, and lead-time constraints [Kilger & Schneeweiss, 2000]. While such mechanisms have provided a structured foundation for commitment management, they were largely designed for relatively stable supply and demand conditions.

In the last decade, however, supply chains have become increasingly characterized by [Bennett & Lemoine, 2014]. The globalization of production networks, the rise of e-commerce and omnichannel fulfillment, and the impact of geopolitical and environmental disruptions have all placed unprecedented pressure on organizations to respond quickly and accurately to customer demands. Customers today no longer evaluate firms solely on cost or product quality; they also judge them based on . In this environment, static rule-based ATP/CTP checks embedded in ERP systems often fail to provide accurate and adaptive commitments, leading to mismatches between customer expectations and operational realities [Chen & Zhao, 2007].

This challenge has stimulated the evolution of what can be termed . Unlike traditional OP, which functions mainly as a , IOP envisions order promising as a within the supply chain. It integrates the transactional backbone of with the optimization capabilities of and the adaptability of and predictive analytics [Stadtler, 2005; Saberi et al., 2019]. The core premise of IOP is that order commitments should not only reflect current system constraints but should also anticipate potential disruptions, optimize profitability, and align with broader strategic goals such as customer experience, resilience, and sustainability.

Theoretical and managerial discussions increasingly highlight that order promises are not merely operational commitments but also . For instance, in highly competitive markets, the ability to make differentiated promises (e.g., premium customers receive prioritized allocation) can significantly influence customer loyalty and profitability [Madhavaram & Varadarajan, 2008]. Similarly, in global supply chains where uncertainty is high, dynamic promise adjustments can enhance resilience by redistributing commitments based on risk predictions. At the same time, sustainability considerations are prompting organizations to rethink promises from an environmental perspective, where "green promises" may balance service performance with reduced carbon emissions [Golgeci et al., 2020].

Despite these emerging perspectives, there remains a in understanding OP as an integrative, intelligence-driven framework. Existing research streams largely fall into three silos: (a) traditional deterministic ATP/CTP models, (b) ERP-centric transactional OP, and (c) optimization-focused APS approaches. While recent studies have started to address AI and digital technologies in OP, there is a lack of holistic conceptualization that unites these streams into a coherent framework for IOP. Without such a framework, both academics and practitioners risk treating OP as a fragmented set of tools rather than a unified strategic capability.

The purpose of this paper is to contribute to closing this gap by developing a . The framework positions IOP as a bridge between ERP-driven transaction processing and AI-enabled planning and decision-making. Specifically, it conceptualizes OP as a multi-dimensional construct characterized by . By doing so, the paper makes three contributions. First, it extends the academic understanding of OP beyond its traditional boundaries as a logistics execution mechanism. Second, it offers a managerial perspective on how firms can leverage IOP to simultaneously improve operational efficiency and customer-centricity. Third, it highlights avenues for future research at the intersection of digital transformation, sustainability, and supply chain resilience.

# 2. LITERATURE REVIEW

Order Promising (OP) has been extensively studied within supply chain management, operations research, and information systems literature. While the terminology and technological enablers have evolved, the core challenge of OP has remained the same: aligning customer expectations with the realities of supply, production, and logistics constraints. To position the proposed framework for Intelligent Order Promising (IOP), it is essential to examine prior work across four major domains: (i) traditional OP models, (ii) ERP-centric approaches, (iii) Advanced Planning Systems (APS) integration, and (iv) the impact of digital transformation, including artificial intelligence (AI), blockchain, and sustainability considerations.

## 2.1 Traditional Order Promising Models

Early conceptualizations of OP were primarily rooted in deterministic models designed to ensure feasibility of commitments. The Available-to-Promise (ATP) mechanism, first formalized within materials management and early ERP systems, matched incoming customer orders against inventory on hand and planned receipts [Kilger & Schneeweiss, 2000]. ATP became a foundational mechanism for industries where lead times were short and demand variability was limited. However, as supply chains became more global and complex, ATP alone was insufficient for industries where capacity constraints and production lead times were significant.

To address this, the concept of Capable-to-Promise (CTP) emerged, which extended ATP by incorporating production capacity and routing information into the promise logic [Chen & Zhao, 2007]. CTP enabled organizations to not only check whether an item was in stock, but also whether it could be manufactured within the required timeframe. While CTP provided more accurate commitments, it remained deterministic, assuming stability in production schedules and ignoring uncertainties such as supplier delays, machine breakdowns, or transportation disruptions.

Scholars have also explored probabilistic and optimization-based extensions to ATP/CTP. For instance, some studies introduced allocation rules for scarce capacity, where firms must decide how to distribute limited resources among competing orders (e.g., prioritizing high-margin or strategic customers) [Rong et al., 2008]. Others emphasized multi-site ATP, where promises are made based on global inventory visibility across multiple warehouses or plants [Stadtler, 2005]. Despite these advances, the underlying limitation of traditional OP models was their static nature—they operated on snapshots of data rather than continuously adapting to dynamic conditions.

## 2.2 ERP-Centric Approaches to OP

The rise of Enterprise Resource Planning (ERP) systems in the 1990s and early 2000s transformed how firms executed OP in practice. ERP platforms such as SAP R/3, Oracle E-Business Suite, and later SAP S/4HANA embedded ATP and CTP functionality directly into the order entry process, allowing customer service representatives or sales teams to receive immediate delivery date confirmations [Madhavaram & Varadarajan, 2008]. This integration streamlined operations, reduced manual intervention, and ensured a single source of truth for order commitments.

However, ERP-centric OP approaches also exhibited key limitations. First, they were typically constrained to transactional visibility within the ERP system itself. While ERP systems could see inventory and planned production orders, they often lacked full visibility into multi-tier supplier networks or transportation constraints. Second, ERP-based OP was inherently reactive: it confirmed orders based on current system status but did not proactively account for anticipated disruptions or demand fluctuations [Stadtler, 2005].

Researchers have criticized ERP-driven OP for being "rigid and deterministic," highlighting that it fails in highly volatile environments such as consumer electronics or pharmaceuticals, where lead times are short and demand uncertainty is high [Chen & Zhao, 2007]. Furthermore, ERP systems often lacked advanced allocation logic, meaning that in situations of constrained supply, orders were either confirmed or rejected without consideration of customer prioritization, profitability, or long-term relationship value [Madhavaram & Varadarajan, 2008].

Despite these challenges, ERP systems remain the transactional backbone of OP. They capture orders, execute credit checks, and serve as the system of record for confirmations. The challenge for both scholars and practitioners is to augment ERP's deterministic OP with more adaptive, intelligence-driven mechanisms.

## 2.3 Advanced Planning Systems (APS) Integration

To address ERP's limitations, organizations increasingly turned to Advanced Planning Systems (APS) such as i2 Technologies (now Blue Yonder), Kinaxis RapidResponse, and SAP Advanced Planning and Optimization (APO). APS platforms introduced global ATP (GATP) capabilities, enabling firms to consider network-wide constraints such as multisite inventory, supplier capacity, and distribution lead times when making promises [Stadtler, 2005].

APS-based OP approaches emphasized optimization, allowing companies to design sourcing rules (e.g., prioritize local plants to reduce transportation cost), apply allocation priorities (e.g., allocate scarce stock to high-margin customers first), and perform real-time simulations of capacity and lead times. This represented a significant theoretical and practical advance compared to ERP-only OP.

However, APS integration also introduced complexities. First, there was often a data synchronization lag between ERP (as the system of record) and APS (as the optimization engine). This sometimes resulted in conflicting promise outcomes, where the ERP system confirmed one date but APS later suggested a different one [Stadtler, 2005]. Second, APS systems were heavily reliant on forecast accuracy and planning master data quality. Without reliable inputs, even the most sophisticated optimization algorithms could produce misleading commitments [Kilger & Schneeweiss, 2000].

From a theoretical perspective, APS-based OP represented a shift from transactional confirmation to optimization-driven promise management. Yet, APS still operated largely on deterministic assumptions, with limited capacity to predict disruptions or learn from past promise outcomes. This gap has opened the door for integrating AI and predictive analytics as the next frontier in OP.

## 2.4 Digital Transformation and AI in OP

The current wave of digital transformation in supply chain management has brought new perspectives on how OP can evolve into a more intelligent and adaptive capability. Three major trends dominate this literature: artificial intelligence (AI) and machine learning, blockchain, and sustainability-oriented OP.

### 2.4.1 AI and Machine Learning

AI and machine learning offer the ability to move OP from deterministic to probabilistic and predictive models. For example, AI algorithms can analyze historical promise reliability to predict the likelihood of a promise being met under current conditions [Saberi et al., 2019]. Machine learning models can also detect patterns in demand shifts, supplier delays, or seasonal disruptions, enabling the system to adjust promises dynamically. Recent studies highlight that AI-driven OP can improve not only reliability but also profitability, by recommending commitments that maximize margin while minimizing risk exposure [Golgeci et al., 2020].

### 2.4.2 Blockchain and Transparency

Another emerging research stream explores the use of blockchain technology to enhance transparency and trust in order commitments. In multi-tier supply chains, one of the challenges of OP is ensuring that promises made to customers are consistent with upstream supplier capabilities. Blockchain offers the possibility of a shared, tamper-proof ledger where commitments and actual deliveries can be recorded, thereby reducing the risk of misinformation and disputes [Saberi et al., 2019]. Although still in early stages, blockchain-enabled OP is being theorized as a mechanism to enhance supply chain trust and accountability.

### 2.4.3 Sustainability-Oriented OP

Sustainability has also entered the discourse on OP. Traditional OP systems optimize primarily for customer service and efficiency, often ignoring environmental impact. Recent research has proposed the concept of "Green Order Promising," where promises incorporate carbon footprint, energy use, or sustainability metrics into the decision-making process [Golgeci et al., 2020]. For example, a firm may offer customers a choice between a faster delivery with higher emissions or a slower, more environmentally friendly alternative. Theoretically, this positions OP as a tool for sustainability strategy as well as customer service.

### 2.4.4 Synthesis and Research Gap

The literature demonstrates that OP has evolved from inventory-based checks (ATP) to capacity-inclusive models (CTP), from ERP-driven transactional confirmations to APS-based optimization, and is now entering an era of AI-enabled intelligence and sustainability-conscious commitments. Despite this evolution, two major gaps remain.

First, research is fragmented: ERP, APS, and AI perspectives are often studied in isolation, with few efforts to integrate them into a holistic theoretical framework. Second, most existing studies remain operational in nature, focusing on algorithmic improvements or system implementations, without adequately theorizing OP as a strategic, multi-dimensional construct that balances reliability, profitability, responsiveness, resilience, and sustainability.This paper addresses these gaps by developing a framework for Intelligent Order Promising (IOP) that integrates ERP's transactional backbone, APS's optimization capabilities, and AI's predictive intelligence. By doing so, it contributes to advancing both the academic discourse and managerial practice of OP.

# 3. CONCEPTUAL FOUNDATIONS OF INTELLIGENT ORDER PROMISING (IOP)

The concept of Intelligent Order Promising (IOP) extends the traditional scope of OP from a deterministic, system-driven confirmation activity to a strategic, intelligence-driven decision-making process. The theoretical basis of IOP rests on the recognition that order commitments are not merely operational outputs but strategic levers that influence customer satisfaction, profitability, risk resilience, and sustainability performance.

While ERP systems and APS platforms provide the structural foundation for OP, they often fail to adapt to the dynamic, uncertain, and customer-centric environment of modern supply chains. To bridge this gap, IOP must be conceptualized as a multi-dimensional construct comprising five key dimensions: reliability, profitability, responsiveness, resilience, and sustainability. Together, these dimensions define the theoretical scope of IOP and distinguish it from conventional OP models.

## 3.1 Reliability

Reliability refers to the accuracy and consistency of promises made to customers. From a customer perspective, reliability is the most fundamental dimension of OP, as it directly affects trust and satisfaction. Research indicates that even if delivery lead times are long, customers often prefer firms that consistently meet promised dates over those that provide shorter but unreliable commitments [Chen & Zhao, 2007].

In traditional ERP-driven ATP/CTP, reliability was limited by deterministic assumptions and incomplete visibility. IOP enhances reliability by integrating real-time data (e.g., inventory positions, supplier updates, transport delays) with predictive analytics. For instance, machine learning models can identify historical patterns where promises were frequently delayed and proactively adjust commitments. Thus, reliability in IOP is not a static metric but a probabilistic and adaptive function, continuously learning from execution outcomes.

## 3.2 Profitability

While reliability ensures trust, firms must also consider the economic implications of promises. Profitability in OP refers to the extent to which commitments support the organization's financial objectives. Traditional ATP/CTP models focused narrowly on feasibility, without evaluating whether a given promise contributed positively to margins or overall business strategy.

IOP introduces profitability-aware promise mechanisms, where the system considers revenue, cost-to-serve, and opportunity costs before confirming an order. For example, when capacity is constrained, the system may prioritize allocating stock to high-margin products or strategic customers. In advanced scenarios, AI-enabled OP can even perform profit optimization, recommending delivery dates that balance service level agreements with cost efficiency.

From a theoretical standpoint, profitability adds a strategic-economic layer to OP, positioning it as a contributor to competitive advantage rather than a purely operational function [Madhavaram & Varadarajan, 2008].

## 3.3 Responsiveness

Responsiveness captures the speed and agility of OP decisions in adapting to customer requests and environmental changes. In today's digital economy, customers expect near-instant confirmations, whether they are placing orders on an e-commerce platform or negotiating contracts in a B2B environment. Traditional ERP systems often struggled with responsiveness due to batch data processing and limited computational capacity.

IOP leverages in-memory computing, cloud infrastructure, and real-time analytics to provide immediate promise responses. More importantly, responsiveness is not only about speed but also about adaptability. For instance, if a supplier delay occurs after a promise has been made, IOP can proactively re-promise alternative delivery dates, communicate options to customers, and dynamically reallocate resources. This agility differentiates IOP from deterministic OP, which tends to lock in commitments without flexibility.

### 3.4 Resilience

Resilience refers to the ability of OP systems to withstand and adapt to disruptions such as supply shortages, transportation delays, or geopolitical risks. The COVID-19 pandemic, semiconductor shortages, and global shipping crises have highlighted the need for OP mechanisms that go beyond short-term feasibility checks.

Traditional OP models are fragile under uncertainty because they assume that planned supply and capacity will materialize as expected. In contrast, IOP incorporates risk-aware promise mechanisms that explicitly account for uncertainty. This may include probabilistic lead times, scenario simulations, or AI-driven risk forecasting. For example, IOP may avoid committing to a supplier that has a high historical probability of delay, even if capacity exists on paper.

Theoretically, resilience in IOP transforms promises from static commitments into risk-managed contracts, enhancing both customer trust and operational stability [Saberi et al., 2019].

### 3.5 Sustainability

The final dimension of IOP is sustainability, which reflects the growing importance of environmental and social responsibility in supply chain management. Traditionally, OP systems were designed to optimize efficiency and customer service, with little regard for sustainability outcomes. However, increasing regulatory pressures, consumer awareness, and corporate sustainability commitments are reshaping how firms approach OP.

Sustainability-oriented OP (Green OP) introduces environmental and ethical considerations into promise logic. For example, instead of always selecting the fastest delivery option, IOP may provide customers with alternatives that reduce carbon emissions, such as consolidated shipments or slower but greener modes of transport [Golgeci et al., 2020]. Similarly, OP may account for suppliers' sustainability performance when making sourcing promises.

By embedding sustainability, IOP positions promises not only as customer commitments but also as corporate responsibility statements, aligning operational decisions with long-term societal goals.

## 4. INTEGRATING THE DIMENSIONS

These five dimensions—reliability, profitability, responsiveness, resilience, and sustainability—together define the theoretical foundations of IOP. Importantly, they are not independent but interdependent and often conflicting. For instance, a highly reliable promise may reduce profitability if it requires costly expedited shipping. Similarly, a sustainable promise may lengthen lead times, affecting responsiveness.

Thus, IOP must be conceptualized as a multi-objective decision-making framework that balances these dimensions rather than optimizing any single one in isolation. From a theoretical perspective, this positions IOP as a bridge between ERP's transactional order capture, APS's optimization logic, and AI's predictive intelligence

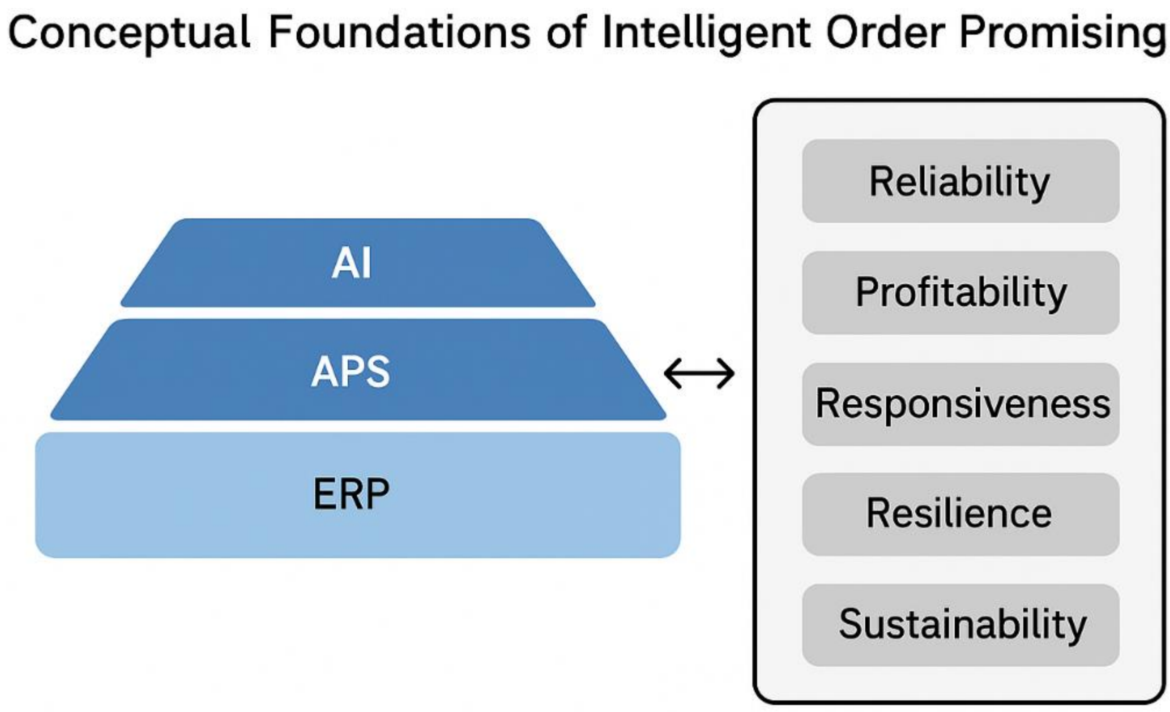


**Figure 1** Conceptual Foundations of Intelligent Order Promising

## 4.1 Conceptual Foundations and Methodology

Order promising, at its core, is not only a transactional activity but also a strategic decision-making process that integrates demand management, supply chain visibility, and optimization. In this section, the conceptual foundations of order promising are articulated, followed by an explanation of the methodological approach adopted in this study.

### *4.1.1 Conceptual Foundations*

Order promising traditionally draws upon three major constructs: Available-to-Promise (ATP), Capable-to-Promise (CTP), and Profitable-to-Promise (PTP).

• Available-to-Promise (ATP): ATP provides visibility into current and projected inventory levels. It matches demand against existing stock and planned receipts, thereby enabling firms to confirm whether an order can be met on the promised date. ATP is foundational in environments with stable demand and relatively short lead times (Meyr, Wagner, & Rohde, 2005).

• Capable-to-Promise (CTP): CTP extends ATP by incorporating capacity constraints such as production schedules, resource availability, and supplier lead times. It is particularly relevant in engineer-to-order or make-to-order environments where inventory alone cannot guarantee fulfillment. CTP requires close integration of order promising engines with Advanced Planning and Scheduling (APS) systems (Kilger, Schneeweiss, & Zimmermann, 2017).

• Profitable-to-Promise (PTP): PTP integrates profitability metrics into the order promising decision. By considering margin, contribution to customer lifetime value, or strategic priority, firms can decide not only whether to accept an order, but also whether it should be prioritized over competing requests (Chen, 2018).

These constructs underscore the evolution of order promising from an operational decision (ATP) to a strategic lever (PTP). Modern implementations, such as those in Blue Yonder Order Promiser (BYOP) or SAP Advanced ATP (aATP), increasingly blend these perspectives using advanced algorithms and real-time data integration.

### *4.1.2 Methodological Approach*

This paper adopts a conceptual research methodology grounded in framework development and illustrative application. The choice of methodology is guided by the dual objectives of the research: (1) to integrate existing knowledge into a coherent theoretical framework, and (2) to demonstrate the framework's relevance through application in enterprise contexts.

The methodological design includes the following steps:

1.. Literature Synthesis: A systematic review of scholarly and practitioner-oriented literature on order promising, advanced planning systems, and digital supply chain integration. This ensures that the framework is theoretically robust and aligned with contemporary practices.

2. Framework Development: Building on insights from the literature, a conceptual framework is proposed (see Section 3). The framework emphasizes the interplay between supply chain visibility, optimization algorithms, and decision support mechanisms.

3. Case Illustration: To demonstrate applicability, the framework is contextualized within a hypothetical but industry-representative scenario: the integration of SAP S/4HANA with Blue Yonder Order Promiser. This allows us to discuss challenges of data integration, credit check blocks, location substitution rules, and demand prioritization in a real-world inspired setting.

4. Evaluation through Analytical Generalization: Instead of empirical testing, this study employs analytical generalization (Yin, 2014). The framework is compared with extant theories in supply chain planning and order fulfillment, enabling assessment of its theoretical contributions and practical value.

### *4.1.3 Justification of Methodology*

The decision to adopt a conceptual and illustrative methodology is grounded in three key considerations:

• First, order promising remains a domain where theory and practice often diverge. By structuring existing practices into a coherent theoretical model, this study aims to bridge that gap.

• Second, empirical data on order promising processes is typically proprietary and difficult to access, especially in enterprise-level implementations (e.g., SAP, Blue Yonder, Oracle). Thus, conceptual frameworks with case illustrations are more feasible for advancing knowledge.

• Finally, a conceptual approach allows the identification of emerging trends—such as AI-driven promise optimization, blockchain-enabled supply visibility, and sustainability-oriented promise metrics—that may not yet be empirically documented.

# 5. THEORETICAL FRAMEWORK

The theoretical framework for order promising integrates supply chain theory, decision sciences, and information systems into a cohesive model that captures the multi-dimensional nature of fulfillment commitments. The framework proposed in this study is designed to conceptualize order promising not merely as a transactional verification process, but as a decision-making architecture that balances operational feasibility, customer satisfaction, and organizational profitability.

At its foundation, the framework rests on three interconnected dimensions: Visibility, Optimization, and Decision Support.

## 5.1 Supply Chain Visibility

Visibility constitutes the informational backbone of order promising. It refers to the extent to which organizations can access, in real time, data about inventory positions, production schedules, transportation availability, and supplier capacities across the network. Theoretical contributions from resource-based and information-processing perspectives (Galbraith, 1974) suggest that visibility reduces uncertainty and enhances responsiveness. Within order promising, visibility ensures that ATP, CTP, and PTP calculations are based on accurate and timely data rather than static or siloed records.

## 5.2 Optimization Algorithms

Optimization represents the analytical core of the framework. Building on operations research and mathematical programming traditions, optimization algorithms transform raw visibility into actionable commitments. Linear programming, heuristic methods, and increasingly machine learning approaches allow the simultaneous consideration of multiple constraints (e.g., inventory, capacity, transportation) and objectives (e.g., service level, cost, profit). This aligns with classical supply chain optimization models (Chopra & Meindl, 2020) while extending them to real-time, customer-specific decision contexts. Importantly, optimization within order promising is not a single-shot calculation but a dynamic process that must adapt as new orders, disruptions, or cancellations occur.

## 5.3 Decision Support Mechanisms

Decision support closes the loop between analytical optimization and managerial action. Drawing upon decision support system (DSS) theory (Power, 2002), this component highlights the importance of presenting optimized commitments in a manner that is transparent, explainable, and aligned with organizational strategy. Decision support in order promising includes not only the system-generated delivery dates or quantities but also guidance on trade-offs, such as whether prioritizing a high-margin order may delay fulfillment for a lower-margin but strategically critical customer.

## 5.4 Integrative Perspective

By linking visibility, optimization, and decision support, the framework captures the transition of order promising from an operational tool to a strategic enabler. The theoretical implication is that effective order promising requires organizations to simultaneously invest in data integration, analytical sophistication, and managerial interpretability. Neglecting any one of these dimensions risks undermining the overall effectiveness of the promise process: without visibility, optimization operates on flawed assumptions; without optimization, visibility yields no actionable insights; without decision support, optimal results may fail to translate into strategic alignment.

## 5.5 Dynamic Capabilities View

Finally, the framework can be situated within the broader theoretical lens of dynamic capabilities (Teece, Pisano, & Shuen, 1997). Order promising is inherently dynamic, as it requires continuous sensing of demand signals, seizing of profitable opportunities, and reconfiguring of resources in the face of uncertainty. The proposed framework thus conceptualizes order promising not as a static decision but as an ongoing organizational capability, central to competitive advantage in digital supply chains.

# 6. APPLICATION AND CASE ILLUSTRATION

To demonstrate the practical applicability of the proposed theoretical framework, this section presents a conceptual case illustration drawn from a global manufacturing supply chain. The example highlights how visibility, optimization, and decision support interact to improve the quality of customer commitments, without relying on proprietary system references.

1. Case Context

Consider a mid-sized electronics manufacturer with a global supply network spanning component suppliers in Asia, assembly plants in Europe, and distribution centers across North America. The company faces increasing customer demands for shorter lead times, customized configurations, and reliable delivery dates. Traditional rule-based order confirmation methods have proved insufficient, often leading to missed deadlines, excess safety stock, or costly expedited shipping. The adoption of a structured order promising framework offers an opportunity to enhance both operational performance and customer trust.

2. Visibility in Practice

The first step involves integrating real-time data streams from suppliers, production lines, and logistics partners. For instance, component inventory levels from multiple suppliers are continuously updated, while production capacity utilization is monitored through connected shop-floor systems. Transportation schedules from logistics providers are also linked to the platform, offering an end-to-end view of supply chain status. This visibility allows the manufacturer to move away from static assumptions and toward dynamic availability checks.

3. Optimization in Practice

With reliable visibility in place, the system applies optimization models to evaluate order requests. For example, when a high-volume order arrives from a North American retailer, the optimization engine simultaneously considers:

• Available raw material inventory across suppliers.

• Assembly line capacities over the next four weeks.

• Transit times and shipping costs from European plants to U.S. distribution centers.

By balancing these variables, the system identifies the most cost-effective fulfillment plan while meeting the retailer's requested delivery window. Importantly, alternative scenarios are also generated—for example, splitting the order across two plants to reduce lead time.

4. Decision Support in Practice

The results are presented to the sales and planning teams through an interactive decision-support interface. Instead of merely outputting a promised delivery date, the system provides transparency into the rationale behind the recommendation. Decision-makers are shown trade-offs: accepting the order in full may delay smaller but higher-margin orders; alternatively, partial shipment commitments may satisfy multiple customers simultaneously. By aligning the decision with corporate strategy—whether prioritizing volume, margin, or customer loyalty—the system transforms optimization results into informed managerial action.

5. Strategic Outcomes

The case illustration demonstrates several strategic benefits:

1. Reduced uncertainty through real-time visibility.

2. Improved efficiency by aligning production and logistics to demand commitments.

3. Customer satisfaction via reliable and explainable delivery dates.

4. Strategic flexibility through scenario-based decision support.

Overall, the application highlights how the theoretical framework is not limited to academic abstraction but can be operationalized across industries with complex supply chains. The value lies in its adaptability—whether in electronics, pharmaceuticals, or consumer goods—where the ability to promise orders accurately is increasingly a source of competitive differentiation.

# 7. DISCUSSION

The proposed framework for intelligent order promising extends the traditional role of order management from a transactional function to a strategic capability. While existing approaches often emphasize rule-based availability checks or static allocation policies, this framework integrates visibility, optimization, and decision support to create a more adaptive and resilient process. In this section, we discuss the broader implications, challenges, and research opportunities that emerge from this conceptualization.

1. Theoretical Implications

From a theoretical standpoint, the framework contributes to the growing body of supply chain literature by situating order promising at the intersection of operations planning, analytics, and organizational decision-making. Whereas past research has often treated order promising as an operational extension of production planning, this study positions it as a decision layer that directly shapes customer experience, profitability, and strategic differentiation. This reframing encourages future studies to investigate order promising not merely as a technical problem but as a socio-technical system that combines data, algorithms, and human judgment.

2. Managerial Implications

For managers, the framework emphasizes that successful order promising requires a holistic perspective. Visibility ensures that decisions are grounded in accurate, real-time data rather than static assumptions. Optimization provides a structured means to balance competing priorities such as cost, lead time, and customer service. Decision support, finally, bridges the technical outputs with managerial strategy, ensuring that commitments reflect not only operational feasibility but also business objectives. Managers adopting this framework are better positioned to handle uncertainty, align supply chain capabilities with market demands, and strengthen customer trust.

3. Challenges in Implementation

Despite its potential, several challenges remain. Integrating visibility requires data standardization across diverse partners, which can be difficult in global networks with heterogeneous systems. Optimization models, while powerful, often face the trade-off between computational complexity and real-time responsiveness. Additionally, decision support requires organizational willingness to embrace transparency, which may be resisted in hierarchical or siloed structures. Addressing these barriers necessitates investments not only in technology but also in change management, governance, and cross-functional collaboration.

4. Comparison with Existing Approaches

Compared with conventional rule-based order promising, the proposed framework offers greater adaptability and responsiveness. Traditional systems typically confirm orders based on available-to-promise (ATP) or capable-to-promise (CTP) logic without fully incorporating cost structures, demand volatility, or long-term strategic goals. By contrast, the framework accommodates multi-objective optimization and allows scenario-based exploration of trade-offs. It also differs from purely algorithmic approaches by embedding a decision-support dimension, recognizing that human judgment remains essential in balancing short-term efficiency with long-term customer relationships.

5. Research Opportunities

The discussion opens several avenues for future research. Empirical studies could investigate how organizations adopt such frameworks across different industries, assessing contextual factors such as supply chain complexity, digital maturity, and market volatility. Simulation-based studies could evaluate the performance of alternative optimization models under varying demand scenarios. Finally, interdisciplinary research could explore how behavioral factors influence managerial use of decision-support tools in order promising contexts.

In summary, the discussion underscores that intelligent order promising represents both a technological innovation and an organizational transformation. Its success lies not only in the sophistication of algorithms but also in the ability of firms to integrate visibility, optimization, and decision support into a coherent and adaptive system.

# 8. CONCLUSION

This study has proposed a conceptual framework for intelligent order promising, positioning it as a strategic capability that extends beyond the boundaries of traditional transactional systems. By structuring the framework around three pillars—visibility, optimization, and decision support—the paper highlights how organizations can transform order promising into a dynamic process that not only meets operational feasibility but also advances broader business objectives.

The emphasis on visibility reflects the critical need for real-time, accurate, and comprehensive information across global supply networks. Without synchronized data flows, firms risk making commitments based on outdated or incomplete information, undermining customer trust and operational reliability. Optimization, in turn, underscores the role of advanced algorithms and decision models in balancing competing objectives such as cost efficiency, lead time reduction, and service differentiation. Finally, the integration of decision support acknowledges that managerial judgment and strategic priorities must guide technical outcomes, ensuring that order promising aligns with long-term organizational goals rather than short-term expediency.

The proposed framework contributes to the academic literature by reframing order promising as a socio-technical system situated at the intersection of operations research, supply chain management, and decision sciences. Rather than viewing it as a back-end function of production planning, the framework situates order promising as a strategic touchpoint that directly shapes customer experience and firm competitiveness. This conceptualization invites further empirical and theoretical research on how firms implement such systems under varying industry conditions.

For practitioners, the framework offers a roadmap for navigating the complexities of modern supply chains. By investing in integrated visibility tools, scalable optimization engines, and user-oriented decision-support mechanisms, organizations can not only improve fulfillment accuracy but also enhance profitability, responsiveness, and resilience. However, the paper also acknowledges the implementation challenges that arise, particularly with respect to data integration, computational trade-offs, and organizational change management. These challenges highlight the need for future research that blends technical innovation with managerial insights.

In closing, intelligent order promising is not merely a technological upgrade but a strategic transformation of how firms engage with their customers and structure their supply chains. Its true potential lies in the capacity to integrate information, analytics, and decision-making into a unified framework that balances efficiency with adaptability. As supply chains continue to face heightened uncertainty and demand volatility, the relevance of such a framework will only increase. Future research should build upon this foundation, advancing both the theoretical understanding and practical applications of order promising in the digital age.

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