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Integrating Artificial Intelligence into Sales and Operations Planning

A Case Study for Operational Efficiency at Ascom

Master's thesis in Supply Chain Management

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Abstract

Artificial Intelligence is increasingly discussed to improve supply chain planning, but its value depends on how it is integrated into existing organizational processes. This thesis investigates how AI can support operational efficiency and quality performance in Sales and Operations Planning at Ascom Global Supply Chain. The study is based on a qualitative case study, where interviews, document analysis, observations and literature review were used to analyze the current S&OP process and its conditions for AI integration.

The findings show that Ascom's S&OP process has a formal monthly structure, but that execution is constrained by fragmented information flows, manual consolidation, spreadsheet dependency, forecast uncertainty and uneven cross-functional coordination. These challenges reduce operational efficiency through recurring rework and manual interpretation. They also weaken quality performance by making planning inputs and outputs less reliable and less fit for use.

The main conclusion is that AI should not be understood as a standalone solution to S&OP maturity problems. Instead, AI could create value when used as human-supervised decision support within clearly defined planning routines. Its most relevant contribution is to improve the usability, comparability, validation and traceability of planning information before decisions are made. AI can support activities such as input validation, forecast review, deviation learning and scenario evaluation. However, it cannot by itself resolve weak ownership, unclear handoffs, inconsistent regional routines or conflicting functional incentives.

The thesis concludes that successful AI integration in S&OP depends on organizational and process-related conditions as much as on technological capability. Seven enabling conditions are identified, including governance, process alignment, data quality, performance evaluation, implementation capability, trust and long-term adaptability. For Ascom, the most realistic path is therefore to introduce AI gradually through targeted use cases that strengthen the existing S&OP process, while keeping final judgment and accountability with human planners and established decision forums.

Keywords: Artificial Intelligence, Sales and Operations Planning, AI Integration, Operational Efficiency, Supply Chain Planning, Demand Planning, Organizational Adaptability.

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List of Abbreviations

AI	Artificial Intelligence
S&OP	Sales and Operations Planning
ERP	Enterprise Resource Planning
CRM	Customer Relationship Management
CPQ	Configure, Price, Quote
BOM	Bill of Materials
OEM	Original Equipment Manufacturer
BI	Business Intelligence
DWH	Data Warehouse
SCM	Supply Chain Management
IBP	Integrated Business Planning
BDAC	Big Data Analytics Capabilities
RQ	Research Question
AX2012	ERP system
Dynamics 365	ERP system
MBR	Monthly Business Review
MOQ	Minimum Order Quantity
KPI	Key Performance Indicator

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1. Introduction

This chapter introduces the thesis by presenting the case company Ascom and the context of the topic studied. It also presents the aim, delimitations and research questions guiding the study.

1.1 Background

Ascom is a global organization headquartered in Baar, Switzerland, with approximately 1,400 employees and operations across multiple countries. The company offers communication and collaboration solutions. The solution portfolio operates in mission-critical and safety-critical environments across three core market segments, including acute care, long-term care and enterprise. The acute care segment supports health systems, hospitals, doctors and caregivers. Long-term care supports caregivers and helps seniors live more independent lives. Enterprise optimizes operations and elevates the safety, efficiency and performance of enterprises worldwide. The solutions focus on timely and accurate information flows and are designed to support decision-making in complex operational contexts. Ascom combines software and hardware solutions with digital system integration to transform large volumes of data into actionable information.

Ascom Global Supply Chain headquarters is located in Gothenburg, Sweden, and is part of Ascom's global operations. Ascom Global Supply Chain consists of three main functions, including Supply Chain Quality, Sourcing and Logistics, serving all global supply chain operations with around 50 employees. The Supply Chain Quality function ensures product and supplier quality by managing deviations, compliance requirements and continuous quality improvement across the supply chain. The Sourcing function selects and manages suppliers, negotiates agreements, and secures cost-efficient and reliable supply aligned with business needs. The Logistics function plans and coordinates global material flows, including demand planning, order handling, inventory and distribution, to ensure timely and accurate deliveries.

Ascom has a strong focus on operational efficiency, reliability and quality, supported by continuous improvement and competitiveness. In line with this, Ascom Global Supply Chain has started exploring the use of Artificial Intelligence (AI). A pilot group of selected employees is testing the full license of Microsoft Copilot to identify use cases for AI. Ascom Global Supply Chain is interested in understanding how AI tools can create real business value in daily operations.

While AI is becoming an increasingly discussed topic, there is still limited knowledge about how it can practically support supply chain processes and improve operational efficiency and quality performance from an organizational perspective. Although AI technologies are readily available, it remains unclear how such tools should be integrated into existing processes in a structured and value-creating way. Current initiatives have primarily focused on exploratory and individual use, while the broader organizational implications of applying AI in core supply chain processes are less understood.

To define a relevant and analytically meaningful scope for the study, initial exploratory interviews were conducted with managers from the Sourcing, Logistics and Supply Chain Quality functions at Ascom Global Supply Chain. The purpose of these interviews was to identify core supply chain processes with the highest potential for AI-supported improvements, particularly related to operational efficiency and quality performance from an organizational perspective.

Based on these early insights, Sales and Operations Planning (S&OP) was identified as a central process of interest. S&OP plays a key role in coordinating demand, supply and planning decisions across the organization, and outcomes from the process influence multiple parts of the supply chain. At the same time, planning activities within S&OP are characterized by a high degree of manual work and reliance on experience-based judgment. This may create challenges related to consistency, transparency and decision support. In Ascom's context, where high requirements on reliability and quality apply, limitations in planning accuracy may therefore have broad operational implications. Furthermore, there is uncertainty regarding how AI-supported insights can be interpreted, trusted and used in planning decisions, particularly in relation to historical data and exceptional events.

1.2 Aim

The thesis aims to investigate how AI can support operational efficiency and quality performance at Ascom Global Supply Chain through its application in S&OP, which was identified as a core supply chain process with high AI potential. The thesis further aims to develop concrete recommended use cases for how Ascom could integrate AI into the S&OP process and to identify key success factors for successful and sustainable AI implementation.

1.3 Delimitations

This thesis is delimited to a single case study at Ascom Global Supply Chain and focuses on supply chain operations within the S&OP process. The empirical focus is mainly on Global Supply Chain and the supply-side execution of S&OP. The Sales perspective is included to provide insight into upstream demand input generation, but the study does not examine regional sales practices, Marketing, Finance or supplier perspectives in depth.

The study is based on the current system tools, information flows and working methods used within the studied process. The thesis focuses on how existing AI tools could support S&OP activities and does not include the programming, technical development or implementation of new AI models.

1.4 Specification of the issue being investigated

To achieve the aim, the thesis is structured around three research questions. To establish a baseline and identify potential improvement, the first research question maps current challenges and inefficiencies within Sales and Operations Planning.

RQ1: What are the main current challenges and inefficiencies within Sales and Operations Planning?

The second research question focuses on how these challenges and inefficiencies can be addressed through AI tools to improve operational efficiency and quality performance.

RQ2: How can AI tools be applied to address these challenges and potentially enhance operational efficiency and quality performance within Sales and Operations Planning?

Building on the findings from the first two research questions, the third research question aims to identify key factors for the successful and sustainable integration of AI into Sales and Operations Planning. Sustainable integration refers to the use of AI tools from a long-term perspective, where usability, adoption and continuous creation of value are central. This includes alignment with existing processes, development of internal capabilities and the ability to adapt AI to changing business needs over time.

RQ3: What key factors enable the successful and sustainable integration of AI within Sales and Operations Planning?

2. Methodology

This chapter describes the methodological approach used in the thesis. It describes the research design, data collection methods and considerations regarding reliability and validity. The methodology is structured to answer the research questions while also providing relevant insights for the case company, Ascom.

2.1 Research Design and Methodological Approach

The thesis is based on a qualitative case study at Ascom Global Supply Chain. Exploratory research approaches were used when prior knowledge was limited, in order to gain an initial understanding of the processes (Blomkvist & Hallin, 2015). The case study is exploratory because it investigates current challenges in Ascom's S&OP process. It also examines how AI is currently understood, used and how AI-supported tools could support selected planning activities within Global Supply Chain. Qualitative methods were therefore used to identify recurring patterns, process-related issues and conditions for AI integration. The thesis aims not only to provide theoretical insights but also to develop concrete recommendations for Ascom's future implementation of AI. This is achieved through an applied research approach, combining theory and practice to develop insights through scientific methods (Blomkvist & Hallin, 2015).

Given the exploratory nature of the study and limited prior knowledge regarding where AI could create the greatest operational value within Global Supply Chain, an initial exploratory phase was conducted. This phase was used to compare several supply chain areas and to guide the selection of S&OP as the focal process for the empirical investigation. This approach aligns with Blomkvist and Hallin (2015), who emphasize the importance of preserving ambiguity in early research phases, allowing the aim, research questions and analytical focus to evolve and avoid premature delimitation.

2.2 Data Collection Methods

Multiple qualitative research methods were used to deepen the understanding of the studied problem. The combination of methods provides structure to the analysis while strengthening the credibility of the findings. The use of different interview formats was considered necessary to capture both an initial exploratory understanding of the S&OP process and more detailed descriptions of how the process is carried out in practice. Unstructured and semi-structured interviews were therefore used in different stages of the study to balance openness and comparability, which is recommended in exploratory qualitative case studies (Blomkvist & Hallin, 2015).

2.2.1 Unstructured Interviews

Unstructured interviews are characterized by a high degree of openness, meaning that no predefined interview guide is used. Blomkvist and Hallin (2015) describe unstructured interviews as useful in the early stages of a thesis, when prior knowledge is limited and an initial understanding is needed. However, they were primarily used as a preparatory method because comparability between answers is limited.

The respondents for the unstructured interviews were selected based on their overview of core supply chain functions and their ability to provide an initial cross-functional understanding of how planning processes were structured at Ascom Global Supply Chain. Managers from Supply Chain Quality, Logistics, Sourcing and Material Planning were therefore included to support the early scoping of the study and to help identify which supply chain process had the greatest relevance for further investigation.

All interviews were conducted within Global Supply Chain, except for one interview with the Head of Global Sales Operations, which was conducted to obtain an overview of the process and its challenges from the Sales perspective. One of the interviews was conducted jointly with two respondents holding the same role, allowing interaction between participants during the discussion. One respondent was interviewed on more than one occasion. In that case, all statements are reported under the same respondent identifier. For an overview of the respondents, see table 1.

Date	Respondent	Role	Interview type	Length	Copilot user
20/01	R1	Head of Global Supply Chain	Unstructured	N/A	Yes
23/01	R2	Head of Supply Chain Quality	Unstructured	100 min	Yes
28/01	R3	Head of Logistics	Unstructured	61 min	Yes
29/01	R4	Head of Sourcing	Unstructured	99 min	Yes
05/02	R5 & R6	Special Supply Project Managers	Unstructured joint interview	56 min	Yes
10/02	R7	Head of Material Planning	Unstructured	61 min	Yes
05/03	R11	Head of Global Sales Operations	Unstructured	50 min	Yes

Table 1: Summary of unstructured interviews.

2.2.2 Semi-Structured Interviews

Semi-structured interviews were used to set topics in advance, creating a guide to be used for the interviews (Blomkvist & Hallin, 2015). These interviews constituted a primary source of empirical data. The semi-structured interviews were conducted primarily with employees directly involved in material planning and forecast-related activities within Global Supply Chain, including Material Planning Specialists and the Head of Material Planning. Some respondents were part of the Copilot pilot group, while others were not, which allowed the study to capture both AI-exposed and non-AI-exposed perspectives. Most questions were formulated before the interviews and asked to several respondents to enable comparison and capture nuanced answers. This format enabled comparability between respondents while allowing individual follow-up questions to explore more in-depth information.

The respondents were selected to provide deeper insight into the operational execution of S&OP. The inclusion of both the Head of Material Planning and Material Planning Specialists enabled the study to capture both a managerial perspective and detailed operational perspectives.

All participants of the study were contacted beforehand and asked for their voluntary participation. The interview questions were sent to the respondents beforehand, enabling the respondents to be prepared. Answers were handled confidentially and used in a way that avoided identifying individuals.

The interview questions were open-ended and focused on understanding underlying needs and how current processes work, rather than asking respondents to suggest specific solutions (Blomkvist & Hallin, 2015). The aim was to understand why activities were performed in a certain way and where challenges existed, instead of focusing on potential AI applications at an early stage. This approach helped reduce solution bias and allowed the study to identify gaps between existing supply chain processes and actual needs. For an overview of the respondents, see table 2.

Date	Respondent	Role	Interview type	Length	Copilot user
24/02	R8	Material Planning Specialist	Semi-structured	75 min	Yes
25/02	R9	Material Planning Specialist	Semi-structured	46 min	No
25/02	R10	Material Planning Specialist	Semi-structured	50 min	No
10/03	R7	Head of Material Planning	Semi-structured	57 min	Yes
12/03	R12	Material Planning Specialist	Semi-structured	60 min	No

Table 2: Summary of semi-structured interviews.

2.2.3 Document Analysis

Document analysis was used as a complement to the interviews to provide contextual grounding and support the description of Ascom's current S&OP process. The material analyzed included internal process-related documents and planning material. These documents were used to understand the formal process structure, system context and planning routines, and to compare this with the interview-based descriptions of how the process is carried out in practice.

2.2.4 Observations

To support interviews and documents, observations were used as a complementary method. Observations were useful for understanding how daily work practices were performed and for contrasting them with how the process is formally described (Blomkvist & Hallin, 2015). They were initially used to form a relevant interview guide and get a basic understanding of the context at Ascom. Observations helped validate interview findings and strengthen empirical credibility by allowing comparison between responses, documents and observed practices.

2.2.5 Literature Review

A structured literature review was used to establish the theoretical foundation for the thesis. Scientific articles and books were used and primarily retrieved through academic databases, such as Chalmers Library. The literature search was conducted using predefined keywords related to supply chain management, artificial intelligence, operational efficiency and quality management. In addition, AI-based tools were used as a supportive aid to identify and screen relevant literature. The literature review was conducted throughout the thesis process, with additional literature gathered as the analytical focus developed. Source validation was conducted continuously, using multiple sources where possible to strengthen reliability.

2.3 Data Analysis

The data analysis followed a systematic approach for analyzing qualitative empirical data and identifying patterns related to the research questions (Miles et al., 2014). The analysis was conducted as an iterative process throughout the thesis, where newly identified patterns continuously informed and shaped the analysis. The analysis was inspired by the qualitative framework proposed by Miles et al. (2014), where data collection, analysis and writing are treated as interconnected activities. The data analysis consisted of three main steps: data condensation, data display, and conclusion drawing and verification.

Data condensation included transcription of interviews, selection of relevant empirical material, and focusing and simplification of the data. Data display involved structuring the condensed data through visual organization, such as matrices, to enable identification of patterns and comparisons across functions. In the final step, conclusions were drawn based on identified patterns in the empirical data and linked to the research questions. These conclusions were continuously verified and refined through iterative comparison with the empirical material to ensure consistency with the scope of the study.

The outcome of the analysis was a set of identified patterns and recurring themes, which formed the basis for the proposed recommendations. The data analysis is structured around the three research questions to ensure analytical focus. This approach supported systematic, transparent and reliable conclusions.

2.4 Reliability and Validity

To enhance the reliability and validity of the qualitative case study, several measures were used. According to Blomkvist and Hallin (2015), the credibility of the study is strengthened by having a structured process of research, utilizing multiple sources of data and having logical, transparent methods to collect data. These measures strengthened credibility, reliability and validity by ensuring that findings were supported by an appropriate research approach and methods.

In the thesis, multiple methods were used for data collection. These included interviews, document analysis and a literature review, which strengthened the validity of the results. Collecting and utilizing data from three different sources allows for different perspectives to be examined on the same topic. This reduces the risk that information and results are based on individual interpretations. To further enhance validity, several interviews were held with different respondents across the different functions at Ascom Global Supply Chain. The use of multiple sources reduced the risk of individual bias and strengthened the findings by capturing variation.

However, a potential limitation is that the benchmarking material used in the literature review is primarily based on industry and consultancy reports, which may contain some bias toward practical benefits and technology adoption. To reduce this risk, these sources were used as complementary reference points and were interpreted together with academic literature and empirical findings.

Reliability was addressed through a structured and systematic research process. When data collection methods are clearly described and applied, reliability in qualitative studies is improved (Blomkvist & Hallin, 2015). Throughout the study, interview guides were used across multiple respondents to support comparability. Describing the data collection methods also enabled transparency, making the research process easier to follow and assess.

A potential source of bias was the Microsoft Copilot pilot group, as voluntary participation may have attracted respondents with a more positive attitude toward AI. This may have influenced the empirical findings by downplaying the challenges and limitations of the technology while emphasizing benefits and opportunities. To mitigate this, the study did not rely solely on pilot group interviews. Interviews were also conducted with respondents outside the pilot group to validate findings with multiple responses, documents and observations. Furthermore, the interview guides were designed to focus on current challenges and needs rather than on potential AI solutions.

By aligning the document analysis and interview guide with the research questions, validity was strengthened. The interview guide also helped structure respondents' answers around themes linked to the research questions, while still allowing clarification and elaboration on related issues.

2.4.1 Use of AI

AI tools were used as supportive aids during the research process. Their use was limited to assistive tasks and did not replace empirical interpretation, analytical reasoning or independent judgment by the authors. More specifically, AI tools were used for

language refinement, translation support and as a supplementary aid in identifying potentially relevant literature. To ensure reliability and transparency, all AI-generated suggestions and information were critically reviewed, verified and evaluated for accuracy before being used in the thesis.

2.5 Sustainability Considerations

The ethical considerations of the study include confidential handling of interview data, with no sensitive or personally identifiable information used in the analysis or reported results. Participation in the interviews was voluntary, and transparency was ensured by informing respondents about the purpose of the study and how the data would be used. Recording and transcription of interviews were conducted only with the informed consent of the respondents, and the transcriptions were used solely for analysis purposes. Raw data is not shared externally. The study considers AI strictly as a supporting tool, and no individual performance assessment is conducted.

The societal considerations of the study relate to its indirect societal impact. As Ascom delivers solutions to healthcare and other critical sectors, improved internal supply chain processes may indirectly contribute to increased delivery capability and system reliability. The use of AI as a decision-support tool can enhance decision-making within the supply chain, potentially improving supply stability in critical systems. Furthermore, the study contributes to an increased understanding of how AI can be used responsibly in organizational contexts, which may be relevant for other organizations within the societal sector.

Ecological aspects were considered to a limited extent, as the study focuses on organizational processes rather than physical production. Consequently, environmental impacts such as resources or water consumption were not assessed within the scope of the thesis.

3. Literature Review

This chapter presents the theoretical foundation of the thesis. It outlines key concepts and research related to S&OP, AI and performance dimensions such as operational efficiency and quality. The literature review provides the analytical foundation for interpreting the empirical findings and developing recommendations aligned with the research questions.

3.1 Sales and Operations Planning

S&OP represents a central cross-functional planning process in supply chain management. The process integrates demand and supply perspectives over a medium- to long-term horizon and aims to align operational capabilities with market expectations. This section presents the theoretical foundations of S&OP, including its purpose, structure, planning logic and maturity perspectives, which form the basis for analyzing Ascom's S&OP process.

3.1.1 Purpose and Role of S&OP

Planning for a company needs to be made both short- and long-term as described by Jonsson and Mattsson (2009). The longer the planning horizon, the greater the uncertainty and the lower the reliability of the plan, which is why companies use different planning horizons for capacity and demand planning. Sales and Operations Planning represent the highest planning level with the longest planning horizon and is used to establish overall plans for sales and production operations.

S&OP represents the highest and least detailed level of the planning hierarchy, with the primary aim of balancing supply and demand to support efficiency and competitiveness (Jonsson & Mattsson, 2009). Through this balancing role, S&OP translates business objectives and strategic intentions into feasible aggregate plans that guide the rest of the planning system. The role of S&OP is to support the company's business mission, strategies and overall goals while reconciling conflicting business objectives. See figure 1 for an illustration of the different planning levels.

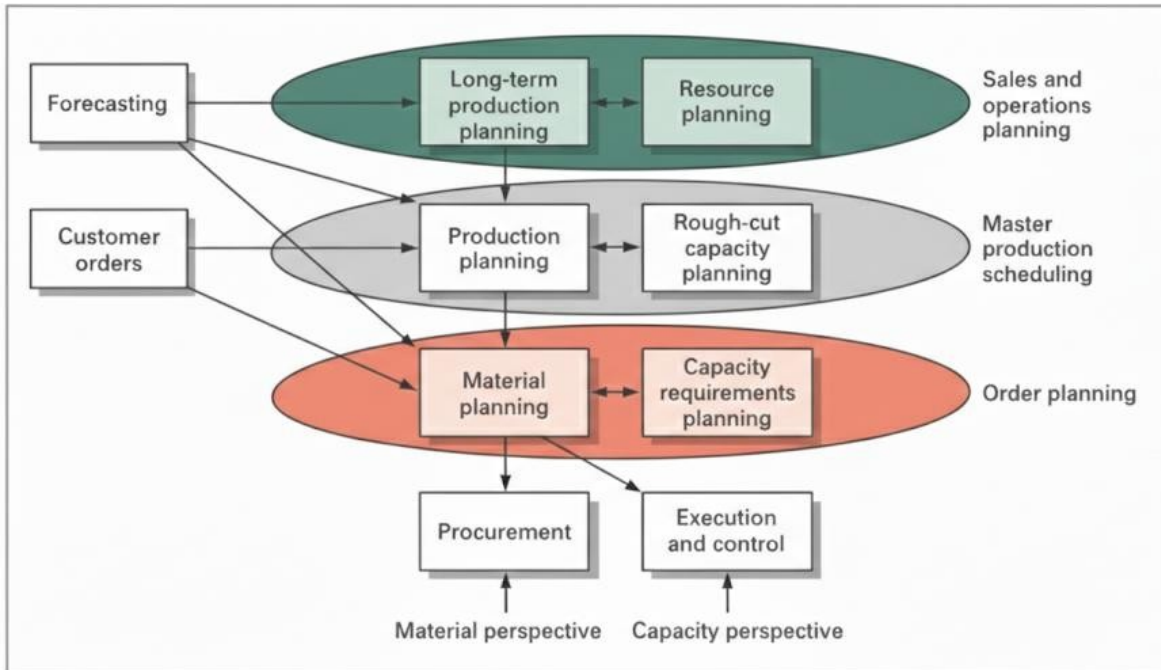


Figure 1: The relationship between Sales and Operations Planning and other planning processes. Recreated by the authors based on Jonsson and Mattsson (2009) using an AI-based visualization tool.

3.1.2 Cross-Functional Coordination and Planning Horizon

S&OP is characterized by its cross-functional nature, where interactions take place between multiple organizational units, such as sales, production, material supply and finance (Jonsson & Mattsson, 2009). The process functions as a formal coordination mechanism, where different functional perspectives, objectives and constraints are jointly evaluated and aligned into a shared plan. Rather than optimizing individual functions, S&OP aims to create an overall plan that is acceptable and feasible for the organization.

The planning horizon for the S&OP process typically ranges from one to two years and is influenced by accumulated product lead time and how far in advance planning is required in order to adapt supply capacity (Jonsson & Mattsson, 2009). As the planning horizon extends further into the future, uncertainty increases and the reliability of plans decreases, which implies that S&OP decisions are inherently based on forecasts, assumptions and experience-based judgment rather than exact data.

3.1.3 Decision Scope, Planning Objects and Time Fences

The key planning objectives within S&OP are usually defined at the product group level, where appropriate units in volume are decided (Jonsson & Mattsson, 2009). Inputs to the process include forecasts of expected future sales and, where applicable, actual customer orders. The outcome of the S&OP process is not detailed schedules, but agreed decisions regarding sales volumes, production volumes, inventory targets or order backlog levels, which serve as guiding targets for subsequent planning activities.

Changes in S&OP plans are connected to time fences, which are formal rules that regulate the extent to which existing plans may be changed over time (Jonsson &

Mattsson, 2009). Time fences are used to balance the need for planning stability with the need for flexibility, by limiting late changes close to execution while allowing greater adaptability further into the future. The design of time fences varies between companies and depends on accumulated lead times, capacity flexibility and the cost of rapid adjustments.

3.1.4 S&OP Process Structure and Balancing Logic

The S&OP process is commonly described as a five-step planning process (Jonsson & Mattsson, 2009). It begins with forecasting future demand and continues with preliminary delivery and production planning, where expected demand is translated into inventory, backlog, material and capacity implications. These plans are then reconciled in cross-functional meetings, where functional managers analyze trade-offs and resolve conflicts before top management approves the final plans. The process thereby links demand, supply and resource planning into an agreed planning basis for continued operations. See figure 2 for an illustration of the five steps.

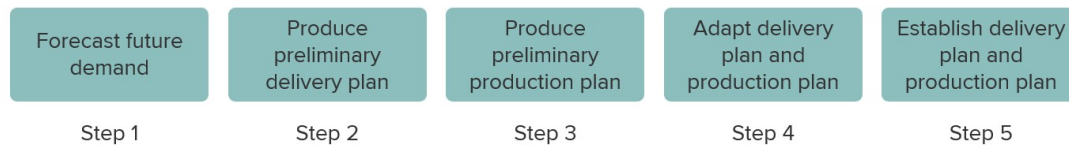


Figure 2: The planning process in sales and operations planning, adapted from Jonsson and Mattsson (2009).

3.1.5 Manufacturing Strategies and Implications for S&OP

The application of S&OP is influenced by the company's manufacturing strategy (Jonsson & Mattsson, 2009). In make-to-stock environments, S&OP primarily focuses on managing inventory levels and stabilizing production in line with sales forecasts. In make-to-order, assemble-to-order or engineer-to-order environments, the focus shifts toward managing the order backlog, which can be seen as a form of negative inventory. As a result, the planning logic, decision focus and performance trade-offs within S&OP differ depending on the applied production strategy.

3.1.6 Demand Planning

Within the planning hierarchy of S&OP, demand planning constitutes a central activity and serves as the structured process for estimating future demand over a predefined planning horizon (Jonsson & Mattsson, 2009). Demand planning differs from forecasting because forecasting refers to the statistical estimation of future demand. Demand planning also integrates market information, managerial judgment and cross-functional input into an agreed demand plan. Within the structure of S&OP, demand planning is conducted at an aggregate level, typically planning in product groups or product families to form the primary input for the supply planning activities.

There is demand uncertainty associated with demand planning, as future sales cannot be known with certainty. Forecast errors occur in this uncertainty, and the longer the

planning horizon is, the more uncertainty increases in the forecasting (Jonsson & Mattsson, 2009). Silver et al. (2016) describe how demand variability and forecasting inaccuracy influence inventory requirements and service levels, since inaccurate forecasts require larger safety stocks to maintain service performance. As a result of this, the quality of demand planning has a direct effect on both operational stability and capital tied up in inventory.

Although quantitative forecasting methods provide statistical estimations based on historical data, demand planning combines these with managerial judgment and market knowledge, where this integration aims to introduce qualitative information such as market trends, product introductions or exceptional events into the planning process (Jonsson & Mattsson, 2009). However, Jonsson and Mattsson (2009) describe that reliance on judgment may create bias and inconsistency if it is not supported by structured processes. This is why demand planning is often conducted as a consensus-based process within S&OP, where multiple functions jointly agree on the demand plan. Introducing human judgment moves forecasting from only using statistical models and historical data to interpreting information and organizational contexts (Perera et al., 2019).

3.1.7 Supply Planning

The translation of the agreed demand plan into feasible material and capacity plans is referred to as supply planning (Jonsson & Mattsson, 2009). The objective of supply planning is to evaluate whether the expected demand can be fulfilled within the existing capacity from existing material availability, supplier capacity and operational constraints. In supply chains characterized by external sourcing rather than internal manufacturing, supply planning includes the translation of aggregate demand plans into material requirements and purchasing plans (Jonsson & Mattsson, 2009). These plans are shaped by supplier lead times and capacity constraints, requiring coordination with external suppliers.

The central role of S&OP is the balance between supply, including current production capacity and material stocks, and demand, including forecasts and actual customer orders (Jonsson & Mattsson, 2009). This balance is based on the Basic Equation of Logistics:

$$\text{Closing Inventory} = \text{Production Volume} + \text{Opening Inventory} - \text{Volumes Delivered}$$

The Basic Equation of Logistics is closely linked to supply planning, as it directly illustrates how material requirements arise (Jonsson & Mattsson, 2009). The nature of supply and demand differs between make-to-stock and make-to-order environments in terms of inventory and order backlog management. In both environments, an imbalance where demand exceeds supply may result in lost sales, reduced delivery performance, longer lead times and increased costs, while an imbalance where supply exceeds demand leads to increased inventory levels, tied-up capital and reduced capacity utilization.

3.1.8 S&OP Maturity and Process Integration

Organizations' S&OP processes differ substantially in terms of structure, integration and effectiveness. Grimson and Pyke (2007) describe S&OP as evolving through different levels of maturity, where higher maturity reflects increased cross-functional integration, clearer organizational ownership and more structured planning routines. Grimson and Pyke (2007) propose a five-stage maturity framework for S&OP, ranging from organizations with no formal S&OP practices to highly integrated processes where demand and supply plans are concurrently aligned across functions. Figure 3 illustrates how S&OP evolves from functionally siloed planning to fully integrated cross-functional processes. The framework distinguishes between business processes and information processes, emphasizing that well-defined business processes and leadership are central, while information technology alone does not guarantee higher levels of S&OP maturity, as integration primarily depends on defined processes, organizational ownership and structured coordination.

At lower maturity stages, planning is typically functionally siloed, with limited interaction between sales and operations (Grimson & Pyke, 2007). Plans are often developed sequentially, where the sales plan drives operations without feedback from capacity or material constraints. As maturity increases, organizations establish formal cross-functional S&OP meetings, define roles and responsibilities, and structure performance measures to evaluate both forecast accuracy and operational outcomes. At more advanced stages, planning becomes increasingly collaborative and concurrent, where demand and supply constraints are jointly considered in the development of an integrated plan.

Higher S&OP maturity has been associated with improved plan integration and more coordinated decision-making, as more structured and cross-functional planning processes enable earlier identification of supply-demand mismatches (Grimson & Pyke, 2007). Prior research further indicates that higher levels of S&OP maturity depend on clearly defined processes, organizational ownership and cross-functional coordination, where information technology alone is not sufficient to achieve integrated planning.

Dimension	Stage 1 No S&OP Process	Stage 2 Reactive	Stage 3 Standard	Stage 4 Advanced	Stage 5 Proactive
Meetings & Collaboration	• Silo Culture • No meetings • No collaboration	• Discussed at top level management meetings • Focus on financial goals	• Regular S&OP meetings • Executive S&OP meetings • Some supplier/customer involvement	• Advanced, collaborative process • Customer data incorporated • Cross-functional participation	• Proactive meetings • Integrated with strategic planning • Real-time access to external data
Organization	• No S&OP organization	• No formal S&OP function • Components of S&OP exist	• S&OP function part of SCM • Regular participation from functions	• Formal S&OP team • Executive participation	• Clear ownership • Strategic-level participation • Enterprise-wide alignment
Measurements	• No measurements	• Measures low-level operational performance	• Forecast accuracy becomes a key performance metric	• Stage 3 plus: • New product introduction metrics	• Stage 4 plus: • Company profitability focus
Information Technology	• Individual managers use spreadsheets • No information consolidation	• Many spreadsheets • Primarily manual processes	• Centralized information system • Advanced planning software	• ERP integration • Optimization software • Advanced analytical tools	• Integrated S&OP systems • Full financial integration • Advanced forecasting systems
S&OP Plan Integration	• No formal planning • Operations attempts to meet incoming orders	• Sales plan drives operations • Top-down process • Capacity utilization dynamics ignored	• Some supply chain integration • Bottom up plans - tempered by business goals	• Highly integrated plans • Constrained optimization applied	• Seamless integration of plans • Profit optimization for whole company

Figure 3: S&OP maturity and integration framework adapted from Grimson and Pyke (2007).

This suggests that process leadership and governance mechanisms are central to achieving integrated S&OP rather than merely implementing advanced planning systems. Complementing this perspective, Wagner et al. (2014) conceptualize S&OP as a cross-functional coordination mechanism, where alignment between sales, operations and finance depends on structured interaction and clearly defined coordination processes. Their analysis highlights S&OP as a cross-functional coordination mechanism, where structured interaction supports plan alignment and helps avoid the negative consequences of functional silos.

3.2 Artificial Intelligence

There is no single, widely agreed-upon definition explaining what AI is. The difficulty in specifying a definition does not stem from a lack of research but rather the origin of artificial intelligence, which attempts to simulate human intelligence, which itself lacks a clear and widely agreed-upon definition (Sheikh et al., 2023). As a result, the multiple definitions and confusion of AI are not due to a lack of agreement, it stems from the nature of AI itself. Building on this, Bawack et al. (2021) emphasize that professionals and organizations have differentiating yet recurring, perspectives on the definition of

AI. They identify four different perspectives of AI as a field of study, a concept, an ability or a system (Bawack et al., 2021). Each perspective constitutes a different perspective of what artificial intelligence is in practice, ranging from more abstract concepts to concrete applications and perspectives (Bawack et al., 2021). Depending on which perspective is adopted, AI is designed and implemented in different ways according to organizational contexts.

In this sense, artificial intelligence can be referred to in both a broad and a narrow manner. To be precise and accurate with research papers, the defined application and technology of AI will be consistent with the description in each article. Consequently, if AI is referred to as generative AI or agentic AI, this will be analyzed from the author's perspective. Therefore, a broad definition of artificial intelligence will be applied to get an initial understanding before deep diving into specific applications. Accordingly, Khanashyam et al. (2025) describe AI as “the capability of machines and computers to mimic human abilities, such as learning, understanding, problem-solving, decision-making, creativity, and autonomy” (p.2). Since AI is developing rapidly, this thesis applies a broad definition that includes capabilities and applications used in supply chain management.

3.2.1 Generative AI

Generative AI is reactive in nature, responding to user inputs and generating outputs based on patterns learned from training data (Bandi et al., 2025). The use of generative AI is to create new content from the input prompts, which could be text or images, based on its learning algorithms and pattern recognition (Bandi et al., 2025). Generative AI is a good tool for communication and generating knowledge, but it is limited to being prompt-driven rather than executing workflows or exploring goals.

3.2.2 AI Agents

AI agents incorporate functions beyond generative AI, including selecting possible actions, interpreting their environment and acting toward a given goal (Bandi et al., 2025). Compared with generative AI, agents have a basic degree of autonomy that enables reasoning and action within a defined workflow. AI agents execute given tasks by adhering to predefined goals under the supervision of a human, allowing for autonomy with limited capabilities of adaptation (Bandi et al., 2025).

3.2.3 Agentic AI

Agentic AI represents a further step in AI autonomy and capability. Instead of only responding to a prompt or generating content, agentic AI plans sequences for a given prompt, breaking down goals into smaller objectives, executing them and readjusting plans dynamically (Bandi et al., 2025). This allows for the system to adapt to given circumstances, working toward a goal and breaking down the sequence into several smaller tasks to reflect and evaluate actions. By combining generative AI with external systems, memory and task coordination mechanisms, agentic AI can manage processes from start to finish (Bandi et al., 2025). Based on multi-step reasoning and planning, agentic AI includes iterative loops to reach a given goal (Bandi et al., 2025).

The three types of AI describe an increased level of system complexity and autonomy. The simplest form, generative AI, is primarily an assistive technology which incorporates reactive measures, while AI agents introduce a basic autonomy and agentic AI gives room for an adaptable and step-by-step manageable process.

3.2.4 Limitations and Risks

While advances in AI expand its possible applications, the literature also highlights important risks and limitations. Sheikh et al. (2023) argue that seeing AI as a tool or application is insufficient and should instead be viewed as a system technology. This stems from the fact that AI is often difficult to predict due to its interaction with processes and structures. As artificial intelligence becomes more autonomous, responsibility and accountability become more important in relation to control (Sheikh et al., 2023). Responsibility becomes increasingly blurred when decisions are automated or influenced by AI. These risks are important to take into account when evaluating what potential impact artificial intelligence has on an organization.

3.3 Artificial Intelligence in Sales and Operations Planning

S&OP has traditionally relied heavily on manual data consolidation, decision-making capabilities and cross-functional collaboration. This may limit responsiveness, increase resource use and create bias risks in qualitative forecasting, especially in contexts with complex products or fluctuating demand (Jonsson & Mattsson, 2009). AI is increasingly becoming an enabler for transforming S&OP through automation of manual data handling, supporting decision-making flexibility and enhancing forecast accuracy (Polo, 2024). Instead of focusing on adjustments based on experience and manual inputs, systems supported by AI handle larger data volumes, allowing organizations to generate more efficient scenario analyses.

Demand forecasting and demand planning are two of the promising areas where AI can be utilized to improve the value of forecasting and minimize downstream errors (de Mattos et al., 2024). De Mattos et al. (2024) explain that demand planning is central to the supply chain, since forecast outputs influence production, inventory and order decisions across the system. Further, AI in demand planning is not only a matter of technical difficulty, but it also requires coordination between departments, change management skills, collection of data and consolidating data for AI preparation (de Mattos et al., 2024). Integration and coordination across departments can be seen as an application of AI, but also an outcome. The AI improvement potential in S&OP is not limited to algorithms, but also includes changes in roles and information flows (de Mattos et al., 2024).

Jackson et al. (2024) propose six generative AI capabilities relevant to supply chain and operations management, namely learning, perception, prediction, interaction, adaptation and reasoning. Jackson et al. (2024) further highlight prediction, interaction and adaptation as key capabilities for usage in S&OP processes. Prediction refers to AI's ability to analyze historical data and anticipate possible future outcomes. Interaction is the AI's ability to interact with its environment, including systems and

humans. Adaptation describes the modification of the AI by itself when conditions have changed or new data is introduced. The three capabilities move opportunities for AI from analytical support toward semi-autonomous decision support. Integrating AI can increase system responsiveness by enabling faster adaptation to changes in supply and demand and quicker evaluation of different scenarios (Polo, 2024). Accelerated processing and more frequent adaptations reduce planning time, meaning that preparation for meetings can be shorter and the time between the collection of data and decisions can be reduced. In addition, AI integration allows for better alignment across functions by giving visibility of data, allowing for information to be used cross-functionally (Polo, 2024).

In supply chain and operations management, the terminology of predictive approaches and prescriptive approaches is discussed (Jackson et al., 2024). Predictive approaches refer to predicting forecasts and risks through the use of machine learning, while prescriptive approaches refer to recommendations of actions or decisions based on algorithms optimized under constraints. Schlegel et al. (2021) mention that predictive analytics are used as forecasting automation, combining demand and supply, by integrating AI methods such as deep learning, machine learning and textual analytics. Schlegel et al. (2021) further argue that S&OP processes moving toward higher maturity, often into integrated business planning (IBP), have increasing requirements on data processing. Big data analytics capabilities (BDAC) can increase organizations' capacity to process large volumes of data and thereby support more advanced S&OP processes (Schlegel et al., 2021).

While AI strengthens abilities of better forecast and enables in-depth scenario planning, it also introduces new tensions in structures (Jazairy et al., 2025). The tensions stem from paradoxes that cannot be solved by only choosing one side. Examples include the tension between immediate performance impact and long-term planning maturity, and the tension between centralized governance and local planning flexibility (Jazairy et al., 2025). These tensions and paradoxes give a separate view that AI in S&OP is not only a technological advancement but a transformation requiring mechanisms of alignment in organizations (Jazairy et al., 2025). The effectiveness of AI in S&OP depends on the structure of the process, where defined routines have to align with the outputs of the algorithms (Jazairy et al., 2025). Further, Jazairy et al. (2025) argue that to achieve value creation with AI, organizations should integrate a strategy of smaller introduction phases with incremental steps, such as pilot projects, while incorporating specialized expertise into the testing. The introduction of AI is dependent on existing processes and structures, where centralized AI systems have to account for different regional variations in the maturity of the S&OP process, making it a matter of process maturity. Jazairy et al. (2025) describe AI as a way to improve the S&OP process rather than replace it, since a purely AI-managed S&OP process remains largely theoretical.

3.3.1 Artificial Intelligence in Demand Planning

Building on the role of demand planning within S&OP and its inherent uncertainty, recent literature has examined how AI can support the demand planning process (Walter et al., 2025). Walter et al. (2025) identify three knowledge clusters in the literature on AI in demand planning and show how AI can be deployed in ways associated with improved supply chain performance. Walter et al. (2025) describe AI

predominantly as decision support rather than replacing demand planning activities, as few planning systems operate fully autonomously and outputs require trust and action by human planners. Demand forecasting is identified as a dominant application area in the literature, with many studies focusing on predictive models, model selection and forecasting accuracy (Walter et al., 2025). Beyond demand forecasting, AI has been used in market, consumer and product analysis. This allows external parameters such as market conditions, competitor actions, consumer sentiment and product life cycles to be incorporated into demand planning models (Walter et al., 2025).

The effects associated with AI-supported demand planning include improved inventory management, such as reduced stock levels and cost reductions, and increased agility through real-time adjustment of forecasts based on external parameters (Walter et al., 2025). Studies also discuss the bullwhip effect, suggesting that AI techniques used for agile forecasting can contribute to mitigating bullwhip dynamics in supply chains (Walter et al., 2025).

The effectiveness of AI in demand planning depends on the availability and relevance of data inputs, including historical demand data and external market-related parameters (Walter et al., 2025). AI-supported demand planning, therefore, relies on the integration of internal and external data sources to generate planning outputs. Walter et al. (2025) highlight organizational contingency factors, such as readiness for AI adoption, as influencing the implementation context of AI-based demand planning.

3.3.2 Artificial Intelligence in Supply Planning

Recently, there has been a growing interest in research on the intersection of artificial intelligence and supply chain management (Elammari et al., 2025). However, research on how artificial intelligence can enhance supply planning remains limited. Traditional supply planning uses demand plans to translate demand into material and capacity plans through calculations and judgment. Artificial intelligence introduces further enhancements to the process through the usage of predictive capabilities based on data (Elammari et al., 2025). The literature suggests that machine learning can be applied in inventory management and production-related decision-making (Cannas et al., 2024). Machine learning can be used to detect outliers in data, capture different patterns of changing demand and update predictions in real time (Cannas et al., 2024). To ensure reliable outputs, both data volume and data quality must be sufficient (Cannas et al., 2024).

Reinforcement learning, a form of machine learning, is emerging in the field of supply chain management, especially inventory management, where making sequential decisions is central (Rolf et al., 2023). Reinforcement learning is based on agents that learn to take actions in dynamic systems and adaptive decision-making, where the objective is to maximize long-term value (Rolf et al., 2023). This makes it relevant in environments that are characterized by dynamic conditions and uncertainty, in order to adapt decisions over time (Rolf et al., 2023). See table 3 for a full summary of the theoretical framework on AI in S&OP, demand planning and supply planning.

Process	Applications of AI	Sources
S&OP	Automate manual data handling; support decision-making; enhance forecast accuracy; handle larger data volumes; faster adaptation to changes; cross-functional data visibility; support predictive and prescriptive analytics	Polo (2024); Jackson et al. (2024); Schlegel et al. (2021); de Mattos et al. (2024)
Demand Planning	Machine learning-based forecast; predictive model selection; improved forecast accuracy; enhanced demand planning with internal and external factors; real-time forecast adjustment; improved inventory management; mitigate bullwhip effects	Walter et al. (2025); de Mattos et al. (2024)
Supply Planning	Predictive capabilities based on data; Machine learning for detecting outliers; pattern recognition and prediction updates; reinforcement learning for inventory management; agents for adaptive decision-making in dynamic systems	Elammari et al. (2025); Cannas et al. (2024); Rolf et al. (2023)

Table 3: Summary of theoretical framework on AI in S&OP, demand planning and supply planning.

3.4 Data and Information Integration

Data constitute the basis for both operational and strategic decision-making in organizations, and poor data quality can therefore have negative impacts on efficiency and performance (Haug et al., 2011). Haug et al. (2011) argue that poor data quality results in both direct and hidden costs, as well as operational and strategic consequences. Direct costs may include order processing errors or incorrect deliveries, while hidden costs may arise from inefficient decision-making or suboptimal strategic choices based on unreliable data. The authors describe that organizations incur costs both from improving data quality and from operating with poor quality data, demonstrating a trade-off between data maintenance efforts and the costs inflicted by poor data quality. Perfect data quality is therefore neither realistic nor economically optimal. Instead, organizations must determine an appropriate level of data quality relative to its cost implications, as argued by Haug et al. (2011).

Rai et al. (2012) demonstrate that relational value in interfirm relationships depends on IT capabilities that facilitate flows of goods, information and finances, complemented by structured interfirm communication. Haug et al. (2011) further describe how information silos and fragmented systems may create inconsistencies in data definitions and formats, limiting the effective use of shared information within the organization. As a result, both internal data quality and interorganizational information integration represent conditions for achieving efficient and coordinated planning processes.

3.5 Performance Dimensions

The following sub-chapter defines the performance dimensions that the thesis draws upon. The dimensions of quality, operational efficiency in supply chains, and forecast accuracy and planning performance constitute the analytical foundation for the evaluation of the results.

3.5.1 Definition of Quality

Quality in this thesis is defined as fitness for use, as described by De Feo and Juran (2016), meaning that outputs, decisions and processes must fulfill their intended purpose without introducing defects, errors or additional downstream costs. While quality can be conceptualized as a multidimensional concept, this thesis adopts a narrower interpretation by focusing on the performance and reliability dimensions (Garvin, 1987). These dimensions emphasize primary operating characteristics and a low probability of failure.

3.5.2 Operational Efficiency in Supply Chains

The concept of operational efficiency in this thesis refers to the extent to which supply chain processes deliver their intended outputs while minimizing the use of resources such as time, cost and labor. There is a distinction between the concepts of efficiency and effectiveness, where efficiency concerns doing things right, while effectiveness concerns doing the right things to achieve the desired output (Neely et al., 1997). This distinction implies that improvements in efficiency do not necessarily lead to improved overall performance if achieved at the expense of quality or effectiveness. Neely et al. (1997) highlight that narrowly defined efficiency measures may result in sub-optimization if they are not aligned with broader performance objectives.

3.5.3 Forecast Accuracy and Planning Performance

For the S&OP process, forecast accuracy is identified as a central performance indicator. Lapide (2005) describes the purpose of S&OP as improving the execution and accuracy of supply-demand plans, enabling better alignment between anticipated demand and operational capabilities. Lapide (2005) further states that accurate demand forecasts contribute to improved customer service while simultaneously reducing inventory levels and operating costs.

Fildes and Goodwin (2007) show that forecast accuracy is a central concern in practice, and that organizations frequently rely on management judgment through judgmental adjustments of statistical forecasts. However, Fildes and Goodwin (2007) describe that judgment is frequently subject to bias and inconsistency. When managers adjust forecasts to reflect preferred outcomes, for example, to avoid stockouts, the boundary between forecasting and decision-making becomes blurred, which may introduce systematic bias and reduce forecast accuracy if not properly evaluated.

Fildes and Goodwin (2007) further show that many organizations do not systematically evaluate whether judgmental adjustments improve forecast accuracy, and that

structured review processes are often lacking. Without formal feedback mechanisms, organizations risk committing significant managerial time to adjustments without evidence of performance improvement.

3.6 Benchmarking Industry Practices and Maturity in S&OP

In addition to academic literature on S&OP, industry reports describe how planning processes are structured in practice, what characterizes mature planning organizations and how AI is applied in planning activities. These reports provide a reference point for typical planning practices, performance levels and technology adoption in modern supply chain environments.

3.6.1 Planning Maturity and Cross-Functional Integration

Industry research describes supply chain planning as a critical capability for achieving operational performance in environments characterized by demand uncertainty, global sourcing and complex product structures (Boston Consulting Group, 2026). Higher levels of planning maturity have been associated with stronger service levels, forecast accuracy, inventory management and responsiveness, as advanced organizations align demand, supply and financial plans through integrated planning processes (Boston Consulting Group, 2026). In such environments, planning is commonly organized as an integrated cross-functional process where demand, supply and financial plans are reviewed jointly and aligned through recurring planning cycles, often described as integrated S&OP or cross-functional planning processes (Deloitte, 2023b).

A recurring characteristic of more mature planning organizations is the presence of clearly defined planning processes supported by stronger data foundations, improved system integration and more formalized planning structures (Boston Consulting Group, 2026). Industry reports emphasize that effective planning requires alignment across functions such as sales, supply chain and finance, as well as clearly defined roles and responsibilities in planning decisions (Deloitte, 2023a). In practice, S&OP is often described as the primary coordination mechanism, as the process provides a recurring forum where forecasts, supply constraints and business priorities are reviewed and reconciled to support coordinated decision-making across functions (Deloitte, 2023b).

Planning maturity is also dependent on the combination of process discipline, data quality and organizational governance rather than on technology alone (Boston Consulting Group, 2026). Even in companies with advanced planning systems, manual reconciliation work and fragmented data structures remain common when planning information must be aligned across systems, functions or regions (Boston Consulting Group, 2026).

An industry example is Procter & Gamble's digital supply chain transformation, where concurrent planning and real-time scenario analysis were used to adjust supply and demand plans based on new information (Kinaxis, n.d.). During disruptions such as Hurricane Irma, scenario simulations supported proactive inventory decisions and helped maintain service levels under uncertainty (Kinaxis, n.d.).

3.6.2 Artificial Intelligence in Supply Chain Planning

Recent industry reports indicate that artificial intelligence is increasingly being introduced into supply chain planning, although adoption levels vary between organizations (Accenture, 2024). Current applications are commonly found in areas such as demand forecasting, data analysis and exception handling, where advanced analytics are used to support planning decisions based on large volumes of historical and operational data (Boston Consulting Group, 2026). AI is also described as supporting planners in evaluating alternatives and understanding the potential effects of changes in demand, supply conditions or constraints before decisions are finalized (Accenture, 2024).

Despite these developments, many organizations remain in early stages of adoption, where AI is used in pilot projects or targeted implementations rather than fully embedded across planning processes (McKinsey & Company, 2025). Organizations frequently experience difficulties scaling AI solutions due to limitations in data quality, legacy systems, insufficient infrastructure or organizational readiness (McKinsey & Company, 2025). Industry reports therefore emphasize that successful adoption of advanced analytics requires changes not only in technology, but also in planning processes, roles and decision structures (McKinsey & Company, 2025).

Another example is MAAG Food, where manual spreadsheet-based forecasting was replaced by an AI-supported planning system using machine-learning-based forecasting and exception-driven logic (RELEX Solutions, n.d.). The implementation reduced the need for manual adjustments and allowed planners to focus more on deviations and decision-making activities (RELEX Solutions, n.d.).

3.6.3 Human Judgment and Data-Driven Decision-Making in S&OP

Another recurring observation is that planning processes continue to require human judgment even when advanced analytics are available (Deloitte, 2023a). In S&OP environments, forecasts and supply plans often need to incorporate information that cannot be fully captured in historical data, such as large projects, customer negotiations or strategic decisions (Deloitte, 2023a). Artificial intelligence is therefore typically described as decision support rather than as a replacement for planners (Deloitte, 2023a).

Industry reports also indicate that supply chain decision-making is becoming more data-driven and responsive, supported by improved data availability, digital integration and advanced analytics capabilities (World Economic Forum, 2025). These developments enable organizations to respond more quickly to demand volatility, supply disruptions and shorter product lifecycles, which increases the need for more flexible and responsive planning processes (World Economic Forum, 2025).

3.7 Organizational Integration and Sustainable Change

The implementation of AI in supply chain processes requires organizational integration beyond the deployment of new technology. Prior research suggests that realizing value from advanced analytics depends on how technologies are embedded in organizational

structures, cross-functional coordination and decision-making processes. This section therefore examines AI implementation from the perspectives of organizational integration, cross-functional planning, sociotechnical change and dynamic capabilities supporting long-term adaptation.

3.7.1 Organizational Integration for AI in Supply Chain Processes

The implementation of AI in supply chain processes is not only a technological challenge but also an organizational one. While Rai et al. (2012) study IT capability more broadly, they show that digital technologies create value only when embedded in structured communication and coordination mechanisms. This suggests that the value of advanced analytics and AI depends on how such technologies are integrated into organizational structures, decision-making processes and coordination mechanisms rather than treated as technical tools alone. When AI applications are developed in isolation from other functions, there is a risk of local optimization and misalignment with broader strategic objectives, a concern highlighted in performance measurement literature (Neely et al., 1997).

3.7.2 AI as Cross-Functional Operating Model Redesign

S&OP is not only a forecasting or balancing process, but a structured cross-functional model for aligning demand, supply and financial objectives across organizational boundaries. Thomé et al. (2012) highlight coordinated inputs, structured meetings, defined organizational roles and performance measurement as central elements for aligning the firm horizontally and vertically. Tuomikangas and Kaipia (2014) similarly describe S&OP as a cross-functional coordination framework rather than an isolated planning activity. Tuomikangas and Kaipia (2014) argue that S&OP performance should be viewed more in terms of how well organizational structures support collaboration, conflict resolution and joint decision-making rather than as a technical forecasting process. Together, these studies show that S&OP effectiveness depends on structured meetings, clear ownership, defined performance metrics, decision rights and interaction mechanisms.

Berente et al. (2021) extend this perspective by arguing that the management of AI involves the development of governance mechanisms that address accountability, control and human oversight in AI-supported decision processes. Rather than treating AI as a purely technical enhancement, the authors conceptualize AI as embedded within organizational routines and sociomaterial practices. Berente et al. (2021) argue that AI implementation requires careful organizational choices regarding the configuration of authority between human actors and AI systems, particularly in relation to responsibility, oversight and control of algorithmic outputs. Without clearly defined governance arrangements, AI-supported decisions may create ambiguity in accountability and weaken cross-functional coordination.

3.7.3 Sociotechnical Foundations of AI in Cross-Functional Planning

Raisch and Krakowski (2021) conceptualize AI integration through the lens of the automation–augmentation paradox, where AI simultaneously enables both substitution

of human tasks and complementarity between human and algorithmic capabilities. In this perspective, Raisch and Krakowski (2021) argue that firms must manage the tension between automation and augmentation rather than maximizing automation alone. Human roles remain critical in contextual interpretation, trade-off evaluation and exception handling, while AI can support data processing, pattern recognition and scenario simulation.

Weiner (2009) describes organizational readiness for change as a shared psychological state characterized by change commitment and change efficacy. This means that members collectively believe they are capable of implementing the change and are committed to its execution. According to Weiner (2009), change efficacy is formed through organizational members' cognitive appraisals of task demands, resource availability and situational factors. In the context of AI, Hasijsa and Esper (2022) demonstrate that AI acceptance in supply chain contexts is strongly influenced by organizational tactics used to signal AI trustworthiness. Their findings indicate that a gap often exists between the projected benefits of AI and its actual acceptance and use within organizations. Perceptions of AI trustworthiness are shaped by managerial framing, communication practices, leadership, internal champions and social influence mechanisms. This suggests that AI acceptance should be understood not only as a matter of perceived usefulness, but also as a collective interpretation process in which trustworthiness and legitimacy are actively constructed.

3.7.4 Dynamic Capabilities and Long-Term Adaptation

From a dynamic capabilities' perspective, sustained competitive advantage depends on the firm's ability to integrate, build and reconfigure internal and external competencies in response to environmental change (Teece et al., 1997). In contrast to static resources or isolated technological investments, dynamic capabilities emphasize adaptive processes rooted in organizational routines, asset positions and path-dependent trajectories (Teece et al., 1997).

The sensing dimension refers to the organization's ability to identify relevant signals in its environment, for example, through scanning, learning and interpretative processes (Teece, 2007). The seizing dimension refers to the organizational ability to mobilize resources and make timely decisions based on identified opportunities, including the design of governance structures and decision models that capture value from such opportunities (Teece, 2007). The reconfiguring dimension highlights the organization's capacity to continuously adapt its structures, processes and assets to stay up to date, by transforming and recombining existing resources and routines in response to environmental change (Teece, 2007).

4. Empirical Findings

The following chapter presents empirical findings derived from interviews, internal documentation and observations. The chapter describes how the Sales and Operations Planning process is structured and executed at Ascom, including the information flows, system interactions and governance mechanisms that shape the monthly planning cycle. The empirical material forms the basis for identifying current challenges and inefficiencies in the S&OP process, which are later analyzed in relation to the research questions.

4.1 Overview of S&OP at Ascom

Sales and Operations Planning at Ascom is structured as a recurring monthly planning cycle integrating regional sales inputs, project requirements and supplier-facing forecasts. Ascom's S&OP refers to the process of coordinating forecast, demand and supply planning across regions, OEM business and central planning functions. The purpose of S&OP is to align demand, supply and financial plans into one coordinated plan that creates value for customers. The monthly cycle produces a rolling twelve-month demand plan per product in ERP and a supplier-facing supply forecast, supported by regular forecast meetings with regions and OEM stakeholders.

4.1.1 Process Structure

The S&OP process is supported by several system inputs and information sources. These include CRM and CPQ, which are used to manage opportunities and generate BOM structures. ERP data related to project plans and purchase orders, historical add-on sales and portfolio changes such as new product introductions or end-of-life transitions also form important inputs to the planning cycle.

The process consists of Tactical Sales Planning and Project Planning, mainly driven by Sales, and Demand Planning and Supply Forecasting, mainly driven by Global Supply Chain, as illustrated in figure 4.

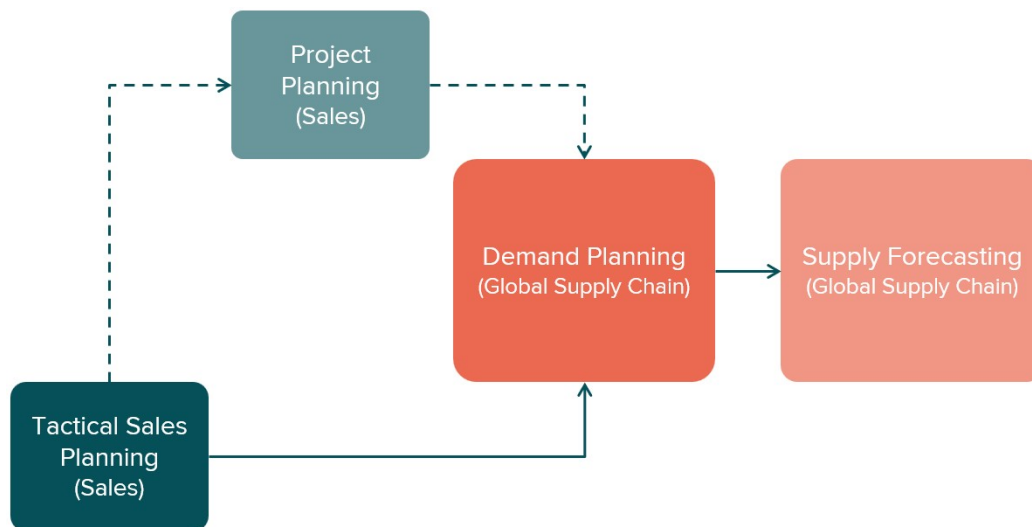


Figure 4: Ascom's S&OP process structure.

While figure 4 provides a structural overview of functional ownership, figure 5 visualizes the monthly operational cycle through which demand signals flow across regions, central planning and suppliers. The process begins with the regions, where Sales, Purchase, Project Management and Logistics collaborate to collect and prepare demand information. Regional teams prepare and validate demand inputs based on central planning reports, BI DWH data and CRM-based opportunity information. These inputs are submitted to Global Supply Chain several days before the monthly forecast meeting. At the central level, Global Supply Chain consolidates and reviews the regional submissions before the formal forecast meetings. The process then moves into monthly meetings. First, a demand meeting is held where regions present the updated file and explain significant changes. A second meeting with management verifies that the forecast is ready to be issued externally. Finally, the forecast is presented in a supplier forecast meeting, where suppliers receive the updated signal, discuss constraints and align on the upload of the forecast into their ERP systems.

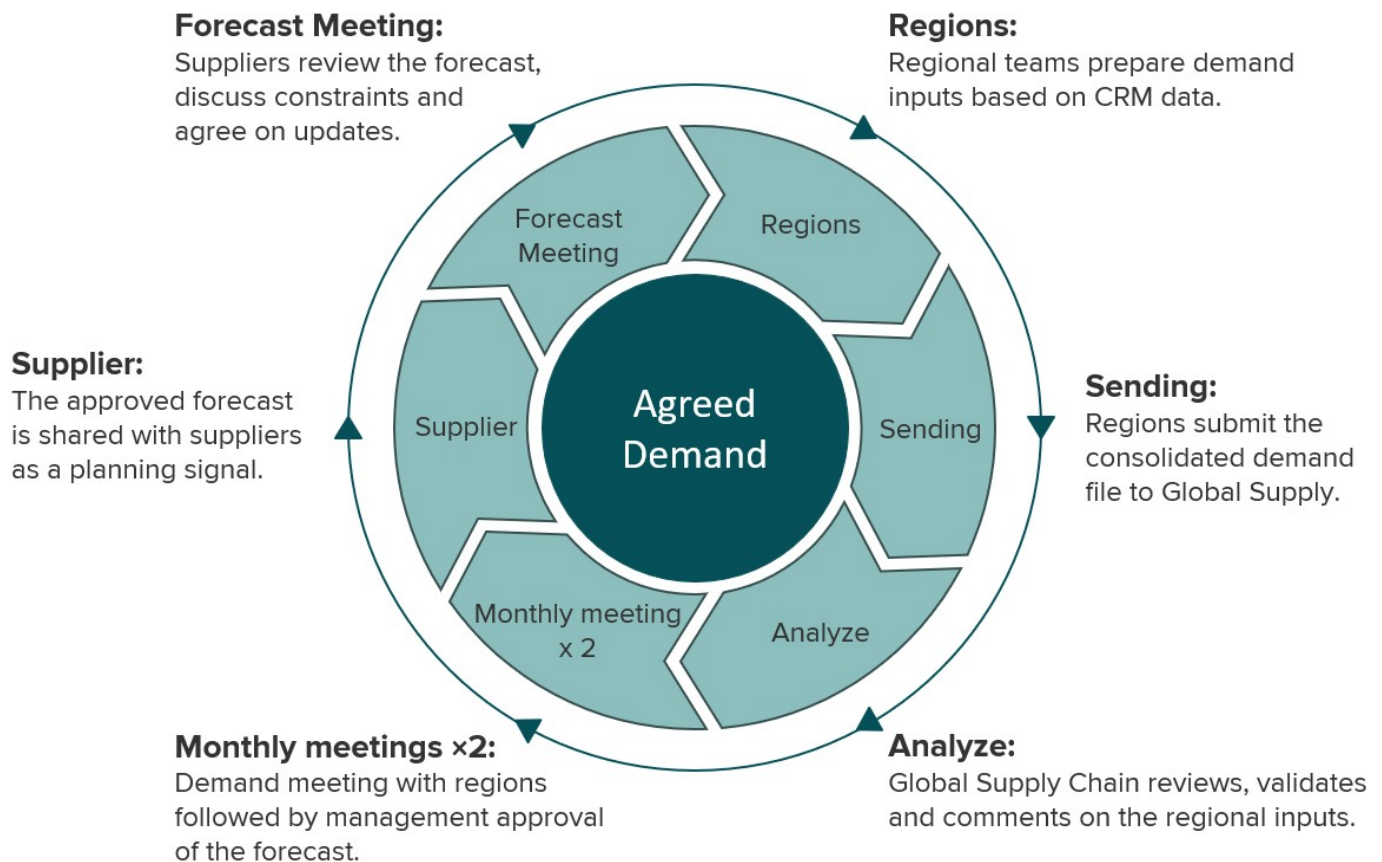


Figure 5: Summary of the recurring monthly S&OP cycle.

4.1.2 Tactical Sales Planning

Tactical sales planning constitutes the front-end of Ascom's S&OP information flow, where regional sales maintain opportunity data in the CRM, including probability, estimated closing date and requested delivery dates. Product configurations and bill-of-materials (BOM) structures are defined in CPQ to ensure that opportunities contain accurate product-level information for planning. The purpose of tactical sales planning is to prepare a bottom-up sales plan that delivers a short- to mid-term signal (3 to 6

months) for the demand planning process. In addition to the opportunity data maintained in CRM, the information flow is supported by system integration between CRM, CPQ and the BI DWH, which enables planning data to be consolidated and analyzed across systems. When an opportunity reaches the activation stage in CPQ, the configured BOM and product configuration details are automatically transferred to CRM and further to the BI DWH. This makes product-level information available for downstream planning activities.

This step provides probability-based forecast input, where CRM and CPQ data feed into the central planning cycle and probability assessments rely on sales judgment. Opportunities with a probability level of $\geq 80\%$ are typically treated as confirmed demand for planning purposes.

The inclusion of opportunities in the planning process depends on their stage in the CRM system. Opportunities in stages such as forecasted, negotiated or closed are included in the demand signal used by Global Supply Chain for demand planning. Estimated closing dates and requested delivery dates therefore constitute important inputs for the demand planning process and are expected to be updated continuously as customer dialogue progresses.

Probability levels and closing dates may change between monthly cycles as customer discussions progress, and such adjustments are reflected in the upcoming regional demand submissions. In partner-driven markets, visibility into end-customer decision processes is more limited, and probability assessments are therefore based on indirect communication and estimates from local representatives.

4.1.3 Project Planning

While tactical sales planning forms a probabilistic, opportunity-based forecast input, the project planning process represents the transition to deterministic demand. Once a project is won, the uncertainty inherent in early sales forecasts becomes concrete ERP requirements, creating a bridge from market-driven signals to operational planning.

When an opportunity is formally closed as won in CRM, the order information can be transferred into the ERP system when CPQ has been used in the configuration process. This transfer includes the configured BOM and solution scope defined during the sales process. Opportunities are typically not closed as won until a legally binding purchase order or signed agreement has been received, ensuring that only confirmed orders generate deterministic demand in the planning system.

Item requirements from projects are registered in the ERP system to reflect concrete product demand tied to projects, ensuring that the supply chain prepares for future demand. The project pipeline is updated continuously to ensure that newly won projects are registered, schedules are revised and purchase orders are aligned correctly. The outputs from the project planning process are critical components of deterministic demand within the S&OP cycle.

During technical refinement of projects, adjustments to quantities or component structures may occur. These changes are updated in the ERP system and incorporated into the next demand planning iteration.

4.1.4 Demand Planning

With the project pipeline continuously updated in the ERP system, these deterministic requirements are integrated into the broader monthly demand planning process. Demand planning therefore consolidates both the firm's project-driven demand and the more uncertain opportunity-driven sales forecast. The output from this process is a rolling 12-month demand plan per product based on sales, won projects, historical demand and product management. Each month, every region compiles a demand planning report according to a common template. In addition, a forecast meeting is held to review projects, market changes, products and demand shifts, providing qualitative context to the data in the demand planning reports.

Once the regional forecasts are updated, they are put into the ERP system, where the final output includes a 12-month demand plan for each product. Regional demand files follow a predefined template to enable ERP bulk upload.

4.1.5 Supply Forecasting

Once the consolidated demand plan is loaded into ERP, the planning focus shifts from forecasting to feasibility. Supply forecasting translates the demand plan into supplier-facing commitments, taking into account stock availability, purchase orders, constraints and product lifecycle information.

The monthly supply forecasting at Ascom is carried out after the demand plan has been uploaded to ERP and is handled centrally by the Global Material Planning Team. The inputs to the supply forecast include the monthly demand plan for each product, current stock levels, active purchase orders, and planned new product introductions or end-of-life changes.

Based on these inputs, the Global Material Planner compiles a twelve-month supply forecast for each product. This forecast is created outside the ERP system, typically in Excel, in a format agreed with the supplier. In some cases, the forecast is prepared jointly with sourcing representatives or management when product constraints, commercial considerations or strategic adjustments are involved.

The supply forecast is then sent to suppliers monthly, forming the primary communication of expected purchasing needs. The Global Material Planner verifies supply feasibility by considering open purchase orders, stock positions, known constraints and information from product managers and project teams.

A form of informal time-fence logic applies where the current month is effectively frozen, the following month is semi-frozen and later months have greater flexibility. Changes within the frozen or semi-frozen windows may still occur when escalations require urgent prioritization, but such changes can lead to reallocation of material or express shipments.

As part of supplier collaboration, Ascom also monitors supply forecast accuracy, defined as the deviation between the issued supply forecast and the purchase orders ultimately placed. This is used as a trend indicator in the process.

System-generated forecasting and safety stock calculations within ERP are available but are routinely reviewed by planners. In situations involving project-driven volume fluctuations or low-frequency items, manual adjustments are incorporated before finalizing the supply forecast.

4.2 Operational Execution of S&OP within Global Supply Chain

This section describes how the S&OP process is carried out in practice within Global Supply Chain at Ascom. It builds on interviews with material planning specialists and related roles and complements the formal process description by describing actual workflows, routines, challenges, system dependencies, cross-functional interactions and risk-related events. The findings describe how planning work is carried out in the operational reality and which recurring characteristics shape the monthly cycle.

4.2.1 Monthly and Daily Planning Routines

Interviewees describe the S&OP cycle as a structured monthly rhythm, where responsibilities are distributed across roles and activities are organized into repeated weekly patterns. R8 described this as a four-week operating rhythm. In week 1, planners extract historical demand and review item run-rates and stock coverage to prepare for changes in the upcoming cycle. In week 2, regional forecast meetings are held to discuss pipeline opportunities, timing shifts and project developments. In week 3, Global Supply Chain consolidates updated demand inputs and translates them into material implications, identifying what must be purchased and when. In week 4, supplier-facing forecasts are compiled and communicated. The monthly cadence aligns with the formal S&OP structure described in internal documentation, but interviews indicate that the practical execution involves substantial manual consolidation and interpretation between formal steps.

Respondents also described the geographical scope of the monthly forecasting cycle as part of the practical execution of the planning routine. Approximately eighteen regions contribute to the monthly demand submissions, although some areas, such as the Nordic countries, may occasionally be consolidated into joint sessions. Forecast meetings are normally scheduled individually for each region in short time slots, where the pipeline, major deviations and forecast template are reviewed before ERP upload.

Daily operational routines and lead time maintenance

In addition to the monthly planning cycle, interviews highlight recurring daily routines that influence planning outcomes within the supply planning work. A central routine is the maintenance of lead time parameters. Respondents describe that planners update lead times frequently when suppliers provide revised dates, and that updated parameters are uploaded so that customer promise dates can reflect the latest supply situation. This activity is described as essential for order handling and delivery reliability.

“This is a daily cycle, if lead times are wrong, order [administration] can’t promise correctly, so we update and upload every morning.” - R8

Respondents describe that planning quality is influenced by daily master data maintenance, not only by monthly forecast routines.

Supplier-facing forecasting horizon

The respondents describe working with a rolling twelve-month forecast toward suppliers. At the same time, purchase orders are placed primarily for near-term coverage and then extended strategically across periods associated with increased risk of disruption, such as holiday peaks and seasonal patterns. Respondents mention that lead time risk and logistical constraints influence how far ahead purchase orders are extended, even when the formal forecast horizon remains twelve months.

For local suppliers with very short lead times, respondents describe that the supplier forecast still functions as a longer-term signal to communicate expected needs, while purchase orders may be placed closer to execution due to supplier responsiveness. This illustrates that the supplier forecast is used both as a planning instrument and as a relationship-oriented coordination mechanism toward suppliers.

Planner judgment in forecasting

The practical forecasting work is described as item-based and experience-intensive. Planners export sales history and identify patterns and outliers to determine a reasonable demand signal. Interviews emphasize that single large projects and bulk orders can distort the statistical base and therefore require manual filtering. The aim is to avoid overreacting to short-term spikes that would inflate buffers or create unstable supplier signals.

Respondents further highlight an explicit ambition to provide a stable forecast signal to suppliers, even when demand fluctuates significantly.

“There, you have a responsibility to present an image of stability and calm, even if our system was actually in chaos.” - R8

Similarly, planners deliberately try to protect suppliers from internal volatility by smoothing supplier-facing forecasts.

“We try to protect the suppliers by keeping the forecast stable.” - R7

This suggests that forecast stability is considered an important aspect of the planning work, in addition to forecast accuracy.

Supplier constraints and minimum order quantities

Interviews highlight that purchasing work is shaped by supplier constraints such as minimum order quantities or minimum family quantities. Planners describe that they must coordinate volumes across items within the same product family to meet the minimum without generating excessive inventory. This work is described as manual puzzling, where planners adjust the timing of related items to reach required order quantities while still aligning with inventory turnover targets.

“If I need 50 of item A but the family MOQ is 250, and the next family need is in May, I try to move either A or the other family items so we hit MOQ without hurting turnover.” - R10

This illustrates that a large part of supply planning involves constraint-based judgment and coordination outside standard ERP outputs, particularly for families with shared minimum constraints.

Time fences and exception handling in planning

While the formal process includes time fences to maintain stability in the near-term horizon, respondents describe that escalations can override these boundaries. Large project confirmations, urgent customer needs or sudden disruptions may lead to expedited shipments, reprioritizations or reallocations within the month. This suggests that the time fence logic functions as a stability principle, but that practical execution requires flexibility through exception handling.

Interviews also indicate that late changes in regional demand may have direct consequences for supplier coordination. Respondents describe situations where updated demand inside the planning horizon forces suppliers to deviate from the agreed production plan. In such cases, suppliers may need to purchase components on the spot market, use alternative sourcing or arrange expedited transport at a higher cost in order to meet requested delivery dates. This creates a trade-off between delivery performance, inventory exposure and purchasing cost, where planners must evaluate whether to accept increased cost to deliver on time or delay delivery to avoid unnecessary risk. The example illustrates how late demand changes propagate upstream and influence both operational stability, supplier commitments and cost levels.

“Is it worth paying more to get it in time or can we wait?” - R12

Respondents further describe that uncertainty originating at the regional sales level tends to propagate through multiple tiers of the supply chain, referred to as a snowball effect. When customer decisions are delayed, revised or communicated late in the cycle, the resulting changes affect regional forecasts, central demand planning, supplier commitments and inventory decisions in sequence. This cascading behavior is described as a recurring characteristic of the planning process, where even moderate uncertainty in early stages may result in repeated replanning, increased workload and reduced plan stability throughout the supply network. As material commitments are made and suppliers are notified, such changes may also affect delivery reliability, inventory exposure and purchasing cost, requiring additional coordination across functions.

4.2.2 Manual Work and System Dependencies

Several respondents described manual handling of data and coordination across multiple systems as recurring features of the planning process. Limitations in system integration, traceability between sources and the need for manual adjustments were highlighted as key contributors to this pattern. These limitations become particularly visible in the consolidation of planning data across systems.

Manual consolidation of planning data

Respondents also emphasize that consolidating planning data requires substantial manual effort. Information from CRM, regional forecast files and historical planning data must be extracted, aligned and compared across cycles without system support.

“There is a lot of manual work involved in finding, analyzing and comparing with the previous cycle. It is entirely manual work.” - R3

Multiple respondents describe that manual file cleansing, reconciliations and template corrections peak just before upload deadlines. This creates recurring time pressure and increases the risk of errors in formatting, mapping or consolidation. The issue is described as structural rather than occasional, since it is tied to recurring deadlines and varying regional routines.

Spreadsheet-based forecast preparation

Several respondents noted recurring manual adjustments related to formatting and consolidation of regional inputs before ERP upload. Supplier-facing forecasts are prepared outside the ERP system, typically in Excel, in formats agreed with suppliers.

Across interviews, respondents describe that planning work relies heavily on manual tools, particularly Excel templates agreed with each supplier for supplier-facing forecasts. Regional demand files often require manual cleaning before ERP upload. Respondents describe that data must be reformatted due to template deviations, column mapping differences or regional variations in input routines.

“We still do the heavy lifting in Excel.” - R9

Respondents further describe that the manual spreadsheet workflow also introduces specific risks during data preparation. Examples mentioned include selecting incorrect date fields, copying outdated values or using the wrong data range when consolidating files before uploading them to the ERP system. This illustrates how data quality in the current process depends heavily on individual handling rather than system-based validation.

Traceability from sales opportunities to ERP orders

Respondents highlight that traceability between opportunity data in CRM and the resulting sales orders in ERP is not always preserved. This issue is partly related to the system landscape and the way information is transferred between tools, but it also affects the ability to verify forecast inputs used in planning. When opportunities progress through the sales process and are eventually converted into orders, the linkage to the original opportunity record may be lost. This makes it difficult to analyze forecast deviations or connect realized demand to earlier sales opportunities.

“The Opportunity-ID number does not always follow through, and then it becomes difficult to know, you don’t know what the case actually refers to or whether it belongs to one of the projects they previously submitted.” - R3

Several interviews noted that this creates a limitation in the ability to trace forecast assumptions back to individual sales cases during follow-up discussions. Interviews further highlight that lost links between opportunity records in CRM and ERP orders complicate systematic learning on forecast deviations. The inability to trace forecast assumptions to individual cases makes follow-up discussions more qualitative and less evidence-based, since deviations cannot be clearly attributed to specific causes.

Respondents describe that this limits the ability to refine forecasting routines over time and makes it harder to distinguish whether deviations originate from sales judgment, customer changes, lead time assumptions or internal processing.

System integration and planning dependencies

In practice, the S&OP process relies on integration between CRM, CPQ, ERP and BI reports. CRM, CPQ, ERP and BI reports support opportunity management, configured BOM structures, deterministic project demand and demand planning data. Regional teams compile standardized demand planning files, which are thereafter uploaded to ERP.

Respondents describe that ERP contains built-in forecasting and safety stock calculation logic. However, planners frequently review and adjust system-generated proposals in cases of project-driven bulk orders, irregular demand patterns or when historical patterns are not considered representative.

System coexistence during ERP transition

Ascom is currently transitioning from AX2012 to Dynamics 365 across regions. Interviews describe that the coexistence of systems creates differences in reporting structures, master data configurations and planning routines. Since regions are at different stages of the transition, the consolidation work requires additional interpretation and manual adjustments. Respondents describe that this coexistence reduces process standardization and increases the need for local adjustments during global planning.

Supplementary tools and lifecycle tracking

In addition to core systems, interviews highlight reliance on supplementary tools and trackers. Respondents refer to tools used for lifecycle and component visibility, including legacy trackers and platforms used for end-of-life context and last-time-buy visibility. Some of these tools are described as sensitive to change and associated with email-heavy workflows to ensure that information is communicated and visible in time.

4.2.3 Forecast Volatility and Input Uncertainty

The empirical findings indicate that volatility in front-end inputs, regional differences in planning practices and late demand changes create recurring uncertainty in the forecast inputs used throughout the S&OP cycle. These patterns affect the reliability of forecast inputs and make planning outcomes more difficult to predict.

Forecast volatility across planning cycles

In addition to the traceability limitations described above, respondents describe recurring volatility in forecast inputs across planning cycles. Changes in opportunity probabilities and closing dates between monthly cycles lead to recurring adjustments in regional demand submissions and supplier-facing forecasts.

If probability levels do not reflect the actual likelihood of a deal, this may lead to premature material commitments. This is particularly prevalent in partner-driven regions, where lower visibility into end-customer decisions often results in shock orders that bypass the standard forecasting window.

Respondents also emphasize that forecast values should be interpreted as planning signals rather than firm commitments. Even when opportunities are included in the demand plan, the underlying probability assessments may change and planners must rely on judgment when deciding whether to secure material. As described in the interviews, a forecast does not necessarily become an order, which means that experienced planners evaluate the reliability of different inputs rather than treating all forecast values as equally certain. This increases the dependence on individual interpretation in the planning process.

“A forecast does not always become an order, it only gives you a sense of the quantity of what to expect” - R12

In addition to the volatility described above, respondents noted that high-value or strategically important projects may sometimes be discussed in MBR meetings before they are reflected with the same level of detail in the formal demand files submitted to Global Supply Chain. MBR was described as a recurring management meeting where sales performance, forecast development, key business opportunities and budget follow-up are reviewed at country level. Such early visibility in MBR discussions does not always result in immediate updates in CRM or in the regional forecast templates, which may require additional follow-up work to reconcile verbally communicated information with the documented planning inputs.

“It [strategically important projects] can be discussed in the MBR meetings, but it is not always visible in the reports that are sent in” – R7

Regional differences in planning practices and parameters

Interviews highlighted significant variation in how different regions work with CRM, CPQ and forecasting routines. Some regions update opportunity information continuously, while others update probability levels and delivery dates mainly close to monthly deadlines. Regions with partner-driven sales models have limited visibility into end-customer decisions, resulting in greater uncertainty and more frequent revisions. Respondents described that these differences across countries contribute to differences in input quality, planning horizon and the stability of monthly submissions.

In addition to timing shifts and probability changes, interviewees indicate that some regional inputs may reflect an optimistic bias, particularly where regions aim to promise short delivery lead times to customers. Respondents describe that this optimism is partly structural in partner-driven markets where information is mediated through indirect channels.

“Regional teams present their forecasts in an optimistic way because they sell by promising that they can deliver on time. They want to safeguard themselves by making sure material is available, even when it is not entirely certain that the order will go through. This tendency is linked to how they assure customers that delivery will be made on time and it means that forecasts may appear more confident than what the actual probability levels would justify” - R9

R7 also describes a case where a French sales campaign forecasted exceptionally high volumes, which led Supply to purchase large quantities of material in advance. The

respondent describes that the realized sales volumes were significantly lower than expected, resulting in considerable overstock and strained supplier relations.

Linked to this, delivery dates were used inconsistently across regions, with some using the project win date and others using the agreed requested delivery date. Additionally, items discussed at the regional sales pipeline meetings are not always consistent with the forecast files submitted monthly to the material planning team at Global Supply Chain. This creates a gap between verbally signaled demand and formal planning inputs, increasing consolidation work in upcoming cycles.

Mismatch between supply planning horizons and regional updates

Respondents explained that the time horizon required for supply planning often differs from the timing of regional forecast updates. Supply typically requires at least three months' advance visibility to secure material availability, and up to six months for large-scale projects. When project information is communicated later than this, suppliers cannot realistically meet the requested delivery timelines.

"We need at least three months' notice to buy materials and for very large projects six months." - R7

Respondents also described situations where regions submit forecast updates only one month before the requested delivery date.

"They forecasted the first time last month for delivery next month, that is impossible for us"- R7

R12 described a recent case where a large customer order had been discussed for several months with an estimated probability below confirmation level, but without a formal sales order in the system. When the order was finally confirmed, the supplier could not scale production in time due to component lead times, which resulted in delivery constraints. According to the respondent, material cannot be secured based on uncertain opportunities, since this would expose the company to significant financial risk. The example illustrates how incomplete upstream information may lead to material shortages, urgent replanning and reduced delivery reliability.

R7 further explains that short customer lead-time expectations sometimes influence how regions communicate forecasts. Competitors may be able to deliver within approximately 20 days, but Ascom can only respond to such timelines if project information is communicated significantly earlier in the planning process.

Limited validation of regional forecasts

Some regional teams also submit forecast reports without conducting a detailed internal analysis of volume changes or probability updates.

"Some regions send in a forecast without analyzing it at all." - R7

The interviews further indicate that some regions may increase forecast volumes to safeguard material availability, which can result in supplier-facing forecasts that do not fully reflect actual demand probability. Respondents describe that Global Supply Chain must handle the consequences of this uncertainty in material planning and supplier coordination.

Project spikes and unexpected demand surges

Planners describe that single project spikes often distort both forecast interpretation and safety stock proposals if not manually filtered. Bulk orders create spike patterns in history that do not represent normal run-rates. Interviewees describe that experienced judgment is required to avoid translating a one-off project into a permanently inflated baseline. This includes campaign-driven or once-a-year events that can lead to irregular patterns of several thousand units.

“You need a trained eye, history shows 0-500-0 patterns, you can’t let one project rewrite the base.” - R8

“You want the clean data, you exclude that spike of 4000 because it skews the view” - R12

One example concerned demand for a UK-specific pull-cord product, which increased rapidly in the Netherlands after a hospital adopted the solution. According to R7, the installation spread to other hospitals that replicated the setup, which resulted in a sudden increase in demand that had not been anticipated in earlier forecasts.

4.2.4 Cross-Functional Coordination and Information Flow

Supply planners describe frequent coordination with several functions. This includes coordination with Sourcing on supplier constraints, agreements and MOQ rules, Order Handling on customer confirmations and lead time updates, Supply Chain Quality on deviations and containment actions, and product- and project-related roles on portfolio changes such as new product introductions and end-of-life transitions. Respondents describe that supply planning work therefore depends on cross-functional information flows and interaction rather than being isolated within the planning team.

“We have contact with everyone across the process, not packing boxes ourselves, but planning when it ships and what it takes to get there” - R9

Ad-hoc coordination and silo dynamics

While monthly demand meetings and structured governance exist, respondents describe that a major share of coordination occurs ad hoc through email and Teams, particularly when urgent adjustments are required within the monthly cycle. Decision rights related to prioritization, allocation and escalations are formally governed by defined role structures and established escalation pathways. During constrained situations, decisions may be elevated across hierarchical levels. However, several respondents describe strong competence within functions, but weaker coordination when issues cut across functional boundaries.

“You work in silos within the company, very skilled within each department, working with each department’s own processes, but things fall through the cracks between departments, creating frustration” - R8

This is described as particularly visible in escalations, urgent reprioritizations and lifecycle transitions, where responsibilities and ownership may become less clear despite the formal governance structure.

Quality deviations and cross-functional response

Interviews describe that quality-related deviations can significantly disrupt planning and require cross-functional coordination in short timeframes. When widespread or safety-critical issues occur, cross-functional groups are convened to decide containment actions such as inventory blocks, delivery stops, sorting activities or temporary supplier stops. Respondents describe that such actions reshape material availability and supply plans within the ongoing cycle, requiring reallocations, express deliveries and revisions of supplier-facing forecasts within the same month.

Differences between sales and supply perspectives

Respondents further emphasize that differences in understanding of lead time constraints contribute to coordination challenges. While sales teams may commit to short delivery times in customer discussions, supply planning requires several months of visibility to secure materials from suppliers. When such information is communicated late, planners must either attempt costly adjustments or accept delayed deliveries. This reflects a structural mismatch between customer-facing commitments and the operational realities of the supply chain.

Interviews indicate that coordination challenges partly arise from differences in functional perspectives between sales and supply-focused roles. Sales teams are primarily oriented toward customer negotiations and opportunity development, while supply functions rely on timely and structured information to plan procurement and inventory. In the interviews, the implications of delayed or incomplete CRM updates are not always fully understood upstream.

“You have to create understanding within the sales organization. What is reasonable and what is not reasonable within the supply chain, we are no longer in a just-in-time supply chain, some people may not understand that.” - R7

Respondents also recalled situations where regional sales teams have promised short delivery lead times to customers without consulting Supply beforehand. Such commitments may lead to urgent escalations within the supply chain when the requested timelines are not feasible.

Information gaps in regional communication

Respondents noted that regional sales teams may possess project-related information that is not fully reflected in the system-generated forecast reports. As a result, important demand signals may remain invisible to Global Supply Chain unless they are communicated directly outside the formal reporting structure.

The interviews describe an example where a large project was known at the regional level for several months but was not communicated to Global Supply Chain due to a breakdown in the regional communication flow.

“One person completely failed to pass on the information, and the whole organization suffered because of it.” - R7

This resulted in the project being discovered only shortly before the required delivery date, creating extensive emergency planning work.

4.2.5 Disruptions, Exceptions and Planning Instability

The interviews indicate that planning outcomes are not only shaped by recurring routines and structural process conditions, but also by unexpected events that introduce instability, increase workload and require exception handling. These events originate both internally and externally and affect planning through supply constraints, logistics issues, delayed information and broader environmental uncertainty.

Supply chain disruptions and shortage periods

Interviews describe several categories of events that influence planning stability and workload in the S&OP cycle. Respondents recall periods during component shortage where lead times were unstable and standard routines did not function as intended. Planning during such periods required repeated replanning and extensive exception handling.

“Nothing was standard, we rewrote routines constantly” - R8

The empirical findings indicate that such periods increase manual workload, reduce plan stability and require closer managerial involvement.

Geopolitical and trade-related uncertainties

Respondents describe that geopolitical developments and changes in trade conditions can require proactive adjustments, such as phasing inventory earlier than normal or shifting transport plans. Such actions influence purchase order timing and inventory exposure, and may introduce planning trade-offs between flexibility and cost.

Demand shocks and supplier constraints

Interviewees describe sudden shifts in demand that may persist over several months and collide with long component lead times. In such cases, planners escalate to suppliers, reprioritize within product families and adjust plans to protect near-term availability while avoiding long-term overbuy. The need to combine demand interpretation with supplier constraint handling is described as recurring in project-based environments.

Supplier-side disruptions

Respondents further describe that under-notification of supplier constraints, such as machine stops or sub-supplier shortages, can create unplanned slippage. This triggers replanning, customer communication and prioritization decisions within the cycle.

Internal logistics disruptions and inventory visibility issues

In addition to supplier-related risks, respondents also described internal logistics disruptions and inventory visibility issues, which in some cases affected material availability and required replanning. One example from R8 concerns goods that are dispatched but not received in the system, creating inconsistencies in inventory status and complicating subsequent planning steps. Interviewees describe that such issues trigger time-consuming follow-up work to locate goods, correct records and restore system visibility before planning can proceed smoothly.

Consequences of delayed demand communication

As described above, quality deviations may result in immediate inventory blocks or supplier stops, which require emergency logistics and revisions of forecasts. These

events are described as particularly disruptive due to their uncertainty and the need for rapid cross-functional decision-making. Respondents further noted that delayed demand communication has, in some cases, resulted in lost customer projects. According to the respondent, when demand is communicated too late for Supply to secure the necessary materials, customers may instead choose competitors with shorter delivery times.

“We have lost projects because they didn’t forecast early enough.” - R7

4.3 Sales Perspective on S&OP

This section complements the supply perspective through an interview with the Head of Global Sales Operations (R11), providing insight into Sales’ role in S&OP, how information flows from Sales into Supply and what shapes collaboration between the two functions. According to R11, Sales’ primary contribution to S&OP is the provision of opportunity information through CRM and CPQ. This links the quality of sales data directly to the accuracy of the forecasting process.

“Sales provides the process with information, the information around each opportunity is collected in our CRM system, and that information forms the basis for supply-demand planning”- R11

4.3.1 Opportunity Progression and Data Reliability

Sales describes the journey from early opportunity identification to forecast visibility as gradual and highly dependent on the maturity of the opportunity. When opportunities are first entered into CRM, they often contain limited information.

“When you create an opportunity in the qualification stage, you don’t know very much, it’s only in Develop and then Propose that we start to understand what the customer wants and build the solution” - R11

Once an opportunity reaches the Propose stage and has passed the internal approval checkpoint, it becomes a key trigger for Supply.

“When you pass Checkpoint 2, that’s when we allow an offer to be sent to the customer. That’s the trigger point for material planning” - R11

However, Sales does not always follow the process strictly. For example, some opportunities progress far in reality but are not updated in CRM, which means Supply receives outdated information.

“They can be in negotiations for a long time without updating CRM. Then it looks like they move from Propose to Close in a few hours, when in reality they’ve been working on it for months” - R11

This creates situations where Supply is surprised by late orders.

“If they don’t activate the opportunity, it stays under the radar until it’s very close to closing, then Supply gets the information too late.” - R11

4.3.2 Visibility in Partner Sales and Data Quality Challenges

Sales also emphasizes that visibility differs significantly depending on the sales model. In direct sales, Sales has detailed insight into the customer dialogue. In partner sales, visibility is much lower, which creates the risk for shock projects.

“When we sell through a partner, we don’t always know what discussions the partner has with the end-customer. Sometimes we only find out when they place an order, and then we have zero forecasting” - R11

“Sometimes you only find out when they send the purchase order, there’s no forecasting, it just comes as a shock” - R11

One of the recurring themes is the struggle to ensure consistent data quality in CRM. Although Sales has quality checkpoints and KPIs, the respondent notes a gap between formal compliance and practical usefulness:

“You can fill in CRM correctly from a technical point of view, but still not enter reliable information, the KPIs say we do a good job, but Supply still can’t trust the data” - R11

“The challenge is getting salespeople to update CRM properly. They must understand that the information they put in is important, not just for us looking at this information but for themselves” - R11

4.3.3 Interaction between Sales and Supply

The respondent states that Sales and Supply approach the process with different priorities, but clarifies that this is not a conflict, but a structural difference.

“Sales’ main task is to deliver business. Their focus is not on updating systems so Supply can plan.” - R11

“It’s not a conflict, it’s just that we have different priorities. Supply needs stable data while Sales focuses on winning deals.” - R11

This difference affects the S&OP process when urgent escalations occur or when rapid changes in opportunities are not communicated quickly enough.

“If they haven’t told us in CRM that something big is coming, they can’t come to Supply and say they want the material tomorrow.” - R11

The formal S&OP structure includes monthly meetings between Sales regions and central supply planning, but interaction between central Sales Operations and Global Supply Chain is more informal.

“We don’t have scheduled meetings, we meet in the corridor or by the coffee machine. Or [Head of Logistics] sends me a message when something is really bad” - R11

At the regional level, Sales often interacts with the local Supply organizations, who in turn compile input for Global Supply Chain. This setup sometimes creates communication gaps.

“The regional Supply teams struggle to get reliable information from Sales, they find it hard to get the attention they need.” - R11

When asked whether regions understand how their forecasts affect supplier planning, the respondent responds:

“I don’t think they understand it. They hear it every time we say it, but I don’t think they feel it’s important for them” - R11

The feedback from Supply is described by the respondent as consistent but often has a limited effect.

“The feedback is always the same, that the quality is poor. Regional Supply says it’s hard to get reliable information from Sales” - R11

The respondent identifies two main areas where improvements could increase S&OP reliability, including better system intelligence and stricter adherence to process.

“Our systems are not intelligent enough, if the system were smarter, we’d probably get better data” - R11

“The biggest improvement would be that Sales follows the process consistently” - R11

The respondent concludes that S&OP fundamentally depends on the opportunity data created in the sales process.

“There is no other way. The information for Supply Demand Planning must come from the sales process” - R11

4.4 Current State of AI Adoption and Organizational Readiness

This section presents the current state of AI adoption, attitudes and cultural readiness at Ascom. The findings build on interview material from Global Supply Chain, including Sourcing, Supply Chain Quality, Logistics and insights from the Copilot pilot group. The section outlines how employees currently perceive AI, which early initiatives exist and how AI is understood within Ascom’s operational context.

4.4.1 Employee Attitudes and Current AI Use

Across interviews, employees express a consistently positive attitude toward AI and a willingness to explore how it can be incorporated into daily work. Respondents describe AI as a natural technological development within Ascom’s broader digital environment, and the internal perception of AI is generally constructive.

“I get Copilot here and there in the system. I haven’t used it much yet, but if it can explain or fetch what I need without me building a report, that’s useful” - R5

“I have very rarely heard anything negative about AI internally. I think it will come more and more.” - R9

Interviewees emphasize AI's potential to handle large volumes of information, reduce repetitive steps and accelerate tasks that currently require substantial manual review in tools such as Excel. They also express a non-threatening view of AI.

"I see potential in using AI as an analytical tool. That we can feed it with all the information and it generates some form of analysis, helping us make decisions based on all the input. That would really make our work more efficient." - R9

"AI will not replace jobs. It will make our processes more efficient and create opportunities to focus on other things." - R9

"If AI can see that connection directly, then it saves me eight hours." - R10

This reflects a perception of AI as a supportive tool rather than a substitute for human judgment.

Employees highlight that AI is particularly suitable for tasks involving information retrieval, document summarization and historical reference checking, such as navigating product material, supplier information or long historical records. AI support embedded within Microsoft applications is described as compatible with existing ways of working.

At the same time, the current use of AI remains largely individual and exploratory. Employees who have access to Copilot use it at their own discretion to support personal tasks rather than as an integrated part of formal processes. AI is not currently embedded within forecasting routines, supply forecasting activities or Excel-based consolidation work. This individual and limited use is also reflected in the description of current practice.

"AI is helpful for writing and checking if I missed something, but not yet for planning." - R7

The interviews indicate openness toward applying AI in areas such as forecasting, supply forecasting, Excel consolidation and traceability challenges. However, no structured initiatives targeting these specific S&OP-related process steps are currently in place.

4.4.2 Copilot Pilot and Organizational Support

Ascom currently has an active pilot group working with Microsoft Copilot. The pilot group originates from a corporate-level initiative and has been implemented within Global Supply Chain as part of this broader program. The purpose of the group is exploration and familiarization, enabling selected employees to test Copilot within their everyday environment.

Participation in the pilot has increased awareness of AI capabilities and provided opportunities to experiment with document summarization, information retrieval and drafting support. These activities are described as self-driven testing, where individuals evaluate potential use cases relevant to their own tasks and share experiences during recurring pilot meetings.

The experimentation is primarily individual-based and focused on personal efficiency rather than redesign of cross-functional processes. Learning and follow-up take place through discussions within the pilot group meetings, where participants exchange practical examples. There is currently no formal evaluation framework measuring impact on process performance.

In contrast to the generally optimistic view of AI in the interviews, R7 expresses that the organization currently lacks the internal structure and competence required to support more advanced AI-driven planning tools. According to R7, implementing such solutions would require dedicated expertise and organizational support functions that are currently not in place. Chapter 4 is summarized in table 4.

Chapter	Empirical focus	Summary
4.1	S&OP structure	The S&OP process follows a monthly cycle that combines regional sales inputs, project requirements, demand planning and supplier-facing forecasts. Sales mainly drives Tactical Sales Planning and Project Planning, while Global Supply Chain mainly drives Demand Planning and Supply Forecasting.
4.2	Operational execution	The process is carried out through recurring forecast preparation, regional meetings, demand plan updates, supplier forecast preparation and follow-up. The work involves several systems and manual activities, including Excel-based preparation, interpretation of changes and communication with regions and suppliers.
4.3	Sales perspective	Sales information in CRM and CPQ provides important input for planning, including opportunity probability, closing dates, delivery dates and product configuration. The findings also show changes in opportunity progression, delayed updates and limited end-customer visibility in partner-driven markets.
4.4	AI adoption and readiness	AI use is mainly exploratory and connected to individual use and the Copilot pilot. Respondents identify potential in information handling, summarization, Excel support, repetitive tasks, analysis and is perceived positively.

Table 4: Summary of empirical findings.

5. Analysis

This chapter analyses the empirical findings in relation to the literature review and the research questions. It examines current challenges and inefficiencies in Ascom's S&OP process, how AI may address these challenges, and the conditions required for successful and sustainable AI integration. The chapter is structured around the three research questions and forms the analytical basis for the discussion and recommendations presented later in the thesis.

5.1 Challenges and Inefficiencies in the Current S&OP Process

This section addresses the first research question by analyzing the empirical material collected through interviews, documents and observations in order to identify current challenges and inefficiencies in the S&OP process. The analysis was conducted by systematically reviewing the material to identify recurring patterns related to the first research question. Statements describing similar issues were coded and grouped into themes, including forecast inaccuracy, manual work, data quality challenges, system dependencies and cross-functional coordination. These themes were compared across respondents and data sources to ensure consistency. The identified themes form the basis for the following analysis of the current challenges and inefficiencies in the S&OP process.

5.1.1 Low Maturity in S&OP Execution

Low execution integration across planning steps

The empirical findings indicate that Ascom's S&OP process should not be understood as lacking formal structure, since the process includes defined monthly meetings, recurring routines and a shared planning cadence. The main maturity constraint instead lies in execution. In practice, planning still depends on fragmented information flows, manual interpretation and repeated coordination across functions and systems. The process is therefore formally defined, but not fully integrated in execution.

In this study, S&OP maturity is understood in relation to the framework presented in figure 3, where higher maturity is associated with cross-functional integration, clear ownership and consistent coordination across functions (Grimson & Pyke, 2007; Thomé et al., 2012). Compared with this framework, Ascom's process shows several characteristics associated with lower to intermediate maturity stages, including spreadsheet-based work, fragmented information flows, sequential handoffs and reactive coordination. Several respondents also describe how the sales plan drives operational decisions without fully synchronized feedback from supply constraints, requiring manual consolidation before information becomes usable for planning. The issue should therefore not be interpreted as isolated inefficiencies, but as a broader constraint in execution maturity.

Interpreted through the Grimson and Pyke (2007) maturity framework, Ascom does not fit precisely into a maturity stage. There are several characteristics connected with stage 3, including a recurring monthly cycle, formal meetings with both regular forecast and management and S&OP as a part of the broader supply chain. These features indicate that Ascom has moved beyond a purely reactive or informal planning process.

However, the high degree of manual spreadsheet-based consolidation, repeated follow-ups and inconsistent regional routines reflect stage 2 characteristics. Therefore, Ascom can be interpreted as positioned between stage 2 and 3 in the maturity framework. The meeting structure and formal organization resemble stage 3, while information technology, plan integration and measurements still represent stage 2 maturity characteristics. This becomes a challenge because the formal process structure is not fully supported by equally mature execution capabilities. As a result, Ascom has established the forums for S&OP coordination, but still lacks some of the integration, standardization and performance follow-up needed for the process to consistently function as a stable planning mechanism.

System and data fragmentation

The empirical material further indicates a fragmented system and data landscape, where S&OP relies on several parallel platforms and information sources without full end-to-end transparency. Respondents describe that information visibility is often recreated through manual communication and follow-up outside the formal systems, suggesting that transparency remains dependent on human coordination rather than being embedded in the information infrastructure. As a result, coordination risk increases, process reliability decreases, and standardization becomes more difficult, since information must be reconciled before it becomes operationally usable. From an S&OP perspective, this indicates limited execution maturity, as integration is achieved manually rather than through a system-based planning structure (Thomé et al., 2012).

Cross-functional coordination limitations

The empirical findings also indicate that coordination weaknesses extend beyond systems into the cross-functional planning flow itself. Regional inputs vary in timing, quality and stability, as some updates are made continuously while others are submitted closer to monthly deadlines or project closures. This increases the need for follow-up, interpretation and corrective coordination downstream.

Respondents also describe that issues can “fall through the cracks between departments”, suggesting that responsibility is relatively clear within functions but less clear across functional handoffs. As a result, Global Supply Chain becomes reactive to upstream uncertainty rather than operating from a stable and jointly governed planning basis. This should therefore be understood not as poor planning within Global Supply Chain, but as a broader problem of process integration and structural inefficiency.

Another aspect related to maturity concerns ownership of the planning process. In higher maturity stages, S&OP is characterized by clearly defined process ownership and shared responsibility across functions (Grimson & Pyke, 2007). The empirical findings indicate that responsibility within each function is relatively clear, but that ownership of the overall planning flow between functions is less defined. When problems occur, they must often be resolved through ad-hoc coordination rather than predefined escalation paths or standardized procedures. This suggests that the process lacks the level of governance typically associated with more mature S&OP implementations.

Planning instability and reactive behavior

Another indicator of limited maturity is the reactive and exception-heavy nature of execution. Although the monthly cycle provides formal structure, late changes,

incomplete information, disruptions and escalations repeatedly force planners to replan within the cycle. As a result, planners must manually assess trade-offs between delivery performance, inventory exposure, supplier stability and cost, which moves planning work closer to operational problem-solving than to stable aggregate coordination. This suggests that planning stability is not fully achieved and that the process does not fully separate tactical planning from operational adjustment.

Compared with the aggregate planning level described by Jonsson and Mattsson (2009), the limitation therefore lies less in the formal definition of Ascom's S&OP process and more in the extent to which execution still depends on manual bridging between systems, functions and planning steps. Rather than providing a stable framework for balancing demand and supply before detailed planning decisions are made, the process relies on recurring follow-up, reconciliation and exception handling to remain operationally feasible. This moves planning work closer to operational problem-solving, reduces operational efficiency through repeated coordination and replanning, and weakens quality performance by making planning outputs less reliable and less fit for use. It also means that planners often have limited structured transparency regarding the consequences of alternative planning decisions, since trade-offs must frequently be assessed manually under time pressure rather than through systematic scenario-based evaluation.

5.1.2 Forecast Inaccuracy and Uncertainty in Demand Signals

Non-representative and judgment-intensive demand signals

The empirical findings indicate that forecast inaccuracy in Ascom's S&OP process should not primarily be understood as a narrow problem of numerical forecasting. Rather, it reflects broader uncertainty regarding which demand signals are representative, comparable and timely enough to support feasible supply decisions.

A first challenge concerns representativeness. Single project spikes, campaign-driven demand and low-frequency items make historical patterns a weak guide to future demand. As a result, planners must manually distinguish between underlying baseline demand and exceptional events before forecasts and safety stock proposals can be treated as meaningful. Forecast quality therefore depends not only on generating a forecast value but on establishing which demand should influence the planning basis, including demand and safety stock decisions. If exceptional demand is not filtered appropriately, forecasts may distort supply signals and contribute to unnecessary inventory exposure.

This also makes forecast evaluation heavily judgment-intensive. When planners repeatedly review and adjust system-generated proposals in irregular cases, forecast quality becomes partly dependent on tacit knowledge and individual experience rather than on a consistently trusted planning logic. This may improve short-term flexibility, but reduces robustness, standardization and scalability over time.

Regional inconsistency in forecast inputs

A second challenge concerns the organizational production of forecast inputs. Regional submissions vary in timing, definitions, reliability and planning logic, while some inputs are also shaped by optimistic assumptions linked to customer commitments. This

means that forecast inaccuracy is not only a data or model issue, but also appears to reflect differing functional incentives. Sales objective is to win new business and to maintain customers, while Global Supply Chain aims to have stable information at the right time to ensure material availability. This creates a structural tension where Sales teams might incorporate demand in order to protect customers and be able to promise delivery, even though the probability or timing is uncertain. In partner-driven markets, visibility into end-customer decisions is also more limited.

However, the issue is not purely structural. Findings also indicate that there is a process discipline dimension. Opportunities might progress without being updated in CRM, which further introduces a challenge where Supply cannot trust the planning. Forecast optimism should therefore be interpreted as three underlying causes, where structural incentives, inconsistent compliance to the planning routines at Sales and limited market visibility. As a result, Global Supply Chain not only receives demand data, but must also interpret how the data was produced, what it actually represents and to what extent it can be trusted. Forecasting therefore becomes a translation problem as much as a calculation problem, reducing comparability across regions and shifting the burden of alignment downstream into the global planning process. This means that responsibility for forecast quality cannot be placed only on Global Supply Chain's ability to interpret and forecast data, but mostly on how regional Sales and regional Supply govern the creation, validation and communication of demand inputs.

Regional inconsistency also appears to include differences in definitions and planning logic, as delivery dates and forecast fields may not represent the same planning meaning across regions. In addition, items discussed verbally in meetings are not always fully consistent with the forecast files later submitted to Global Supply Chain. Such inconsistency creates systematic noise in the planning process, weakens comparability and increases the need for manual follow-up and clarification.

This challenge is likely reinforced by the coexistence of different ERP environments across regions, which may shape reporting structures, master data configurations and local planning routines in different ways. Rather than being resolved where it originates, this uncertainty appears to be transferred downstream into the global planning process, where it must be absorbed through interpretation, material planning adjustments and supplier coordination.

Weak traceability and limited learning

Another recurring inefficiency is limited traceability between opportunity data in CRM and realized orders in ERP. Because forecast assumptions cannot always be linked back to specific cases, follow-up discussions become more qualitative and less evidence-based. This weakens organizational learning, since deviations cannot be clearly attributed to their source and forecasting routines therefore become harder to systematically refine over time. Perera et al. (2019) note that forecasting depends on how human interventions are embedded in organizational processes, which in this case, appears weakened by limited traceability and reduced feedback quality.

Timing mismatch between demand communication and supply requirements

Forecast inaccuracy is also affected by timing. The empirical findings indicate that supply planning often requires several months of forward visibility, and up to six months for larger projects, while some regional updates are communicated

considerably later. Under such conditions, the main problem is not only whether the forecast is numerically correct, but whether relevant demand information reaches the process early enough to support feasible supply decisions. Forecast inaccuracy should therefore also be understood as a temporal mismatch between demand communication and supply planning requirements, which increases the need for reactive replanning, additional supplier coordination and in some cases, delayed deliveries. This means that forecast quality is constrained not only by the signal itself, but by whether it enters the process early enough to be operationally useful.

Altogether, the findings suggest that forecast inaccuracy in the current S&OP process is a broader problem of representativeness, comparability, traceability and timing, rather than an isolated deviation between forecast and actual demand. It also reflects judgment-intensive translation of uncertain demand signals into feasible supply decisions. In this sense, forecast inaccuracy should be understood not only as a forecasting problem, but also as a source of instability in downstream supply planning.

5.1.3 Manual Consolidation, Excel Dependency and Rework

Manual quality control and validation burden

A central operational inefficiency in the S&OP process is the extensive manual consolidation work required before ERP upload and supplier communication. Cleansing, mapping and validating regional inputs are necessary to transform uneven data into a usable planning basis, but this creates recurring rework before the information can be used in planning.

Manual consolidation should therefore be understood as both an inefficiency and a compensatory control mechanism. It partly protects planning quality by filtering poor inputs, but it also reflects upstream variation, fragmented system support and limited standardization. Because much of this work is concentrated close to deadlines, it also increases time pressure and reduces the window for detecting and correcting errors. This further suggests that automation alone would not solve the problem unless the underlying control logic is also replaced. This is because poor-quality data might otherwise move faster through the process rather than being prevented from affecting planning outputs.

Recurring rework from structural variation

This rework is not occasional, but structurally tied to regional variation in update routines, input quality and data preparation. The concentration of consolidation work close to the deadline creates a batching effect, where issues that could have been identified and resolved gradually upstream are instead accumulated and handled in a compressed time window. This reduces the time available for validation and correction, increasing the likelihood that inconsistencies remain undetected.

Manual work in the S&OP process is not limited to cleansing and formatting. The empirical findings also show constraint-based coordination, where planners manually adjust timing and volumes across product families to satisfy supplier minimum order quantities while avoiding excessive inventory. This indicates that part of the inefficiency is embedded in the need to resolve cross-item constraints outside standard

ERP outputs, making planning dependent on planner judgment and manual balancing across multiple objectives.

Excel dependency

Another aspect of the inefficiency is the process's dependence on spreadsheets as a practical coordination tool. The empirical findings show that supplier-facing forecasts are prepared outside ERP in Excel and that regional demand files often require manual reformatting before upload. This means that Excel is not merely a supporting tool, but an operational dependency through which core parts of the planning process are executed. As a result, planning quality becomes sensitive to template deviations, manual handling errors and individual working methods, which increases rework and reduces standardization across cycles. In performance terms, this not only reduces operational efficiency through recurring rework but also weakens quality performance by increasing the risk of errors and reducing the reliability of planning outputs.

Recurring master data maintenance dependency

Planning reliability also depends on recurring daily master data maintenance, particularly lead time updates. This reveals a hidden operational dependency beneath the formal S&OP structure. This is because as part of the planning effort is absorbed by maintaining the data conditions required for reliable execution rather than by improving planning quality more proactively. More broadly, the findings suggest that manual consolidation functions as a recurring compensatory mechanism for upstream variability, fragmented system support and uneven input quality. As a result, planning quality remains dependent on human intervention through spreadsheet-based coordination, planner judgment and repeated correction rather than on standardized and system-supported data flows.

5.1.4 Summary of Current Challenges and Inefficiencies

Across the empirical findings, the main challenges in the current S&OP process are not isolated technical issues but interconnected execution problems. Low execution maturity is reflected in fragmented systems, weak cross-functional handoffs, limited process ownership across functions and recurring reactive adjustments within the planning cycle. Forecast inaccuracy is driven by non-representative demand patterns, optimistic bias, regional inconsistency, uneven demand visibility, weak traceability and timing mismatches between upstream demand communication and downstream supply requirements.

At the same time, the process is characterized by planning instability and exception-heavy execution, where disruptions, late changes and escalations repeatedly trigger replanning and manual trade-off evaluation under time pressure. This means that the process is not only challenged by inaccurate inputs but also by the limited transparency of consequences across alternative planning decisions.

In addition, the process depends heavily on manual consolidation, spreadsheet-based routines and planner judgment, not only for data cleansing and correction, but also for constraint resolution, daily maintenance of lead time data and corrective coordination across the cycle. Altogether, these findings suggest that the current S&OP process is constrained by challenges that weaken forecast accuracy and planning performance,

reduce operational efficiency through manual work, replanning and coordination, and lower quality performance by making planning outputs less reliable and less fit for use. These challenges form the baseline for evaluating how AI may and may not enhance operational efficiency and quality performance in the following sections. For illustration of the key challenges identified, see figure 6.

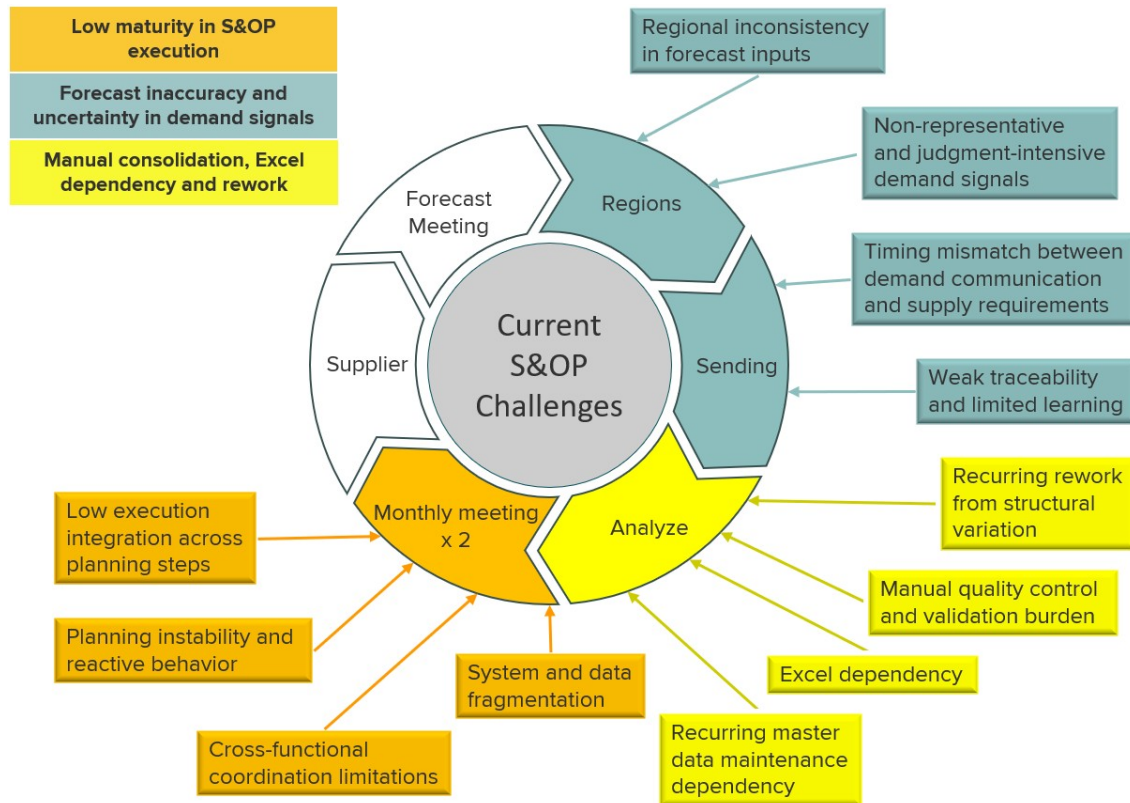


Figure 6: Main challenges identified in Ascom's current S&OP process and where they occur across the monthly planning cycle.

5.2 Addressing S&OP Challenges and Inefficiencies through AI

This section addresses the second research question by analyzing how AI tools may address the challenges identified in section 5.1 and potentially enhance operational efficiency and quality performance within the S&OP process. The analysis is structured around the main challenge areas identified in the previous section, namely low execution maturity, forecast inaccuracy and manual consolidation. This matters because readiness and openness toward AI exist at Ascom, but AI is not yet integrated into the process itself. AI should therefore not be understood as an immediate solution that automatically raises S&OP maturity. Its relevance lies instead in whether it can strengthen the specific weak points identified in the current process.

5.2.1 AI Support for Low Maturity in S&OP Execution

A central challenge identified in section 5.1.1 is that Ascom's S&OP process is formally structured, but constrained by low execution maturity in practice. In this context, the most direct contribution from the literature concerns the ability of AI to

support planning environments characterized by high information-processing requirements. Schlegel et al. (2021) argue that S&OP processes moving toward higher maturity require stronger data-processing capabilities and that big data analytics capabilities can increase the ability to process larger volumes of planning data. For Ascom, this means that AI should be understood primarily as support for strengthening execution within the existing S&OP structure, rather than as a tool that can independently move the process to a higher maturity stage.

A related inefficiency in Ascom's S&OP execution is that transparency is not consistently embedded in the planning architecture itself, but often has to be recreated through manual coordination outside the formal systems. Jackson et al. (2024) emphasize interaction and adaptation as central AI capabilities in S&OP, whereas Polo (2024) points to AI's potential to increase responsiveness, shorten planning preparation and make relevant planning information more visible across functions. In Ascom's current maturity position, this suggests that AI is particularly relevant for making planning information more visible, comparable and usable before decisions are made, especially where low maturity appears as delayed access to information, weak cross-functional transparency and slow conversion of available data into planning input.

Another relevant aspect concerns the major manual bridging currently required between planning actors, systems and process steps. De Mattos et al. (2024) argue that AI in demand planning is not only a technical matter but also involves coordination between departments, data collection and data consolidation, and that applying AI affects both roles in the process and the flow of information. This supports the view that AI may contribute where low maturity is reproduced through fragmented data preparation and weak information flow between planning steps. At the same time, the literature support is broader than the specific empirical problem. It does not explicitly demonstrate that AI resolves the exact handoff problems observed at Ascom. However, Rai et al. (2012) suggest that the value of digital support depends on whether planning-relevant information is embedded in coordinated structures rather than remaining fragmented across systems and functional handoffs.

The empirical findings also show large regional variation in how planning inputs are updated, how stable they are and how consistently upstream routines are followed. In relation to this, Jazairy et al. (2025) argue that the effectiveness of AI in S&OP depends on the structure of the process, alignment with defined routines and the ability to manage regional variation in maturity. This means that the literature treats such variation primarily as a condition influencing AI value creation rather than as a problem that AI itself resolves. For Ascom, AI may therefore support planning only to the extent that upstream routines are sufficiently aligned for AI-supported outputs to be reliable and useful.

Further, findings show that competence within individual functions is often strong, but cross-functional coordination becomes weaker when issues require shared ownership or action across departmental boundaries. Such issues are central to S&OP maturity, since Grimson and Pyke (2007), Thomé et al. (2012) and Tuomikangas and Kaipia (2014) all emphasize that mature S&OP processes involve structured interaction, defined roles, organizational ownership and aligned decision rights. However, these sources do not explicitly state that AI solves this type of maturity problem. Berente et al. (2021) are particularly important here, since they argue that AI implementation

requires governance mechanisms addressing accountability, control and human oversight. This suggests that the coordination weaknesses identified should primarily be understood as organizational. AI may support planning within such a context, but the literature does not support the conclusion that AI in itself resolves the challenge.

One potential for low S&OP maturity is reinforcement learning. Rolf et al. (2023) describe reinforcement learning as a type of machine learning based on agents, learning actions to take in a dynamic environment for decision-making to reach long-term objectives. Applied to S&OP, this suggests that planners can use it to evaluate different actions that have an effect on outcomes such as future supply and delivery. However, one identified challenge for reinforcement learning is having continuous access to reliable data (Rolf et al., 2023). Therefore, the identified inconsistency in input quality and information flows have to be addressed before adaptive AI support could be implemented reliably.

The literature indicates that AI can address selected parts of low S&OP maturity at Ascom, particularly transparency and information handling. However, it does not support the conclusion that AI solves challenges such as weak handoffs, fragmented ownership, inconsistent regional routines or issues falling through the cracks between departments. Because low maturity at Ascom is rooted not only in fragmented information handling but also in fragmented ownership, broader coordination and ownership problems remain primarily organizational rather than technical.

5.2.2 AI Support for Forecast Accuracy

One inefficiency described by respondents is that planners must continuously assess whether forecast signals from systems are representative enough to be translated into material commitments. Cannas et al. (2024) show that machine learning can detect outliers, capture patterns of changing demand and have real-time predictions, while Walter et al. (2025) emphasize that AI-supported demand planning can improve planning quality when data inputs with more relevant data are used for the process. In this context, one of the most relevant contributions of AI is not only improved prediction, but also improved classification and interpretation of uncertain demand signals. This suggests that AI could support planners in identifying when unusual demand should be treated as an isolated event rather than as a structural shift in future demand. The value therefore lies in improving how demand signals are evaluated before they are translated into material commitments.

A second relevant application concerns the interpretation of incomplete, inconsistent or delayed demand information. The findings show that forecast inputs vary across regions in timing, reliability and planning logic. Global Supply Chain must therefore interpret how the data was produced and to what extent it can be trusted. Literature on AI in S&OP suggests that AI can support decision-making by combining prediction, interaction and adaptation capabilities, enabling faster reassessment of changing conditions and more responsive evaluation of alternative planning assumptions (Jackson et al., 2024; Polo, 2024). Walter et al. (2025) further highlight that AI-based demand planning can incorporate both internal and external parameters, which is particularly relevant when historical demand alone is insufficient to explain future needs. This indicates that AI could support forecast review by integrating broader

contextual signals and enabling quicker scenario-based assessment of uncertain opportunities, regional changes and market conditions.

Empirical findings also suggest that current forecast evaluation is strongly dependent on tacit knowledge. When planners describe the need for a trained eye and frequently adjust system-generated proposals, this implies that forecast quality is partly maintained through individual experience rather than through a robust and scalable planning logic. Fildes and Goodwin (2007) argue that judgmental adjustments are often subject to bias and inconsistency, particularly when they are not systematically evaluated, while Walter et al. (2025) describe AI-based demand planning primarily as machine-supported decision support rather than as autonomous planning. From this perspective, the most relevant role of AI at Ascom is not to replace human judgment, but to provide a more structured and evidence-based basis for forecast review. This could reduce overreliance on individual interpretation, support more consistent evaluation across planners and regions and strengthen planning quality while preserving human oversight in exceptional or context-specific cases.

However, the potential of AI to improve forecast accuracy remains conditional on the quality of the surrounding planning process. The empirical findings show that weak traceability between CRM opportunities and realized ERP orders limits systematic follow-up and reduces the organization's ability to learn from forecast deviations over time. Similarly, optimistic bias and inconsistent regional routines are rooted partly in functional incentives and coordination conditions rather than in forecasting technique alone. AI may help identify inconsistent patterns, highlight deviations earlier and support more data-driven forecast evaluation, but it cannot by itself resolve weak upstream discipline, unclear planning logic or conflicting functional objectives. Neither can it create direct visibility in partner-driven markets where relevant information is structurally limited or eliminate the effects of demand signals being communicated too late to support feasible supply decisions. Accordingly, AI should be understood as a means to strengthen forecast interpretation, comparability and learning within the S&OP process, rather than as a standalone solution to forecast inaccuracy.

5.2.3 AI Support for Manual Consolidation and Rework

The empirical findings indicate that manual consolidation is one of the most tangible areas for AI support within Ascom's S&OP process. Unlike some broader maturity-related challenges, this part of the process consists largely of recurring and partly rule-based work, including extraction, cleansing, mapping, validation and reconciliation of regional inputs. Because this work reappears in each monthly cycle and is concentrated close to deadlines, it creates both information-processing overload and a narrow time window for detecting and correcting errors. This makes manual consolidation a particularly relevant area for AI-supported mitigation.

The relevance of AI in this area lies not only in reducing workload but also in supporting the transformation of fragmented and uneven data into a more usable planning basis. As shown in section 5.1.3, manual consolidation currently functions as a downstream response to upstream variation, fragmented system support and limited standardization. Schlegel et al. (2021) argue that BDAC becomes increasingly relevant where S&OP processes face high information-processing requirements, while Polo

(2024) highlights the role of AI in reducing the time between data collection and decision preparation. Planners currently need to extract, compare, validate and reconcile data from multiple sources under time pressure. Since much of the work is concentrated late in the cycle, AI could create value by reducing recurring rework and supporting earlier checking of planning inputs. By identifying deviations and unusual changes, AI could reduce manual intervention and shift planners' work from operational handling to evaluation of planning data (Cannas et al., 2024). This could improve operational efficiency through less time pressure and lower process cost, while also strengthening quality performance by reducing the risk that inconsistent or incorrect data remains undetected before planning decisions are made.

At the same time, the empirical findings suggest that manual consolidation should not be understood only as inefficient administrative work. It also functions as a compensatory quality gate, since planners currently use cleansing, reformatting and reconciliation to prevent poor-quality inputs from moving further through the process. This means that the value of AI does not lie in simply removing manual work, but in supporting the underlying control logic more systematically. Industry perspectives similarly indicate that AI in planning is most effective when used to reduce repetitive preparation work while leaving contextual assessment and exception handling to human planners (Deloitte, 2023a). From this perspective, AI is best understood as a means of strengthening and partly automating the validation layer of the consolidation process, rather than as a full replacement for human review.

However, the potential of AI to improve manual consolidation remains conditional on the quality and standardization of the surrounding process. If regional inputs continue to vary in structure, definitions and update discipline, AI may support validation and reduce workload, but it cannot by itself create standardized input quality. Similarly, AI may help planners work more efficiently across fragmented data environments. However, it does not in itself resolve underlying architectural issues such as ERP coexistence, differing master data structures or system transition-related variation across regions. It also cannot eliminate the need for contextual judgment where exceptions are frequent, planning logic is inconsistent or local interpretation remains necessary. Accordingly, AI should be understood as a means to reduce repetitive consolidation work, identify inconsistencies earlier and lower error exposure, rather than as a standalone solution that removes the need for control and review. For an overview of the AI capabilities for identified challenges and inefficiencies at Ascom, see figure 7.

	Low maturity in S&OP execution	Forecast inaccuracy and uncertainty in demand signals	Manual consolidation, Excel dependency and rework
What AI may help with	✓ Improved visibility ✓ Fragmented information ✓ Manual searching ✓ Information processing	✓ Support evidence-based forecast review ✓ Detect outliers ✓ One-time project spikes	✓ Automate extraction, cleansing and validation ✓ Detect inconsistencies ✓ Reduce rework
What AI cannot solve on its own	× Weak ownership × Unclear handoffs × Inconsistent upstream	× Conflicting functional objectives × Late demand signals × Visibility in partner-driven markets	× Structural variation × Need for human review as a quality gate

Figure 7: Potential and limitations of AI support for identified S&OP challenges and inefficiencies.

5.3 Key Success Factors for Sustainable AI Integration in S&OP

Building on sections 5.1 and 5.2, this section addresses the third research question by analyzing which factors enable successful and sustainable AI integration within Ascom's S&OP process. The empirical material indicates that attitudes toward AI at Ascom are generally positive, but that current use remains individual, exploratory and largely disconnected from the formal planning process. At the same time, no structured framework currently exists for evaluating AI's impact on process performance. This suggests that the key issue is no longer only where AI may be useful, but what conditions must be in place for such use to become sustainable over time. The analysis therefore shifts from AI potential to AI integration conditions. Drawing on the literature on organizational integration, sociotechnical change and long-term adaptation, the following section identifies the main factors that appear necessary for successful and sustainable AI integration within Ascom's S&OP process.

5.3.1 Governance and Process Alignment

Ownership and decision authority

A first enabling condition for successful and sustainable AI integration in Ascom's S&OP process is clear governance of AI use, ownership, decision authority and accountability. The earlier analysis shows that the process is formally structured, but that ownership is weaker across the total flow between functions. When issues cut across departmental boundaries, they are often handled through ad hoc coordination rather than through clearly defined end-to-end process ownership. Grimson and Pyke (2007) argue that higher S&OP maturity depends on defined ownership and governance structures rather than on technology alone, while Thomé et al. (2012) and Tuomikangas and Kaipia (2014) describe S&OP as a cross-functional coordination structure requiring clear roles, interaction mechanisms and decision rights. In relation to Ascom, this indicates that AI cannot be integrated sustainably as an isolated technical add-on. It

must be embedded in a planning process where responsibility for its use is clearly defined across functions.

The need for such governance becomes stronger because planning at Ascom still depends heavily on human judgment. Employees also tend to describe AI as a supportive tool rather than as a replacement for human planners. Walter et al. (2025) similarly describe AI in planning primarily as decision support rather than autonomous replacement, while Raisch and Krakowski (2021) show that AI integration is shaped by the tension between automation and augmentation rather than by full substitution of human judgment. For Ascom, this means that the issue is not whether AI can generate useful output, but what AI may recommend and what planners must still interpret, challenge or override.

This further raises a question of who acts on AI-supported output and where final decision authority remains. According to Berente et al. (2021), AI-supported decision-making processes depend on governance mechanisms that establish accountability, control and human oversight. For Ascom, sustainable AI integration depends on clarity regarding who defines and prioritizes relevant AI use cases in S&OP, who owns the process context in which outputs are generated and who controls their interpretation and use. It must also be clear how accountability is allocated when AI-supported insights influence planning decisions. Without such clarity, AI risks being inserted into an already fragmented coordination structure, where outputs may be generated but not consistently owned, trusted or acted upon.

Alignment between AI and the actual S&OP process design

A second enabling condition is alignment between AI and the actual operating logic of the S&OP process. The earlier analysis shows that AI is currently not integrated into S&OP. At the same time, the S&OP process still depends on repeated monthly handoffs, manual consolidation and reactive adjustments between formal process steps. This makes the issue not only whether AI is useful in principle, but whether it fits the way planning is actually carried out at Ascom.

Thomé et al. (2012) and Tuomikangas and Kaipia (2014) describe S&OP as a structured cross-functional coordination process in which planning depends on recurring interaction, defined handoffs and coordinated decision points rather than on isolated analytical tasks. In relation to Ascom, this means that AI cannot be evaluated only by whether it can support individual activities such as summarization or analysis. It needs to be accounted for whether it fits the actual coordination logic of the process through which planning is carried out. For AI to become sustainable in S&OP, its outputs must fit the actual process, including when information is needed, where it is transferred between functions and in what form it is used.

This interpretation is reinforced by de Mattos et al. (2024), who argue that AI in demand planning changes roles and information flows rather than only improving technical tasks. This is directly relevant in Ascom, where planning still relies on monthly regional submissions, central consolidation, forecast meetings, supplier-facing updates and reactive adjustments between formal process steps. AI support that does not fit these handoffs, meetings and timing structures risks remaining a separate analytical support tool rather than becoming process-integrated. Jazairy et al. (2025) further argue that AI value creation in S&OP depends on alignment with defined routines and existing

process maturity. Sustainable integration therefore depends not only on what AI can do, but on whether AI-supported outputs are generated in a form and at a time that match the real sequence of the S&OP process.

5.3.2 Data Quality and Performance Evaluation

Data quality and traceability

A third enabling condition is that the planning process must generate a reliable and trusted information base for AI-supported analysis and decision support. Poor data quality has both visible and hidden performance consequences (Haug et al., 2011). This is particularly relevant in Ascom's S&OP process, where planning data is spread across several systems and often requires manual correction and reconciliation before it becomes usable. Lost opportunity IDs, limited traceability between forecast inputs and realized orders, inconsistent use of delivery dates and system coexistence indicate that the main issue is not data volume. The problem instead lies in data coherence and interpretability across planning stages.

Walter et al. (2025) argue that the effectiveness of AI in demand planning depends on the relevance, availability and integration of data inputs. Similarly, Rai et al. (2012) show that digital capabilities need to be complemented by integration mechanisms and reinforced with communication to create value. This means that AI cannot be expected to generate planning support if the underlying information is fragmented across systems. If it is also inconsistently interpreted across regions and manually reworked before each cycle, AI instead risks reproducing rather than reducing inconsistencies.

The findings show that problems with data quality occur throughout the process, as inputs vary in timing, consistency issues and mismatches between what is said verbally and what is submitted. Grimson and Pyke (2007) argue that reaching higher levels of S&OP maturity is dependent on having standardized, integrated process execution rather than only information technology. Thomé et al. (2012) and Tuomikangas and Kaipia (2014) similarly emphasize that having effective S&OP processes relies on cross-functional planning structures that are aligned, interactions that are defined and coordinated routines. Jazairy et al. (2025) further argue that routines and existing processes have to be aligned in order to benefit from the value creation AI brings to S&OP. In relation to Ascom, this suggests that AI may support interpretation, data processing and exception handling but is not compensating for unstable upstream routines. If demand signals are not standardized, AI-supported outputs are unlikely to be trusted or used as decision support. Sufficient data quality, traceability and upstream process discipline should therefore be understood as necessary to integrate AI sustainably.

Performance evaluation tied to S&OP outcomes

A fourth enabling condition is that AI use must be evaluated in relation to relevant S&OP outcomes. Grimson and Pyke (2007) identify performance measurement as one factor influencing the maturity of planning processes. Similarly, Thomé et al. (2012) describe structured performance measurement as part of integrated S&OP design. Neely et al. (1997) further argue that performance measures should align with the organization's broader goals, since narrow measures may result in sub-optimization. This means that AI usefulness should not be evaluated only in subjective terms of

individual test users or time saving on individual tasks. Instead, assessing AI should be in relation to planning-relevant outcomes such as forecast accuracy, planning reliability and operational efficiency.

This is reinforced by Fildes and Goodwin (2007), who show that forecasting changes are often implemented without evaluating their broader effect on forecast quality. If AI-supported analyses or forecasting inputs influence planning decisions, then the organization must also evaluate whether this improves the quality and reliability of the planning process or only how work is performed. Without evaluation tied to the S&OP process, it becomes difficult to distinguish between process improvements with actual benefits or a shift in perceived benefits.

Formal performance evaluation also matters for organizational learning and has long-term effects. If relevant indicators are assessed, the organization can better determine where value creation with AI is most useful, under which conditions this applies and with what limitations. This is especially important because current AI use is largely separated from the formal S&OP process and remains based on individual exploration. Sustainable integration therefore depends on moving toward more structured process support.

5.3.3 Implementation Capability, Trust and Long-Term Adaptation

Implementation capability and structured experimentation

A fifth enabling condition is organizational implementation capability, supported by appropriate support structures and structured experimentation. One respondent also explicitly states that the organization currently lacks the internal structure and competence required for more advanced AI-driven planning tools. Ascom has a starting point for AI-related learning, but it remains weakly connected to formal process development within the S&OP process.

De Mattos et al. (2024) argue that AI in demand planning depends not only on technical feasibility, but also on coordination, change management and data preparation. Jazairy et al. (2025) similarly highlight incremental introduction phases, pilot projects and specialized expertise, while also showing that AI value creation in S&OP depends on alignment with existing routines and process maturity. This means that sustainable AI integration requires more than access to AI tools and a general interest in experimentation. It also requires the ability to identify relevant use cases in relation to concrete planning needs, test them in a structured way and support implementation beyond isolated user initiative.

The empirical findings also show that current AI use remains assistive, while the S&OP process itself is still characterized by fragmented execution, manual consolidation and strong dependence on human judgment. This is consistent with Grimson and Pyke (2007), who argue that technology alone does not raise S&OP maturity unless it is supported by stronger organizational structures and more integrated process execution. It is also consistent with Rai et al. (2012), who show that value from digital technologies depends on how they are embedded in coordination structures and communication processes rather than introduced as isolated tools. For Ascom, this means that motivated

users and pilot activity are not sufficient to enable sustainable integration if experimentation remains detached from cross-functional process development.

The empirical findings further indicate that learning in the pilot currently takes place mainly through discussion and exchange of examples rather than through a more structured implementation logic. Industry literature similarly shows that many organizations struggle to scale AI beyond pilot use when organizational readiness, support capacity and implementation structures remain limited (McKinsey & Company, 2025). For Ascom, this suggests that the main limitation is not lack of interest, but limited capability to translate exploratory use into structured process integration.

Given the current process maturity at Ascom, this points more clearly toward the gradual development of AI-supported decision support than toward highly autonomous planning solutions. In this sense, the current pilot activity demonstrates exploratory readiness, but not yet the implementation capability required for sustainable process integration.

Trust, legitimacy and user adoption

A sixth enabling condition is that AI-supported outputs are perceived as credible, understandable and relevant enough to be acted upon in actual planning work. The empirical findings show that employees at Ascom generally express positive attitudes toward AI and view it as useful for summarization and other support tasks. At the same time, AI is not yet used in core planning routines such as forecasting, supply forecasting or formal consolidation work. This indicates that current acceptance is positive in principle, but still limited in process terms, since AI has not yet become embedded in the planning activities where decisions are made.

Weiner (2009) describes organizational readiness for change as depending on organizational members' commitment to the change and their belief that they are capable of implementing it under actual task conditions. This means that a positive attitude toward AI is a relevant starting point, but not sufficient for sustained use in S&OP. For AI to move beyond exploratory use, planners must also perceive its use as workable and appropriate in the judgment-intensive planning context.

This interpretation is supported by Hasija and Esper (2022), who show that AI acceptance in organizational settings depends on whether AI is perceived as trustworthy, credible and appropriate for decision-making, not only as generally useful. Their findings also indicate that trustworthiness and legitimacy are shaped through organizational context and practical use. For Ascom, this is relevant because current AI use remains largely assistive, while the S&OP process still depends heavily on human judgment in situations involving uncertainty, manual adjustments and exception handling. Under such conditions, sustainable integration depends on whether planners come to regard AI-supported outputs as trustworthy and legitimate within actual planning decisions. Walter et al. (2025) similarly describe AI in demand planning primarily as decision support rather than autonomous planning, highlighting that AI-based planning depends on human trust and action.

Long-term adaptability and reconfiguration capability

A seventh enabling condition is long-term adaptability and reconfiguration capability. The empirical findings show that Ascom's planning environment is characterized by ERP transition, regional variation, recurring disruptions, exception-heavy execution and shifting business conditions. The earlier analysis also shows that planning work is repeatedly affected by supply-side volatility, unstable inputs and reactive adjustments across the cycle. This indicates that the context in which AI would be integrated is not stable, but continuously evolving. Under such conditions, sustainable integration cannot be understood as a one-time implementation of a fixed AI solution.

This is consistent with Teece et al. (1997) and Teece (2007), who argue that sustained adaptation depends on the organization's ability to sense changes in its environment, seize relevant opportunities and reconfigure competencies and routines over time. In relation to Ascom, this means that sustainable AI integration depends not only on whether a given AI application is useful under current conditions, but also on whether the organization can revise its use as planning needs, system conditions and process maturity evolve. If AI use is designed too narrowly around a specific version of the process, it risks losing relevance as the surrounding planning environment changes.

This is also consistent with Jackson et al. (2024) and Polo (2024), who describe adaptation and responsiveness as central features of AI-supported planning environments. Their work suggests that the value of AI in planning is linked to the ability to respond to changing conditions, reassess inputs and support more responsive decision-making. For Ascom, this is particularly relevant because the S&OP process still depends on manual consolidation, frequent replanning and adjustment to changing demand and supply conditions. Sustainable AI integration therefore depends on whether AI use can evolve together with these process conditions rather than remain tied to a fixed planning structure.

For Ascom, this means that sustainable AI integration is not only a matter of introducing AI into the current process. It is also about maintaining the ability to revise use cases, adjust routines and adjust the appropriate level of AI support over time. As process maturity, governance structures and data conditions develop, the form of AI support that is appropriate may also change. A use case that is relevant under the current process design may therefore need to be redesigned, expanded or reduced as the planning environment changes. Otherwise, even a well-designed initial solution may become misaligned with the process it was intended to support.

5.3.4 Summary of Factors and Enabling Conditions

Across the analysis, the main enabling factors for sustainable AI integration in Ascom's S&OP process are not limited to technology, but consist of interrelated organizational and process conditions. Governance and process alignment are required to make sure that AI use is owned, controlled and adapted to the actual coordination logic of the S&OP process. Data quality, traceability, upstream process discipline and formal performance evaluation are necessary to make sure that AI-supported outputs are based on sufficiently reliable inputs and can be assessed in relation to relevant planning outcomes.

At the same time, sustainable integration depends on the organization's broader implementation capability, including support structures, structured experimentation and the ability to move beyond individual and exploratory AI use. It also depends on whether AI-supported outputs become credible and legitimate enough to be acted upon in actual planning work. In addition, sustainable integration requires long-term adaptability, since the planning environment is dynamic and AI use must remain relevant as process conditions, system contexts and planning needs evolve.

Altogether, these findings show that sustainable AI integration within S&OP depends not on a single success factor, but on seven main enabling conditions identified in this study. This includes governance, process alignment, data foundations, evaluation capability, implementation support, trust and legitimacy, and adaptive capacity. The analysis further suggests that these conditions are not equally foundational. Governance and process alignment, together with sufficient data quality, traceability and upstream process discipline, emerge as the most foundational conditions for credible AI integration at Ascom. Formal performance evaluation also appears to require early establishment. By contrast, implementation capability, user trust and long-term adaptability remain necessary, but are more realistically strengthened during the implementation process. For an illustration of these enabling conditions in Ascom's S&OP process, see figure 8.

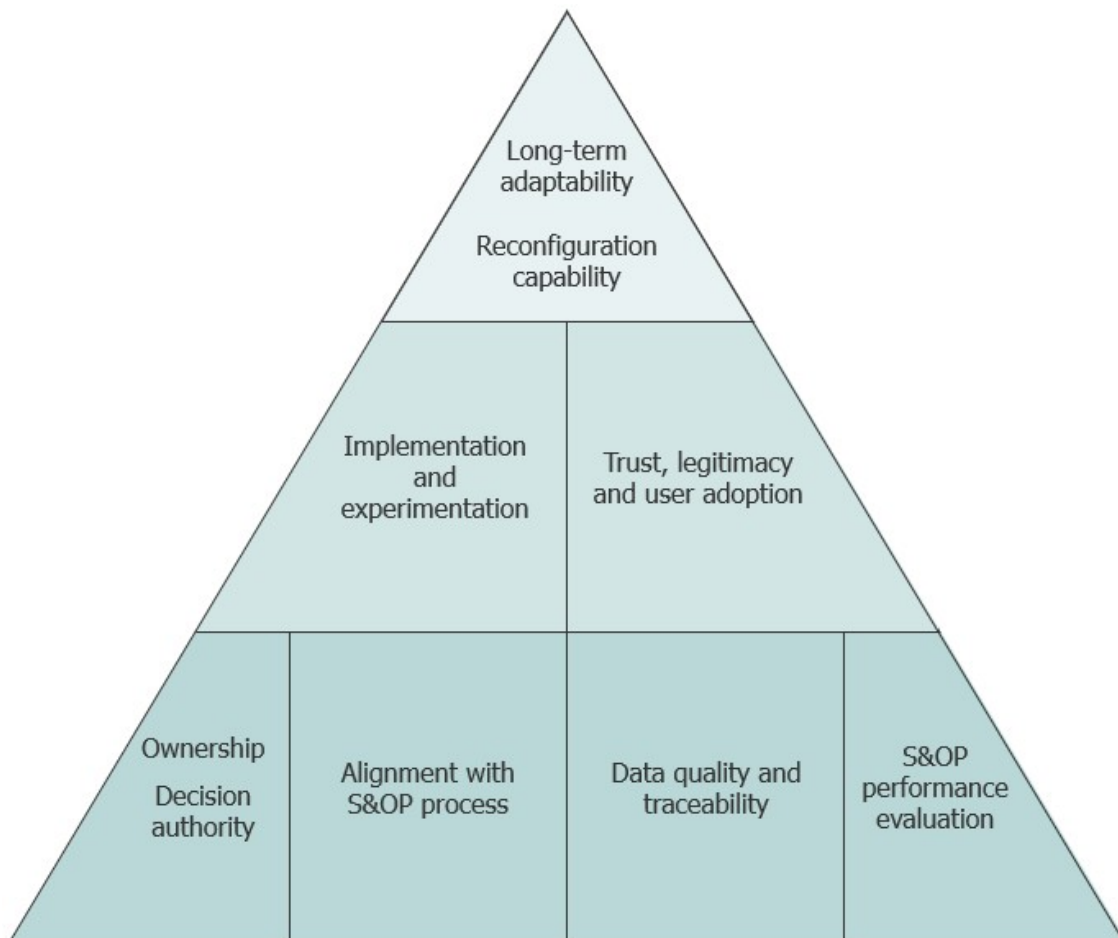


Figure 8: Key factors for successful and sustainable AI integration in Ascom's S&OP process.

6. Discussion and Recommendations

This chapter discusses the implications of the analysis and presents recommendations for how AI can be integrated into Ascom's S&OP process in a realistic and process-relevant way. It first discusses the role of AI in relation to Ascom's planning context, literature and similar organizations. It then presents recommendations for Ascom, followed by suggestions for future research and limitations of the study.

6.1 Discussion

The discussion interprets the role AI can realistically play in Ascom's current planning environment and reflects on what the case reveals about AI integration in S&OP more broadly. It also relates the findings to existing literature and benchmarking, before discussing their relevance beyond the case in similar planning contexts.

6.1.1 Implications of Ascom's S&OP Context for AI Integration

A broader implication of the Ascom case is that AI integration in S&OP depends on both the availability and credibility of the information used by AI. In some cases, the main issue may be data availability, meaning that relevant information exists but is not sufficiently connected, accessible or structured for AI-supported analysis. In other cases, the issue may be data credibility, meaning that information is available but cannot be fully trusted as a basis for planning decisions. These situations require different responses. Limited availability points toward better information sharing, system integration and access to relevant data sources. Limited credibility, in contrast, points toward stronger routines, validation and follow-up of the information entering the process.

The case also illustrates an important distinction between having data available and having data that is useful for decisions. Ascom has large amounts of planning-related information across its systems, but the empirical findings indicate that information is not always easy to interpret, compare or trust. This creates uncertainty not only in the internal planning process, but also in the next steps of the supply chain, since supplier-facing forecasts are partly built on the information Ascom is able to provide. If the input to the S&OP process is uncertain, this uncertainty may be transferred further upstream to suppliers and affect their own planning assumptions. AI may support this situation by identifying patterns, detecting unusual inputs and improving validation over time, but credible AI output still depends on the quality and credibility of the information used as input.

AI may function not only as an analytical tool, but also as a validation layer that gradually improves data credibility by detecting recurring inconsistencies, unusual patterns and inputs that deviate from established planning logic. However, AI cannot be assumed to create process integration on its own. If surrounding process conditions remain weak, faster information processing may reinforce poor inputs rather than improve planning quality. Useful AI integration therefore depends on process fit and practical decision relevance rather than technological capability alone.

6.1.2 AI Potential in Relation to S&OP Maturity

The role of AI must be understood in relation to the current maturity of the process. Rather than indicating that AI is irrelevant, the case suggests that AI value is likely to be strongest where it improves the usability, comparability and visibility of planning information within the existing process. The challenge is therefore not only to identify promising use cases, but to translate scattered individual experimentation into an organizational capability supported by shared routines, governance, learning and follow-up.

This also challenges the conclusion that AI can support low execution maturity. AI may contribute to higher planning maturity if it is used to make deviations visible, strengthen validation, improve traceability and support more transparent cross-functional decision-making. However, AI may also mask maturity problems if it is mainly used to compensate for weak upstream routines without changing the behavior that creates poor input quality. For example, an AI tool may clean, classify or flag problematic inputs. However, this does not automatically improve regional discipline, process ownership or the understanding of how upstream information affects downstream planning. In that sense, AI can make the current process more efficient without necessarily making it more mature. This distinction is important because AI may improve individual work efficiency without improving the reliability, transparency or quality of the planning output itself.

The distinction between using AI to handle symptoms and using AI to improve the process is therefore central. If AI is used only to reduce repetitive work or correct weak inputs late in the cycle, the process may become more efficient in terms of workload without improving the underlying planning logic. A more process-oriented use of AI would instead aim to identify where errors repeatedly occur, why certain inputs become unreliable and how deviations can be detected earlier in the cycle. This would shift AI use from reactive correction toward proactive process improvement. In this interpretation, AI should not only support the current S&OP process but also help the organization learn where the process itself needs to develop.

Taken together, sustainable AI integration is not mainly a question of introducing a capable tool, but of ensuring that AI-supported outputs can be governed, interpreted, evaluated and trusted within the process.

6.1.3 The Realistic Role of AI in Ascom's S&OP Process

More autonomous AI applications may become relevant over time, but introducing autonomous planning support before the process has developed further would risk automating existing weaknesses. This is particularly important in situations involving project spikes, uncertain customer commitments, supplier constraints or late changes, where the meaning of a demand signal is not always evident from the data itself. AI may reduce dependence on individual planners by providing clearer inputs, validation support and more structured analyses, but it cannot remove the need for experienced interpretation.

The implementation of AI therefore involves important trade-offs. While AI may reduce manual work, it also creates a greater need for guidance, oversight and

appropriate use. Although AI may increase standardization, it may also fail to capture the context of irregular planning situations. If AI outputs are treated as more reliable than the underlying inputs allow, the process may gain confidence without gaining accuracy. Transparency around both input quality and AI-supported reasoning is therefore necessary to avoid a false sense of certainty.

6.1.4 Relevance Beyond the Case in Similar Planning Contexts

The findings of this study are unlikely to be equally relevant across all organizations. Their relevance appears strongest in planning contexts similar to that of Ascom. In this study, Ascom is understood as a medium-sized global company with a centralized global supply chain function, operating in a context where reliability and quality are particularly important. Its S&OP process is further characterized by cross-regional coordination, supplier dependence and early-stage exploratory AI use. In such contexts, the challenges identified in this study are unlikely to be unique to the case company. The combination of fragmented information flows, manual consolidation, judgment-intensive forecast review and the need to make planning outputs sufficiently usable for coordinated decision-making is likely to be relevant also in other organizations operating under similar planning conditions.

From this perspective, the conclusions in section 5.2 also appear relevant beyond Ascom in planning environments characterized by manual review burdens, weak traceability, uneven information quality and recurring coordination across functions. Under such conditions, AI is likely to be most useful where it strengthens validation, traceability, comparison and structured decision support, rather than where the underlying challenge is primarily one of organizational ownership or upstream process discipline.

At the same time, the findings in section 5.3 suggest that the successful and sustainable realization of such AI support depends on a set of enabling conditions. These should not be viewed as a generic checklist for all organizations, but rather as conditions that appear particularly relevant in planning environments of this kind. Governance, process alignment, data quality, traceability, implementation capability, trust and long-term adaptability become important not because they are unique to Ascom. Rather, they matter because AI in this type of S&OP context depends on whether outputs can be embedded into an existing cross-functional planning process and acted upon in a credible way.

In relation to this, the relevance of these findings is likely to be lower in organizations with substantially different planning conditions, such as highly mature and fully integrated planning environments. The relevance may also be lower in very small and locally bounded supply chains, or in contexts where S&OP is less dependent on supplier-facing coordination and cross-regional information flows. In such settings, both the practical role of AI and the relative importance of the identified enabling factors may differ. The contribution of this study should therefore be understood as analytically transferable to similar planning contexts rather than as equally applicable across all firms.

6.2 Recommendations for Ascom

The recommendations are structured according to the logic of the analysis and Ascom's current planning conditions. The section first addresses the prerequisites required to make AI-supported outputs usable in the S&OP process, then presents the most relevant AI-supported use cases, and finally clarifies implementation conditions and limitations. The purpose is not to propose broad AI adoption from the outset, but rather to outline a realistic path for how AI can support operational efficiency and quality performance within Ascom's current context.

6.2.1 Prerequisites for AI-Supported S&OP Improvement

Before introducing broader AI-supported use cases, Ascom should first strengthen the key conditions for credible AI integration in the current S&OP process. The most immediate priorities are clearer ownership and process alignment, together with a shared planning information foundation supported by sufficient data quality and traceability.

A first recommendation is therefore to establish clearer ownership and process alignment for AI-supported outputs within the monthly S&OP cycle. For AI-supported use cases to create practical value, it must be clear where in the process the output is used, who reviews it, who acts on it and where final decision responsibility remains. Without such clarity, there is a risk that AI support becomes a parallel analytical layer beside the process rather than an integrated part of it. Clear ownership and process alignment are therefore necessary both for creating value in practice and for avoiding stagnation in the implementation effort.

A second recommendation is to establish a shared planning information foundation across the most critical process steps. This should give the process a more unified source of truth instead of relying on fragmented information across separate systems and functions. In Ascom's context, this should be understood as a foundational condition rather than a large standalone solution. The purpose is to connect relevant planning data across CRM, CPQ, ERP, forecast files and other relevant sources into a more consistent and comparable information basis for the process. This would reduce information gaps across the process and provide a more reliable data foundation for later AI-supported use cases. Without such a shared foundation, AI-supported outputs risk remaining constrained by the same fragmented searching, matching and clarification work that currently limits the process. The objective should not be perfect data or full process maturity before progress can begin. Rather, the objective should be a level of structure, consistency and traceability that is sufficient for the intended use case.

Formal performance evaluation should be established early as a supporting condition rather than the primary starting point. As AI is introduced into selected S&OP activities, its effects should be followed through planning-relevant dimensions such as operational efficiency, quality performance and forecast accuracy. More specific indicators can then be used to assess whether the process is improving in practice. These may include reduced manual rework, stronger traceability, earlier detection of inconsistencies and improved usability of planning inputs. This creates a basis for evaluating whether AI-

supported outputs contribute to meaningful S&OP improvement rather than only appearing useful at the individual user level.

6.2.2 Recommended AI-Supported Use Cases

After introducing the prerequisites, the most useful applications are likely to involve AI agents that support specific planning activities within the S&OP process. The use cases are presented in an order that reflects increasing complexity and implementation maturity. Input validation is the most immediate starting point, as it addresses recurring and partly rule-based work in each cycle. Forecast review support remains close to the operational process but requires more contextual interpretation. Forecast learning depends on repeated cycle data and is mainly relevant for follow-up and governance, while scenario planning and feasibility support have the broadest scope and are therefore more suitable as a later step.

All use cases should be positioned as decision-supportive, augmenting existing capability in the process. The final decision remains at human judgment and the established roles and forums within the S&OP process. The purpose of the AI-supported use cases is to improve the quality, structure and availability of planning information before decisions are made.

Input Validation Agent

A first recommended use case is an input validation agent. This use case should strengthen the validation layer before forecast review and ERP upload by helping users identify input issues before they create rework later in the process. It would be used before the regional submission and again in the central pre-consolidation phase. Its primary users would be regional forecast owners and the responsible Material Planning Specialists in Global Supply Chain.

In practice, the agent could check forecast files against the previous cycle, template rules and required fields. It could flag major volume or date changes, missing fields, template deviations and other inputs that require manual follow-up. It could also assign severity levels so that critical issues can be separated from lower-priority warnings.

The regional forecast owner could use the output to correct the file before submission, while Global Material Planning could use it to assess whether the input is usable enough to proceed to formal review. The main value lies in fewer late corrections, less manual checking and more consistent inputs earlier in the process. This is expected to support operational efficiency by reducing recurring validation work and quality performance by improving the reliability and fitness for use of planning inputs.

Forecast Review Assistant

A second use case is a forecast review assistant. This use case should support the monthly forecast review by helping planners identify products that require attention and suggested forecast changes to assess. It would be used after regional submission and central consolidation, and before or during the demand meeting. Its primary users would be the responsible Material Planning Specialists in Global Supply Chain, while Head of Material Planning would be involved in larger uncertain cases or major projects.

In practice, the assistant could compare qualitative forecast input with AI-supported quantitative forecast logic. It could flag major changes between planning cycles, trend shifts, seasonal patterns, recurring orders and discontinued or non-representative spikes. It could also help distinguish baseline demand from project-driven or event-driven demand and highlight products where the forecast may need to be adjusted.

The responsible planner could use the output to request clarification, revise the interpretation of the demand signal or escalate selected cases for further discussion. The main value lies in creating a more structured and consistent basis for monthly forecast review decisions, reducing dependence on planner-specific judgment and improving the identification of exceptions, trends and non-representative demand patterns. This is expected to support forecast accuracy, operational efficiency and quality performance by improving the usability and consistency of forecast review outputs.

Forecast Learning Agent

A third use case is a forecast learning agent. This use case should support learning, follow-up and governance between planning cycles rather than the operational review of the current forecast. It would be used after each completed cycle in post-cycle review, monthly follow-up and performance evaluation. Its primary users would be Head of Material Planning, Head of Logistics and relevant process owners responsible for follow-up, improvement and governance.

In practice, the agent could identify recurring forecast deviations, root causes and regional patterns over time. It could classify deviations such as optimistic bias, late updates, missing activation, wrong delivery date logic and spike misclassification. It could also build traceability between forecast assumptions, opportunities, projects, orders and realized demand outcomes across cycles.

Process owners and managers could use the output to adjust routines, tighten definitions, follow up on regions, revise KPI logic and prioritize data quality improvements. The main value lies in stronger traceability, better KPI follow-up and more evidence-based process improvement over time. This is expected to support quality performance by improving follow-up reliability, while also supporting forecast accuracy and planning performance through more systematic learning from recurring deviations.

Scenario Planning and Feasibility Agent

A fourth use case is a scenario planning and feasibility agent. This use case should support larger uncertain cases, major projects, disruptions or other situations where alternative outcomes need to be evaluated before the process becomes reactive. It should not be used for every forecast line, but for larger cases where uncertainty, timing or constraints make alternative outcomes important to assess. Its primary users would be the responsible Material Planners and Head of Material Planning, with management and Sourcing involved when needed.

In practice, the agent could create a limited number of scenario views, such as conservative, most likely and upside risk. It could show the assumptions behind each scenario, run sensitivity checks, indicate a simple confidence level and assess feasibility against lead times, time fences and basic constraints such as capacity limits and

minimum order requirements. It could also make timing risks and constraint-related consequences more visible before decisions are escalated.

The responsible planner could use the output to initiate earlier follow-up, adjust assumptions, escalate to the right forum or prepare alternatives for supplier dialogue and internal prioritization. The main value lies in clearer assumptions, earlier escalation and better decision support under uncertainty. This is expected to support planning performance by improving preparedness for alternative outcomes, while also contributing to operational efficiency and quality performance by reducing reactive handling and improving fitness for use of planning assessments in larger uncertain cases. This is particularly relevant in Ascom's context, where late or weak signals can create timing mismatches and constraint-based judgment under time pressure.

6.2.3 Implementation Conditions and Limitations of the Recommendations

A further condition is that some of the enabling factors identified earlier should not be understood as prerequisites that must be fully in place before implementation can begin. In Ascom's context, implementation capability, user trust and long-term adaptability are more realistically strengthened during the implementation process itself. The proposed use cases should therefore be introduced in a way that allows the organization to learn from actual use and adjust the support over time.

A first condition during implementation is therefore the gradual development of implementation capability around the selected use cases. This requires a practical ability to test them in the actual planning flow, identify where outputs create value and adjust the setup when the support does not fit the task, timing or user need. A second condition is user trust. AI-supported outputs must become sufficiently understandable, credible and useful for planners and managers to rely on them in actual planning situations. A third condition is long-term adaptability. As process routines, system conditions and planning needs evolve, the design and scope of the proposed use cases must also be revised when needed. Without these conditions being strengthened during implementation, the recommendations risk remaining technically relevant but practically underused or misaligned with the process.

These recommendations should not be interpreted as suggesting that AI can resolve all weaknesses in the S&OP process. Several identified challenges are organizational in nature, although AI may support parts of them. For this reason, the recommendations should be understood as support for better planning execution rather than as a substitute for broader process and organizational development. Their value lies in improving the usability, timing and interpretability of planning-relevant information within the existing process.

6.3 Future Research

The literature on how AI can be applied in S&OP processes remains limited. This study contributes by providing insights into challenges and inefficiencies identified in a real S&OP context and by relating these to AI capabilities that could potentially support the

process. Future research could therefore focus on the implementation of such capabilities in practice, in order to examine how AI may enhance operational performance after being implemented. Further studies could also investigate to what extent process discipline, governance structures and system integration influence the value and effectiveness of AI-supported S&OP.

In addition, future research could explore how trust and legitimacy around AI-supported planning outputs develop over time. Identified factors for successful integration depend on more than technical capability, it is also based on how outputs are perceived as credible, relevant and usable in practice.

Further, the supplier perspective and the broader interorganizational supply chain deserve further attention. Future studies could examine how suppliers interpret and use forecasts generated through the focal company's S&OP process, as well as how greater interorganizational transparency and information sharing may affect coordination, quality performance and operational efficiency.

Beyond the direct supplier relationship, future research could also investigate AI-supported end-to-end supply chain visibility. This could include shared information from material suppliers, transport providers, manufacturers, focal companies and customers. Such research could examine whether AI-supported coordination across organizational boundaries can create more coherent planning flows, reduce sub-optimization and strengthen collaboration between supply chain actors.

Future studies could also explore the sustainability implications of such integration. This includes economic, environmental and social sustainability. Potential effects could include improved resource efficiency, reduced unnecessary transport or inventory, greater transparency and stronger mutual understanding between actors. At the same time, future research should address the practical challenges of interorganizational AI integration. These include data ownership, confidentiality, system compatibility, governance, trust, responsibility and the willingness of independent organizations to share operationally sensitive information.

6.4 Limitations of the Study

One limitation of the study is that the sales side of the S&OP process was represented by one manager from the sales department. While this interview provided a relevant overview of how Sales contributes, it mainly reflects one central managerial perspective. The study therefore does not capture possible differences between regional sales teams, frontline sales roles or local sales practices to the same extent as it captures the supply-side perspective. In addition, other functions commonly associated with S&OP, such as Marketing and Finance, were not included in the empirical material. Because the study was empirically focused on Global Supply Chain, the potential for AI to support Sales activities, decision-making and upstream demand input generation was therefore not explored in the same depth.

While the study is based on 12 interviews, it is acknowledged that Ascom is a global organization and the sample does not fully represent all regions and functions. The majority of respondents are from Global Supply Chain, which may introduce a

functional bias, particularly regarding perspectives on sales and regional practices. However, the selected participants hold central roles in the S&OP process and provide cross-functional insights, supporting the analytical relevance of the findings despite limited geographical representation.

Another limitation of the study is that no suppliers were included in the interviews. Although supplier-related planning challenges, forecast communication and coordination issues are discussed in the empirical material, these findings are based only on internal perspectives from Ascom. This means that the study does not capture how the quality of the forecast signals are perceived by the suppliers, the usefulness of the planning information or the challenges in responding to changes. Like Global Supply in relation to the Sales side, suppliers may likewise need to interpret the forecast signals themselves or choose not to rely on them at all.

Another limitation of the study is that AI, particularly in relation to S&OP, remains a field that is new and rapidly growing in both academic research and practice. This means that the available literature is still evolving, while organizational applications, much like exploration at Ascom, are at an early stage of maturity. This was also reflected in the interviews, where respondents' experiences of AI were in many cases exploratory and limited rather than based on long-term operational use. As a result, parts of the empirical material may reflect expectations and early interpretations of AI's potential rather than established practices and evaluated outcomes. This supports the exploratory design of the study, which aimed to identify realistic opportunities and enabling conditions for AI integration.

7. Conclusions

RQ1: What are the main current challenges and inefficiencies within Sales and Operations Planning?

Regarding the first research question, several challenges and inefficiencies were identified in the S&OP process. These were grouped into three connected themes of low execution maturity, forecast uncertainty and manual consolidation. Low execution maturity refers to an existing structure and monthly cadence in the S&OP process but an unstable execution with inconsistent information flows and fragmented cross-functional coordination. Forecast uncertainty stems from inconsistencies in regional routines, project spikes and irregular demand patterns, which weaken the reliability of planning inputs and make it difficult to distinguish representative demand from exception signals. Manual consolidation functions as a compensatory mechanism for weak data flows and uneven input quality. This increases rework and exception handling, reduces operational efficiency and weakens quality through less reliable planning inputs. Taken together, these themes reinforce each other and lead to reactive, exception-heavy execution, replanning and planning instability, which limits transparency regarding the consequences of alternative planning decisions.

RQ2: How can AI tools be applied to address these challenges and potentially enhance operational efficiency and quality performance within Sales and Operations Planning?

Regarding the second research question, the findings show that AI may support several parts of the S&OP process, while some challenges remain organizational at their core. For low execution maturity, AI may support better information processing, transparency and responsiveness through BDAC and reduced time between data collection and decision preparation. Regarding forecast inaccuracy, AI may identify outliers, distinguish baseline demand from project spikes, highlight non-representative historical data and detect inconsistent patterns. For manual consolidation, AI could support cleansing, mapping and validation of information.

However, some of the root causes of identified challenges remain organizational rather than technical and can therefore not be solved using AI alone. These include weak process ownership, unclear handoffs, inconsistent regional routines, weak market visibility, conflicting functional incentives and optimistic bias in demand inputs.

RQ3: What key factors enable the successful and sustainable integration of AI within Sales and Operations Planning?

To enable successful and sustainable integration of AI, the central issue is not the availability of AI tools, but whether the S&OP process is sufficiently aligned to make such tools usable in practice. To define the enabling conditions for successful and sustainable AI integration, seven factors were identified. These are governance, process alignment, data quality, performance evaluation, implementation capability, trust and long-term adaptation. AI tools need to be embedded into existing planning routines and decision points, so they align with how work is actually performed in the S&OP process rather than becoming separate analytical tools. Strong data discipline and data quality are also necessary, since fragmented or inconsistent inputs limit the reliability and value

of AI-supported outputs. Accountability and ownership are also needed to clarify how AI outputs are interpreted and acted upon, while performance measurement is required to evaluate AI's effectiveness. Sustainable integration therefore requires a gradual implementation approach, where AI is introduced through targeted use cases, tested in practice, trusted by users and continuously adapted to changing planning conditions.

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Appendices

Appendix A - Semi-Structured Interview Guide

Hello, we are Andreas and Martinus, master's students in Supply Chain Management at Chalmers and we are conducting our thesis here at Ascom. The aim of our study is to examine how AI can enhance operational efficiency and quality performance in the sales and operations planning (S&OP) process. Along with that we are looking at how this can be achieved sustainably.

In this interview we are mainly touching three themes:

- How the S&OP process is organized and how you contribute to it
- What and where are the current challenges in the S&OP process
- Your insights on AI being used in the S&OP process and in your day-to-day work

The discussions today are anonymous and the data that is collected is stored in-house at Ascom's systems.

Is it okay that we record and transcribe this interview?

It's fully optional and you can stop the recording or delete any statement.

Can we use your answers and cite anonymously in the report for our Master thesis?

That's the background to this interview, do you have any questions before we start?

Introductory, current S&OP process and challenges

- What is your role in the organization and what does your typical workday look like?
- Which parts of the S&OP cycle do you actively contribute to?
- How long have you been working with S&OP at Ascom?
- Can you briefly describe how the S&OP process currently works from start to finish?
- Which functions are involved in S&OP and who is responsible for each part?
- Which inputs are used in the S&OP process? For example inventory, forecast, etc.
- What outputs does the S&OP process produce and how are they used afterward?
- What are the main challenges you experience in the current S&OP process
- Which parts of S&OP consume the most time?
- Are there any other parts of the process that you or other coworkers find frustrating?
- What is the most problematic part for forecast inaccuracy?
 - How does this impact the supply and demand planning?
- Where do you see the biggest gaps or uncertainties in the information used for S&OP decisions?
- How much effort is put into collecting the data for S&OP?

- Does this data have to be revised in any way, for example be cleaned and consolidated?
- How are risks and uncertainties discussed and handled within S&OP?
- How transparent are the consequences of different S&OP scenarios today?
- What tools are currently used to support the S&OP process?

Use of digital tools and AI in S&OP today

- Are you part of the Copilot pilot group?
- How do you view AI?
- How do you use AI in your work?
 - In S&OP?
 - In day-to-day tasks?
 - Do you find it helpful?
- Do you see any potential use cases for AI in your work?
- Are any AI-based or advanced analytical tools used today within S&OP?
- Where do you see limitations in today's digital support for S&OP?
- Do you see any challenges or concerns with introducing AI more into the S&OP process?

Preparedness for AI

- How prepared do you feel your department is for AI?
 - Processes
 - Systems
 - People
 - Any potential knowledge gaps?
- If you introduced AI in S&OP, how would you approach it, what would be your first steps and which would be most important?
- Have you had any experiences with similar changes before?

Closing questions

- If you could change one thing in the current S&OP process, what would it be and why?
- Is there anything important about the S&OP process or AI that we have not discussed but should have?
- Is it possible for us to send extra questions afterwards?



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