Sales and Operations Planning – Augmenting Existing Maturity Models with New Practices

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DOI
https://doi.org/10.18690/um.fov.4.2026.54

ISBN
978-961-299-152-4

Sales and Operations Planning (S&OP) is a vital mechanism for aligning operations with financial objectives. Despite its importance, traditional S&OP maturity models often lag behind advancements in data science, resulting in a "digital blind spot" for companies implementing S&OP. This paper investigates how existing maturity models should be complemented to incorporate recent advances in data science. We arrived at our results by first synthesizing five prominent maturity models into four core dimensions: process, people and organization, performance management, and IT and data. We then conducted a systematic literature review of 24 articles, detailing how emerging technologies affect S&OP maturity in these four dimensions. Ultimately, this research provides key considerations for aligning S&OP excellence with modern technological capabilities.

Keywords:
sales and operations planning,
S&OP,
maturity model,
probabilistic forecasting,
machine learning,
artificial intelligence

University of Maribor Press

1 Introduction

Sales and Operations Planning (S&OP) is a staple of the modern supply chain, serving as the primary mechanism for aligning demand, supply, and financial objectives (Danese et al., 2018; Seeling et al., 2022). It has also become a distinct research stream, featured in prominent supply chain journals (see, e.g., the special issue editorial by Jonsson et al., 2021). Historically, the purpose of S&OP has been to build a consensus demand forecast and to align supply, either in the form of purchases, production, or both, against demand. Recently, it has evolved into a more holistic business planning process, integrating financial considerations and strategic objectives with supply chain management (Nyman et al., 2025; Schlegel et al., 2021). A key feature of S&OP is its cross-functional nature, focusing on joint decision-making to meet financial goals (Oliva & Watson, 2011). To navigate process complexities, organizations have historically relied on maturity models (see, e.g., Danese et al., 2018). S&OP maturity models are frameworks designed to benchmark current capabilities and provide a structured roadmap for cross-functional integration. Like maturity models in general, S&OP maturity models describe different maturity stages that allow practitioners to assess their processes against desirable characteristics (e.g., Pöppelbuß & Röglinger, 2011). For S&OP, increased maturity signifies a shift from siloed, reactive behaviors toward integrated, proactive decision-making that enhances overall company profitability.

Despite the widespread adoption of maturity models, a critical gap has emerged in existing literature. One of the authors of this paper also works as a consultant, implementing S&OP in a corporate context. Based on his experience, one area in particular falls short: the way uncertainty is considered in planning. Most maturity models were developed when supply chain planning relied on manual inputs or, at best, statistical methods. More recently, supply chain planning has evolved to manage uncertainty through probabilistic forecasting, machine learning (ML), and AI (Hu et al., 2025; Kagalwala et al., 2025). We observe that a significant shortcoming of traditional approaches is their deterministic nature; while they acknowledge uncertainty, they offer little guidance on handling volatility. Here, probabilistic planning and AI's ability to process unstructured data offer significant improvements (Hu et al., 2025; Kagalwala et al., 2025). Consequently, we argue that existing maturity models fail to account for these rapid advances in data science.

This technological lag creates a "digital blind spot" where an S&OP process might be deemed mature by traditional standards while remaining technologically obsolete (Jazairy et al., 2025). While studies highlight the benefits of probabilistic forecasting (e.g., Hewage et al., 2025; Hu et al., 2025; Klug, 2011) and call for AI integration in supply chain management (Cohen et al., 2025), current maturity models lag behind. Consequently, we argue that maturity must be re-evaluated through the lens of advancements in data science in general, probabilistic forecasting, machine learning, and AI. As such, this paper will address the following research question: what are the key areas of existing S&OP maturity models that need to be complemented to incorporate recent advancements in data science?

In Section 2, we first synthesize prominent S&OP maturity models into a baseline representing the prevalent view on maturity. In Section 3, we describe how we performed a comparative analysis between this baseline and the capabilities of emerging technologies, specifically examining how advancements in data science, probabilistic planning, and AI/ML improve planning. The results are presented in Section 4. Finally, in Section 5 we present key considerations on complementing existing maturity models, aligning S&OP maturity with recent technological advancements.

2 Related literature

In this section, we review five prominent S&OP maturity models, selected for their academic or industrial influence, and highlight their key assessment criteria for S&OP maturity. These include four academic models and one from a commercial research lab (Gartner). After synthesizing the key findings from these models, we conclude with an overview of data science advancements that impact supply chain planning and S&OP.

2.1 S&OP maturity models

Grimson and Pyke (2007) provide an exploratory study that introduces a five-stage S&OP maturity model across five dimensions. The stages depict an organization with “no S&OP process”, moving to “reactive”, “standard”, “advanced”, and “proactive” S&OP. Their framework explicitly points toward profit optimization as the goal of S&OP, shifting the focus from simply balancing demand and supply volumes to maximizing financial outcomes. The dimensions in the maturity model include meeting and collaboration practices, the organizational structure, process measurements, information technology, and S&OP plan integration. The study concludes that a seamless plan integration (both demand and supply) at the "proactive" stage forms the basis for profit optimization. The authors note that advanced analytics is needed to achieve this, "when optimization tools are available" (p. 336), noting that meeting practices, organization, and measure support higher maturity while IT plays a more supportive role if sufficient IT capabilities are not readily available.

Wagner et al. (2014) present a maturity model designed to help firms align operational and strategic plans. They highlight how S&OP can overcome functional silos that lead to suboptimal corporate plans and inventory discrepancies. Their model evaluates maturity across four dimensions: process effectiveness, process efficiency, people and organization, and information technology. Maturity across these dimensions is evaluated starting from "rudimentary", going to "reactive", "consistent", "integrated", and culminating in "proactive". Their results indicate that many organizations operate at a "reactive" maturity level, leaving significant room for improvement.

Danese et al. (2018) note that previous maturity models tend to be descriptive in nature. In other words, earlier models define the specific characteristics needed for any given maturity stage. Moving beyond descriptive models, the authors detail the required conditions and prerequisites for moving from one maturity level to another. Their maturity model consists of five stages across four dimensions: people and organization, process and methodologies, information technology, and performance measurement. They find that while early transitions follow a serial sequence, advanced transitions require parallel actions because dimensions become highly interdependent. A key finding is the growing criticality of the "people and organization" dimension, which requires more effort as maturity increases to ensure commitment and cross-functional alignment. The stages in the model go from "no S&OP" to "reactive", "standard", "advanced", and "proactive". The study notes that advanced S&OP stages are increasingly difficult to reach due to this rising complexity in human and organizational integration.

Vereecke et al. (2018) focus specifically on demand planning as a critical cornerstone of the broader S&OP process. They develop and validate a maturity assessment model comprising six dimensions: data management, forecasting methods, forecasting systems, performance management, organization, and people management. Their empirical study reveals that while demand data is generally well-managed, significant gaps remain in forecasting systems and performance tracking. Unlike some previous studies, they find a positive correlation between company size and demand planning maturity, likely due to larger firms having greater resources for formal systems and higher integration needs.

The Gartner S&OP maturity model (Tohamy et al., 2013) offers a five-stage framework across six dimensions: outcome, process focus, organization, metrics, time horizon, and technology. In the first stage, reacting, processes are siloed and focused on short-term fixes for supply shortages using inconsistent data. The second stage, anticipating, involves basic supply-demand balancing, typically with less focus on longer-term plans. By the third stage, integrating, cross-functional alignment matures to incorporate some financial targets and broader organizational participation. The fourth stage, collaborating, shifts the focus towards a supply response that is analysed for profitability. The S&OP process is still coordinated by the supply chain organization, but ownership resides with the business unit leaders that have profit and loss responsibility. Focus is on a planning horizon one to two years ahead. Finally, the fifth stage, orchestrating, actively manages trade-offs (e.g., between availability and capital tied to inventory). At this stage, scenario planning and advanced analytics becomes important, whereby alternative plans are analysed for profitability and risk. The S&OP process is coordinated either by the supply chain organization or finance.

2.2 Current state of maturity models: a synthesis

To synthesize common themes across maturity models, we cross-examined all the dimensions outlined for each maturity model described in Section 2.1. Table 1 details how we have synthesized these based on key features derived from the maturity models in extant literature (see the last column on the right in Table 1). Next, we will explain key characteristics of each dimension in more detail, detailing how we arrived at our synthesis of S&OP maturity.

Table 1: Maturity model dimensions

Grimson and Pyke (2007)	Wagner et al. (2014)	Danese et al. (2018)	Vereecke et al. (2018)	Gartner, Tohamy et al. (2013)	This paper
Meetings and collaboration S&OP plan integration		Process and metho-dologies		Process focus Time horizon Outcome	1) Process
Organization	People and organization	People and organization	People management Organization	Organization	2) People and organization
Measure-ments	Process effectiveness Process efficiency	Performance measurement	Performance management	Metrics	3) Per-formance management
Information technology	Information technology	Information technology	Data management Forecasting methods Forecasting systems	Technology	4) IT and data

1) Process

All five maturity models characterize S&OP as a structured, iterative, and cross-functional process typically following five core steps and meetings: data gathering, demand planning, supply planning, a pre-meeting, and an executive meeting. There is a consensus that the process evolves through sequential maturity stages, moving from a reactive, "siloed" state to an integrated, proactive state where plans are developed to optimize the overall profitability of the company. A key part of proactive planning is scenario planning, whereby alternative plans and related risks are considered to support better decision-making.

2) People and Organization

An important theme in previous maturity models is that "soft issues", including culture, commitment, and organizational structure, are significant drivers for high S&OP maturity. Previous models emphasize the need for a dedicated S&OP owner or team, clear roles and responsibilities, and the participation of top management in the process. They also stress the need for a widespread understanding of the process as a driver for profitable growth. At higher stages of maturity, the process ownership resides with finance or business unit leaders, as opposed to the supply chain organization.

3) Performance management

Previous maturity models highlight performance measurement as vital for evaluating S&OP effectiveness. This can relate to the process, like measuring meeting attendance or meeting cadence, but most maturity models focus on the business metrics in the process. Mature organizations shift from using purely functional metrics (like capacity utilization or forecast accuracy) to KPIs that manage trade-offs between, for example, customer service levels, capital tied to inventory, and total supply chain costs. Ultimately, previous literature suggests that advanced S&OP should move toward profit optimization as the primary metric of success.

4) IT and data

Previous research stresses that while information technology is a necessary enabler for advanced S&OP, it is not a primary driver for initial success. Maturity in this dimension shifts from a reliance on disparate, manual spreadsheets to centralized, integrated systems and, with higher maturity, optimization tools that support scenario planning and automation of manual tasks (e.g., in forecasting).

2.3 Advances in data science that affect supply chain planning and S&OP

There have been numerous calls for improving practices in S&OP with the help of technology (see, e.g., Jonsson et al., 2021; Nicolas et al., 2021). While previous maturity models recognize this, the full implications of recent technology advancements on the S&OP process needs clarification (see, e.g., Nicolas et al., 2021). This involves the utilization of, for example, digital twins (i.e., a digital representation of a physical system), Advanced Planning Systems (APS), and big data analytics for supply chain planning (Sengupta & Dreyer, 2023; Wolfshorndl et al., 2020; Xu et al., 2021).

Probabilistic planning in supply chain management shifts the focus from single-point deterministic models to frameworks that explicitly account for uncertainty and risk (Hewage et al., 2025). In demand planning, this implies that a single-point value for any given point in time is replaced with a demand range with associated probabilities, representing the breadth of potential outcomes for that same time bucket (Hu et al., 2025). Utilizing techniques like Monte Carlo simulation, probabilistic planning has also been applied to risk quantification in logistics network planning (Klug, 2011). All in all, probabilistic forecasting and planning allows organizations to model a spectrum of potential outcomes rather than relying on single-point estimates, thus mitigating inventory imbalances or service failures more efficiently than with previous deterministic approaches (see, e.g., Schmitt & Singh, 2009).

AI and ML enable organizations to move beyond traditional statistical models by capturing complex, non-linear relationships. In demand forecasting, ML enriches traditional methods by incorporating external factors like weather, social media sentiment, and economic indicators (Feizabadi, 2022; Kagalwala et al., 2025; Walter et al., 2025), boosting accuracy of "traditional" statistical forecasts (Mediavilla et al., 2022), and improving supply chain performance (see, e.g., Kagalwala et al., 2025). Beyond forecasting, AI-driven insights and real-time dashboards facilitate exception-based reviews. This shift allows human intervention to focus on high-impact anomalies rather than routine data processing (Jazairy et al., 2025; Walter et al., 2025).

3 Research design

To identify how S&OP maturity models should adapt to data science developments, we conducted a systematic literature review (SLR). This approach allowed us to synthesize existing knowledge in different domains to understand their impact on the S&OP process. Furthermore, since extending a maturity model requires a rigorous conceptual foundation (Becker et al., 2009), an SLR provided a methodologically sound basis for deriving our proposed adaptations. Our research was guided by established SLR frameworks in information systems research and followed three phases: 1) planning, 2) execution, and 3) analysis and synthesis (vom Brocke et al., 2009).

Drawing on our existing knowledge of S&OP maturity, we searched for literature at the intersection of new technology, data science, and supply chain management. The search string was iteratively refined to include specific topics like probabilistic forecasting, with the review limited to peer-reviewed journal articles and conference proceedings. To ensure comprehensive coverage across relevant fields, we utilized Google Scholar Labs, which is an AI-powered extension of Google Scholar specifically designed to retrieve relevant articles. To capture recent technological advancements, the search focused on articles from 2020 onwards, with the exception of two older, highly relevant papers on probabilistic planning identified during the search refinement.

Conducted in December 2025, the initial search yielded over 60 articles. After filtering for peer-reviewed journals and conference proceedings and screening titles and abstracts for relevance, 45 articles remained. During this stage, topics like IoT and blockchain were removed as they were deemed less impactful on a holistic planning process like S&OP. For the remaining papers, content was analyzed for applicability to S&OP process, organizational structures, performance management, and IT & data; mathematical modeling papers without empirical data were excluded. Ultimately, 24 articles were retained for final analysis.

To systematically extract implications for S&OP maturity, both authors independently analyzed the final article set to enhance reliability and minimize bias. Based on the search strings used in data gathering, articles were categorized into three groups based on Section 2.3: supply chain planning and technology, probabilistic planning, and AI/ML. We used deductive coding to analyse content in each article, clustering the results in the four synthesized maturity dimensions outlined in Section 2.2. Table 2 includes example quotes from the articles to illustrate our coding. The "process" dimension focused on impacts to structure, decision-making, and cross-functional integration. The "people and organization" dimension addressed required changes in competencies, roles & responsibilities, and governance structures. Under "performance management," we captured necessary adaptations for process effectiveness, KPIs, and profit optimization. Lastly, “IT and data” considered implications on planning applications and integrated systems, automation, forecasting algorithms, predictive and prescriptive analytics, and scenario planning.

Table 2: Coding examples

Category	Example Quotes
Impact on process	"Data which, in the past, had been considered monthly according to the planning cycle were afterwards refreshed daily, hourly or even transmitted in real time, which ... ignited the idea of event-based planning." (Ohlson et al., 2022, p. 45) "Unlike point forecasting, probabilistic forecasting encompasses a spectrum of potential outcomes, each with associated probabilities ... This enables decision-makers to evaluate associated uncertainties and risks" (Hu et al., 2025, p. 9933)
Impact on people and organization	"Planning decisions can be augmented, where the planner is responsible for assessing the system recommendations ... Alternatively, it may be automatic or autonomous" (Cohen et al., 2026, p. 25) "LLM-based assistants can help planners test pricing scenarios, examine elasticity patterns ... via natural language prompts. ... these tools ... will increasingly automate routine decisions while humans guide strategic trade-offs." (Cohen et al., 2026, p. 25)
Impact on performance management	"in inventory management ... higher quantiles (e.g. the 95th percentile) might be important to ... maintain a high service level" (Hewage et al., 2025, p. 19) "LLMs address a different bottleneck: the gap between sophisticated optimization tools and the practitioners who use them." (Cohen et al., 2026, p. 7)
Impact on IT and data	"Analysis of data from social media, point of sales, and clickstream helps to improve ... demand forecasting accuracy" (Xu et al., 2021, p. 664) "Through our [probablistic planning] analysis, we quantified the disruption threat at various locations in the supply chain and developed risk profiles for each." (Schmitt & Singh, 2009, p. 1247)

4 Results

Table 3 outlines a summary of our key findings. It reviews 24 articles with a focus on SCP and technology (SCP), probabilistic planning (PP), and AI & ML, and cross-references these with how these advancements impact the four dimensions in our synthesized S&OP maturity model. Each S&OP maturity dimension is further broken down to the topics derived from the characteristics of each dimension outlined in Section 3.1. With a summary of the key results at hand, we will move to discussing implications in Section 5.

Table 3: Recent technology advancements and their impact on S&OP maturity

Category/ Reference	Impact on process	Impact on people and organization	Impact on performance management	Impact on IT and data
SCP and technology (SCP) (Dolgui & Ivanov, 2025; Gallego-García & García-García, 2020; Holmström & Romme, 2012; Nicolas et al., 2021; Schlegel et al., 2021; Sengupta & Dreyer, 2023; Wolfshorndl et al., 2020; Xu et al., 2021) **Probabilistic planning (PP)** (Hewage et al., 2025; Hu et al., 2025; Klug, 2011; Schmitt & Singh, 2009) **AI and ML (AI)** (Cohen et al., 2025; Feizabadi, 2022; Jazairy et al., 2025; Kagalwala et al., 2025; Kochakkashani et al., 2024; Mediavilla et al., 2022; Melançon et al., 2021; Ohlson et al., 2022; Tirkolaee et al., 2021; Vlachos & Reddy, 2025; Walter et al., 2025; Younis et al., 2022)	<u>*Process structure:*</u> **SCP:** Enables an event driven, as opposed to a monthly, process **SCP:** Drives exception management, rather than data review **PP:** Builds a stronger foundation for simulation and "what-if" analysis **AI:** Reduces the need for data preparation/more effective error mitigation <u>*Decision making:*</u> **SCP:** Enables augmented decisions rather than intuition-based assessment **PP:** Enables risk-aware decision-making **AI:** AI models non-linear relationships between data for better decisions <u>*Cross-functional integration:*</u> **SCP:** Provides a "single source of truth" **PP:** Allows functions to align on trade-offs	<u>*Competencies:*</u> **SCP:** Requires technical and data literacy as well as financial acumen **PP:** Requires capability to interpret and communicate probability distributions **AI:** Requires a better understanding of non-linear relationships between variables <u>*Roles & responsibilities:*</u> **SCP:** Planners become exception managers rather than data integrators **AI:** S&OP owners' responsibility move to a "decision-first" role using scenario-based planning <u>*Governance structures:*</u> **SCP:** Automated routine decisions complement augmented human decisions **PP:** Business targets are better aligned with risks, uncertainty, and opportunities **AI:** Algorithmic bias requires management	<u>*Process effectiveness:*</u> **SCP:** Improves communication between departments **PP:** Moves the process from static averages to stochastic variability **AI:** Large language models can enable native language access to complex data and models <u>*KPIs:*</u> **SCP:** Enables holistic, rather than local, optimization of business targets **PP:** Enables risk-adjusted performance metrics <u>*Profit optimization:*</u> **SCP:** Enables profit optimization as a metric **SCP:** Enables better incorporation of sustainability metrics **PP:** Enables analysis of the "cost of availability" (capital tied to inventory vs service level)	<u>*Integrated systems:*</u> **AI:** Enables task-specific agentic AI <u>*Automation:*</u> **SCP:** Automates routine tasks/enables less time on data preparation **AI:** Automating, e.g., data scraping, reports <u>*Forecasting algorithms:*</u> **SCP:** Enables external data integration (e.g., point of sales data, social media) **PP:** Enables the quantification of uncertainty **AI:** Can enrich forecasts based on external variables <u>*Pred.& prescriptive analytics:*</u> **SCP:** Enables early anomaly detection **PP:** Enables prescriptive risk mitigation **AI:** Enables resource allocation that aligns with financial & strategic goals <u>*Scenario planning:*</u> **SCP:** Enables what-if analysis/ objective trade-offs **PP:** Enables quantification of risks and opps.

5 Discussion and conclusion

In this section, we summarize key points from Table 2. This provides an answer to our research question, outlining the key areas of existing S&OP maturity models that need to be complemented to incorporate recent advancements in data science.

Advancing S&OP *process* maturity with the help of technology requires a shift towards a structure that prioritizes exception management and "what-if" simulations over traditional static monthly data reviews (Melançon et al., 2021). This enables more sophisticated decision-making, moving the organization away from intuition-based assessments toward risk-awareness (Hu et al., 2025). Ultimately, these capabilities enhance cross-functional integration by establishing a "single source of truth," allowing disparate teams to move past conflicting organizational goals and align on trade-offs (Jazairy et al., 2025; Schlegel et al., 2021). Further, modern technology can partly automate and thus lessen the need for a separate data gathering process step (Jazairy et al., 2025).

New technology also affects *organizational* aspects of S&OP; high process maturity might require new competences. Advances in data science demands technical literacy from the S&OP team (Cohen et al., 2025), wheres a shift in focus from demand and supply balancing to profit optimization requires financial acumen (Schlegel et al., 2021). In practice, teams must master the ability to understand fundamental principles of data science, prioritize topics that require human input, and communicate more complex probability distributions rather than just static figures (Hewage et al., 2025). Consequently, roles and responsibilities are redefined; planners increasingly focus on excpetions (Walter et al., 2025), while S&OP owners use scenario planning to prioritize decision-making over a traditional prediction-first mindset (Cohen et al., 2025). Supporting this is a governance structure that complements automated routine decisions with augmented human judgment (Sengupta & Dreyer, 2023).

By enhancing S&OP *process management and measures* with technology, KPIs detail operational trade-offs to optimize profit. This allows leaders to utilize sensitivity analysis and probabilistic planning to, for example, balance the "cost of availability" against capital constraints, ensuring decisions align with strategic priorities (Hewage et al., 2025; Kochakkashani et al., 2024).

Lastly, advances in data science mean that the *IT and data* S&OP maturity dimension enables a move from reactive planning to foresight. Disparate data streams can be consolidated, while automation eliminates the manual work of data scraping and report generation (Jonsson et al., 2021; Schlegel et al., 2021). This foundation allows forecasting algorithms to incorporate external signals and quantify uncertainty, moving beyond simple historical trends (Walter et al., 2025). When combined with predictive and prescriptive analytics, organizations can detect anomalies early and receive recommendations for resource allocation. These capabilities culminate in sophisticated scenario planning that can be supported by probabilistic analysis. This allows for "what-if" analyses that assess financial trade-offs with precision, transforming S&OP into a proactive process to support growth (Cohen et al., 2025).

This paper acts as a first steps towards complementing existing S&OP maturity models. A clear limitation of the research is the amount of articles included for review; the authors have a plan to continue the research, expanding the analysis to cover further relevant research.

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