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Impact pathways: walking a tightrope—unveiling the paradoxes of adopting artificial intelligence (AI) in sales and operations planning

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Abstract

Purpose – This research aims to examine the potential tensions and management strategies for adopting artificial intelligence (AI) within Sales and Operations Planning (S&OP) environments.

Design/methodology/approach – We conducted in-depth interviews with eight S&OP professionals from different manufacturing firms, supplemented by interviews with AI solutions experts and secondary document analysis of various S&OP processes, to scrutinize the paradoxes associated with AI adoption in S&OP.

Findings – We revealed 12 sub-paradoxes associated with AI adoption in S&OP, culminating in 5 overarching impact pathways: (1) balancing immediate actions with long-term AI-driven strategies, (2) navigating AI adoption via centralized systems, process redesign and data unification, (3) harmonizing AI-driven S&OP identities, collaboration and technology acceptance, (4) bridging traditional human skills with innovative AI competencies and (5) managing the interrelated paradoxes of AI adoption in S&OP.

Practical implications – The findings provide a roadmap for firms to proactively address the possible tensions associated with adopting AI in S&OP, balancing standardization with flexibility and traditional expertise with AI capabilities.

Originality/value – This research offers (1) a nuanced understanding of S&OP-specific paradoxes in AI adoption, contributing to the broader literature on AI within operations management and (2) an extension to Paradox Theory by uncovering distinct manifestations at the AI–S&OP intersection.

Keywords S&OP, Paradox theory, Machine learning, Supply chain management, Interviews

Paper type Impact Pathways

Background and purpose

Traditional Sales and Operations Planning (S&OP) practices have long relied on rigid frameworks designed to balance supply capacities with demand fluctuations. While effective in the past, these frameworks are becoming increasingly insufficient for handling the volatility of modern supply chains (Jonsson *et al.*, 2021), especially in an era marked by rapid disruptions ranging from pandemic-induced shocks to geopolitical tensions (Harper, 2022).

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In parallel, fast-paced technological advancements in supply chains have prompted firms to upskill their workforce across digital, soft and technical competencies to maintain competitiveness (SDC, 2024). As a result, S&OP professionals find themselves at a critical juncture; they must adapt their practices and skillsets to navigate modern supply chain challenges while preserving structured decision-making frameworks traditionally regarded as hallmarks of effective planning (Goh and Eldridge, 2024).

Amid these shifting dynamics, S&OP professionals now operate in environments where firms increasingly leverage emerging technologies like Artificial Intelligence (AI)—defined as "the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks" (Duan *et al*., 2019, p. 63). This movement is driven by AI's potential to enhance forecasting accuracy and decision-making speed (Zhu *et al*., 2021), promote supplier scouting competencies (Guida *et al*., 2023), reduce bias in human judgment (Brau *et al*., 2024), manage supply chain uncertainties (Belhadi *et al*., 2024) and boost supply chain resilience (Dai *et al*., 2024). AI is thus frequently hyped as one of the most transformative technologies to reshape the realities of S&OP professionals (Deloitte, 2023; Forbes, 2022), with promises to bridge the renowned gap between supply chain planning and execution (KPMG, 2024). According to Rockwell Automation (2024), 83% of manufacturers anticipate adopting AI in their operations before the end of 2024, reflecting the industry's accelerated commitment toward the technology. However, this rapid push for AI adoption, often driven by consulting and IT firms' agendas, could lead to conflicting tensions for S&OP professionals themselves—given the delicate interplay between established practices and disruptive technologies (Sengupta *et al*., 2024).

Although multiple studies have surfaced to elucidate AI adoption within operations management (OM), most address the topic from a broad, supply chain perspective—taking either a conceptual stance (e.g. Pournader *et al*., 2021; Sharma *et al*., 2022; Toorajipour *et al*., 2021) or, more recently, an empirical stance (e.g. Cannas *et al*., 2024; Gupta *et al*., 2023; Hasija and Esper, 2022; Helo and Hao, 2022; Wamba *et al*., 2022). A further wave of studies has begun exploring AI across different OM-related contexts such as procurement (Spreitzenbarth *et al*., 2024; van Hoek, 2024), retailing (Brau *et al*., 2024), lean manufacturing (Tortorella *et al*., 2024), production relocation (Kinkel *et al*., 2023) and healthcare (Guo *et al*., 2024). Yet, no empirical research can be found that examines the nascent conflicts accompanying AI adoption for S&OP professionals—separating the technology's hype from its reality for this particular segment.

This impact pathway (IP) article aims to establish the first empirical foundation for this inquiry. Specifically, we examine the potential tensions and management strategies for adopting AI within S&OP environments. We utilized Paradox Theory as a lens for investigation, given its suitability for unraveling the tensions associated with embracing emergent technologies in OM (Kocabasoglu-Hillmer *et al*., 2023; Yang *et al*., 2023) and propensity to elucidate the simultaneous existence of conflicting dualities (Barbieri *et al*., 2023). Empirically, we conducted in-depth interviews with eight senior S&OP professionals at different manufacturing firms who have either implemented or are seriously considering implementing AI in their S&OP roles—supplemented by interviews with three AI solutions experts and secondary document analysis from various S&OP processes.

This research advances the literature on AI adoption in OM by offering nuanced insights into its implications for S&OP—a vital process that bridges strategic and operational decision-making tenets in organizations (Thomé *et al*., 2012). Unlike other OM functions that focus on specific operational aspects, S&OP uniquely integrates multiple planning horizons, stakeholder perspectives and business objectives into a cohesive, enterprise-wide framework (Jonsson and Holmström, 2016). Given this distinct orchestrating role, understanding AI's impact on S&OP unlocks actionable insights that extend beyond isolated OM functions, providing a foundation for understanding technology adoption in processes spanning organizational boundaries and hierarchies.

Next, we briefly discuss Paradox Theory alongside the potential tensions that could impact AI adoption in S&OP, concluding with an analytical framework that serves as a foundation for our investigation. We then describe the methods, followed by presenting the results and their connection to the paradox types outlined in the framework. Finally, we propose five unique pathways for future research aimed at understanding and managing the revealed paradoxes of AI use for S&OP professionals as they enter the future—offering a roadmap for both scholars and practitioners to navigate the complexities of AI adoption in S&OP.

Paradox thinking for AI adoption in S&OP

A paradox is defined as "contradictory yet interrelated elements—elements that seem logical in isolation but absurd and irrational when appearing simultaneously" (Lewis, 2000, p. 760). Rooted in the classical premise of the theory (Lewis, 2000; Smith and Lewis, 2011), these contradictions manifest in four primary types: (1) performing paradoxes, which arise from tensions between the immediate pressures of performance and the long-term needs for development and continuity; (2) organizing paradoxes, which arise from the conflict between the necessity for structured, efficient processes and the flexibility required to adapt to evolving circumstances; (3) belonging paradoxes, which highlight the challenges in fostering a unified organizational identity while also promoting diversity and individual autonomy; and (4) learning paradoxes, which encapsulate the struggle between exploiting existing knowledge and the pursuit of innovations essential for discovering new opportunities. These tensions, which highlight the intricate interplay between stability and change, are expected to become more pronounced in modern supply chains due to their increasing complexity and volatility (Kocabasoglu-Hillmer *et al*., 2023).

In the evolving landscape of S&OP, AI adoption introduces under-explored complexities for this particular segment. While we aim to bridge this gap by examining AI's unique implications in S&OP, we first draw upon initial insights from related OM fields. For instance, performing paradoxes may stem from skepticism about AI's long-term potential driven by a culture that prioritizes immediate results from technology investments (Cannas *et al*., 2024), especially if AI solutions have not matured enough to justify significant investments (Guida *et al*., 2023). This skepticism can be further amplified by a firm's level of AI readiness; less prepared firms are likely to see minimal benefits from AI solutions when responding to unforeseen events (Lerch *et al*., 2024). Organizing paradoxes, in turn, might emerge as AI-driven automation optimizes current business processes (Helo and Hao, 2022) yet simultaneously demands greater flexibility to accommodate real-time data and unpredictable market changes (Wamba *et al*., 2022).

While feeding AI models with high-quality data is seen as a primary barrier to its adoption (Cannas *et al*., 2024), the intersection of data and AI seems to play a dual role in adoption success; AI can automate the processing of historical data to improve accuracy and reduce bias, yet it still depends on human input to interpret anomalies and sudden demand shifts (Brau *et al*., 2024). This highlights the challenge of balancing AI's predictions with human contextual understanding (Spreitzenbarth *et al*., 2024). In turn, belonging paradoxes can arise, for example, when centralized AI integration blurs accountability in work environments and yields anxiety over who is responsible for AI-driven outcomes, especially in hierarchical organizations where clear decision-making structures are paramount (Hasija and Esper, 2022). Similarly, learning paradoxes may surface as AI integration drives a shift from traditional practices to holistic end-to-end platforms (Gupta *et al*., 2023), raising questions about whether AI will ultimately replace or enhance human decision-making (Brau *et al*., 2024; Guida *et al*., 2023). While some research highlights AI's role in strengthening supply chain resilience through explorative learning (Dai *et al*., 2024), findings from healthcare suggest a more complex dynamic. After surveying 400 physicians, Guo *et al*. (2024) concluded that AI is

"neither strictly substitutive nor solely assistive" (p. 28), highlighting the ambiguity of AI's role in (re)shaping organizational roles.

These potential tensions, as mentioned, remain speculative for S&OP contexts due to the lack of empirical evidence for this segment—motivating a deeper exploration to elucidate the uncertainties surrounding AI adoption in this area. Figure 1 presents our analytical framework, which will serve as the foundation for the empirical investigation.

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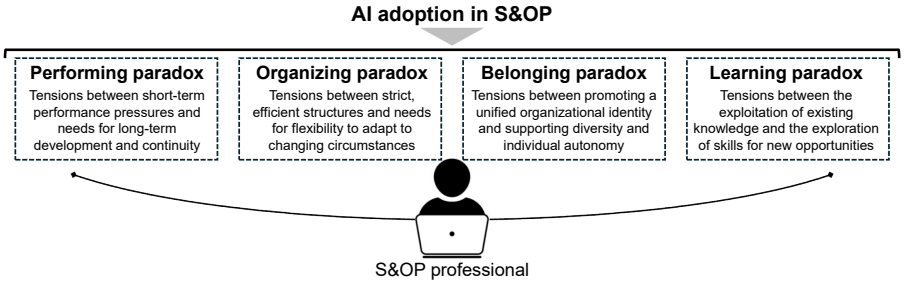
Methodology

This research adopts an abductive, theory elaboration approach that combines both deductive and inductive elements (Ketokivi and Choi, 2014). Deductively, we utilized Paradox Theory to structure our investigation and drew upon AI literature within OM to corroborate our findings, which were inductively derived from our empirical exploration of AI adoption in S&OP-specific contexts. To this end, we conducted in-depth interviews with eight experienced S&OP professionals, supplemented by interviews with three AI experts and secondary data analysis from different S&OP processes, as detailed in the following text and summarized in Table 1.

We applied Yin's (2018) aggregate replication logic for case selection, with each S&OP informant representing a distinct case. This entailed combining literal replication to identify consistent patterns of AI adoption across S&OP setups and theoretical replication to uncover theory-driven patterns based on diverse informants' contexts. As such, we approached nine S&OP informants from varied backgrounds, characterized by (1) employment in different manufacturing sectors (industrial machinery, $N = 4$; heavy machinery, $N = 3$; electrical components, $N = 1$); (2) plant locations across Europe and North America; and (3) varying levels of AI experience, ranging from consideration ($N = 3$) and testing ($N = 3$) to implementation ($N = 2$).

The interview questions focused on the informants' familiarity with AI in their S&OP tasks alongside perceived potentials and tensions arising from AI adoption. The interviews were fully transcribed and electronically filed to establish a trail of evidence (Yin, 2018). The data underwent abductive thematic analysis (Braun and Clarke, 2006), employing theory-driven themes as initial coding lenses (i.e. performing, organizing, belonging and learning paradoxes) and data-driven themes as advanced coding lenses [i.e. emergent sub-paradoxes (SPs) under each paradox type]. The analysis was also informed by the Gioia approach (Gioia *et al.*, 2013; Magnani and Gioia, 2023), where a systematic data structure was developed by starting with first-order informant codes then synthesizing them into second-order researcher-centric themes. This dual-layered coding, performed iteratively between theory and data, ensured a clear distinction between informants' assertions and our theoretical



Source(s): Authors' own work

Figure 1. Analytical framework

Table 1. Study informants and secondary data

S&OP informants and AI experts						
				Company profile		
ID	Title	Experience, interview duration	AI experience	Industry	Product portfolio	Plant location
S&OP informants						
I1	S&OP manager	>10 years, 120 min	Considering AI	Heavy machinery	Renewable energy solutions	Sweden
I2	S&OP manager	>10 years, 90 min	Implementing AI	Heavy machinery	Power generation equipment	Sweden
I3	S&OP manager	>10 years, 60 min	Testing AI	Electrical components	Wiring devices, IT infrastructure	France, USA
I4	S&OP manager	>10 years, 120 min	Testing AI	Heavy machinery	Hydraulic systems	Canada
I5	Planning specialist	>10 years, 90 min	Implementing AI	Industrial machinery	Pneumatic systems	Germany
I6	Demand planner	>10 years, 90 min	Considering AI	Industrial machinery	Industrial machinery	UK
I7	Project planner	>10 years, 90 min	Testing AI	Industrial machinery	Aerospace components	Germany
I8	Supply and demand planner	>8 years, 45 min	Considering AI	Industrial machinery	Machining solutions	Sweden
AI experts						
E1	AI solutions architect	>10 years, 90 min	>8 years	End-to-end IT consultation and implementation solutions	IT transformation for high-tech manufacturing	Netherlands (HQ), Germany USA
E2	Lead manufacturing and managing consultant	>25 years, 60 min	>6 years			
E3	AI adoption consultant	>4 years, 75 min	>4 years			

Secondary materials			
ID	Data type	Description	Use in this study
D1	Planning tools	Excel, ERP, SIOP/MPS tool	To infer the potential for AI integration in current companywide systems
D2	Process documentation	S&OP Playbook	To provide insight into current S&OP practices
D3	Forecasting	Current forecasting methods and outputs	To infer forecasting specifics concerning the potential for AI integration
D4	Demand planning	Current demand planning processes	To infer the potential for AI integration in demand planning processes
D5	Accuracy metrics	Demand plan accuracy metric	To demonstrate potential for controlling AI improvement in forecasting
D6	Decision making	Decision log	To show current reliance on human judgment
D7	Manufacturing planning	CMMS SAP R/3 PM module	To infer the potential for AI integration in manufacturing scheduling systems
D8	Issue management	Escalations and actions under SIOP	To infer the potential for AI integration in future collaboration systems
D9	Continuous improvement	CI need reports	To infer the potential for AI integration through current continuous improvement processes
D10	Workforce planning	Strategic Workforce Planning tool (SWP) TM1	To infer the potential for AI integration in workforce planning systems
D11	Strategic planning	Strategic plan	To infer the potential for AI integration for informing strategies across S&OP practices
D12	Process flow	S&OP flow swim lane diagram	To show current data flow and potential for AI integration
D13	Simulation	Plant simulation for discrete event simulations	To infer the potential for AI integration in current plant simulation systems
D14	Change management	Change board meeting outputs	To reveal organizational approach to potential AI adoption
D15	Market projections	Customer projections/R10	To illustrate the need for AI in market forecasting
D16	Training	S&OP Playbook and training material	To reveal current platforms for AI learning and areas where AI could enhance training
D17	Sales materials	Request for Quotation (RFQ)	To infer AI integration potential in forecasting and demand planning

Source(s): Created by authors

interpretations, resulting in aggregate insights for context-specific SPs of AI adoption across S&OP cases.

We took two additional steps to complement the initial interviews and corroborate their findings. First, we interviewed three AI experts from a Dutch-based firm specializing in IT transformation projects, including tailored AI solutions for manufacturing and S&OP environments. Each expert was provided with a synthesized summary of the results (similar to Table 2 in "Results") prior to their interview. During the interviews, we followed a paradox-by-paradox format to gain the experts' technical views on (1) how realistic each SP is (see "reflections" in Table 2) and (2) possible strategies for managing the SP (see "suggestions" in Table 2). These insights enabled triangulating S&OP informants' views by providing both technical validation and resolution strategies, thus grounding the revealed SPs in actual AI capabilities and limitations. This, in turn, enhanced the robustness and applicability of our results for S&OP environments.

Second, we collected a comprehensive set of secondary data from the participating firms (D1–D17; Table 1). These documents and tools, ranging from S&OP playbooks to software systems, were selected for their relevance to current S&OP practices and AI-driven developments. Accordingly, we used the secondary data to (1) triangulate interview findings and provide concrete examples of the revealed SPs and (2) infer AI adoption potentials across various S&OP contexts. For instance, comparing S&OP playbooks (D2) with strategic plans (D11) illuminated the performing paradox between short-term efficiency and long-term AI-driven optimization. S&OP flow swim lane diagrams (D12) and forecasts (D3) revealed organizing paradoxes between current processes and potential AI-driven redesigns. Documents like CI need reports (D9) and change board meeting outputs (D14) provided insights into organizational approaches to AI adoption. In turn, the S&OP playbook and training materials (D16) highlighted current AI learning platforms and possible areas for AI-enhanced training.

Results

Table 2 provides a detailed synthesis of the results—organized across the revealed SPs for AI adoption in S&OP under each paradox type from Figure 1. It includes descriptions of the contrasting poles of each SP, its meaning, and examples to enhance its understanding in typical S&OP scenarios. The table also features exemplary quotes from S&OP informants that facilitated the extraction of each SP, along with reflections and suggestions from AI experts together with secondary documents used for further validation. Accordingly, we identified three unique SPs under each paradox type specifically tied to AI adoption in S&OP—using them as backbones for our IPs.

Impact pathways (IPs)

IP1: balancing immediate S&OP actions with long-term AI-driven strategies

S&OP professionals expressed tensions between using existing tools (e.g. Excel for demand planning, ERP for inventory management) to achieve immediate results and awaiting the full maturation of AI technologies. Here, I3 highlighted the urgency of meeting sales targets with current methods, while I2 noted the lengthy time required for AI algorithms to generate accurate insights (SP1). While all AI experts acknowledged this tension, they stressed that AI's maturity is not the primary issue; rather, successful AI adoption requires gradual integration through "shadow runs" (i.e. trial simulations) (E2), long-term planning horizons (E1) and small-scale implementation (E3)—with E2 noting that "AI doesn't get better if you wait; it gets better by using it." In turn, skepticism about AI's current capabilities was expressed by I8, who doubted significant improvements over traditional methods unless AI integrates both internal and external data, such as market intelligence revealing trends in the automotive industry. E2, however, pointed to industries like semiconductors, where firms

Table 2. Revealed SPs and management strategies for AI adoption in S&OP

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
Performing paradox	*Short-term performance vs long-term development*			
SP1: Attaining short-term efficiency of using existing tools vs. awaiting fully developed AI maturity	The tension between relying on quicker and readily available S&OP tools and methods (e.g. Excel for demand planning, ERP for inventory management, PowerPoint for executive presentations) and allowing sufficient time for a fully mature and integrated AI system that enhances predictive capabilities for demand forecasting, inventory optimization and production planning	An S&OP team continues using Excel to manually consolidate demand forecasts for the next quarter, while simultaneously investing in machine learning algorithms that can analyze years of data to produce more accurate long-term forecasts	*I2:* "I think AI's support for S&OP professionals will take time to show good results because, as you know, machine learning algorithms require time to mature and generate accurate data. This is a problem [for S&OP professionals], and I guess it is hard to ask them to wait and put a lot of time." *I3:* "We are always running out of time to achieve our sales targets, so we have to use existing methods such as analyzing current RFQs and entering their data into the system . . . So, waiting for AI to be developed and ready to create a market analysis will take time and will not help in achieving our current targets, especially that it [AI] doesn't collect data specific to our projects." *I8:* "I can't really see a difference between [traditional] statistical forecasting and AI-driven forecasting. If you add market intelligence into the AI model, like data showing the automotive industry is booming from external sources, it could be beneficial for us. Once AI matures to integrate both internal and external data, it will be very useful. But as long as it relies solely on internal inputs, I'm skeptical there will be a significant improvement over our current methods."	D1, D2, D3, D4, D11, D17
AI experts' reflections	*E1:* "Preparing AI for forecasting takes a really long time. You have to consider at least 3–5 months ahead to be able to provide the customer with what they want with the AI model." *E2:* "I fully recognize this paradox. AI maturity takes time, and at the start, the models are often not as good as experienced humans because there's so much data and knowledge that need to be fed into the system. It doesn't happen overnight . . . But the AI itself is mature enough to make its own decisions in a well-defined environment where all the data and constraints are clear." *E3:* "I don't think the issue is with AI itself—I believe AI is mature enough. It's more about taking small steps and not making the process too big initially."			

(*continued*)

Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
AI experts' suggestions	*E1:* "As long as they [S&OP professionals] are well ahead in their planning efforts, AI will be useful. But if they are much of ad-hoc executors who change their plans rapidly based on highly fluctuating customer demands, then maybe AI would not be that much of use." *E2:* "AI doesn't get better if you wait; it gets better by using it. Do it on a very small scale. Do it in shadow runs. Make your first analysis, but don't immediately act on them—just gain experience. Without that, it [AI] could immediately disrupt your whole business. Start using it with small impact, then slowly build the accuracy. Build the trust, and then do a cutover, one by one, on different components." *E2:* "I know a semiconductor company in a very dynamic market that uses market performance indicators in its models to predict demand fluctuations over time. These aren't visible in immediate demand forecasts, but they're factored into overall forecasting. This isn't unique to semiconductors; many sectors also rely on external data. Technically, it's no harder than using internal data—external sources are often already curated." *E3:* "You should take small steps and not make it too big at the start. Focus on solving short-term efficiency first, and then build up to address more long-term problems."			
SP2: Relying on gut-feeling decisions vs. indisputably following AI-generated insights	The tension between relying on experienced planners' intuition for S&OP decisions (e.g. adjusting forecasts based on market knowledge, setting safety stock levels based on experience) and indisputably following AI-generated insights over the long term (e.g. accepting AI-generated demand forecasts automatically, implementing AI-suggested inventory policies over the long term without periodic review of their effectiveness)	During an S&OP meeting, a senior demand planner suggests increasing the forecast for a product based on their market intuition, while an AI system recommends decreasing it based on its analysis of point-of-sale data, social media sentiment, and economic indicators	*I3:* "If you are expecting formal procedures according to well-planned criteria, which is expected by AI analytics, this will not work in our current situation as decision makers usually make their decisions not on well-planned bases, rather intuition." *I6:* "At the moment everything is based on the gut feeling of some people, and if there are some machine learning tools that look at data piles and say OK, your gut feeling is right, then it [AI integration] would be a good idea." *I8:* "I feel AI could be riskier than gut feelings for forecasting because gut feelings involve human consciousness, while AI lacks that."	D1, D3, D5, D6
AI experts' reflections	*E1:* "That's a known paradox. I've seen it and experienced it when using AI in my personal life. It comes down to that AI is a black box—you don't know what knowledge, experience, or data it's drawing on to give you answers, or if those answers are even correct. So if I'm an S&OP planner and those AI recommendations constantly go against my gut feeling, I'll start to see the model as, so to speak, useless—right?" *E2:* "You need the tribal knowledge. S&OP is a hard field to fully automate with AI because a lot of knowledge is in people's heads. That's why, at the start, AI models are often worse; they only get better once you start bringing the gut feelings into the model." *E3*: "I think this is a spectrum. Solely relying on gut feeling is wrong, but solely following everything AI throws at you is also wrong."			

(*continued*)

Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
AI experts' suggestions	*E1:* "The people with the gut feeling are the ones best able to adjust the model. Typically, I say, rely on your gut feeling because you have the experience, and let AI provide extra insights. AI can either support your intuition or suggest, for example, ordering new capacity two months earlier—but this only works if the model can explain why." *E1:* "If you need predictions on future demand and supply, you have to test and ensure those predictions are accurate. We run 'what-if' scenarios to see which choices the model makes to identify the best ones. This helps us determine if the supply chain process or capacity is more efficient than relying on gut feelings. We validate machine learning outcomes before production by using historical test data to make and verify predictions. This is standard practice for AI." *E2:* "Always have someone review the results to check if any recent gut-feelings are missing from the model. It's a genuine problem and challenge for these models, but it is solvable." *E3:* "Experienced supply chain professionals need to use their intuition to check if something feels off with AI's recommendations."			
SP3: Reactive (firefighting) vs. proactive (AI-driven) demand-supply balancing	The tension between reactively addressing S&OP issues as they arise (e.g. expediting orders to meet unexpected demand, adjusting production schedules to address material shortages) and using AI to develop proactive, forward-looking strategies (e.g. analyzing social media trends and point-of-sale data using AI algorithms to anticipate product demand, utilizing predictive maintenance algorithms to prevent equipment failures)	An S&OP team traditionally adjusts production plans monthly in response to actual demand. They are now implementing an AI-driven demand sensing tool that can detect demand shifts in near-real-time and automatically suggest production plan adjustments daily	*I2:* "We are now trying to predict safety time on the inbound material – trying to predict that based on historical data to set the safety time more correctly." *I3:* "Usually, once our customers request certain materials, they want them now with immediate delivery. AI's algorithms will not be able to build a clear process based on customer sudden demands." *I6:* "You may have a supplier in a particular region that's more likely to experience those interruptions like wars, and we might not spot it, whereas machine learning could predict these interruptions for you and say 'hey, don't you know this?' – this will be fun."	D1, D7, D8, D9
AI experts' reflections	*E1:* "I agree with this one because in a reactive approach, the demand party often doesn't recognize their needs until it's too late. They usually realize they need more resources, like extra capacity, only when it becomes critical. But that's not what S&OP is about, right? That's more of a tactical issue . . . Quick reactions to unexpected changes fall outside the typical role of AI in S&OP." *E3:* "Here's the situation: companies often don't have the luxury to consider new solutions because they're constantly dealing with last-minute demands. They're always just about managing to keep up with customer needs."			

(*continued*)

Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
AI experts' suggestions	*E1:* "We are currently introducing an AI-based solution for a client, but the first step is to mature the S&OP process. Right now, their process is still in a 'firefighting' mode. That's why we're starting with a solution to bring transparency and observability. It allows users to see their current consumption, making them aware of the costs they incur and the wait times they face when they don't plan or forecast far enough ahead." *E2:* "You might be able to reduce firefighting by looking at how much firefighting you typically have and incorporating these into your [AI] scenarios." *E3:* "You need to start by identifying common disruptions and preparing for those. AI can help by analyzing potential issues before they become critical, which doesn't mean all reactive work will disappear, but it can significantly lessen the impact of unexpected problems."			
Organizing paradox *SP4:* Centralized vs. decentralized AI implementation	*Strict structures vs. flexibility to adapt* The tension between implementing AI for S&OP through a centralized, company-wide approach (e.g. a single AI-driven demand forecasting system for several product categories and regions) and enabling individual units to develop their own most suitable/specific AI solutions (e.g. region-specific demand forecasting models, product-specific inventory optimization algorithms)	The corporate S&OP team develops a centralized AI-driven demand forecasting system for all product categories. However, the regional teams argue that they need to develop their own AI models that account for local market nuances and unique product behaviors in their regions	*I3:* "Overall, in developed countries, we have specific plans that are working, and this will help AI to build its algorithms. However, in developing countries we don't have well-developed plans . . . The inconsistencies in S&OP plan maturity between developed and developing countries will not allow AI to be implemented company-wide, especially for international corporations like us." *I7:* "There's a central department that is working on AI who has offered some support to us, but we're still not sure what we need."	D1, D3, D10, D11, D12
AI experts' reflections	*E1:* "From a platform perspective, AI would be centralized because it needs a lot of compute power and data—and data access must be governed centrally. A major challenge for AI is ensuring access is limited to authorized users, and this is crucial for cybersecurity. For instance, we need to make sure the AI model doesn't disclose sensitive data, like sales figures or HR information, to unauthorized users. That's why centralized AI governance is important." *E2:* "You have two ways to start, right? Either you break the process up into regional pieces and go all the way, or you keep the whole thing but keep it superficial. If you're not taking regional factors into account, then you end up with an inaccurate model that can't work effectively across all cases."			
AI experts' suggestions	*E1:* "My conclusion is that we should definitely take into account regional settings and influences, while the model itself runs centrally with central access to a lot of enterprise data sources that are being governed." *E2:* "If you immediately take the big central approach, it's going to take a very long time before you get things accurate, so adoption will go very slow. Do it on a smaller scale, it will not be 100% accurate because you only include the regional part and not the bigger scale, but at least you can achieve something." *E3:* "It depends on what you want to achieve with the model. For example, the headquarters of a big company with 20 factories worldwide can create an overall plan. They might say 'this particular factory in this part of the world needs to produce this many products per month.' That becomes the demand target for that factory. Then the factory can have its own S&OP AI program that takes these headquarters figures as input and determines 'Hey, how do we plan to meet this target?'"			

(*continued*)

Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP5: Maintaining traditional S&OP processes vs. redesigning toward AI-based S&OP frameworks	The tension between adhering rigidly to traditional S&OP processes (e.g. monthly planning cycles, static Excel-based reports) and redesigning processes entirely to fully leverage AI capabilities (e.g. continuous planning with real-time updates, dynamic dashboards with AI-generated insights and recommendations)	A company maintains its traditional monthly S&OP cycle with set meetings and reports. They are considering moving to a continuous planning process enabled by AI, with real-time updates and exception-based meetings, but this would require a complete redesign of their S&OP process	*I2:* "If you think of how AI can totally transform the way we run S&OP, you can imagine a complete redesign over time into continuous planning processes with real-time updates and exception-based meetings." *I3:* "Although redesigning for AI will make our work easier, I am concerned that AI adjustments might complicate things in some cases, especially when trying to find a specific file or material that was manually entered into Excel." *I4:* "It obviously depends on how it [the AI system] is set up and how many parameters you put into it and how."	D1, D13, D14, D16
AI experts' reflections	*E1:* "I don't see AI completely taking over the orchestration of the entire process anytime soon, where people say I trust AI blindly to order $20 million worth of new equipment because it's needed for a forecast that AI has seen for the next two months. Somebody still needs to be the brains to check." *E2:* "I've not seen a single company yet that's fully moved away from traditional S&OP and built everything around AI. I know how you could do it, but I've not seen it in practice yet." *E3:* "Yeah, that's maybe just their lack of understanding about what AI does. They think AI hides their Excel sheets or takes them away, like suddenly you don't need that Excel file anymore, so it's gone. But AI will never just delete your Excel file."			
AI experts' suggestions	*E1:* "Maintain the traditional process because the AI model must learn to work with and support the existing setup. That's where all the data is available. If you change the process too soon, there will be no data for the new process. So make sure that the traditional process keeps working but works better." *E2*: "For the AI model, you don't start with 100% accuracy—you can get close, maybe 90% or so, but it requires ongoing training, testing, and validation. It's similar to people; most decisions people make aren't 100% accurate either. That's something important to keep in mind." *E3:* "AI can function in parallel. I don't have to delete the system to implement the solution I have. It operates through a different portal. What we often do is set up a database because we don't want people having their own Excel files going off on their own journey, which can't be tracked."			

(*continued*)

Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP6: Relying on data silos vs. utilizing integrated AI-driven data systems	The tension between maintaining separate data sources for different S&OP functions (e.g. sales data in CRM, inventory data in WMS, production data in MES) and transitioning to integrated, AI-driven data systems (e.g. a unified data lake with machine learning models that analyze cross-functional data for holistic S&OP insights)	Currently, a company's demand data is stored in the sales system, inventory data in the warehouse management system, and production data in the ERP system. They are considering creating a unified data lake to enable AI-driven S&OP, but this would require substantial changes to data management processes	*I1:* "The main challenge with AI is data consistency. We need to ensure no false signals are presented due to biased reporting . . . Often, data appears to have changed because of how it's reported, not because of actual changes." *I4:* "There are differences in each dataset that you can handle with machine learning. For load and capacity planning, there is a big mountain of data that you could utilize. But at the moment, we don't use this big mountain of data, we only use a small part of it to perform our calculations and planning." *I8:* "I think AI might be a bit biased towards one function over another. If the data is collected from sales information, the algorithm will be biased towards sales, not towards production or production management."	D1, D10, D12
AI experts' reflections	*E1:* "You say it's biased, I say it's not. It just has too little information across the end-to-end process. Therefore, the model cannot do anything other than learn from the sales or forecasting processes, but not from the backend manufacturing process, because the model has no other data to learn from." *E2:* "But now you get organizational politics into the mix. The AI itself doesn't influence or change anything. It's people who do that. So you have to agree on the basis of your data—whether you put it in a silo or on a platform, that's your choice." *E2:* "The source of truth should remain the same, right? So even if you bring data to a data lake, there's a difference between just copy-pasting data from your ERP vs. changing it into reports and using that as your basis." *E3:* "Taking the AI side, we always say, 'garbage in, garbage out.' So if what goes into the AI isn't controlled well, the output will be unreliable."			
AI experts' suggestions	*E1:* "Successful AI solutions should be able to quickly integrate and learn from new datasets that are essential for the overall process." *E2:* "The silos just make it impractical. You rather need a single layer where everything is combined without processing—no transformations, no cleaning, just a basic layer. This works because pulling data from different silos is unmanageable otherwise." *E3:* "For AI to really make a difference, you need multiple data sources, and they need to be connected. You need a centralized database for the entire company—one that people can access based on their permissions. This becomes your single source of truth. That's really the only way."			
Belonging paradox	*Unified organizational identity vs. individual autonomy*			

(*continued*)

Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP7: Collective AI-driven S&OP identity vs. individualistic S&OP identities	The tension between establishing a collective, forward-looking identity via standardized AI-driven S&OP processes (e.g. deploying uniform AI-based models for demand forecasting that adjust inventory levels automatically across all regions) and preserving diverse, traditional planning identities (e.g. continuing to use local market knowledge and manual demand assessments in regions where relationships and/or individuals dictate business dynamics)	A global company implements a standardized AI-driven S&OP platform to be used by all regions. However, the European team argues that their unique market requires a more relationship-based planning approach, while the Asian team prefers a more hierarchical decision-making process that the AI system does not accommodate	*I3:* "If we have a fully integrated AI system, we will not know who is in charge for what or from where this data has been collected." *I3:* "For optimal results, you need function-wise AI integration, otherwise errors will arise." *I7:* "There could be some cultural, technical, or organizational factors at play if you want to implement AI for more than one location. Different sites might have unique attitudes about how to input data in a way that allows a central department to evaluate it effectively and provide benefits. Although we are all part of 'X' [the company], individuals at different locations might prefer to handle things in their own way. This often depends on the mindset of the people involved."	D1, D2, D4, D15
AI experts' reflections	*E1:* "We often see equipment data used differently across regions even when producing the same product—it carries different meanings. So, looking at those identities—regional vs. central—is one thing, but also the identity of each function. Sales thinks differently from manufacturing, and this way of thinking is really hard to capture in an AI model." *E2:* "It's about the AI model being a black box and needing transparency on how it reaches its conclusions . . . If you remove AI and run a full S&OP process by combining demand with production, don't you still have the same issue? It all depends on who provides the data and whether that data is trustworthy."			
AI experts' suggestions	*E1:* "You might train AI to 'think like a sales expert' with knowledge of products and upcoming releases, but the model needs all the data and solid training in sales processes. It's like telling it to think like a five-year-old describing their favorite food—teaching AI to think like sales, forecasting, or production experts takes focused training and data." *E2:* "To build trust, you'll need to make the process transparent and involve end users and organizational leaders to agree on how it's done. The same applies even without AI; if a controversial analysis is presented, the CEO will still ask, 'Who provided that number?'" *E3:* "I think it's about finding a balance. You really need to set all your priorities straight and keep company goals in mind. Based on those goals, you have priorities, and you should be able to provide that input."			

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Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP8: Streamlining AI-driven collaboration vs. preserving specialized S&OP expertise	The tension between promoting AI-enabled cross-functional collaboration in S&OP (e.g. using AI to generate a single consensus forecast) and maintaining distinct functional roles and specialized expertise (e.g. sales maintaining their own forecast based on customer relationships, finance keeping separate financial projections)	A new AI-driven S&OP system provides a single, data-driven forecast that it suggests should be used by all functions. However, the sales team insists on maintaining their own forecast based on customer insights, while the finance team wants to keep their separate financial forecasting process	*I2:* "I believe that building such a platform [AI-assisted system that combines all forecasts from sales, finance, and production] is very possible. But again, it is not the system that is the issue here. Sales want their forecasts to be dictating because they are closer to the market and customers. We know from experience that they [sales and marketing] prefer to resolve their issues in isolation. They have their own informal meetings for market assessments and changing that takes away this cultural aspect from them." *I8:* "Production planning might be more efficient with AI due to its predictable nature and reliance on internal data and parameters. But this is not the case with forecasting, who by nature rely on future forecasts with external data sources that are hard to feed into the AI algorithm."	D1, D3, D12
AI experts' reflections	*E1:* "I think specialized expertise will always be needed. You can't just capture all this expertise in datasets and feed it into a model that has to learn—it's unlikely to happen anytime soon." *E2:* "It really depends on the industry. In some industries, sales are easy to predict, and you can achieve high accuracy. In others, it's much harder. The same goes for production—if the process is simple, you can get high accuracy, but in high-tech industries, it may vary a lot." *E3:* "It depends on what you want from AI. You might say, 'Hey, I don't want AI to handle forecasting or predict future demand—I'll use it solely for production planning.' Or, 'I don't want it to consider production factors; I just want it to look at specific variables and give me a forecast or multiple forecast scenarios.'"			
AI experts' suggestions	*E1:* "But I do think AI models can help improve communication and collaboration, making sure everyone in the end-to-end process is better informed about product status, past releases, and what went wrong. You can simply ask the AI, and it will provide answers based on available data for everyone involved." *E3*: "Ideally, AI should combine everything—it should evolve to bring together all these different perspectives. For example, if I'm using AI for forecasting, it might tell me, 'Hey, this intel comes from production—do you need to collaborate more closely with the production team?'"			

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Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP9: Resisting vs. embracing AI-driven S&OP	The tension between embracing AI in S&OP to streamline tasks (e.g. automating routine forecasting and inventory management tasks) and resisting the adoption of AI in S&OP in fear of losing jobs or reduced perceived value within the organization (e.g. demand planners concerned about AI replacing their role in forecast generation)	In an S&OP initiative, a firm integrates AI to automate forecasting and inventory planning, raising concerns among demand and supply planners about AI diminishing their roles and threatening their job security	*I2:* "We talked to several people [concerning AI in S&OP], and yes, we saw some variations in opinions. I would not say a specific department is more negative about it than the other . . . Some [S&OP professionals] seem to have the wrong idea about what AI is, and that it will make them do little and look less important. That is a possibility for resistance I guess." *I3:* "Back-office employees might risk their positions with AI integration but front office workers who meet clients frequently would be very happy to utilize AI as it will result in conducting more meetings and reducing paperwork."	D1, D10, D14, D16
AI experts' reflections	*E1:* "If you look at how much manual work is happening in the S&OP process—both on demand forecast and supply side—which can be automated? Yeah, then some people will lose their jobs." *E2:* "Yes. Currently we have a project where one guy is responsible for most of the demand forecasting process and he's putting up a lot of resistance because he sees that 'before I was the guy who did all the demand forecasts, and now 80% of that is going to happen through the tool—or maybe the tool will even show that my own forecasts were quite bad sometimes.'" *E3:* "In most cases AI won't take your job. It will change your job. I think that's what people are really scared of. Also, if you automate everything and something goes wrong, you can't blame anyone anymore."			
AI experts' suggestions	*E1:* "Right now, firms are spending a lot more money on additional work, like having people build dashboards or gather data in one place, just to ensure there are some insights for better planning in S&OP meetings. But these are extra investments they don't want to make. So I want to turn it around—it's not about people losing their jobs, but about saving money on additional hires needed for this work." *E2:* "You have people who are enthusiastic from the start because they like technology, and you have those concerned for valid reasons. Then you have people who are concerned because they're just worried for their position. The last are irrational views, at least from a company perspective."			
Learning paradox	*Exploiting existing knowledge vs. exploring new skills*			

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Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP10: Developing traditional S&OP skills vs. acquiring AI-related competencies	The tension between developing traditional S&OP skills (e.g. cross-functional communication, business acumen, Excel-based analysis) and acquiring new competencies more focused on AI (e.g. data science skills, machine learning model development and interpretation, AI ethics understanding)	An S&OP team with years of experience in consensus building and cross-functional communication is now being asked to learn data science skills to develop and interpret machine learning models for demand forecasting, requiring a momentous shift in their skill set	*I2:* "The goal of our two AI projects in S&OP is to be data-driven and reduce reliance on human error. For example, a person might interpret market dynamics as indicating more customer orders are coming, while the data suggests the opposite. We should either train our salespeople on how to assess trends accurately, or we should let the data speak for itself through a trained model. Perhaps we need some kind of combination." *I3:* "I need our new employees to understand the history of our work as it is today. At the same time, I want them to learn how to use AI to optimize performance and efficiency." *I8:* "Not every supply chain person knows how to use Python [for developing AI algorithms], as its typically made for developers. However, if AI interfaces are made user-friendly for supply chain purposes, it could work. Currently, I'm not aware of any AI models that are specifically designed for S&OP functions."	D1, D10, D11, D16
AI experts' reflections	*E2:* "You have people with AI skills to prepare the models, run simulations, handle the data, and understand what's happening in the back end. And then you still need people with traditional S&OP skills who do the balancing and negotiations." *E3:* "When you hire a new S&OP professional, you want, on one end, to teach them how to do things traditionally. On the other, you need to teach them the latest, including how to work with AI and how to inform their decisions using AI."			
AI experts' suggestions	*E1:* "S&OP people using AI don't have to be AI experts. They don't need to understand the model's inner workings or how data is accessed. It's more about being good users—knowing how to prompt the AI effectively and adjust the guardrails so it provides the best answers for their process." *E2:* "You need to train them [S&OP professional] on how to work with the AI models, but they don't have to become data scientists. I don't think you need S&OP people to use Python a lot. If you have good models with good interfaces, you get IT people who handle that in the backend, and you get S&OP people who are savvy enough to work with those tools and understand what the model does and how to interpret it." *E3:* "Traditional S&OP is very important for decision-making, and AI should really focus on having the data ready, giving you the correct scenarios, and putting you in the driver's seat. It shouldn't be about making S&OP people experts in programming."			

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Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP11: Relying on human learning vs. leveraging machine learning	The tension between relying on acquired human learning from S&OP experience in isolation (e.g. understanding of market dynamics, knowledge of product lifecycles) and leveraging easily accessed machine learning algorithms for continuous improvement (e.g. AI systems that automatically detect and adapt to changing demand patterns or supply chain disruptions)	Inventory planners have traditionally adjusted safety stock levels based on their experience with stockouts and excess inventory. The company is now implementing a reinforcement learning algorithm that continually adjusts safety stock levels based on various factors, potentially outperforming human decision-making in this area	*I3:* "Human learning will always result in creative proposals. At the same time, machine learning will produce well-organized proposals that might not be as creative as those generated through human learning." *I5:* "Machine learning eventually requires accurate data input from us, humans. If you fill in data that shows what you want rather than the reality, then you end up with useless calculations from these machines." *I8:* "AI can give superpowers to normal people . . . However, whether it's AI-based forecasting or [traditional] statistical forecasting, you still need human expertise and interaction, especially for negotiations with the production unit. This is something AI will never be able to replace."	D1, D3, D4, D5
AI experts' reflections	*E1:* "I don't think AI will ever have gut feelings—it will always react to the data it's been given. If certain data hasn't been fed into the model, AI will never be able to produce anything that depends on that missing data." *E3:* "Data always has to come from somewhere. So, in the end, it should always come from a person—or at least be supervised by a human. Otherwise, it's just random, generated, or not real."			
AI experts' suggestions	*E2:* "You will still rely on human expertise for some part of it. And you can put that into a model, but new human expertise will pop up that you don't have in the model, and there's a cycle of continuously adding it, even though you'll never reach 100% accuracy." *E2:* "AI will always have boundaries; it performs the assignment you give it. At the same time, humans also have biases. If you look at a game of chess, you'll see models doing things no human has ever thought of, so there's definitely creativity there. But it's always within the scope you set. I've never seen a model think outside the rules you give it."			

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Table 2. Continued

Revealed SP	Meaning of SP	Exemplary scenario	Exemplary quotes by S&OP informants	Validated in
SP12: Making incremental improvements vs. embracing disruptive AI innovation	The tension between making small, continuous improvements to existing S&OP processes (e.g. refining statistical forecasting methods, gradually improving inventory policies) and embracing disruptive AI innovations (e.g. implementing autonomous planning systems that dynamically adjust forecasts, inventory levels, and production schedules based on real-time data and complex algorithms)	An S&OP team has been gradually refining their ABC classification for inventory management over years. They are now considering implementing an AI system that dynamically classifies SKUs based on multiple factors including demand volatility, supply risk, and strategic importance, fundamentally changing how inventory policies are set	*I2:* "We had the idea and option to choose between going all in with AI integration, but we preferred to narrow it down to our project only. We know that only smaller steps are realistic and can be approved, if you know what I mean." *I3:* "Well-established companies like us cannot fully adopt disruptive technologies as this will affect their annual figures, but slow changes will be smooth and will not affect annual turnover." *I6:* "Currently, a lot of our processes are just informal rules noted in Excel sheets or kept in mind. It seems these could be partially automated. My colleague, who is responsible for the new [AI] tool, mentioned that we might implement AI features slowly later on."	D1, D9, D11, D13
AI experts' reflections	*E1:* "That [incremental improvement] is really the most important part for getting customers to adopt AI solutions, especially given it's a black box. Looking at machine learning examples, you can see accuracy gradually improving from 80% to 95%. And this improvement depends on how much time and effort you invest in learning and retraining the models." *E1:* "If you change the process too early, then you won't have any data for the new process—there's nothing for the AI model to learn from." *E2:* "If you're discussing using AI for preparing the S&OP process, like predicting your demands, forecasting supply, measuring them, or running simulations, understand that these aren't quick, short-term actions. They're part of a longer-term strategy."			
AI experts' suggestions	*E2:* "Yeah, start with incremental, smaller steps. There's a lower risk if things going wrong. It's a safer way to begin, especially when there's uncertainty about whether it will work or how much budget it will require. It's a clear, easy way to get started." *E2:* "We put all your knowledge into the system, and then, if we're lucky, we can gradually automate 40% of the easier decisions, leaving you with the harder ones. Over time, this might reach 50% or 60%, and we'll see how far we can go. We don't force it on anyone; instead, we let them decide if the model can take over their repetitive tasks or not." *E3:* "Baby steps is the only way to do it—like optimizing the recent approach a little bit, or take one small part of it, optimize that, make it a bit more efficient, and then move to the next process. And then, with those steps, you combine maybe a few of them, and slowly you work towards it."			

Source(s): Created by authors

currently use market indicators to enhance forecasting decisions—suggesting that integrating external data into AI models is feasible in some cases. S&OP professionals' skepticism also coincided with their reliance on gut feelings and intuitions rather than AI's insights to make decisions (I3, I6, I8; SP2). AI experts recognized this tension, attributing it to the perception of AI as a "black box" (E1) and insufficient testing of AI models (E1, E2). As such, they proposed integrating S&OP professionals' "tribal knowledge" into the AI model to fine-tune it based on their intuition (E1–E3) and validating AI predictions through "what-if" scenario testing before system launch (E1). S&OP professionals further expressed doubts about AI's capacity to handle sudden market demands (I3; SP3), with I8 going further by portraying AI as risky for forecasting tasks due to its lack of human intuition. All AI experts reframed this as a process maturity issue rather than an AI limitation, with E2 and E3 suggesting that AI could shift S&OP from reactive "firefighting" to proactive planning by incorporating historical disruptions into AI models to mitigate similar future events.

Our findings on the performing paradoxes SP1–SP3 contribute to the AI adoption literature in OM by revealing S&OP-specific nuances. While Cannas *et al*. (2024) discuss general skepticism about AI's long-term potential, we found that in S&OP contexts, the performing paradox (SP1) manifests as a tension between immediate decision-making pressures and extended timelines for AI implementation—with experts suggesting running trial simulations and engaging in proactive planning to address this issue. In turn, while Guida *et al*. (2023) noted that firms often hesitate to invest heavily in AI due to the immaturity of current solutions, we found that AI maturity does not develop on its own but rather benefits from incremental use—suggesting that gradual investments are better positioned to accommodate the technology (at least in S&OP contexts). Our findings also diverged from Lerch *et al*.'s (2024) emphasis on AI readiness for unforeseen events, as SP3 reveals that in S&OP, the challenge is not solely about AI capability but also process maturity. Here, co-development and maturation between process and technology are crucial, since a firefighting mentality contradicts both the essence of S&OP and the prerequisites for AI adoption.

These insights suggest a key IP for research: balancing immediate S&OP actions with long-term AI-driven strategies. Derived practical implications include (1) gradually implementing AI in S&OP through small-scale pilots ("shadow runs") to avoid disrupting current operations, (2) enhancing AI models by incorporating S&OP domain expertise ("tribal knowledge") through structured feedback loops and (3) proactively reducing firefighting tendencies by identifying common disruptions from historical data and feeding them into AI models.

IP2: navigating AI in S&OP via centralized systems, process redesign and data unification

S&OP professionals may encounter difficulties when implementing centralized AI systems across different departments and regions, as expressed by I3, who noted discrepancies in S&OP maturity between developed and developing countries, thus impeding company-wide AI adoption (SP4). Nonetheless, AI experts emphasized the necessity of centralized AI systems to uphold governance, cybersecurity and computational efficiency (E1), advocating for a balanced approach that combines centralized infrastructure with regional customization (E1–E3) and a phased implementation where global targets cascade into localized, AI-driven planning (E2, E3). Tensions between tradition and reform were also stressed in the cases; while I2 optimistically envisioned transitioning to continuous planning and real-time updates with AI, both I3 and I4 expressed concerns about the complexity of such holistic redesigns (SP5). Here, all AI experts collectively voiced that a fully AI-driven S&OP process remains largely theoretical, proposing instead a parallel approach where AI improves rather than replaces traditional S&OP processes, with E1 highlighting the importance of

retaining existing S&OP processes for data collection and validation. Though, such perceived complexity was further manifested in relying on data silos vs. utilizing integrated AI-driven data systems (SP6); all S&OP informants unanimously highlighted the challenge of accurately selecting and feeding the right, function-specific data into AI systems from extensive datasets, with I1 particularly emphasizing the importance of maintaining data consistency across different systems to avoid receiving false or skewed signals. Grounded in the "single source of truth" principle, AI experts reframed the data silos paradox as an organizational challenge driven by internal politics rather than a technical limitation (E2, E3)—advocating for a unified, well-governed data layer and comprehensive integration across S&OP functions to avoid bias (E1) and prevent "garbage in, garbage out" scenarios (E3).

While Hasija and Esper (2022) discuss hierarchical challenges in AI adoption within supply chains, our analysis of SP4 reveals a more nuanced tension in S&OP between the need for centralized AI governance and variations in regional S&OP settings, with experts suggesting a hierarchical, context-specific AI implementation to bridge these gaps. In turn, Wamba *et al.*'s (2022) emphasis on real-time data adaptation attains new complexity in SP5, where experts view the shift to holistic live planning not as a technical hurdle but as a gradual process evolution that requires maintaining both traditional and AI-driven models. Similarly, while Cannas *et al.* (2024) identify securing high-quality data as a primary barrier to AI adoption, SP6 shows that in S&OP, the challenge specifically involves balancing functional data autonomy with integrated planning needs, supported by a "single source of truth" principle represented in unified data layers. Finally, Brau *et al.*'s (2024) note on AI's dual role in data processing and human interpretation in retail contexts gains new depth in SP6, where in S&OP, this organizing paradox is heightened by the need for cross-functional alignment and data consistency—stressing the importance of well-governed data integration to enable accurate, localized AI planning.

These insights suggest a key IP for research: navigating AI in S&OP via centralized systems, process redesign and data unification. Derived practical implications include (1) developing centralized AI governance frameworks to secure data access while allowing for model customization to meet regional S&OP requirements, (2) establishing a centralized data layer as a "single source of truth" for the organization while enabling localized access needs across S&OP functions and (3) integrating AI with traditional S&OP processes to enhance workflows and improve model accuracy through continuous training.

IP3: harmonizing AI-driven S&OP identities, collaboration and technology acceptance

We expect S&OP professionals to experience tensions between establishing a collective, AI-driven S&OP identity and preserving diverse planning identities when adopting AI. Here, I3 expressed concerns about losing visibility of different responsibilities with fully integrated AI systems, while I7 mentioned attitudinal and organizational factors influencing data-entry practices that may impede identity unification efforts (SP7). AI experts recognized the challenge of capturing diverse functional identities in AI systems (E1) but reframed it as a matter of transparency, trust and goal alignment rather than identity preservation (E2). As such, they recommended training AI models to "think like" different S&OP functions (E1) and voiced the need for a transparent adoption process involving both end users and leadership to foster trust in AI outputs (E2, E3). Looking at different S&OP functions, I2 stressed resistance from sales and finance teams to unified forecasting schemes (SP8), while I8 expressed a likely bias of AI systems toward serving one function over another based on the data at hand. AI experts acknowledged this challenge but saw it as industry-dependent (E2), suggesting that AI could enhance cross-functional collaboration rather than compromise functional autonomy by providing accessible insights into product status, past releases and inter-functional needs (E1, E3). While perceived functional bias could yield resistance to

accepting AI systems across all S&OP functions, I3 felt that it is mainly back-office employees who might lose their jobs to AI, as opposed to customer-facing sales who would rather embrace AI to enhance their productivity (SP9). On that front, AI experts validated AI's threats to S&OP jobs but framed this situation as job transformation rather than outright elimination (E3). While E1 noted that AI might reduce hiring needs (and operational costs) by automating data-entry tasks, E2 asserted that resistance often stems from concerns over diminished responsibilities or status, even as some employees welcome AI's potential to streamline their work.

While Guo *et al*. (2024) portray AI's ambiguous role as "neither strictly substitutive nor solely assistive" in healthcare, our findings through SP7–SP9 reveal a more delicate understanding shaped by S&OP's cross-functional nature. The challenge here manifests not only as role ambiguity but as a complex interplay between preserving distinct functional identities (such as I3's concern about responsibility visibility) and achieving integrated planning through AI. Technology experts frame this as a transparency and trust barrier rather than a straightforward identity preservation issue, suggesting that AI can be trained to "think like" different S&OP functions. While Hasija and Esper (2022) note accountability challenges for AI adoption in hierarchical organizations, our findings under SP8 suggest that S&OP's cross-functional dynamics could, in fact, foster collaboration—but only if AI models are transparent enough to align teams on shared goals. Similarly, where Gupta *et al*. (2023) discuss a general shift toward end-to-end platforms, SP9 reveals S&OP-specific tensions between back-office automation and customer-facing enhancement, with experts viewing these impacts as industry-dependent and reframing AI-driven job shifts as necessary transformations rather than undesirable replacements.

These insights suggest a critical IP for research: harmonizing AI-driven S&OP identities, collaboration and technology acceptance. Practical implications here include (1) training AI models to "think like" the corresponding S&OP functions, (2) leveraging AI to improve cross-functional collaboration by integrating diverse S&OP expertise for more informed decision-making and (3) automating routine S&OP tasks to increase efficiency and reduce resource costs while supporting employees in adapting to new AI-driven roles.

IP4: bridging traditional S&OP human skills with innovative AI competencies

S&OP professionals will likely face challenges in balancing traditional skills with new AI-related competencies. Here, I2 emphasized the need to become more data-driven and reduce reliance on potentially erroneous human interpretations, while I8, with more skepticism, noted that current AI models are not yet tailored to S&OP functions—suggesting that S&OP professionals may need to acquire IT-related skills (e.g. Python) to effectively leverage AI for their roles (SP10). While balancing traditional S&OP skills with tech-savviness was noted (E2, E3), all AI experts rejected the need for S&OP professionals to become technical AI/programming experts. Instead, they advised S&OP professionals to master the skill of "setting the guardrails" for AI models through effective prompts and configurations (E1), leaving technical tasks to IT specialists (E1–3). In turn, indispensable reliance on human judgment vs. fully shifting to AI systems (SP11) was perceived by S&OP informants and attributed to superior human creativity (I3), the need for human input of data (I5) and human-based interactions and negotiations (I8). AI experts affirmed the continued need for human judgment, pointing to AI's limitations in handling missing data (E1) and its creativity being restricted to set boundaries (E2). They further emphasized the ongoing cycle of incorporating human expertise into AI models, noting that while AI can perform creative tasks, it cannot "think outside the rules" predefined by humans without additional input (E2, E3). Last, all S&OP informants favored a gradual AI adoption approach (SP12), which I3 linked to maintaining stable annual figures by avoiding radical investments. AI experts strongly endorsed this "baby steps" (E3) approach, emphasizing the importance of

data accumulation to improve the AI model's accuracy (E1) and recommending incremental automation starting with simpler tasks (E2). This method is posited to build trust in AI models, enhance accuracy gradually and lower risks as more complex tasks are automated over time (E1, E2).

Although Brau *et al.* (2024) highlight the dual role of AI in data processing and human interpretation, SP10 reveals a unique S&OP tension in skill requirements, where AI experts reject the need for technical mastery despite practitioners' perceived pressure to acquire IT-related skills. In turn, Cannas *et al.*'s (2024) challenge of feeding the system with high-quality data gains new dimensions in SP11, as experts emphasize the cyclical nature of incorporating human expertise into AI systems, particularly for handling missing data and maintaining essential negotiation skills. Likewise, Guida *et al.* (2023) point to concerns about justifying AI investments, while SP12 reveals S&OP-specific tensions around gradual adoption, with both practitioners and experts advocating "baby steps" to maintain operational stability while building model accuracy.

These insights prompt a critical IP for research: bridging traditional S&OP human skills with innovative AI competencies. Practical implications include (1) training S&OP professionals to define operational boundaries for AI models (e.g. setting acceptable ranges for forecast adjustments) without requiring advanced technical/programming expertise, (2) preserving human input for creativity, negotiation and complex decision-making tasks and (3) adopting incremental AI adoption strategies that build accuracy and trust over time.

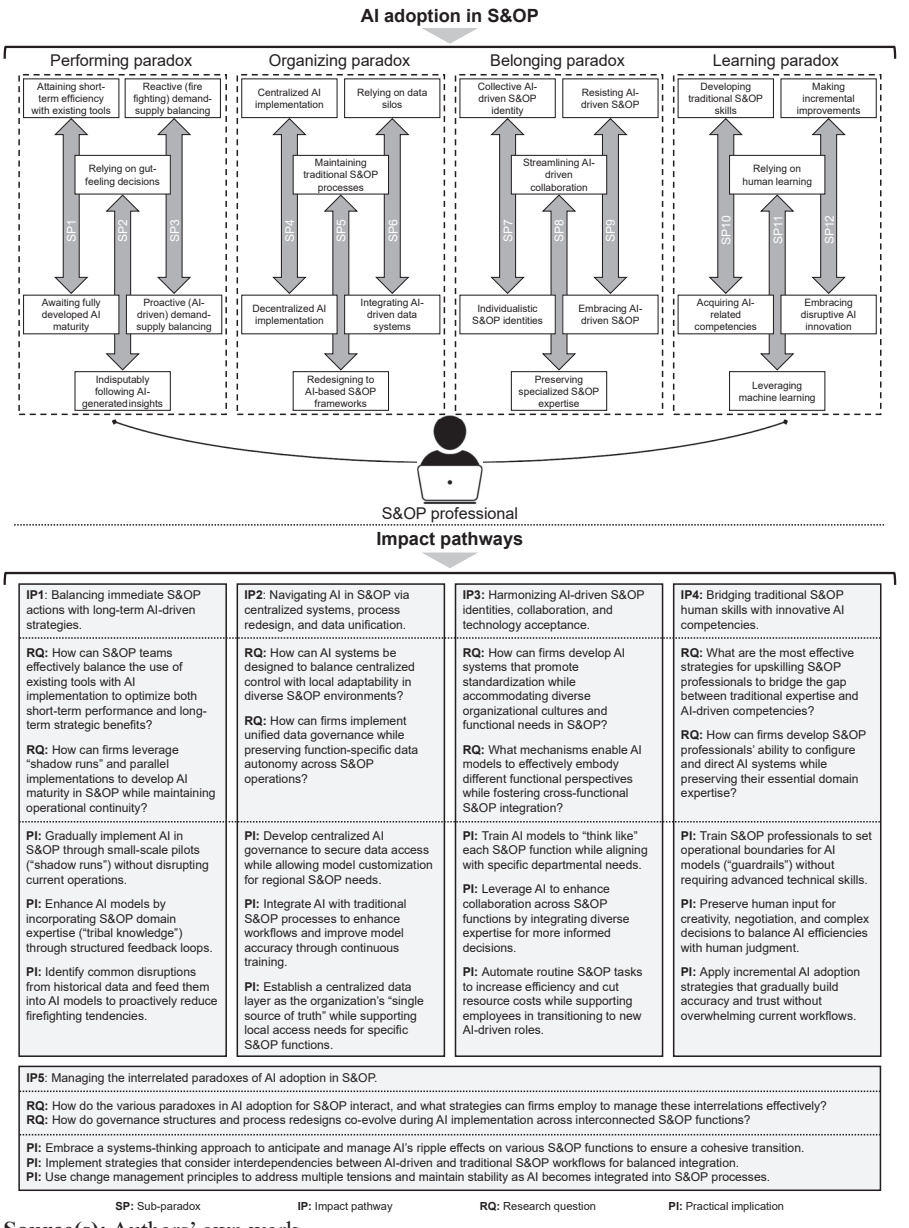
IP5: managing the interrelated paradoxes of AI adoption in S&OP

Our analysis reveals intricate interconnections between AI adoption (sub)paradoxes in S&OP that extend beyond the current understanding of AI adoption in other OM contexts. For instance, the tension between centralized and decentralized AI implementation (SP4) is intrinsically linked to the challenge of maintaining vs. redesigning S&OP processes (SP5), as the shift toward AI-driven frameworks requires addressing governance structures and process evolution at both central and local levels. Here, implementing centralized AI systems must accommodate varying regional S&OP maturity levels while supporting the transformation of traditional planning processes, thus creating a complex web of interdependent challenges. While Helo and Hao (2022) discuss AI-driven process optimization and Wamba *et al.* (2022) emphasize flexibility needs, our findings illustrate how these challenges in S&OP are inherently connected through their combined impact on organizational structure and process design. Similarly, the paradox between relying on data silos and integrated AI-driven systems (SP6) links to balancing traditional S&OP skills with AI-related competencies (SP10), extending Cannas *et al.*'s (2024) insights on data quality barriers to show how data integration shapes capability development. This complexity intensifies as the tension between collective and individualistic S&OP identities (SP7) intersects with balancing AI-driven collaboration and specialized expertise (SP8), expanding Hasija and Esper's (2022) view on hierarchical accountability. Together, these interconnections deepen Gupta *et al.*'s (2023) note on end-to-end platforms by showing how S&OP contexts require addressing multiple paradoxes simultaneously across interconnected organizational dimensions, where changes in one area inevitably influence—and are influenced by—adaptations in others.

These insights highlight a key research pathway: managing the interrelated paradoxes of AI adoption in S&OP. Derived practical implications include (1) embracing a systems-thinking approach that anticipates how AI adoption in one area can influence other S&OP functions, (2) implementing integrated transformation strategies that consider interdependencies between AI-driven processes and traditional S&OP workflows and (3) using change management principles that address multiple tensions at once to maintain operational stability as AI integration advances.

Conclusions and implications

We examined the potential tensions and management strategies for adopting AI in S&OP environments, identifying 12 SPs and five overarching IPs for further research. This study makes two main academic contributions. First, we contribute to the growing literature on AI adoption in OM by demonstrating how S&OP's distinctive orchestrating role generates



Source(s): Authors' own work

Figure 2. Revealed SPs and proposed pathways

complex, interconnected adoption tensions that have gone unnoticed in existing AI-related research. While prior studies emphasized technical hurdles and isolated capability-building challenges with AI, we show that S&OP's unique position—as a bridge between strategic and operational decision-making—creates multifaceted paradoxes that span organizational boundaries and hierarchies. These tensions manifest through temporal integration, where immediate operational needs must align with long-term AI development and gradual capability building, and structural integration, where centralized AI governance must accommodate diverse regional contexts and functional identities while maintaining cross-functional alignment. Our S&OP-focused findings also advance the classical AI-human coexistence debate: rather than replacing professionals or turning them into AI technicians, we find that professionals should focus on setting AI parameters while preserving their unique strengths in creativity, negotiation and complex decision-making.

Second, we extend Paradox Theory by revealing distinct manifestations of each major paradox type through the lens of AI adoption in S&OP. Specifically, we demonstrate how performing paradoxes arise from tensions between operational continuity and technological transformation; organizing paradoxes manifest in the balance between standardized AI systems and localized planning imperatives; belonging paradoxes surface in the struggle to reconcile collective AI-driven identities with specialized functional expertise; and learning paradoxes emerge in the challenge of bridging traditional planning knowledge with transformative AI capabilities. This multifaceted understanding enriches the theory by pushing its conceptual boundaries and uncovering how technological change can yield nuanced forms of organizational tensions. Beyond the paradoxes revealed in this work, we anticipate a new tension to arise between adopting advanced technologies and responding to regulatory pressures, where firms must balance innovation with compliance—an area ripe for future exploration alongside the evolution of modern supply chains.

For practitioners, our findings offer a roadmap for navigating AI adoption in S&OP through a set of practical implications. Figure 2 synthesizes the identified SPs, IPs, targeted research questions and derived practical implications into an actionable framework that both scholars and practitioners can use to address AI adoption tensions in S&OP environments.

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