



Improving Operational Efficiency and Performance in Large-Scale Brewery With the Use of AI

Degree project report in Product Development

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Abstract

This report is the master's thesis of two students at Chalmers University of Technology, carried out at a large-scale brewery. The purpose was to identify where AI could improve operational efficiency and performance within their S&OP department. This was investigated by analyzing **where** an AI would be effective, **what** type of AI that would be suitable, and **how** an implementation could be conducted. The investigation contained a literature study of the current market usages of AI and AI implementations, as well as an empirical study at the large-scale brewery where nine interviews, one focus group, and two shadowing sessions were conducted. The findings indicate that implementing an agentic AI in selected process categories would be beneficial, and the implementation of an LLM would cover the remaining processes. Utilization of the available integrated AI tool would therefore cover all process categories identified in the S&OP department. The thesis also provides a recommendation for how an AI-model can be implemented based on literature and empirical findings. The large-scale brewery has the potential to improve operational efficiency and performance by utilizing existing AI tools, provided that employees receive the necessary training to use them effectively.

Keywords: Agentic, AI, Brewery, Copilot, Efficiency, Implementation, Large-Scale, LLM, Microsoft, S&OP.

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During this master thesis, our supervisor Ala Arvidsson from Chalmers University of Technology has been a trusted guide for how to conduct our study and answer our questions. Thank you for providing us with your insights and for being our examiner. Ala has also coordinated a circle group with four master thesis reports that has met twice before the final presentation. This circle group has helped the thesis with peer review of planning report and half-time report. The feedback and discussion has aided this thesis to mediate understanding and reach higher quality.

We also want to acknowledge our supervisor from the large-scale brewery, who helped organize this master thesis and made it possible to be carried out. Her contribution was extra rewarding in the beginning to help with logistics, coordination and understanding of the organization. She mediated the communication to the head of S&OP at the large-scale brewery. We also want to thank him and his team for all the insights, time, and energy they've contributed with.

The S&OP team at a Large-Scale Brewery has given up time and energy for this thesis. They've let us interview, shadow, and some managers also contributed in a focus group. We want to thank everyone who has given up their time to help us gather data as there wouldn't be a study without their efforts.

Finally, we want to thank the Swedish company AliceLabs for their cooperation and insights into the AI implementation market, their time and expertise have helped us to better understand how this can be conducted in practice.

Rasmus Fischer and Oskar Hultgren, Gothenburg, May 2026

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AI	Artificial Intelligence
API	Application Programming Interface
DP	Demand Planning
ERP	Enterprise Resource Planning
GenAI	Generative AI
KPI	Key Performance Indicator
LLM	Large Language Model
Mgmt	Management
ML	Machine Learning
PCM	Product Change Management
ROI	Return on Investment
RQ	Research Question
SDT	Self Determination Theory
S&OP	Sales and Operation Planning
SP	Supply Planning
SWOT	Strengths, Weaknesses, Opportunities and Threats

Contents

List of Acronyms	ix
List of Figures	xiii
List of Tables	xv
1 Introduction	1
1.1 Background	1
1.2 Purpose	1
1.3 Delimitations	2
1.4 Research Questions	2
2 Methods	3
2.1 Investigating S&OP Department and Benchmarking	4
2.2 Data Gathering	5
2.2.1 Interviews	5
2.2.2 Shadowing	6
2.2.3 Focus Group	6
2.3 Generate Process Map	7
2.4 Matching Process Map and AI Benchmarking	9
2.5 Implementation	9
2.6 Analysis	10
3 Theory	11
3.1 Sales and Operations Planning	11
3.2 The Large-Scale Brewery's S&OP Department	12
3.2.1 Demand Planning	12
3.2.2 Supply Planning	12
3.2.3 Product Change Management	13
3.2.4 The Large-Scale Brewery's Process	13
3.3 Artificial Intelligence	13
3.4 Large Language Models (LLMs)	17
3.4.1 LLM Applications in Supply Chain	17
3.4.2 Example of an Integrated AI Tool	19
3.5 Summary of Benchmarking	20
3.6 Sustainable Implementation	25
3.6.1 Self-Determination Theory	25

3.6.2	Difficulties in AI Implementations	25
3.6.3	AI Implementation in Supply Chain	26
3.6.4	Transformation Efforts	27
4	Findings and Discussion	31
4.1	Data Collection	31
4.1.1	Interviews	31
4.1.2	Focus Group	32
4.1.3	Shadowing	32
4.2	Process Mapping and Comparison	32
4.2.1	Identifying Processes	32
4.2.2	Comparing the Potential of Process Categories	38
4.3	Matching Processes With AI Applications	41
4.3.1	Convert/ Move Data Between Systems	43
4.3.2	Validate Data Between Systems	44
4.3.3	Data Accessibility	45
4.3.4	Procurement	46
4.3.5	Logistics	47
4.3.6	Sales Forecast	50
4.3.7	Production Planning	53
4.3.8	Information Summarization	55
4.3.9	Communication	56
4.3.10	Coordination	57
4.3.11	Performance Analysis	58
4.3.12	Decision Making	59
4.3.13	Strategy	61
4.4	Most Suitable AI Model	62
4.5	Implementation Process Framework	63
4.5.1	Internal Training	63
4.5.2	Responsible Usage	64
4.5.3	Management’s Role	65
4.5.4	Enabling Usage	66
4.5.5	Proposed Implementation Process Framework	67
4.5.6	Ambassador Team	71
5	Conclusion	73
5.1	Answers to Research Questions	73
5.2	Reflection on Research Process	74
5.2.1	Reflections	74
5.2.2	Difficulties and Uncertainties	74
5.3	Limitations and Future Research	75
5.4	Practical Recommendations	76
	References	77
	A Appendix	I

List of Figures

2.1	General overview of methodology followed in this thesis	4
2.2	Visualization of how the ranked process map is derived	9
3.1	S-Curve illustrating the general performance increase over time for innovations, X marks the approximate spot for where AI is today . . .	14
3.2	Overview of the grouping of processes and AI use cases	20
3.3	First iteration of AI use cases clusters using post-it notes	21
4.1	Proposed implementation strategy, broad perspective	68
4.2	Ambassador team needs from Mgmt and expected findings	72

List of Tables

3.1	GenAI primary benefits for supply chain retrieved from Gstettner et al. (2024)	17
3.2	Clustering of potential AI capabilities in S&OP departments based on literature review with summarized areas of capabilities	21
3.3	Conversion table for references including the corresponding AI model each reference analyzes.	24
3.4	Summarized clustering of AI capabilities based on literature review	24
3.5	GenAI implementation steps and explanations derived from Gstettner et al. (2024)	27
4.1	Identified process areas and categories in the large-scale brewery’s S&OP department	33
4.2	Process areas and categories with the corresponding S&OP department that mentioned the process	33
4.3	List of categories and respective score derived from relationship matrix	40
4.4	Mapping of AI applications across process areas and categories.	42
4.5	List of process categories, respective score, and suitable AI model	63
A.1	Relationship matrix (Data Management and Admin Tasks)	II
A.2	Relationship matrix (Optimization Problems and Analysis)	III

1

Introduction

With rapid development and increased usage of Artificial Intelligence (AI), companies need to adapt to keep up. This report aims to investigate how a Large-Scale Brewery's S&OP department can implement and utilize AI. The thesis is conducted during the spring of 2026 as a master's thesis at Chalmers University of Technology. The outcome will be used for decision making in internal implementation and investments at a Large-Scale Brewery.

1.1 Background

The large-scale brewery's S&OP leadership is looking into existing work tasks throughout the organization that have potential for efficiency and operational improvements. They aim to determine whether AI can improve internal processes and create value by freeing up time for employees to focus on other tasks. The problems they face are what, where, and how to implement AI. The area of interest for this thesis is the S&OP department that consists of the Product Change Management (PCM) and Planning-team (SP & DP).

The Swedish brewery industry consists of more than 400 breweries, both larger and smaller ones, with a cumulative turnover of 21 billion SEK in 2023. Breweries connected to "*Sveriges Bryggerier*" (Sweden's Breweries), produce beer, cider, soft-drinks, water and other brewery products. Their members constitutes for roughly 90% of Sweden's brewery production (Sveriges Bryggerier, 2023).

1.2 Purpose

The large-scale brewery has found the need to further utilize AI within their S&OP department. The purpose of this initiative is to investigate this need and how it can be fulfilled. The result of the thesis will be used for decision making connected to effective investment in AI with arguments derived from the research. The thesis will function as support between the company and future use of AI. There is a recommendation on how to implement an AI-model in a suitable way, based on the findings from the empirical data and existing implementation literature.

Although numerous studies have examined AI applications in supply chain management, limited research has investigated which S&OP processes in large-scale breweries are most suitable for AI adoption and how such applications can be implemented

effectively. This thesis aims to address this gap through a case study of a large-scale brewery.

1.3 Delimitations

The master thesis will have delimitations in its geographical area of coverage. Research will be conducted only at the large-scale brewery, in Sweden during the spring of 2026. The thesis will not include the development of any AI, only acknowledge what needs and requirements it must fulfill in future work. There are also economical delimitations since there is no available budget for the thesis. Finally, there is a delimitation regarding the man-power available as there will be two students working on this master thesis in collaboration with a supervisor from Chalmers and a supervisor from the large-scale brewery.

1.4 Research Questions

Based on the background and purpose of this study, the thesis will aim to understand internal customer needs for an AI implementation. To better understand where in the S&OP department an implementation is most lucrative and relevant, RQ1 will be answered.

RQ1: *Which processes within S&OP at the large-scale brewery have the greatest potential for efficiency improvements through AI implementation?*

Connected to RQ1, it's necessary to understand, based on a process mapping, what type of AI that would have most positive effect in S&OP. This results in RQ2.

RQ2: *What type of AI is most suitable in this case?*

RQ1 will show where AI would be the most profitable, and RQ2 will show which type would be the most suitable, and this will result in RQ3 which aims to answer how adoption can be achieved.

RQ3: *How can the implementation of AI be designed and executed within the S&OP process?*

2

Methods

The following sections describe the different work tasks that were used in this thesis and provide a background on why each step is important in the process to achieve the desired outcome. Figure 2.1 shows the overall methodology in this study. Different aspects has been categorized with colors representing the three research questions. The blue category helped the understanding of RQ1, the green category mediated RQ2, and the red category contributed to RQ3. It should be noted that data from all categories affect all research questions, this categorization were only used to mediate the understanding and motivation of the chosen approach. It should also be mentioned that the empirical data collected were conducted under the same period of time and it has been separated in the figure to ease understanding of what type of empirical data are used in the specific methods.

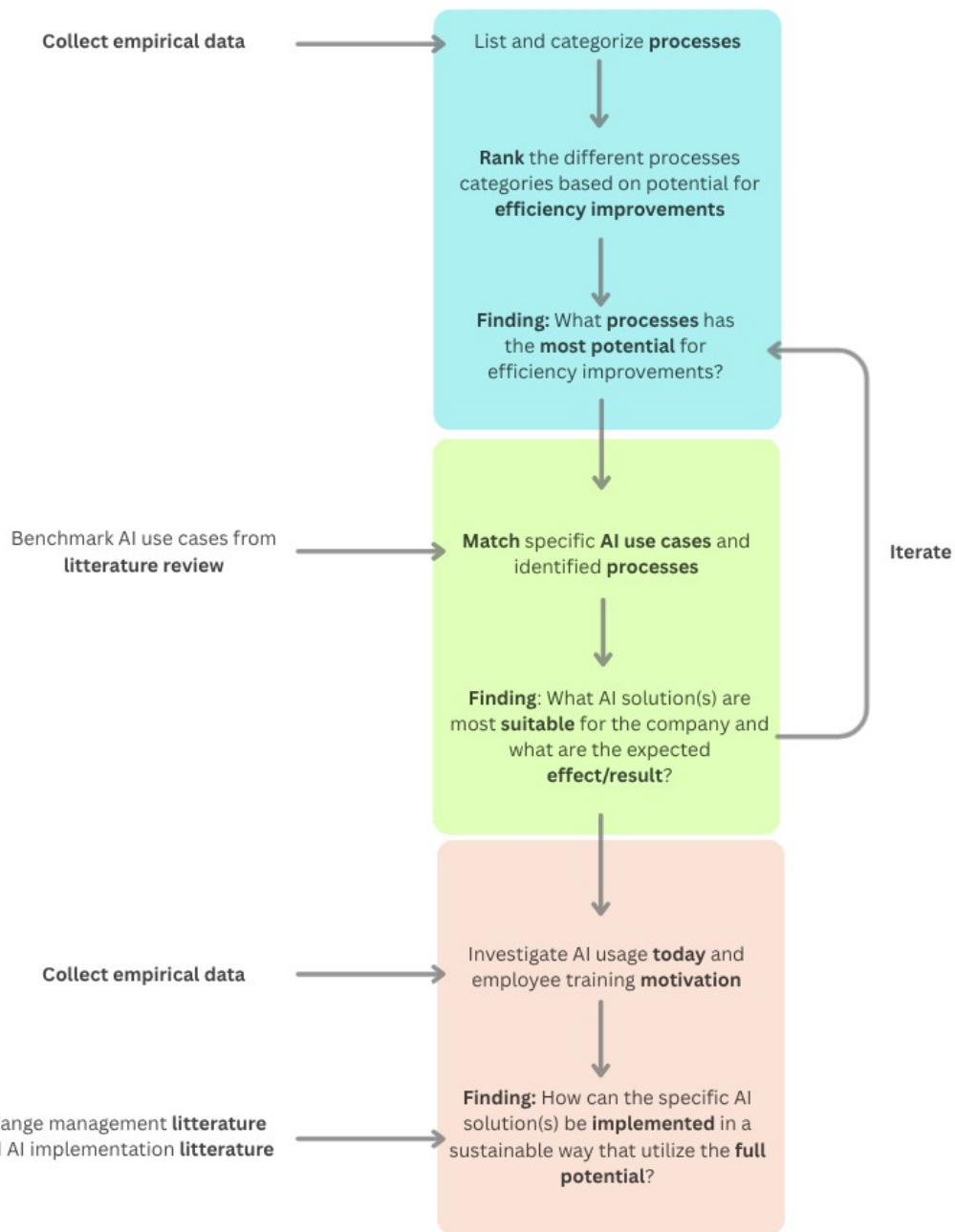


Figure 2.1: General overview of methodology followed in this thesis

2.1 Investigating S&OP Department and Benchmarking

To further understand the S&OP department’s daily work, organizational structure, and responsibilities, an organizational chart from the large-scale brewery were inspected. An organization chart, according to MBA Brief (2026), is usually used to

visualize the interaction between different functions, roles or people. In this thesis, the different stakeholders within the S&OP department represent functions and roles, and the structure in the organizational chart visualizes the flow of information. To gather the information required to understand this specific organizational chart, a study visit to the large-scale brewery were carried out.

A benchmarking of external companies' usage of AI were conducted regarding S&OP functions. To understand how AI is implemented in other companies' S&OP, IT companies who offer AI solutions were analyzed. Their solutions together with AI capabilities found in academic research were then categorized with the use of KJ method to organize and group AI capabilities.

2.2 Data Gathering

In this section the different types of data gathering methods are introduced and described, in terms of purpose and desired outcome for the thesis objectives.

Bell et al. (2022) argues that there are different ways to gather raw data from customers, this thesis was conducted as an empirical study and focused on individuals in the organization to build a case around common touch-points for improvement. Therefore, the main focus were qualitative internal research. The findings from the organizational structure and benchmarking were used to identify relevant stakeholders for qualitative interviews, shadowing, and a focus group.

2.2.1 Interviews

In this thesis project, 10 stakeholders were qualitatively interviewed. Upper management were interviewed to understand the company's vision, strategy, and Key Performance Indicators (KPIs) of interest. The other interviews were conducted to further understand the usage of AI in practice, its potential, and the needs of the user.

Each interview required roughly 40-60 minutes, resulting in around 7 hours of raw data. The interviews were semi-structured to allow interviewees to elaborate their answers and show their point of view. Bell et al. (2022) states that another reason for interviews to be semi-structured is to allow significant departure from the guide it follows, if the interviewer wants to follow up on something the interviewee answered. The interviews were conducted in person to the highest extent, but mediating tools such as *Microsoft Teams* were used to gather data from stakeholders in other regions. The interview guide in those cases were the same since there's no concrete evidence that you should act differently according to Bell et al. (2022). The interview questions differed depending on interviewee, but they were in accordance with to Bell et al. (2022) formulated in a way that helped answer the thesis research questions. During the interviews, notes were taken, and if the interviewee allowed it, it was recorded and transcribed.

2.2.2 Shadowing

Another way this thesis gathered information about an employees work tasks were to conduct a shadowing or a work/ job shadowing. According to University of Cambridge (2026) this is a way to gain insight into the work of an employee which will help you understand how they work and what tasks they perform on a daily basis. In this thesis the benefits were primarily for the students conducting the shadowing, connecting to University of Cambridge (2026) they mention some benefits such as "Seeing how other staff and teams work" and "Understanding how the University works". In this thesis the second benefit were instead *understand how the brewery works* which is critical for the outcome of the thesis. To be prepared by doing research on the company and the role you intend to shadow is an important preparation that were done before the execution of the shadowing, this were also mentioned by Indeed Editorial Team (2026).

In this thesis, the shadowing were conducted on site at the large-scale brewery's warehouse in Sweden with the S&OP department. There were some formalities and procedures taken into consideration when shadowing, and those were the following:

- Explained that we were not there to evaluate their performance
- Explained that the purpose was to understand the daily tasks/ work and investigate where AI can free time for other tasks and not replace the person being shadowed
- Asked if it was okay to take notes, pictures, and videos
- Questions could be asked in regard to work tasks, but not in regard to AI-usage. To obtain as reliable data as possible regarding AI-usage
- Identified processes to map out and present the work conducted
- Took notes when a task was conducted two times or more
- Took notes when AI could be used but wasn't
- Took notes on when AI were used and how

2.2.3 Focus Group

A focus group/ group interview were conducted with the upper management of the S&OP department, this was conducted in a group instead of separate to allow the participants to communicate with each other and build on each others ideas regarding certain questions formulated by the thesis students beforehand. Those questions were in regard to Bell et al. (2022) formulated so that they answered the thesis RQs in one way or another, or gave insight into how AI can improve operational efficiency within S&OP.

During the session, the questions were discussed one by one, and the participants wrote their initial thoughts of the question on a paper, after discussion of the

question, they wrote their new thoughts on the backside on the same paper in case they changed their mind or got new ideas. The focus group moderator asked follow up questions to clarify any uncertainties in the responses from the group. In addition to the moderator of the session, there was a note-taker to make sure that all the information gained at the session were saved, the session were also recorded to be able to quote the participants.

The main questions for this thesis focus group were the following:

- Have the S&OP work changed since advanced AI became accessible?
- Which processes within the S&OP department at the large-scale brewery do you think have the greatest potential for efficiency improvements through an implementation of AI?
- How can an AI implementation look?
- How can you motivate people without experience in AI to learn AI?
- Is it important to be able to measure the effect of AI? If so, how could you do that?
- What are your thoughts on following AI recommendations versus relying on your own experience?
- How could you encourage the usage of AI when users are held accountable for possible errors?
- How do you ensure that employees use AI in a correct way?
- Should AI be integrated as a support tool or a must use tool in the decision making process?
- How do you think that the S&OP process will change in the next 5 years?

2.3 Generate Process Map

In product development, Ulrich et al. (2020) explain how understanding customer needs is one part of the process. As this thesis aimed to identify internal customer needs through an empirical study, the methodology presented by Ulrich et al. (2020) is of high relevance. They use five steps to identify customer needs 1) *Gather Raw Data from Customers*, 2) *Interpret Raw Data in Terms of Customer Needs*, 3) *Organize the Needs into a Hierarchy*, 4) *Establish the Relative Importance of the Needs*, 5) *Reflect on the Results and the Process*. This approach was suitable for the thesis, but the denotation *process map* were used instead of *customer needs list*. This was to ease the understanding and readability of the report.

Although the development of an AI was out of reach for this thesis, the product development process for pre-study described by Ulrich et al. (2020) were used with

some modification to understand customer needs. In this thesis, "customers" were the identified stakeholders at the large-scale brewery and therefore the ones the raw data were gathered from.

Ulrich et al. (2020) mean that the second step in the process of identifying customer needs, is translating the raw data findings into customer needs. To accomplish this, the needs in this thesis was written as "what to do", and not "how to do". Also, they were phrased in a positive way, meaning they were not stated "what *not* to do". The translated needs have the same level of detail as the findings and avoided words such as "should" and "must". The needs in this thesis was therefore all the processes found from the raw data from the customers. Since processes were identified, and not customer needs, some adaptations were done. The wording within the process map has not taken Ulrich et al. (2020) into full consideration. The reason for this was to avoid the loss of important information about the processes due to wording issues.

The third step in the identification of customer needs, according to Ulrich et al. (2020), is organizing the translated needs into categories. Using post-it notes with the processes allowed for categorization into different hierarchies. This step allowed the processes to be sorted into different categories in different areas related to the daily work to easier connect them with the AI capabilities found in the literature study. This was conducted in Excel in this thesis with the purpose of enabling easy editing, handling large amount of processes and sharing the information.

Ulrich et al. (2020) explain the next step as comparing the needs and ranking them against each other depending on importance. In this thesis, all categories in the different areas were compared to each other and scored 0, 0.5, or 1, depending on how important they were in relation to one another. This resulted in weights on the categories, and it was based on the potential of the categories in relation to efficiency improvement. Since this thesis were looking into the potential of different processes it also took into consideration stakeholders wishes of potential in processes.

Finally, when the categories had been identified and weighted, Ulrich et al. (2020) argues that they should be reflected upon, as well as the process. This was conducted by consolidating the result of the categories and weights with the large-scale brewery's S&OP upper management.

The summarization of the five steps conducted is visualized in Figure 2.2 to give a better understanding of the process. In Figure 2.2 the first and second step is illustrated as the first box of identifying processes, the third step is divided into box two and three to give a better understanding of what is happening and the fourth and fifth steps are summarized in text.

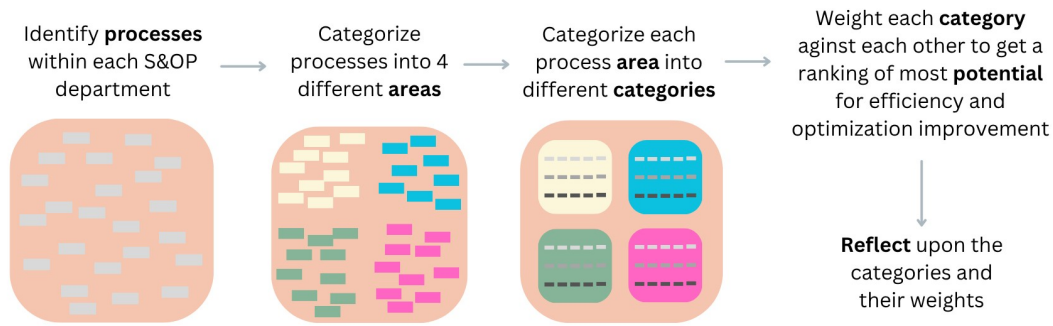


Figure 2.2: Visualization of how the ranked process map is derived

After those 5 steps had been conducted, a ranked process map were created to visualize all the processes and the categories to which they relate with the corresponding weight of potential, this can be seen in Table 4.3.

2.4 Matching Process Map and AI Benchmarking

The benchmarking that summarize the literature study was used to match different processes with AI use cases found. However, the matching of processes and AI use cases were codependent of the ranking of process categories. Therefore, the ranking of process categories was an iterative process. An initial ranking was created based on findings from the empirical study and the processes efficiency potential. This resulted in an understanding for what specific processes affected the scoring within each category and a general understanding of how process categories depend on each other. This was followed by the matching of AI use cases and process categories to analyze what type of AI models that could be used and how they could improve the different process categories. Most conclusions for most suitable AI models took the potential of specific processes into consideration which originated from the process category ranking.

This was then followed by an iteration of the ranked list based on feedback from the management team, resulting in less subjectivity and more strategic alignment. The matching of AI use cases and process categories was then revised to align with the new ranking and analysis. The final result was a conclusion of most suitable AI model for each process category. Together, the ranked list of process categories and matching AI models motivated what AI investments were most suitable.

2.5 Implementation

This thesis made an implementation suggestion for how to implement the solution to gain the most value. This suggestion was based on the environment in the S&OP department and the dedication of the workers, and follows the SDT described in this thesis theory chapter. Possible implementation was considered when analyzing

processes and AI applications, but after the conclusion for most suitable AI model, it was analyzed more in detail based on empirical findings.

2.6 Analysis

When the customer needs had been quantified and visualized in the ranked process map, they were analyzed. This thesis compared different types of AI-models found in the literature review that could optimize the processes found in the empirical study. It was at an abstract level where different implementations fulfilling different processes were compared.

3

Theory

The following sections give a deeper understanding of what a textbook S&OP department consists of and how it operates, in regard to this it makes parallel connections to the S&OP department at the large-scale brewery to highlight similarities and differences from the textbook example of this type of department. The theory chapter also benchmark different types of AIs available on the market, how they can be used in S&OP and how they can be implemented. It ends with a summary of the benchmarking and a table of AI applications that will be used in the matching with processes from the large-scale brewery's S&OP department.

3.1 Sales and Operations Planning

A Sales & Operations Planning (S&OP) department is according to W. Stebbins (2025) constantly working on supply and demand logistics by working with interdepartment collaboration, they do this to be able to give upper management the best possible information to base their decisions on. It's a department that exchanges in goods, thus making it important for the large-scale brewery.

Grimson and Pyke (2007) explain, in their literature review, a five-step process that S&OP typically follow. The process begins with the sales function developing an unconstrained demand forecast based on both formal and informal inputs, resulting in an estimate of customer demand. This forecast considers factors such as promotions and product introductions. The planning horizon may vary depending on contextual factors, such as seasonality, but is generally between 6 to 18 months. Products with higher seasonality or longer lead times tend to require longer planning horizons.

In the second step, the operations function evaluates inventory strategies, internal capacity, and other relevant factors, using the sales forecast as input to develop an initial supply plan. The third step consists of a cross-functional S&OP meeting, the purpose of which is to reconcile demand and supply plans and reach agreement on planning decisions. The frequency of these meetings differs between organizations but is typically regular, with some flexibility to address problems such as operational issues. Following this, the fourth step involves communicating the agreed plan across functions and aligning execution. Finally, outcomes and performance are reviewed to provide feedback and support continuous improvement of future S&OP cycles (Grimson and Pyke, 2007).

This process has evolved into an *integrated business planning* (IBP) approach, in which traditional S&OP is linked with *collaborative planning, forecasting, and replenishment* (CPFR) to enable broader coordination across the organization and with external partners (Smith et al., 2010). IBP is described as a two-stage planning process, where the first stage focuses on developing go-to-market strategies based on customer needs and business objectives, and the second stage translates these strategies into integrated and executable plans. Smith et al. (2010) report that linking S&OP with CPFR provides several benefits, including improved communication, enhanced customer satisfaction, and the creation of new business opportunities.

3.2 The Large-Scale Brewery's S&OP Department

According to the Head of the large-scale brewery's S&OP department, the department consists of three main functions: Supply Planning (SP), Demand Planning (DP), and Product Change Management (PCM). Apart from this, they have two additional employees that are within the S&OP department: Transformation Planning Western Europe, and DP Western Europe. However, this thesis only focus on the Swedish market, therefore are these functions neglected.

3.2.1 Demand Planning

The head of the DP function explains how the main responsibility of the DP function is to ensure that long-term forecasts are relevant. Production can then use this as a guide for how much they need to produce. They also conduct short term forecasts within the S&OP process. To do this, they use both qualitative and quantitative data. These can be explained as judgment data and mathematical data.

The head of the DP function also explains that forecasts which use quantitative mathematical data are using historical data. For example, they can see seasonal trends with historical data. This initial forecast acts as a base line which is strengthened by applying more quantitative data, connected to promotions of the product. The qualitative forecasting is then included in collaboration with sales and marketing. Human input about the market activity is, for example, put into consideration, resulting in a possibly more reliable, but more subjective forecast. The gathering of this subjective information is done through an *innovation board* and through the S&OP department.

3.2.2 Supply Planning

The Head of SP explains the SP function's responsibilities as all of the production planning, long-term planning, and inventory control. There are 15 people in the team with one manager and three senior supply planners. The rest are supply planners with different types of responsibility, from specific bottle-models to logistics problems. The division of work is for some employees based on the type of bottles that will be supplied, resulting in employees being able to do much of their work independently from the SP team. There is some collaboration in specific procurements where orders

can be purchased together, but usually the work is not very collaborative. The collaboration is instead with production as they need to understand how much that can be produced. When the demand plan cannot be produced in main production's factory, products are often outsourced. The outsourcing cost depends on the product. The importance of specific products is decided by DP and market. In addition to this, outsourcing is also used for some inventory.

3.2.3 Product Change Management

S&OP is a process, but the PCM function is responsible for projects. This means that they are part of the process, but with more variability in their daily work. They focus on five main parts: *innovation, master data, value engineering, portfolio management, and sustainability initiative & packaging development.*

3.2.4 The Large-Scale Brewery's Process

The head of the S&OP department explained that the S&OP process is a one month process that begins with DP conducting their forecast, resulting in a demand plan. This is then reviewed by SP that creates a supply plan in response. The third step is reconciliation where sales and supply chain becomes aligned. This is then followed by the fourth step, the monthly S&OP meeting with management. the large-scale brewery's process is similar to the process described by Grimson and Pyke (2007).

3.3 Artificial Intelligence

According to Analysis.org (2025) AI is on the way up on the S-curve described by Ulrich et al. (2020), illustrated in Figure 3.1. It has become a buzzword and a tool that is commonly used in different types of business nowadays. As all types of technological developments from Henry Fords line production discussed by Liberto (2026) to the digital camera bankrupting Kodak argued by Mui (2012), there will always be companies failing to adapt and therefore disappear from the market.

The potential of AI can be shown in various cases, one is the case of a medical company that cut their time spent on documentation by 40% and the document processing turnaround time by 50% thanks to the implementation of AI according to Sweeney (2025). Another example is from an OpenAI (2025) survey, they mention that 75% of the workers who responded have improved the quality or speed of their deliverables after implementing the use of AI in their work, saving them 40-60 minutes every day. It is no longer a choice whether to implement AI or not in a organization, it is a necessity to stay competitive and survive.

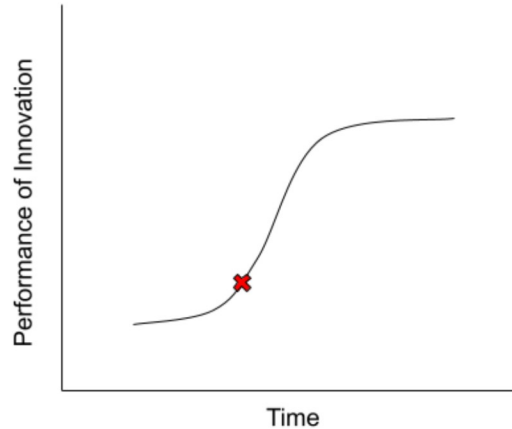


Figure 3.1: S-Curve illustrating the general performance increase over time for innovations, X marks the approximate spot for where AI is today

AI can be used in diverse tasks throughout an organization, some examples on what AI can do and how it can be used in S&OP are the following general examples that are derived from different sources. "Master Data Alignment", "Data Cleaning", and "Runs multi-scenario simulations" is discussed by Kumar Singh (2023). Followed by "Automates Scenario Runs", "Automate Report Creation", and "real-time updates across S&OP data layer" which are discussed by Polo (2024) referring to Chen et al. (2020). Finally predictive Analysis is discussed by Anumula et al. (2025) with an example such as "Forecasts demand using historical & real-time data". Those examples could be categorized into "automation", "data collection & management", "decision intelligence (agentic AI)", and "predictive analysis" which Kumar Singh (2023) argues are four capabilities that are central to AI in S&OP, both in terms of operational efficiency and cost reduction.

Polo (2024) explains how different AI models can benefit S&OP processes. He identifies three AI technologies that benefits the S&OP process; *predictive analytics*, *automation*, and *data integration*. He discusses how "*Integrated datasets with AI predictive analytics employs superior methods of statistical modeling to look for hidden relationships within massive troves of data*", and by using real-time data he means that they will "*obtain better forecast accuracy and reliability of demand*". To manage this, Polo (2024) developed a sequential *ML Neural Network model* with long short-term memory (LSTM). The results showed an increase in forecast accuracy, and decrease in stock-out incidents and overproduction cost.

Lee (2025) describes neural networks in a simple way, which this thesis will relate to when it comes to technical-depth for neural networks. He means that "*A neural network is a machine learning model that stacks simple 'neurons' in layers and learns pattern-recognizing weights and biases from data to map inputs to outputs*". To then understand what an ML model is, Bergmann (2026) means that "*Machine learning is the subset of artificial intelligence (AI) focused on algorithms that can*

'learn' the patterns of training data and, subsequently, make accurate inferences about new data. This pattern recognition ability enables machine learning models to make decisions or predictions without explicit, hard-coded instructions.". These explanations of neural networks and ML gives us the understanding that an ML AI is built on a neural network which is specialized into learning patterns from data. Bergmann (2026) argues that nowadays ML is the backbone to most AI applications whether it is an LLM or an GenAI that is programmed.

Jackson et al. (2024), drawing on existing literature, identify six core AI capabilities in the context of GenAI (GAI) in Supply Chain and Operations Management (SCOM): *"Learning, Perception, Prediction, Interaction, Adaptation, and Reasoning"*. In addition, they argue that GAI enables an additional capability in the form of *creativity*. Their findings suggest that different SCOM areas benefit from AI and GAI adoption in distinct ways, positioning GAI as a potentially transformative development for future AI usage in the industry. The relevance of AI for improving supply chain performance is further reinforced by Sharma et al. (2022), who map existing research on AI in supply chain management and identify several application clusters that are particularly suitable for AI adoption and future research.

In contrast to these perspectives, Jazairy et al. (2025) investigate possible paradoxes in AI implementation within S&OP environments. They show how internal tensions can be the result of AI adoption, such as following AI's decision vs following intuition. They present 12 sub-paradoxes such as this example, and use them to create five impact pathways. These impact pathways are: *"(1) balancing immediate actions with long-term AI-driven strategies, (2) navigating AI adoption via centralized systems, process redesign and data unification, (3) harmonizing AI-driven S&OP identities, collaboration and technology acceptance, (4) bridging traditional human skills with innovative AI competencies and (5) managing the interrelated paradoxes of AI adoption in S&OP"*.

Ohlson et al. (2022) investigated how ML could benefit challenges connected to engineer-to-order context in S&OP. Their study was published in 2022, hence the results are not up-to-date considering the recent development within ML. However, their results can indicate how ML, without constraining themselves to LLMs, can affect supply chain management. They identified several tasks that could be supported by usage of different ML solutions. The identified tasks are:

- *"Find errors and inconsistencies in the data and eventually correct or propose corrections of the data"* (p. 45)
- *"Find patterns in historical data and mirror them on the future forecast and/or demand plan"* (p. 46)
- *"Estimate a projected probability for future projects based on historical data"* (p. 46)
- *"Predict capacity utilization over time and identify bottleneck resources"* (p. 46)

- *“Estimate future bullwhip-effects related to S&OP-decisions based on historical data”* (p. 46)
- *“Estimate future capacity utilization, serviceability and location of future bottlenecks based on historical data”* (p. 46)
- *“Estimate future inventory based on future operations plan and inconsistency patterns in historical actual inventory”* (p. 47)

The ML AI model has been described previously in this section and will therefore be neglected from further comparison, but to separate the different AI models GenAIs, LLMs, and agentic AIs, Verma (2025) has made a comparison table of them. In his paper he compares the different types of AI models with each other with regard to these five features:

- "Core Capability"
- "Output"
- "Autonomy"
- "Real Business Use"
- "Popular Example"

Verma (2025) mentions that GenAIs "Core Capability" is "Content creation", LLMs is "Language understanding & generation", and agentic AIs is "Goal-driven action". For the feature "Output" an GenAI generates "Text, images, audio, code", an LLM generate "Text-based outputs", and an agentic AI generate "Process automation and decision making" according to Verma (2025). Regarding "Autonomy" for the different AI models both an GenAI and an LLM "Needs prompts" while an agentic AI "Operates with minimal guidance" according to Verma (2025). When it comes to "Real Business Use" Verma (2025) presents that an GenAI could be used for "Content generation, art, code", an LLM could be used for "Chatbots, summarization, translation", and an agentic AI could be used for "End-to-end workflow automation". Finally, Verma (2025) mentions that some "Popular Example" of different GenAIs involve "DALL-E, Midjourney", for LLMs it's "GPT-4, Bard, BLOOM", and for agentic AIs it's "Customer support automation, executive assistants".

Verma (2025) also mention that an GenAI creates content based on user input, an LLM also creates content but it's a more specialized version of an GenAI, built to understanding what the user desires. More separated is the agentic AI that are usually used for automating processes since it's not dependent on user input to the same extent as an GenAI or an LLM. Verma, 2025 gives insight into the differences between the AI models when he mention that GenAIs and LLMs are both retroactive while agentic AIs is proactive, this gives a good understanding of the different types of use cases for each AI model.

3.4 Large Language Models (LLMs)

Recent technology innovations, in the form of LLMs, provide many benefits for employees in the supply chain (Durach and Gutierrez, 2024). Simchi-Levi et al. (2025) explain, on a basic level, how LLMs works. By training the model on existing data, it is able to learn and predict what the next word will be, based on user input. The result becomes a generated text as output. The training of the model can be based on fine-tuning, which means training the model for a specific domain. Another common way of training the model is with in-context learning, by including training data in the prompt.

3.4.1 LLM Applications in Supply Chain

Gstettner et al. (2024) explain how GenAI affects supply chain management. They discuss the proven, and potential benefits, along with constraints and levels of AI usage in the supply chain. They divide the benefits into four main areas: "*Enhancing the Data Backbone*", "*Augmenting Supply Chain Analytics*", "*Overhauling the User Experience*", and "*Deeply Automating Processes*". Table 3.1 explains these benefits in more detail with information derived from Gstettner et al. (2024)

Table 3.1: GenAI primary benefits for supply chain retrieved from Gstettner et al. (2024)

Benefits	Explanation
"Enhancing the Data Backbone"	Improving quality in master data for different applications. Continuously cleaning and augmenting for example bills of materials.
"Augmenting Supply Chain Analytics"	Analyzing unstructured data to improve for example demand forecasting. Results in a more reactive supply chain where decisions can be made proactively.
"Overhauling the User Experience"	User-friendly interactions enabled by GenAI help employees better understand and use advanced planning tools. As familiarity with tools such as ChatGPT increases, employees are more likely to identify additional application areas within their work processes.
"Deeply Automating Processes"	Automating processes enables tighter integration and orchestration of multiple tools and workflows, allowing problems to be identified and addressed at an earlier stage.

Furthermore, their study showed a 50% reduction in time spent on data reconciliation and administrative tasks. The study included exploring ChatGPT applications within the supply chain. In demand planning, they found how ChatGPT suggested relevant forecasting methods, as well as highlighting when input data was insufficient

to produce a reliable forecast. In supply planning, ChatGPT instead explained how the prompts' desired outputs were too complex. The users tried to optimize inventory buildup while meeting customer demand based on multiple factors. ChatGPT informed that this sort of computation was not feasible to generate, but assisted in finding a more optimized programming solution (Gstettner et al., 2024).

Simchi-Levi et al. (2025) found that LLMs had multiple benefits within Supply Chain decisions. Applying an LLM in processes allowed employees to better understand their data. They mean that supply chain decisions require time spent on "*understanding recommendations*", "*analyze different scenarios*", and "*update mathematical models*". All of those areas saw improvements from using AI in the form of LLM.

It's not only data that becomes easier to understand, but coding as well. Calore (2025) found that LLMs allowed employees to create code by vibe coding. Employees were able to extract working code from the LLM and saw multiple benefits. "*Inventory allocation logic with dynamic constraints, demand clustering analysis, and scenario modeling*" are ways they mean LLMs can be used in. They further discuss the potential of integrating generated python code with Excel. However, there are limitations such as quality of generated code, and governance.

Nichols (2025) explains how AI Agents, defined as digital assistants that adapt to the context, enable employees in planning to automate repetitive tasks and allocate their time toward more value-adding activities. He means that LLMs' accessibility allows humans to automate work tasks. An example was described where a Copilot agent identified SKUs according to specific criteria. Apart from this they present the following applications: "*Forecast accuracy monitoring*", "*Promotion impact analysis*", "*Inventory risk alerts*", "*Scenario simulation for S&OP/ S&OE*", and "*Data consolidation and reporting*". Applying AI in these areas resulted, according to Nichols (2025), in multiple immediate benefits: *Time Savings, Improved Forecast Accuracy, Reduced Burnout, Cost Efficiency, and Scalability*.

Durach and Gutierrez (2024) investigated chatbots' role in operations, supply chain management and logistics. To evaluate the impact of chatbots, they created a framework called ERI, covering the three dimensions of *efficiency, responsiveness, and intelligence*. They found that chatbots could prevent bottlenecks in operations, and suggested immediate benefits within ERI. Durach and Gutierrez (2024) suggested eight AI use cases that are of use for this thesis:

- "Automated customer service"
- "Order processing and reordering"
- "Training and support"
- "Real-time tracking"
- "Capacity planning"

- "Supplier and customer communication"
- "Predictive insights"
- "Informed decision-making"

The large-scale brewery's S&OP department involves processes that will be investigated and evaluated in regard to the potential of efficiency improvement through AI implementation. Today, there are companies such as Alice Labs (2026) and Gibraltar (2026b) that specialize in implementing AI in different organizations, and the methods vary a lot depending on the market of the company. According to Gibraltar (2026b) the process of unlocking the full potential of Microsoft Copilot requires careful planning, but once the organization is ready for it Gibraltar (2026a) mention benefits such as:

- "Streamline tasks"
- "Generate content"
- "Summarize data"
- "Support daily operations across your organization"

3.4.2 Example of an Integrated AI Tool

Microsoft Copilot is an integrated AI tool that can use sensitive data from a company in a secure way and still be a GenAI model with access to the internet according to Microsoft (2026b). Another thing they mention is the fact that Copilot connects with all applications in Microsoft 365, giving a seamless integration of all your data.

Microsoft (2025) is a Microsoft guide designed to help companies implement Copilot in their businesses. It walks through three essentials for a successful Copilot implementation, which according to them are *leadership*, *human change*, and *technical readiness*.

According to the implementation overview created by Microsoft (2025), *leadership* focus on what an implementation should help you with and the type of business needs that will be fulfilled by identifying value drivers in the company. *human change* explains the importance of getting people on-board with the change and giving them the right training and knowledge to use Copilot in their daily work. And finally, *technical readiness* to identify how to achieve value drivers and continue to improve, extend, and optimize the usage of Copilot.

Implementing something new with just a guide as help could be time consuming, which could be critical to a company. This is the reason why companies like Gibraltar (2026b) and Greymatter (2026) exist. Companies that specialize in implementing Microsoft Copilot in organizations. They have the time to do all the necessary tasks leading up to the implementation and adoption of Copilot. Once implemented, Microsoft (2025) gives examples of how Copilot can help in creativity, productivity and skills scenarios. Some of the examples are:

- "Generate a summary about a document"
- "Give me insights on my data"
- "Get a new coworker up to speed"
- "Create a SWOT analysis of a topic"
- "Highlights of a Teams chat with actions"
- "Save time by helping me search across my organization for information"
- "Provide a gap analysis between documents"
- "Analyze a complex sales report"
- "Provide coaching on generating email replies"

Adding to this, Microsoft (2026a) means that Copilot can also be used within Copilot studio. In this environment, agentic AIs can be designed to automate processes for example.

3.5 Summary of Benchmarking

The definitions that have been used for different levels of processes and AI capabilities is shown in figure 3.2. To clarify, a process conducted by an employee is grouped with similar processes in a category, and the categories are then grouped in different areas. For example, the process *long term planning* mentioned by *SP* is grouped in the category *strategy*, which is then grouped in the area *analysis*. Likewise, *AI use cases* are grouped in *AI applications* which is then grouped in *AI capabilities*. An example of this is the AI use case *"Summarize data"* identified from Gibraltar (2026a) which is grouped in the AI application *help understand data* which is then grouped into the AI capability *AI support*.

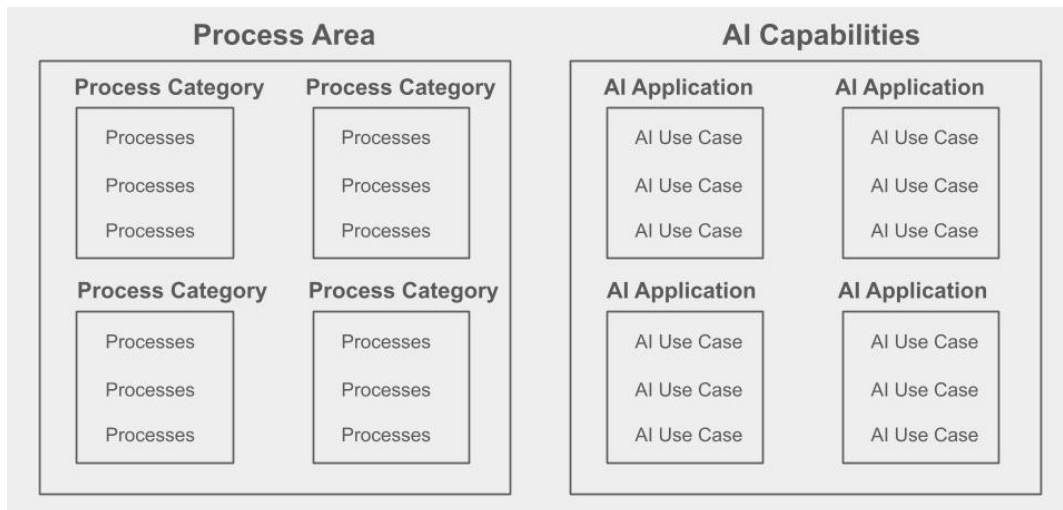


Figure 3.2: Overview of the grouping of processes and AI use cases

The benchmarking of other companies, AI-models, and possible scenarios where AI could be used gave a comprehensive list of capabilities and concrete use cases. In Table 3.2 the use cases have been assigned to the capabilities they fulfill, in this version there are some duplicates since the sources used in this thesis mentioned the same use cases and benefits with the use of AI. The use cases have their referred source connected in the table, and Table 3.3 shows the conversion from numbers to references. This process of identifying the different AI capabilities has been an iterative process, with discussion about the different applications and how they could be categorized. Post-it notes were used to cluster the different use cases of AI found in the Theory chapter. Figure 3.3 shows the first iteration of clusters, which was later revised and resulted in Table 3.4.

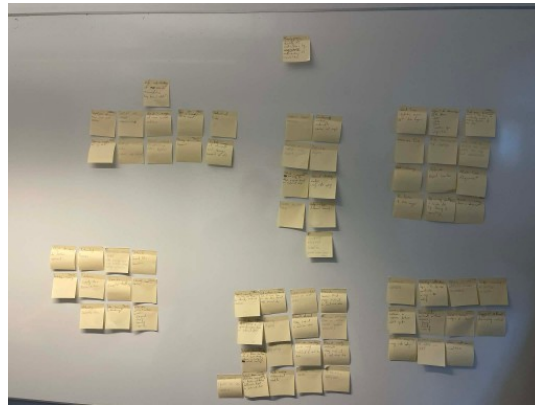


Figure 3.3: First iteration of AI use cases clusters using post-it notes

Table 3.2: Clustering of potential AI capabilities in S&OP departments based on literature review with summarized areas of capabilities

AI Automation	
Automate repetitive tasks & processes in optimal way	
"Order Processing and Reordering"	9
Automate repetitive tasks and allocate time to value-adding activities	8
Automate Demand Plan Generation	1
Automate Supply Chain Reconciliation	1
"Automated customer service"	9
Automates Scenario Runs	1
Executes optimal actions across Demand, Supply, Inventory, Capacity	2
Automate Report Creation	1
AI Support	
Help understand data	

Help understanding data-driven recommendations	5
"Get a new coworker up to speed"	11
Understand data	5
"Give me insights on my data"	11
"Summarize data"	10
"Generate a summary about a document"	11
"Provide a gap analysis between documents"	11
Support administrative tasks	
"Highlights of a teams chat with actions"	11
"Supplier and customer communication"	9
"Provide coaching on generating email replies"	11
"Training and support"	9
Support usage of complex systems	
Highlight insufficient data (when forecasting)	4
Assist in finding more complex and relevant solutions	4
Enable usage of advanced tools through support of AI	4
Help update mathematical models	5
Suggest relevant forecasting methods	4
AI Analysis	
Analyze data	
"Promotion impact analysis"	8
"Analyze a complex sales report"	11
"Create a SWOT analysis of a topic"	11
Support future what-if scenarios	
Continuously evaluate trade-offs (service, cost, margin)	2
"Predictive insights"	9
"Estimate a projected probability for future projects based on historical data"	7
Help analyze different scenarios	5
Support What-if scenarios	2
Learns from outcomes to improve future S&OP cycles	2
Recommends optimal actions across: i) Demand, ii) Supply, iii) Inventory, iv) Capacity	2
Scenario modeling using vibe coding	6
"Scenario simulation for S&OP/ S&OE"	8
Runs multi-scenario simulations	2
Find warning signals in data in real-time	
Flags decisions for human approval	2
"Inventory risk alerts"	8
Early warning signals for S&OP exceptions	2

"Forecast accuracy monitoring"	8
AI Forecast	
Forecast market	
"Find patterns in historical data and mirror them on the future forecast and/or demand plan"	7
"Estimate future bullwhip-effects related to S&OP-decisions based on historical data"	7
Analyze unstructured data to improve for example demand forecasting	4
"Demand clustering analysis" using vibe coding	6
Forecasts demand using historical & real-time data	3
Forecast in-house capacity	
Forecast inventory levels using historical & real-time data	2
Estimate future inventory based on future operations plan & inconsistency patterns in historical actual inventory	7
"Estimate future capacity utilization, serviceability and location of future bottlenecks based on historical data"	7
"Predict capacity utilization over time and identify bottleneck resources"	7
"Capacity planning"	9
"Inventory allocation logic with dynamic constraints" using vibe coding	6
SKUs according to specific criteria	8
AI Data Management	
Data cleaning	
Real-time updates across S&OP data layer	1
Normalization of data	2
"Find errors and inconsistencies in the data and eventually correct or propose corrections of the data"	7
Data Cleaning	2
Improving quality in master data by cleaning & augmenting	4
Data centralization	
Ingest & harmonize data from ERP, CRM, POS, Supplier systems, Logistics	2
"Data consolidation and reporting"	8
Save time by helping search across organization for information	11
Master Data Alignment	2

In table 3.3 the sources are noted with different types of AI models that are used in the corresponding source, the AI models used for this thesis comparison are agentic AI, GenAI, LLM, and ML AI.

Table 3.3: Conversion table for references including the corresponding AI model each reference analyzes.

Reference	AI Model	Number
Polo (2024)	Agentic AI	1
Kumar Singh (2023)	ML AI	2
Anumula et al. (2025)	ML AI	3
Gstettner et al. (2024)	GenAI	4
Simchi-Levi et al. (2025)	LLM	5
Calore (2025)	LLM	6
Ohlson et al. (2022)	ML AI	7
Nichols (2025)	Agentic AI	8
Durach and Gutierrez (2024)	LLM	9
Gibraltar (2026a)	LLM	10
Microsoft (2025)	LLM	11

In Table 3.4 the applications and clusters for AI has been iterated and summarized for easier overview of the possibilities within the different capabilities.

Table 3.4: Summarized clustering of AI capabilities based on literature review

AI Automation
Automate repetitive tasks & processes in optimal way
AI Support
Help understand data
Support administrative tasks
Support usage of complex systems
AI Analysis
Analyze data
Support future what-if scenarios
Find warning signals in data in real-time
AI Forecast
Forecast market
Forecast in-house capacity
AI Data Management
Data cleaning
Data centralization

3.6 Sustainable Implementation

This thesis does not aim to analyze and measure the outcome of the large-scale brewery's AI implementation strategy. It does however aim to investigate what implementation strategy is most suitable based on literature findings and empirical data. Therefore, this section explains employee motivation, connects it to identified AI implementation cases, and discusses how organizational change can be managed.

3.6.1 Self-Determination Theory

Deci et al. (2017) explain that Self-Determination Theory (SDT) is a macro theory about motivation that originates from research connected to intrinsic and extrinsic motivation. They explain different types of motivation, but also the three basic psychological needs: *autonomy*, *relatedness*, and *competence*. Fulfilling these basic psychological needs results in positive effects, e.g. autonomous motivation. Deci et al. (2017) (p. 20) mean that "*Autonomous motivation is characterized by people being engaged in an activity with a full sense of willingness, volition, and choice*".

Fowler (2014) describes the three basic needs in SDT. Firstly, the need for *autonomy* is described as "*Autonomy is our human need to perceive we have choices. It is our need to feel that what we are doing is of our own volition. It is our perception that we are the source of our actions*" (p. 2).

Secondly, Fowler (2014) describes the need for *relatedness* as "*Relatedness is our need to care about and be cared about by others. It is our need to feel connected to others without concerns about ulterior motives. It is our need to feel that we are contributing to something greater than ourselves*" (p. 4).

Finally, Fowler (2014) describes the need for *competence* as "*Competence is our need to feel effective at meeting everyday challenges and opportunities. It is demonstrating skill over time. It is feeling a sense of growth and flourishing*" (p. 5).

3.6.2 Difficulties in AI Implementations

Polo (2024) explains strategic considerations, and challenges that arise when implementing AI in S&OP. Firstly, it is discussed how there is a need to overcome organizational resistance. There is a risk that employees try to resist the implementation of AI due to their fear of being replaced by new technology. This fear can be related to two basic psychological needs explained by Fowler (2014). Fear of losing *autonomy* since there might be a lack of understanding of the effects on future work procedures, resulting in employees not owning their work. Fear of losing *relatedness*, as there is uncertainties about AI replacing employees.

However, Polo (2024) argues that by ensuring employees that AI is to be used as a tool to become better, and not replaced, it is more likely that employees participate in the change. He also means that if employees are part of the change and have ownership for it, they are more likely to not resist. This is in accordance with the relevant basic

psychological needs discussed by Fowler (2014). Ensuring employees that AI is to be used as a tool, and not as a replacement, mediates the basic psychological need of *relatedness*. Following this, including employees in the change and allowing them to lead the change mediates *autonomy*.

Polo (2024) also argues that due to the technology in AI, that there is a need to educate employees and reduce the skill gaps. To support this training, collaboration could be conducted with institutions or technology firms. Comparing this to the basic psychological need of *competence*, described by Fowler (2014), it can be seen that Polo (2024) indirectly emphasize satisfying this basic psychological need. By educating employees in the new technology they feel up to date and are able to understand the changes in work tasks better.

Finally, Polo (2024) discuss the cost management aspect. He argues that "The adoption of a phased approach with an emphasis on high value zones can achieve incremental value at reasonable cost". This is one of the reasons for this thesis' method approach of ranking different process categories against each other. This approach of identifying high value zones can also be related to the basic psychological need of *competence*. Fowler (2014) explain the importance of employees feeling growth, which is likely a feeling that will follow when they find efficiency improvements by applying AI.

3.6.3 AI Implementation in Supply Chain

Haddud (2024) presents benefits of adopting AI in the supply chain, but also discusses the potential implementation process. He recommends that companies start using ChatGPT, the LLM investigated in his study, and learn as they test its applications. He also mentions that training of employees is a way to further enable effective usage. This employee training could be either a broad one for everyone, or a more niche one for every function within the supply chain. Following this, they recommend creating standardized prompts for employees to use. Finally, they recommend developing internal rules on ChatGPT usage. They mean that procedures, policies, and norms need to be clear for users, both in the company and within the supply chain function.

Gstettner et al. (2024) discuss how the implementation of GenAI in the Supply Chain can be conducted through five steps. The steps are presented in Table 3.5 together with an explanation derived from Gstettner et al. (2024).

Table 3.5: GenAI implementation steps and explanations derived from Gstettner et al. (2024)

Step	Explanation
"Set the ambition"	Don't use GenAI without reason, understand how it aligns with company strategies. Assess how work tasks are defined, today and in the future, and where GenAI can fill gaps. The result of GenAI adoption should contribute to measurable impact.
"Map key decisions across the supply chain"	Don't adopt GenAI into every part of the Supply Chain. Instead, locate the decisions where the adoption would have greatest impact in the form of quality and efficiency.
"Prioritize where to start"	Not only key decisions should be identified, but also key areas of potential. For example, identifying a specific processes where the benefits are immediate, result in momentum in the internal AI transformation.
"Rethink the end-to-end workflow relating to key decisions"	Streamline human-operated processes, resulting in more human-designed processes. Automating repetitive tasks for example, can result in more time being spent on strategic decisions. In this step, it's also important to truly embed GenAI into the process, and not only used as a feature, resulting in better adoption.
"Start building with the right ecosystem"	To scale the GenAI implementation and its infrastructure, different in-house stakeholders should be apart of the adoption. A cross-functional ecosystem allows extracting the full capabilities of emerging AI technology, and allow fast implementation.

Another way of implementing AI in S&OP is by creating a whole new platform for all information and data. This is something companies like Capacity (2026) and Datup (2026) are working with. This operation would be more complex than implementing an AI in an organization's already existing systems, but in the end it could possibly have a better ROI. This alternative is not something that will be explored more thoroughly, as the large-scale brewery is only looking to optimize their existing operation and not remodel their entire S&OP.

3.6.4 Transformation Efforts

Kotter (2007) explains in his paper why transformation efforts usually fail. He identifies eight errors for transformation efforts, and uses them to derive an eight step plan for transforming an organization successfully. By following every step of

his framework, the organizational change is less likely to fail according to him. The steps and how to achieve them according to Kotter (2007) are:

1. "Establishing a Sense of Urgency"

This can be achieved by "Examining market and competitive realities" and then move on to "Identifying and discussing crises, potential crises, or major opportunities". The reason is generating some motivation within people that change is required. When a transformation is to be conducted within a department, the department head plays a crucial role for the success. Strong leadership is required to create and communicate the need for change.

2. "Forming a Powerful Guiding Coalition"

This can be achieved by "Assembling a group with enough power to lead the change effort" and then follow up with "Encouraging the group to work together as a team". Initially, a relatively small but influential group may be sufficient to lead the change effort. The team needs to be put together carefully and with a strong leader.

3. "Creating a Vision"

This can be achieved by "Creating a vision to help direct the change effort" and then "Developing strategies for achieving that vision". The vision is likely to change during the change process, but that is acceptable. It helps the change effort to have a direction and develop the required strategy for achieving it. The reason for having a vision is to avoid creating confusing projects, and instead keeping projects in the right direction. The clear vision is the motivation for creating projects and driving the change.

4. "Communicating the Vision"

This can be achieved by "Using every vehicle possible to communicate the new vision and strategies" and by "Teaching new behaviors by the example of the guiding coalition". Even if there is a great vision, it won't have the desired effect if it's only presented during a meeting. Executives have to use all possible means to spread the vision though for example newsletter, management meetings, and facilitate educational training about the vision. Adding to this, the executive that drives the change has to be driving the cultural change as well.

5. "Empowering Others to Act on the Vision"

This can be achieved by "Getting rid of obstacles to change" and "Changing systems or structures that seriously undermine the vision" and also "Encouraging risk taking and nontraditional ideas, activities, and actions". As the transformation grows, so does the number of people involved. To facilitate the growth, all possible obstacles that hinders employees from participating needs to be removed. During this

part, it's crucial to have managerial support so that employees are free to drive change.

6. "Planning for and Creating Short-Term Wins"

This can be achieved by "Planning for visible performance improvements" and then by "Creating those improvements" and afterwards "Recognizing and rewarding employees involved in the improvements".

7. "Consolidating Improvements and Producing Still More Change"

This can be achieved by "Using increased credibility to change systems, structures, and policies that don't fit the vision" and then by "Hiring, promoting, and developing employees who can implement the vision" and "Reinvigorating the process with new projects, themes, and change agents". Even though goals are met, the transformation is not completely achieved since the culture needs to change as well. Wins should be celebrated, but claiming that the transformation is complete too early may cause the progress to disappear.

8. "Institutionalizing New Approaches"

This can be achieved by "Articulating the connections between the new behaviors and corporate success" and also by "Developing the means to ensure leadership development and succession". Showing employees the culture by living it is important, and ensure that the new managers does this is crucial.

4

Findings and Discussion

The following chapter presents the results of the study conducted and analyzes it. Firstly the data collection is described and the different sources of empirical data. This data was then used to identify processes that were sorted into process categories. The different process categories were ranked based on where efficiency improvements had the most potential. Following this, AI applications for the processes were identified and matched. When the most suitable and feasible AI solution was identified, its implementation strategy was analyzed.

4.1 Data Collection

This chapter contains information about the data collection conducted in this thesis, it's divided into the empirical study of interviews, focus group, and shadowing. The thesis conducted a total of ten semi-structured interviews, one focus group, and two shadowing sessions. One of the interviews was with the company Alice Labs, who's working with AI implementations in companies. This chapter presents an overview of the sources of data collection, and more specific findings are presented and discussed as they become relevant in the analysis.

4.1.1 Interviews

The interviews gave insights into both the processes conducted by the different functions and employees, as well as the general usage of AI in the work carried out. All information about processes has been analyzed and grouped into different process areas with respective categories, as seen in Table 4.2.

The processes conducted varied considerably depending on the area in which the employee works. This variation affects the potential of an AI implementation. The potential of a process is decided by what the S&OP department and the literature study would find the most lucrative to optimize.

As for the general usage of AI, the employees are on very different levels of AI usage. Some use AI daily in their work and administrative tasks, and some have never used AI in their work. This difference makes achieving an overall solution more difficult.

The processes identified from the interviews were written down and grouped together with similar processes. For example, if an interviewee from *SP* said "Meeting notes"

(this thesis translation), and another interviewee from *Mgmt* said "Meeting protocol" (this thesis translation), they are assumed to be the same process.

4.1.2 Focus Group

From the focus group, information about how the S&OP management team perceived AI, their thoughts on its potential, and how AI affects work tasks became clearer. The management team agreed on the underlying reason for an AI implementation, to be able to improve the operational efficiency and performance in the daily work as well as in long term strategies. At the same time, they agreed that it would be good to be able to measure this, but it would not be a mandatory thing to measure the impact of all types of usage just for the sake of it. This insight is something that needs to be taken into consideration when suggesting a solution, because it means that the impact that an AI would have doesn't necessarily need to be measurable.

4.1.3 Shadowing

The shadowing of two SP employees gave a great understanding of the actual processes and tasks that employees perform during the day. It gave insights into where potential optimizations could be implemented by following the steps of each process in real time. It also provided a comprehensive understanding of the daily SP work at the large-scale brewery.

Compared to interviews, shadowing gave more detailed information and a better understanding of the tasks that SP employees perform. This helped to understand the processes with the greatest potential, and therefore facilitate the process mapping.

4.2 Process Mapping and Comparison

The data collection enabled identification of processes. The processes were categorized which enabled pairwise comparison between the different categories. The result was a ranked list of the process categories that explains where the efficiency improvements have the most potential which can be used when deciding what sort of AI solutions are most suitable for the large-scale brewery.

4.2.1 Identifying Processes

The processes were divided into four areas: *Data Management and Accessibility*, *Admin Tasks*, *Optimization Problems*, and *Analysis*. Within each area, different categories were identified which is presented in Table 4.1. The processes that each category include is shown in Table 4.2.

Table 4.1: Identified process areas and categories in the large-scale brewery's S&OP department

Area	Categories
Data Management & Accessibility	Convert/move data between systems Validate data between systems Data accessibility
Admin Tasks	Communication Information summarization Coordination
Optimization Problems	Procurement Logistics Production Planning Sales Forecast
Analysis	Performance analysis Decision making Strategy

Table 4.2: Process areas and categories with the corresponding S&OP department that mentioned the process

Data Management and Accessibility	
Convert / Move Data Between Systems	
Manually fills in files with production data	SP
Change work, exchange of pledges and update of articles	SP
Check risk of shortage for every article and add in Excel	SP
Ordering, conversion to PDF, and email for deliveries for locations without ERP system	SP
Manually manage orders from locations without ERP system in Excel and book trucks	SP
Manage different systems	SP
Waybill production (partially automated)	SP
When releasing new products, manually add simple data	PCM
Wish: AI-generated Excel instead of code suggestions	PCM
Wish: Generate process maps from text (Word → PowerPoint)	PCM
Power BI forecasts	Mgmt
PCM inputs and updates master data	Mgmt

Update Excel with KPI numbers	Mgmt
Update KPIs across multiple tools and presentations	Mgmt
Wish: Daily ERP system export to Excel for live data access	Mgmt
Update of large amounts of material	Mgmt
Update of PowerPoint before weekly meeting	Mgmt
Validate Data Between Systems	
Check invoices against deliveries	SP
Compare production plan, stock, and sales	SP
Compare the ERP system planning board with Excel	SP
Manual information checks	SP
Shortage list: what is not in stock?	SP
Stock balance and expiry tracking	SP
Validation of information	PCM
Data may be reviewed multiple times unnecessarily	PCM
Verification of data, material number, VCD (goods certificate)	PCM
Data Accessibility	
Blocked products not accounted for in the ERP system	SP
File search in SharePoint	SP
Move emails into correct categories	SP, Mgmt
Fix inconsistencies when multiple sites are handled in the ERP system	SP
Close drop-shipped products when PCM instructs	SP
Communication due to forecast updates not reflected in the ERP system until Sunday	SP
Another team ensures execution (contact with drivers, etc.)	SP
Information seeking	Mgmt
Wish: Understand other departments via a “meeting bank”	SP, Mgmt
Wish: AI automation for weekly/monthly reporting and KPIs	Mgmt
Admin Tasks	
Communication	
Teams chats	SP
Email conversations	SP, Mgmt
Keep colleagues updated on changes	SP
Internal communication	SP
Meetings	SP, PCM, Mgmt
Difficulty: Hard to keep everyone aligned and updated	SP
Truck booking followed by sending confirmation email	SP

Verbal communication in open landscape office	SP
Short and standardized communication (email/Teams)	SP
Hunt down people for answers	PCM
Draft emails and communication	PCM, Mgmt
Plan meetings (agenda setting)	PCM, DP
Mail and Teams cross-functional communication (Much with DP, and SP, from PCM)	PCM
Daily morning meetings	DP
Information flow between commercial and supply	DP
Contact with other departments	DP - Mgmt
Contact with customers	DP - Mgmt
“AI helps me with formulations” (this thesis translation)	Mgmt
Update department meeting agenda	Mgmt
General communication tasks	Mgmt
Product data to goods certified customer	Mgmt
Position / job descriptions	Mgmt
Information Summarization	
Meeting notes	SP, PCM, DP, Mgmt
“AI helps summarize email threads” (this thesis translation)	Mgmt
“AI helps understand complex topics” (this thesis translation)	Mgmt
Wish: Update on meeting discussions	Mgmt
Meeting actions	DP, Mgmt
Coordination	
Divide tasks between colleagues	SP
Interaction and joint decisions with colleagues	SP
Coordinate with production lines using the same material	SP
Coordinate across production lines during shortage risks	SP
Meetings to solve issues	SP
Coordination with other countries	SP
Meeting invites - facilitator	PCM
Finding the right people for a project, and aligning them towards a common goal	PCM
Project management (supply chain)	PCM
Project management across supply chain and commercial	PCM

Improvement projects	PCM
Innovation projects	PCM
Efficiency improvement projects in production	PCM
General project work	Mgmt
Work across departments	DP - Mgmt
PMS process	Mgmt
Optimization Problems	
Procurement	
Ordering materials	SP
Material call-off	SP
ERP system stop transfer order → purchase order	SP
Logistics	
Tank capacity for storing ingredients	SP
Delivery slot planning to production	SP
Adjust production order size for earlier pickup	SP
Analyze truck schedules and book	SP
Warehouse logistics coordination	SP
Transport to/from external warehouse	SP
Return logistics to main warehouse before shipping to customer	SP
International warehouse management	SP
Adjust logistics based on forecast/sales changes	SP
Manual safety stock adjustments - ERP system's safety stock recommendation is adjusted for external warehouse logistics	SP
Warehouse management	Mgmt
Planning and logistics	Mgmt
Production Planning	
Optimize production plan (time and cost)	SP
Forecast management	SP
Last-minute changes	SP
Short- and long-term forecasting during S&OP weeks	SP
Handle disruptions (e.g., production stops)	SP
Consider multiple parameters, e.g. golden rules	SP
Analyze and move in production plan when shortage is a risk with safety stock as parameter	SP
Create supply and production plans in the ERP system	SP
Evaluate the ERP system recommendations and identify weeks that are not reasonable	SP
Re-planning	Mgmt
"Capacity planning" (this thesis translation)	Mgmt
Sales Forecast	
Manual forecast for seasonal items	DP

Campaign forecasting	DP - Mgmt
Clean outliers in data for statistical forecasting	DP- Mgmt
Ensure correct forecast per product	DP
Analysis	
Performance Analysis	
Follow-up of errors and things that didn't go well	SP
Analyze what happened and why	SP
Shortage analysis in daily meetings - why can we not sell them?	SP
KPI analysis	Mgmt
Savings initiatives (internal AI development)	PCM
Inventory risk analysis	DP
Problem explanations	Mgmt
Risk assessment for future scrap based on e.g. quality, design change or risk of labels requiring scrapping	Mgmt
Manual KPI coding (automation potential)	Mgmt
Capacity, rotation, and risk analysis	Mgmt
Similar risks in different projects	Mgmt
Decision Making	
Gut-feeling decisions (reason for not using AI)	SP
Evaluate risk analysis and decide how risks are to be taken into consideration	SP
Ensure the ERP system recommendations are correct	SP
Master data troubleshooting	SP
Trade-offs with customers and stakeholders	DP
Goal formulation	Mgmt
AI is used for objective setting	Mgmt
Decision statements	Mgmt
Strategy	
Long-term planning	SP
Wish: More focus on change management	SP
Project planning	PCM
Wish: Prioritize risks based on profitability	Mgmt
New product launches	PCM
Portfolio management	PCM, Mgmt
Wish: Understanding of - what is the customer ready to pay for?	Mgmt

4.2.2 Comparing the Potential of Process Categories

Appendix A.1 shows the pairwise comparison between all categories through a relationship matrix. The categories were rated 0, 0.5 or 1 compared to each other, where 0 means less, 0.5 means equal, and 1 means more potential compared to the category in relation. Potential is defined as **time savings** in processes through usage of different AI solutions, with the aspect of being **feasible** enough to align with the large-scale brewery's strategic ambitions.

The matching of the most suitable AI applications depended on the ranking of process categories. In turn, the ranking of the process categories was an iterative process that relied on the outcome of the matching and analysis. The first iteration was discussed with the Mgmt team at the large-scale brewery to get more strategic alignment and feedback. Furthermore, the matching of AI applications to process categories provided insights into the feasibility of different approaches and highlighted which specific processes were most likely to yield desirable effects. Consequently, the second iteration of the ranking was less subjective and more closely aligned with the company's strategic priorities. After the iteration, the main changes was for *data accessibility* to receive a higher score due to the large-scale brewery's wish for "*focusing on the more clear parts*" (*this thesis translation*) as mentioned by *Mgmt*.

Table 4.3 shows the result of the relationship matrix. The higher the score, the more potential the category has. The categories that stand out are *convert/move data between systems*, *validate data between systems*, *data accessibility*, *logistics*, and *sales forecast*. The reason for this was that the empirical study showed what type of processes and strategy the Mgmt team wanted to focus on, and where most employees thought that their time wasn't used in an optimal way.

Convert/move data between systems had multiple processes that showed more potential than others. During the shadowing and interviews, it became clear that employees use data from one system and only convert or move it without adding anything new to it. These tasks showed high potential as the manual processes had potential for efficiency improvements. It is not necessarily through usage of complex AI solutions, but the processes still have efficiency potential. Apart from this, the focus group showed that Mgmt had an explicit vision about using data from the ERP system and automatically converting it to excel with the purpose of always having the latest data. This wish from management contributed to the high scoring of *convert/move data between systems*.

The data collection of the SP employees also showed explicit efficiency potential of tasks connected to validation of data. It was considered that unnecessary steps were taken to *validate data between systems*, resulting in this category's high score. However, there was not enough data to motivate a higher or lower score than *convert/move data between systems*. There are clear findings from interviews and shadowing that employees find this manual process redundant.

The process category *data accessibility* has *information seeking* as a process and this has high potential, but the result of investing in this improvement would not save

more time than automating reoccurring manual tasks for example. Management wanted this category to be higher, and that was taken into consideration. However, *data accessibility* in itself is not solely AI dependent, but requires API integration. This requirement is the reason why Data accessibility is not as high as the other process categories within the Data management area.

Logistics received a score of 9. This score was mainly based on findings during the shadowing of *SP*. It became clear that small changes could require excessive logistical coordination. The score is based on possible automation and AI solutions to optimize certain tasks that might have potential to improve efficiency. For example, in their planning, there could possibly be improvements that predict parts of the planning process through historical data. Although there is potential for efficiency improvement, the solution is not predetermined.

Finally, *sales forecast* is the last category with a score of 9. The scoring was based on their usage of historical data. By using a large data warehouse with quantitative data, there is a possibility of optimizing forecasts by usage of ML AI models. However, data from DP, which is the most relevant for this process category, is more limited compared to other departments. This results in the scoring for *sales forecast* being more uncertain. The amount of AI used in today's systems and model was not clear and could possibly mean that too high of a score is redundant as external forecast systems have already incorporated a valid AI implementation. However, the high scoring of 9 prevails as the forecast is using historical data and AI can possibly help using this data more efficiently. This implementation requires clean data which other process categories supplies.

Production planning received a relatively high score due to processes such as *optimize production plan to save time and money* and *take many parameters into consideration; weight of golden rules etc..* There are possible AI applications, but they risk being more abstract than other solutions due to the complexity of the processes within this category. The identified AI applications are likely to have a big effect if they succeed with their implementation, hence the high scoring for this process category.

Information summarization received its mediocre score due to the large-scale brewery's usage of AI applications today. AI is already used by many to conduct the processes in this category, hence there is not high potential as the time savings wouldn't be big. However, not everyone uses AI in the same way, meaning there is potential in educating everyone to be efficient within *information summarization*. There could be an effect if more people understood in what ways existing applications could be used, hence the scoring of 6.

Communication has a similar reasoning as *information summarization*, but still receives a lower score. This is due to the effect of the improvement efforts. Within *communication* the effect will likely be slightly less tangible and not be relevant for all departments. During the shadowing of SP, there was a large amount of emails, but they were often short and standardized and wouldn't become more efficient with AI applications. Other departments could benefit from efforts within this process

category but there is not enough data to compensate for the findings from the SP shadowing.

Coordination and *performance analysis* are two categories that have been ranked the same, in a ninth place. With *coordination* the potential lies mostly with the employees, and this makes it hard to improve it using an AI since processes such as *project management requires bringing together the right people, and making them want the same thing* has low potential. This tacit knowledge requires an understanding of the employees and the organization that is hard to put into words. However, an employee can learn this knowledge by working with the people, therefore, it results in the low scoring. *Performance analysis* is ranked quite low because of the retroactive aspect, it would not work proactively and therefore has the thesis decided that the improvement potential for this category is not high enough to focus on. The processes are not as tangible compared to the ones with higher scoring, but it still has potential to some regard.

Procurement has potential, but with the identified categorization, there was not enough data provided to motivate a higher potential compared to other categories.

The category *decision making* is hard to improve with the help of AI, since the core of it is that employees make decisions based on the data they have, this would not be profitable to automate in the near future due to the inconsistency of decisions.

Lastly, *strategy* received the lowest score, as that was an area the interviewees wanted to work with more. The interviews showed that employees wanted to work less with the manual tasks, and more with strategic questions and change. Investing in AI solutions in this area would therefore not satisfy interviewees and their motivation for implementing AI risks declining. Strategic processes were also not clearly identified, hence it was not prioritized above other categories with more concise tasks.

Table 4.3: List of categories and respective score derived from relationship matrix

Score	Area	Category
11,5	Data Management & Accessibility	Convert/move data between systems
11,5	Data Management & Accessibility	Validate data between systems
9	Data Management & Accessibility	Data accessibility
9	Optimization Problems	Logistics
9	Optimization Problems	Sales Forecast
6,5	Optimization Problems	Production Planning
6	Admin Tasks	Information summarization
4,5	Admin Tasks	Communication
4	Admin Tasks	Coordination
4	Analysis	Performance analysis
2	Analysis	Decision making
1	Optimization Problems	Procurement
0	Analysis	Strategy

4.3 Matching Processes With AI Applications

For every process category, appropriate and suitable AI applications were identified. AI applications were derived from Table 3.4. Table 4.4 shows AI applications for each process category. The AI applications all correspond to an AI capability area which can also be found in Table 3.4. Colors are used to separate different AI capability categories, and their shades are used to separate AI applications within the AI capability categories. To clarify, the color red is for the AI capability *AI Automation*, shades of blue is for *AI Support*, shades of purple is for *AI Analysis*, shades of green is for *AI Forecast*, and shades of yellow is for *AI Data Management*. Different AI models, from different references, can be suitable for the same AI application. Therefore, a discussion is held with regards to the process categories of interest and AI use cases within the AI applications. This section will, for every process category, discuss why and how the AI applications are relevant in Table 4.4.

During the matching, the most appropriate AI models are discussed as well. The aspects that are taken into consideration are time savings, feasibility, and strategic alignment. These are the same aspects that were considered during the scoring of different process categories. Therefore, the result and analysis of the relationship matrix in Appendix A was also taken into consideration when comparing suitable AI models.

4.3.1 Convert/ Move Data Between Systems

This is one of the process categories with the highest efficiency potential and there are three AI applications that are relevant. This subsection covers why and how these AI applications are relevant.

Automate repetitive tasks & processes in optimal way

Nichols (2025) discuss how an LLM can be used to *Automate repetitive tasks and allocate time to value-adding activities* by designing an agentic AI which is something that is relevant for this process category. During the shadowing it was found that data was converted between ERP system, excel, and into pdf. This repetitive task could possibly become more efficient by applying automation solutions. Therefore, the most suitable AI model for this is **agentic AI**. LLM was used to create the agentic AI, but the output is an automation which this thesis defines as an agentic AI.

Data cleaning

Polo (2024) explain how their agentic AI solution enabled *real-time updates across SCOP data layer*, while Kumar Singh (2023) argues that an ML model could perform *normalization of data*, and *data cleaning*. All of these use cases are explicit findings from the literature review. Management had a wish for automatically moving data from the ERP system, on a daily basis, and move it to excel so that one have access to live information. Using an agentic AI or an ML model in a similar way as Polo (2024) or Kumar Singh (2023) could enable the internal development of this sort of solution. Adding to this, there are processes where data in PowerPoint for example, requires updates. These updates could be automatically conducted as part of the cleaning of the data in the presentation. The automation for this application conclude that an **agentic AI** is the most suitable model. Agentic AI will likely require less resources than the development of an ML, hence it is more suitable for the large-scale brewery as their AI usage is in a novelty stage.

Centralize data

ML AI solutions from Kumar Singh (2023) can also be used for centralizing data. He discusses how data can be converted between systems which is crucial for this process category. Harmonizing data from an ERP system is, for example, of high relevance since the large-scale brewery has their data warehouse in an ERP system and they want to move data in an optimal way with their wish for automated data extraction into Excel for example. Agentic AI can also be relevant in this area as Nichols (2025) explains how *"Data consolidation and reporting"* can be achieved with usage of an agentic AI, which is built using copilot. He also means that manual imports of excel sheets can be automated though an API. In conclusion, due to the ease of implementation, an **agentic AI** is the most suitable AI model. The decision for agentic AI is strengthen by the lack of information connected to ML in centralization of data from Kumar Singh (2023).

Most suitable AI model

Both agentic AI and MLs are relevant solutions for this process category. The processes that contributed to the high scoring in the relationship matrix are used to determine the most suitable AI model. This process category is ranked high in the relationship matrix due to manual processes of *moving data between systems* that could be solved using automated solutions, as well as the managerial wish for *automatically extracting data from the ERP system*. Both of these are suitable for **agentic AI** which is therefore deemed the most suitable AI model. However, it does require API integration between systems which is not an AI application.

4.3.2 Validate Data Between Systems

This section covers the process category of *validate data between systems* that has high potential for efficiency improvements.

Automate repetitive tasks & processes in optimal way

This is the main AI application identified for *validate data between systems* as the empirical study showed high potential for efficiency improvements in this area. It is a reoccurring process to validate information that risks having human errors, it was thought of as repetitive and unnecessary since it should be possible to automate. By using an LLM and creating an agentic AI, Nichols (2025) means repetitive tasks can be automated. This requires the LLM agent to access all the data and give reliable and correct results, but the potential for efficiency is high. Therefore, **agentic AI** is the most suitable model for this AI application.

Help understand data

Different LLMs use cases can be applied to *help understand data* and this is relevant when *validating data between systems*. The use case of highest relevance for *validating data between systems* is "*Provide a gap analysis between documents*" which is explained by Microsoft (2025). This AI use case could be highly beneficial to processes such as *Manual information checks* and *Check invoices against deliveries*. In conclusion, **LLM** is the most suitable AI model.

Find warning signals in data in real-time

Processes such as *Stock balance and expiry tracking* and *Check invoices against deliveries* could benefit from this AI application. Nichols (2025) discuss how LLMs as agents can have use cases such as "*Inventory risk alerts*" and "*Forecast accuracy monitoring*", both can be applied to those processes. "*Forecast accuracy monitoring*" would, for the process of *Stock balance and expiry tracking*, need to be used as a tool for checking and flagging when the forecast is wrong in real-time, and not in retrospective. Using an LLM as an agent makes it an agentic AI and, therefore, is an **agentic AI** the most suitable solution for this AI application.

Data cleaning

The process *Compare the ERP system planning board with Excel* is the main reason for matching of data cleaning and *validate data between systems*. Polo (2024) explains how their agentic AI model enables *real-time updates across S&OP data layer* which can be applied to this process found at the large-scale brewery. By updating data in real-time, the need for comparing numbers between systems is eliminated. For this, **agentic AI** is most suitable.

Most suitable AI model

Three out of four AI applications are relevant for agentic AI solutions, and one is relevant for an LLM solution. The motivation for this process category's high scoring in the relationship matrix was the unnecessary process of manually validating data between two systems. Assuming that an **agentic AI** has access to all data that need validation would make it the most suitable due to the AI application of Automate repetitive tasks & processes in optimal way.

4.3.3 Data Accessibility

Data accessibility received a high score in the relationship matrix in the second iteration. This subsection describes how different AI applications can be used for improvements in this process category.

Help understand data

The reasoning for matching this AI application with the process category Data accessibility is the AI use cases *"Summarize Data"* explained by Gibraltar (2026a), and *"Give me insights on my data"* explained by Microsoft (2025). They describe how copilot can be used and one process that would be covered by this is the managerial wish for an *AI automation for weekly/monthly reporting and KPIs*. This specific wish is not covered entirely in the AI use cases, but if it were to become a reality, these AI use cases would be highly relevant. If an automated system were to retrieve internal information, screen data so the relevant data is used, and summarize it intuitively, these AI use cases could be applied to some extent. However, implementing this type of new automated process might be difficult without taking other AI applications into consideration, such as centralize data. The AI model of relevance within this AI application is **LLM**.

Centralize data

LLMs as agents can, according to Nichols (2025), be used for *"Data consolidation and reporting"*. Using LLMs and creating agentic AIs in this way further enables a solution for the Mgmt wish of *AI automation for weekly/monthly reporting and KPIs*, even though the actual connection between systems is not covered in this AI use case. However, it could be possible by investigating the AI use case of *ingest & harmonize data from ERP, CRM, POS, supplier systems, logistics*, discussed by Kumar Singh

(2023). He uses an ML model to do this, as well as enabling *master data alignment*. These use cases could potentially fulfill the wish of creating this process. Increasing the centralization of data that's placed in different systems would result in more real-time data. This could enable efficiency improvements in processes such as *communication due to forecast updates not reflected in the ERP system until Sunday* as *SP* mention and enable the creation of the process wish for *understand other departments via a "meeting bank" (this thesis translation)* mentioned by *PCM*. Using LLMs as agents could improve the efficiency in these processes. In conclusion, **agentic AI** will likely fulfill the needs, assuming the API integration is valid.

Most suitable AI model

Agentic AI is suitable for *data accessibility*. However, access to data across systems is not provided by AI models themselves, but is enabled through underlying system integration, such as APIs. IBM (n.d.) explains how AI applications depend on data access, which is mediated through API integration. APIs can be described as software that connects different IT systems and enables access to real-time data. By having strong API integration and API management, AI applications can access data from different systems, enabling many of the use cases described. In conclusion, **agentic AI** is most suitable for the processes found in this process category, with the assumption that API integration enables accessibility.

4.3.4 Procurement

Procurement is a process category with limited data as it is only relevant to the SP department at the large-scale brewery. This results in a limited number of relevant AI applications.

Automate repetitive tasks & processes in optimal way

Durach and Gutierrez (2024) explain how LLMs can be used for *"Order processing and reordering"*. This can be applied to the process *ordering materials*. Durach and Gutierrez (2024) describe this AI use case as *"contextual chatbots can streamline order processing, facilitating faster, more accurate outcomes that reduce manual errors and elevate customer satisfaction"* (p. 235). They describe in their literature review, how chatbots with access to various systems within the organization, such as an ERP system in the large-scale brewery's case, enables *"Order processing and reordering"*. They mean that although some ERP systems provide automatic reordering solutions, the chatbots have an advantage since there is a human-like interaction with the chat. The chatbot enables better understanding for the user as the same information can be accessed by users depending on their skills. In conclusion, the most applicable AI model is **LLM**.

Most suitable AI model

This process category has limited process data and only one AI application. Hence, the most suitable AI model is **LLM**.

4.3.5 Logistics

Logistics is a process category with high potential for efficiency improvements. The identified AI applications can contribute in various ways to improvements within this category.

Automate repetitive tasks & processes in optimal way

Kumar Singh (2023) explain the AI use case of *Executes optimal actions across Demand, Supply, Inventory, Capacity* which is applicable to the process category of Logistics. Using an ML model, one could enable efficiency improvements within processes such as *Delivery slot planning to production*, and *Planning and logistics*. More processes could be of high relevance but the processes are not concise enough to recommend a practical use in more detail.

Parallels could also be drawn between the large-scale brewery's S&OP process and the AI use case of *Automate Supply Chain Reconciliation*, explained by Polo (2024) through the usage of an agentic AI model. Reconciliation between departments is crucial within the S&OP process, and during the shadowing it was found that there was continuous communication between SP and DP, and not only during formal reconciliation meetings. It was found that changes in demand plans weren't available for supply planners until Sundays as that's the day they centralize the ERP system's demand plan data. If a change in demand plans occur in the middle of the week the changes have to be communicated to supply planners that manually change their data to fit the new demand. Although this can also be seen as an issue originating from issues with the ERP system and data systems management, the agentic AI model from Polo (2024) could potentially make this reconciliation easier and more efficient. For clarity, the identified process that could benefit from this use case is *Adjust logistics based on forecast/sales changes* mentioned by SP. The formal reconciliation process at the large-scale brewery has not been studied deeply through shadowing, but the AI use case could potentially be applied here as well in a more general way. The **agentic AI** from Polo (2024) is therefore deemed most suitable for this AI application.

Support future what-if scenarios

Ohlson et al. (2022) explain how an ML model enables *"Estimate a projected probability for future projects based on historical data"*. This is highly relevant for *logistics*, particularly for *International warehouse management* and *Planning and logistics*. These processes are more broad than some others, but within these processes it was found that when shortages occur due to various reasons, goods can be produced and shipped from other countries. Although it was not an explicit process, this is assumed to require considerations whether goods should be prioritized for in-house production or out sourced to leave production time for other products. This requires further investigation into exactly how this decision is made. Even if there are clear and optimized rules for this process, *"Estimate a projected probability for future projects based on historical data"* (Ohlson et al., 2022) could potentially enable these standards to become more optimized by adapting the standards to the outcomes.

Adding to this, *Continuously evaluate trade-offs (service, cost, margin)*, explained by Kumar Singh (2023), could also enable this with usage of ML. The limitations to the optimization has to be investigated as Durach and Gutierrez (2024) explain that LLMs can be used for *"Predictive insights"*. Although they do not explain it is an actual limitation, there is a difference between receiving insights and optimizing the trade-off that's more in line with Kumar Singh (2023). Due to the complexity of these processes, the conclusion is that **ML** is most suitable for this AI application. However, it should be noted that one approach could be to use LLMs and through trial and error find the limitations to this model within this AI application.

Find warning signals in data in real-time

By using agentic AI as Nichols (2025) discuss, *"Inventory risk alerts"* can be enabled which is applicable to the process of *warehouse management*. This is a Mgmt process, but more practical process examples that could benefit are:

- *Tank capacity for storing ingredients from SP*
- *Transport to/from external warehouse from SP*
- *Analyze truck schedules and book from SP*
- *Delivery slot planning to production from PCM*

Identifying and assessing supply chain risks is another AI use case that's applicable to *logistics* processes. With ML and Deep learning models, Kumar Singh (2023) shows this AI use case which can be applied to *Adjust logistics based on forecast/sales changes* mentioned by *SP*. The time between exception occurring and the production change would likely become shorter. However, the effect this would have at the large-scale brewery is not obvious since the time spent on communication per person might be the same, only earlier. This is still beneficial as it likely would allow higher accuracy planning, but then the effect is more general and not measured for the specific process of *adjust logistics based on forecast/sales changes*. Instead, the process *Planning and logistics* for Mgmt will become more relevant for the beneficial effect. However, the processes that are matched with Nichols (2025) are more concrete and will likely have larger effect. Therefore, an **agentic AI** are more relevant for this AI application.

Forecast market

Most of the AI use cases for forecasting market is connected to the processes found in the process category *sales forecast*, and not *logistics*. This is natural as that is a deliberate distinction made to separate the departments in this report, but there is still an AI use case that is applicable for *logistics* as well. Ohlson et al. (2022) explain how ML can enable *"Estimate future bullwhip-effects related to S&OP-decisions based on historical data"*. This can be connected to *Planning and logistics* in general for Mgmt, but also *Adjust logistics based on forecast/sales changes* that occur within *SP*. Avoiding bullwhip effects due to demand fluctuations could then be avoided to a higher regard. The amount of bullwhip effect today has not been measured in the

thesis, but decreasing bullwhip effects is assumed to be beneficial for the large-scale brewery.

Adding to this, the AI use case *Forecast demand using historical & real-time data* that Anumula et al. (2025) explain by using ML and Deep learning models can be applied to the processes *Warehouse management* and *Planning and logistics* from Mgmt. Both Ohlson et al. (2022) and Anumula et al. (2025) are discussing ML models which is the most suitable AI model for this AI application.

Forecast in-house capacity

Kumar Singh (2023) explains with usage of ML models, the AI use case of *Forecast inventory levels using historical & real-time data*. This can be directly applied to SP with their process/problem of *Manual safety stock adjustments - the ERP system's safety stock recommendation is adjusted for external warehouse logistics*. During interviews it was found that the data was not always correctly optimized which was taken into consideration in some of the decisions connected to safety stocks. This active consideration could therefore be eliminated by having safety stock on more data-driven information that's more accurate.

This safety stock is something that could potentially be improved by *"Inventory allocation logic with dynamic constraints"* using *vibe coding*, by using LLMs which Calore (2025) explains. Enabling Supply Planners who take this active decision to code their own optimization could be beneficial. They could apply their tacit knowledge and be part of the development of the optimized safety stock.

Mgmt gave the broad processes of *Warehouse management* and *Planning and logistics*, both of which can acquire efficiency improvement by using agentic AI like Nichols (2025). Nichols (2025) identified *SKUs according to specific criteria* to find what SKUs had unexpected forecast variance. This type of AI use case can be applied to both of these processes.

Durach and Gutierrez (2024) explain the use case of *"Capacity planning"*. They explain in their literature review how *"Contextual chatbots, when integrated with ERP, MRP and CRM systems, can continuously monitor capacity utilization, production planning, and human resources, and forecast sales"*. This is discussed in the context of the ERP system's copilot. This would result in real-time tracking and monitoring of capacity utilization, meaning better utilization of resources.

Three ML use cases from Ohlson et al. (2022) are identified within forecast in-house capacity:

- *Estimate future inventory based on future operations plan & inconsistency patterns in historical actual inventory*
- *"Estimate future capacity utilization, serviceability and location of future bottlenecks based on historical data"*
- *"Predict capacity utilization over time and identify bottleneck resources"*

All of these are connected to the processes that have already been discussed in this subsection, adding to the amount of solutions for their process efficiency improvements. ML, LLMs, and agentic AI models are all relevant within this AI application. The most suitable, based on the motivations that gave *logistics* its high scoring in the relationship matrix, is agentic AI. The other ones are still of high potential and LLM can for example be investigated by employees as they try to use it with the purpose of making the specific processes more efficient. However, the one model that is expected to give most effect is **agentic AI**.

Most suitable AI model

Forecasting in-house capacity is a crucial AI application for the process category Logistics. The most appropriate AI model was deemed to be agentic AI which is also the most relevant model for Automate repetitive tasks & processes in optimal way, and Find warning signals in data in real-time. Although other models are relevant, **agentic AI** is the most suitable.

4.3.6 Sales Forecast

Sales forecast is a process category that received a high scoring in the pairwise comparison matrix, in Appendix A. However, the amount of data is limited within this process category, resulting in the discussion and decisions being less specific and more general.

Automate repetitive tasks & processes in optimal way

Polo (2024) shows how their agentic AI solution have multiple benefits within this process category. The most important ones are *Automate Demand Plan Generation* and *Automate Supply Chain Reconciliation* as they have clear connections to the large-scale brewery's S&OP process, and the processes found in Sales Forecast. The processes found for Sales forecast in Table 4.2 are all relevant for this type of agentic AI solution. Nichols (2025) also suggest that agentic AI can be used to *Automate repetitive tasks and allocate time to value-adding activities*. Both references for this AI application use **agentic AI**.

Help understand data

The use cases for help understand data are based on LLMs, and the processes covered are *Campaign forecasting*, and *Manual forecast for seasonal items*. The way these processes could benefit is when data-driven recommendations are generated, and it is not obvious why the data has a specific behavior. AI use cases such as "*Give me insights on my data*" explained by Microsoft (2025), and *Understand data* and *Help understanding data-driven recommendations* explained by Simchi-Levi et al. (2025) are relevant for this. However, the amount of time saving and value this would add is uncertain, but it would be conducted with an **LLM**.

Support usage of complex systems

This is, due to limited data collection for Sales forecast, mostly theoretical parallels between AI use cases and identified processes at the large-scale brewery. Within Sales forecast, or Demand forecasts as it's denoted at the large-scale brewery, they can use LLMs as suggested by Simchi-Levi et al. (2025). This means that the LLM would enable a better understanding of mathematical models and *Help update mathematical models*. Adding to this, Gstettner et al. (2024) mean that an GenAI that *Enable usage of advanced tools through support of AI* saves time in the decision-making process. More explicitly, they state that *"greater use of advanced analytics can boost decision-making speed by more than 30%, enabling faster and more informed choices"*. This can be applied to all demand forecasts that are data-driven, resulting in better understanding of customer behavior and data, for example the DP process *Ensure correct forecast per product*. However, **LLM** is a more suitable model since it exist in the organization and fulfills the needs discussed.

Analyze data

Nichols (2025) explains how *"Promotion impact analysis"* is an AI use case for an agentic AI. This is highly relevant for *Campaign forecasting* within DP. Nichols (2025) explicitly explains *"Promotion impact analysis"* as *"Measure effectiveness and alert planners when promotions deviate from expectations"* (p. 29). In this AI application the **agentic AI** would be the most suitable.

Support future what-if scenarios

When conducting a demand plan, AI use cases from Kumar Singh (2023) can be applied. He means that ML can be used to:

- *Continuously evaluate trade-offs (service, cost, margin)*
- *Support What-if scenarios*
- *Learns from outcomes to improve future S&OP cycles*
- *Recommends optimal actions across: i) Demand, ii) Supply, iii) Inventory, iv) Capacity*
- *Runs multi-scenario simulations*

All of these AI use cases are relevant and can be applied in various ways to DP's main process *Ensure correct forecast on correct product*.

There are other similar AI use cases in Table 3.2 that can be applied in the same way. What stands out more is Ohlson et al. (2022) that argue about ML being used to *"Estimate a projected probability for future projects based on historical data"*. During the process *Campaign forecasts* this can be applied to see parallels that otherwise might be missed. ML can also be used, according to Kumar Singh (2023), to *Support What-if scenarios* which can be applied in a similar way to *Campaign forecasts*, but also standard demand forecasts. Therefore, an **ML** model would be the most suitable in this AI application.

Forecast market

To fully extract the potential of AI applications, today's AI usage within the data systems needs further investigation. Anumula et al. (2025) explain how ML and Deep learning models can be used to *Forecasts demand using historical & real-time data*. This is a great use case but since it is not clear what level of AI exists within the forecasting system where demand forecasts are generated, the effect is unknown. If this investment is to be made with the purpose of developing an AI use case for this, it would likely compete with the forecasting system's software to some extent.

Gstettner et al. (2024) explain how GenAI can be used to *Analyze unstructured data to improve for example demand forecasting*, which is highly applicable when creating demand plans, but also the identified process of *Clean outliers in data for statistical forecasting*. Following this, when outliers have been removed, *"Demand clustering analysis" using vibe coding* using LLMs, explained by Calore (2025), is applicable. This could enable employees within DP to become more efficient and remove some of the manual labor of removing specific data.

Finally, an ML model explained by Ohlson et al. (2022), can be utilized to improve efficiency within sales planning. They explain the AI use case of *"Find patterns in historical data and mirror them on the future forecast and/or demand plan"* which has potential when conducting demand forecasts. However, it risks resulting in similar constraints as complex demand plan processes that was discussed earlier: competition with the forecasting system. However, Ohlson et al. (2022) also explain the AI use case of *"Estimate future bullwhip-effects related to S&OP-decisions based on historical data"*. This case could be more relevant as it involves multiple departments within the supply chain in a clearer way. Using this AI use case could potentially reduce human bias when there's fluctuations in customer demand and ensuring that the bullwhip-effect is not exaggerated. In this AI application there is not enough data to understand the need for support and therefore is it difficult to know whether an LLM or an ML model would be the most suitable in this scenario.

Data cleaning

With an agentic AI model, Polo (2024) explains the AI use case *real-time updates across S&OP data layer*, while Kumar Singh (2023) explains with an ML model the use case *Data Cleaning*. These are both applicable, but to different levels. *Data Cleaning* is highly relevant for especially the DP process of *Clean outliers in data for statistical forecasting*. *real-time updates across S&OP data layer* on the other hand, has more constraints. To apply this, there is a requirement that the S&OP department uses the same data management systems internally, which is not the case. The plan is to have the same system in the future, and when that is the case, this AI use case will be of higher relevance. The way it could be solved today is potentially by using an automation that notifies SP when there are changes in DP, replacing their email threads. Note that this becomes more of a communication solution, and not an efficiency improvement within *sales forecasts*.

ML can be used to "*Find errors and inconsistencies in the data and eventually correct or propose corrections of the data*" described by (Ohlson et al., 2022). This is highly relevant for *Clean outliers in data for statistical forecasting*. A similar AI use case is *Improving quality in master data by cleaning & augmenting* which can be achieved by Gen AI (Gstettner et al., 2024). Due to the possible future use case of *real-time updates across S&OP data layer* and the more feasible "*Find errors and inconsistencies in the data and eventually correct or propose corrections of the data*", an **agentic AI** is most suitable for this AI application.

Most suitable AI model

In this process category there are many AI models that could support improvement efforts. In the relationship matrix, *logistics* received its high scoring due to the large amount of data used within the processes. This data was seen as a possibility for AI solutions to optimize forecasts. To achieve this in the best way, ML models are most appropriate. However, the level of complexity within an ML model for sales forecasts is unclear. Depending on the complexity within the forecasting system's forecasts and suggestions, other models could be more lucrative as an ML would be a larger investment. An agentic AI could possibly be better suited because of the automation of the processes leading to the employee only needing to accept or decline the suggested forecast.

Investigating and measuring the actual effect of an ML investment in demand forecasts is required to decide if ML actually is most suitable. Since agentic AI is easier to implement and requires less integration, it should be prioritized to see its effect and compare to the investigation of MLs. In conclusion, in the short term an **agentic AI** is most suitable.

4.3.7 Production Planning

Production planning is a process category that focuses on production and everything that comes with it, for example when things doesn't go according to plan and you need to "*replan*" (*this thesis translation*) as the *Mgmt team* said during the focus group.

Automate repetitive tasks & processes in optimal way

The processes:

- *Optimize production plan (time and cost)*
- *Create supply and production plans in the ERP system*
- *Consider multiple parameters, e.g. golden rules*

are all three mentioned by *SP*, and they could all be supported or handed over to an **ML** model that *Executes optimal actions across Demand, Supply, Inventory, Capacity*, explained by Kumar Singh (2023). This type of AI would be able to decide how to act and plan in different unforeseen situations that occur.

Help understand data

A process that *SP* mentions is *Analyze and move in production plan when shortage is a risk with safety stock as parameter* this process could be supported with the AI use case "*Give me insights on my data*" that Microsoft (2025) suggest as something an LLM is capable of. Getting insights from an LLM before making a decision whether or not to move in production plan could potentially save a lot of money in regards to extra stock keeping or running out of stock. Therefore is an **LLM** preferred.

Support usage of complex systems

The AI use case described by Gstettner et al. (2024) where an GenAI can *Highlight insufficient data when forecasting* is a use case that could support in two different processes, the process of *forecast management* and the process *short- and long-term forecasting during S&OP weeks* both mentioned by *SP*. The *forecast management* will be supported by alerting the employee when something is missing in the forecast, while *Short- and long-term forecasts during S&OP weeks* will be supported by highlighting data that might be incorrect, both will be conducted by an **GenAI**.

Support future what-if scenarios

The process *Analyze and move in production plan when shortage is a risk with safety stock as parameter* that was discussed by *SP* shows that it's important to understand the data that you have to be able to take the right precautions. This is something an ML model can do according to Kumar Singh (2023). He highlights the AI use case *Continuously evaluate trade-offs within service, cost, and margin*, which can be connected to this analytic process described by *SP* since there is a trade-off needed to be done. Another AI use case that could be supportive in this process is *Help analyze different scenarios* which Simchi-Levi et al. (2025) argues is a use case for an LLM, this would also give the employee the information needed to make a good decision.

Find warning signals in data in real-time

The process *Short- and long-term forecasts during S&OP weeks* mentioned by *SP* could benefit from the AI use case "*Forecast accuracy monitoring*" discussed by Nichols (2025) as something an agentic AI can do. The benefit would be that, after some time, it would be possible to notice patterns in the forecasts and tweak them to achieve more reliable results.

Forecast in-house capacity

The AI application Forecast in-house capacity consists inter alia of the AI use case *Estimate future inventory based on future operations plan & inconsistency patterns in historical actual inventory* (Ohlson et al., 2022), and this is accomplished with an ML model. This AI use case could have an impact on the process *Analyze and move in production plan when shortage is a risk with safety stock as parameter* mentioned by *SP*. If one looks at the future operation plan to produce a product and takes into

consideration the inconsistency patterns from historical data, the recommendation when to produce might vary.

Most suitable AI model

Production planning has six AI applications that could be connected to the category, and three of them would benefit from an LLM, three from an ML AI, and one from a GenAI model. Its scoring in the relationship matrix was mainly based on the abstract ambitions within the processes of *Optimize production plan to save time and money* and *Take many parameters into consideration; weight of golden rules etc..*. Both of these processes can be improved by implementing an ML model.

An ML model can likely have large effect but likely requires larger investments compared to using existing AI models. There is an LLM available at the large-scale brewery, and since there are use cases found for LLMs within this process category, this could be a better start. Even though the effect might be large from ML models, the implementation and investment is heavier, hence **LLM** is more suitable in the near future. In the future after using LLMs, their limitations might become clearer and MLs could then be applied since the "missing pieces" would be more clearly defined.

4.3.8 Information Summarization

The process category Information summarization is not the most extensive category when it comes to identified processes, and that is probably because of the lack of complexity in the processes. In this process category there were also not many processes found during the empirical study and in some of them employees already utilized AI help.

Automate repetitive tasks & processes in optimal way

With the AI use case "Automate repetitive tasks and allocate time to value-adding activities" conducted by an agentic AI discussed by Nichols (2025), two identified processes can be supported. The processes are *meeting notes* highlighted by all departments within S&OP, and *meeting actions* mentioned by *DP & Management team*. This AI use case will free time from employees when conducting said processes which will lead to more time they can spend on value-adding activities. This is already used by some employees today, and would therefore be more of a use case that should be more broadly applied within the organization instead of implemented. The potential time savings from improving these processes are uncertain, as it is unclear to what extent employees already utilize these AI use cases.

Help understand data

In this AI application, processes that involve understanding information and summarizing it can be supported. One of these processes is *understand complex topics* which was mentioned by the *Mgmt team*, the AI use case that would support in this process is *Understand data* which was argued by Simchi-Levi et al. (2025) as

something an LLM can do. This AI use case is very broad, but it shows the ability an LLM has to explain a topic in a thorough way so that the user understands it. Another process the *Mgmt team* mentioned is to *summarize email threads*, this was something they have already tried to use AI for. The AI use cases in this process would be "*Summarize data*" which is an LLM ability according to Gibraltar (2026a). There is also the process *meeting notes* that was mentioned by all departments, and this process can use an LLM that Gibraltar (2026a) mentions to "*Summarize data*" and in that way create notes from meetings that are held.

Most suitable AI model

In the process category *Information summarization*, the AI model that would be suitable is an **LLM**, the work of summarizing data and information is something an LLM can accomplish without problem today. There is no other AI model that is mentioned in this category which is reasonable.

4.3.9 Communication

This category is about different types of communication that the thesis discovered at the large-scale brewery, it involves everything from internal and external email conversations to job descriptions for open roles.

Automate repetitive tasks & processes in optimal way

This AI application has an AI use case that uses an agentic AI which is described by Nichols (2025) as *Automate repetitive tasks and allocate time to value-adding activities*. This AI use case would be able to solve/ support a lot of processes that have been identified. The processes are listed for ease of reading with the corresponding department who mentioned it:

- *Truck booking is followed by sending confirmation email* from *SP*
- *Short and standardized communication (email/ Teams)* from *SP*
- *Hunt down people for answers* from *PCM*
- *Plan meetings (agenda setting)* from *PCM & DP*
- *Mail and teams chat cross-functional communication* from *PCM & DP*
- *Update department meeting agenda* from *Mgmt team*

Help understand data

A process that was mentioned by *SP* was *Keep colleagues updated on changes*. This would be easy to streamline with the LLM that Microsoft (2025) discuss, since they say that it can "*Get a new coworker up to speed*".

Support administrative tasks

For this AI application the processes *Truck booking is followed by sending confirmation email* and *Contact with customers* can both be supported with the AI use case mentioned by Durach and Gutierrez (2024), which is "*Supplier and customer communication*" that involves an LLM. Another AI use case that would be of high importance in this process category is the LLM described by Microsoft (2025) that can "*Provide coaching on generating email replies*". This LLM shows potential across multiple processes, which are listed below along with the departments that identified them.

- *Email conversations from SP & Mgmt team*
- *Internal communication from SP*
- *Truck booking is followed by sending confirmation email from SP*
- *Short and standardized communication (email/ Teams) from SP*
- *Draft emails and communication from PCM & Mgmt team*
- *Mail and teams chat cross-functional communication from PCM*
- *Information flow between commercial and supply form DP*
- *Contact with customers from DP & Mgmt team*

Analyze data

The AI use case "*Analyze a complex sales report*" explained by Microsoft (2025) can be applied to the DP process *Contact with other departments*. DP expressed how they could see potential in using AI as a tool for getting suggestions of what to bring up with the commercial unit during meetings. This AI use case conducted by an LLM applied to this suggested process can possibly result in better communication between departments and more effective cross-functional collaboration. It should be noted that similar cross-functional communication enablers could be found within other departments as well.

Most suitable AI model

In this process category an **LLM** is most suitable, this is not unexpected since the processes within *Communication* require large understanding of text and language, which is something an LLM handles.

4.3.10 Coordination

Coordination is a category where the focus lies in interacting with coworkers and working together. In a company that produce and sell products such as the large-scale brewery, it's essential to master this. As for AI applications in this area, there were only two that could be connected. This might be because coordinating with people most of the time require a human to do so.

Help understand data

Something both *Mgmt team* and *DP* mentioned was the process of *Work across departments*. This can be challenging if the coworker from the other department doesn't share the same knowledge. An AI use case applicable in this situation would be "*Get a new coworker up to speed*" which is something Microsoft (2025) mention in their description about an LLM.

Support administrative tasks

SP mentioned the process *Divide tasks between colleagues*. This is a reoccurring process that require more time than necessary, and it could be solved with the LLM Microsoft (2025) explain can make "*Highlights of a teams chat with actions*". The same LLM could also "*Provide coaching on generating email replies*" for when *PCM* work with *Project management* which according to the interview requires *Finding the right people for a project, and aligning them towards a common goal*.

Most suitable AI model

In this process category there are two AI applications applicable and both of the would be supported with an **LLM**, there were no other AI models identified as support in those AI applications.

4.3.11 Performance Analysis

The category *performance analysis* includes tasks that require the employees to analyze information and actions of different types, the potential of this category is average, but the AI applications will nevertheless be discussed in a thorough way.

Automate repetitive tasks & processes in optimal way

According to *SP* a repetitive task that occur every day is the "*Shortage analysis in daily meetings - why can we not sell them?*", this is a process that require the employee to create the same report every day for something that easily can be managed by an agentic AI with the AI use case *Automate repetitive tasks and allocate time to value-adding activities* that Nichols (2025) describe. One could argue that it would be possible with the use case *Automate report creation* conducted by an agentic AI model described by Polo (2024), but in this case the report creation does not require that level of expertise since it's the same layout of the report every day with different numbers and products. This AI use case is also applicable in the process creating "*KPI analysis*" mentioned by *Mgmt* and "*Inventory risk analysis*" mentioned by *DP* since they also have the same type of information and layout time after time.

Help understand data

In terms of understanding data, processes such as *Analyze what happened and why* mentioned by *SP* and *Problem explanations* mentioned by *Mgmt* could both be

supported with the AI use case "*Give me insights on my data*" which is a typical LLM capability according to Microsoft (2025).

Analyze data

Different types of *Risk assessments* that were mentioned by *Mgmt*, *SP*, and *DP* could all benefit from the AI use case "*Create a SWOT analysis of a topic*" to get a better overview of the risks, this is according to Microsoft (2025) something that an LLM is able to do.

Support future what-if scenarios

The processes about *Savings initiatives (internal AI development)* mentioned by *PCM* and *Similar risks in different projects* mentioned by *Mgmt* will both benefit from an AI use case such as "*Predictive insights*" conducted by an LLM described by Durach and Gutierrez (2024). The "*Predictive insights*" will help analyze the data and material that an employee otherwise would have to analyze alone which will save a lot of time.

Find warning signals in data in real-time

With the process "*Shortage analysis in daily meetings - why can we not sell them?*" (*this thesis translation*) mentioned by *SP*, Nichols (2025) describe an agentic AI that could conduct "*Forecast accuracy monitoring*", and therefore minimize the risk for future shortage by giving insight in why this happens through "*Inventory risk alerts*" as Nichols (2025) also talks about.

Forecast in-house capacity

The process *Inventory risk analysis* mentioned by *DP* can be minimized and maybe eliminated with AI use cases like *Forecast inventory levels using historical & real-time data* described by Kumar Singh (2023) or *Estimate future inventory based on future operations plan & inconsistency patterns in historical actual inventory* described by Ohlson et al. (2022), both these argue that this is something an ML model would be able to do.

Most suitable AI model

The process category *Performance analysis* is a typical LLM area, since it's about analyzing data and help employees understand it. There is two AI use cases that could use an agentic AI in this category but the level of complexity doesn't require an agentic AI and therefore is it unnecessary. An **LLM** is, therefore, the most suitable AI model in this category.

4.3.12 Decision Making

Decision making is a task that is aimed towards making the final call on something that might not have a direct answer, for example processes such as, *Trade-offs with*

customers and stakeholders mentioned by *DP* and seen in the *shadowing* or *Evaluate risk analysis and decide how risks are to be taken into consideration* discussed by *SP*.

Help understand data

To make the right decisions, it's crucial to understand the data behind it. If it's about *Understanding data driven recommendations* like Simchi-Levi et al. (2025) mention or if it's about *"Summarize data"* like Gibraltar (2026a) talks about while looking into for example the process of *"Ensure the ERP system recommendations are correct"* (*this thesis translation*) as mentioned by *SP*, an LLM is the optimal AI model.

Support usage of complex systems

When it comes to processes like *"Ensure the ERP system recommendations are correct"* (*this thesis translation*) or *Master data troubleshooting* both mentioned by *SP*, an AI use case that would be of high importance is the *Highlight insufficient data when forecasting* that Gstettner et al. (2024) talks about, this will be fulfilled with an GenAI model. The same AI-model could also *Suggest relevant forecasting methods* as Gstettner et al. (2024) argues, leading to good support of usage of complex systems. Therefore, an GenAI model would be of preference in this case.

Support future what-if scenarios

A process that is relevant here is *Evaluate risk analysis and decide how risks are to be taken into consideration* mentioned by *SP*. This is a typical scenario where the employee needs to know about the different outcomes of a decision and an AI use case that could be useful is the *Help analyze different scenarios* described by Simchi-Levi et al. (2025) as something an LLM can do. An LLM therefore seems like a preferable choice in this process category. On the other hand, there is an AI use case that *Runs multi-scenario simulations* described by Kumar Singh (2023) as an ML model which could also solve this task.

Another process that *SP* mention is *"Ensure the ERP system recommendations are correct"* (*this thesis translation*). This could be a case of exception handling if either there have been products stopped for quality checks or if a customer wants to order something that usually doesn't sell so much and there is a need to break a "golden rule". Both cases was something the thesis learned during the *Shadowing*, and to handle this, one could argue like Simchi-Levi et al. (2025) that implementing an LLM that *Help analyze different scenarios* would support the problem.

Find warning signals in data in real-time

If an employee needs to *"Ensure the ERP system recommendations are correct"* (*this thesis translation*) or if they are *Master data troubleshooting*, both mentioned by *SP*, an appropriate AI use case would be *Identifying and assessing supply chain risks* described by Kumar Singh (2023) as something that could be handled with an ML AI. Both those processes could also be handled/ supported with the AI use cases

"Inventory risk alerts" which recognize the products that have been stopped for quality check as seen while shadowing *SP* or *"Forecast accuracy monitoring"*, those AI use cases are argued as something an agentic AI can do according to Nichols (2025).

Data cleaning

This AI application can be divided into a reactive and a proactive part. The reactive part has the process *"Ensure the ERP system recommendations are correct"* (*this thesis translation*) mentioned by *SP* which can be supported with the AI use cases *real-time updates across S&OP data layer* with an agentic AI model described by Polo (2024) or *"Find errors and inconsistencies in the data and eventually correct or propose corrections of the data"* which uses ML model described by Ohlson et al. (2022). The proactive part on the other hand, deals with the problem beforehand. A process here could be *Master data troubleshooting* mentioned by *SP*, and that would be an easy fix with an AI use case such as *Improving quality in master data by cleaning & augmenting* conducted with a GenAI model which Gstettner et al. (2024) talks about.

Centralize data

To avoid or improve the current process where employees are making *"Gut-feeling decisions"* (*reason for not using AI*) (*this thesis translation*) as stated by *SP*, an AI use case could be *"Data consolidation and reporting"* which would give the employee more information before making a decision and this would according to Nichols (2025) require an agentic AI.

Most suitable AI model

In the process category *decision making*, help could be found through many different AI models. However, the most suitable in this category would be an LLM, since the decisions will be made by employees and the AI would help the employees understand why certain decisions should be made. In those scenarios the optimal AI model is an **LLM**.

4.3.13 Strategy

The category with the least potential is strategy. One reason for this is the fact that the employees showed interest in focusing on this part of the job themselves and not hand it over to an AI. They would rather have an AI do the unnecessary work as *PCM* mentioned *"unnecessary things takes up the time, I would like to spend more time on value creating activities"* (*this thesis translation*). Another reason is that there are not many AI applications that this thesis could detect that are fit to do strategic work at the current time.

Support future what-if scenarios

Utilizing the AI use case "*Predictive insights*" for *Long-term planning* mentioned by *SP* or *Portfolio management* mentioned by *PCM & Mgmt* can be performed by an LLM like the one Durach and Gutierrez (2024) describes if one wants to get insights and analyze the result. Another support on those processes could be an ML AI that Kumar Singh (2023) describe, if one wants an AI that *Runs multi-scenario simulations*. In the case of strategy, the LLM would have an advantage, as it could *Help analyze different scenarios* as Simchi-Levi et al. (2025) describe, resulting in better insight for strategic decisions. This is why an LLM would be superior in this case.

Most suitable AI model

In this category the thesis found that an **LLM** is the most suitable AI model since it was applicable in the only AI application in this category. There was also discussion about an ML AI in this category but since ML is integrated into most AI models today the logical choice is therefore to use an LLM.

4.4 Most Suitable AI Model

Table 4.5 shows the process areas, process categories, corresponding score from relationship matrix and the most suitable AI-model. The table shows that LLM is suitable for 8/13 process categories, and agentic AI is suitable for 5/13 process categories. The agentic AI is most suitable for the categories with the highest score, resulting in this being the most beneficial AI model to implement. The highest ranked categories in Table 4.5 are covered by agentic AI usage and even if this require some implementation efforts compared to other solutions this would probably be more beneficial in the end.

This conclusion does not eliminate the need and potential effects of implementing another AI model, but it shows that the most effect is likely to be found from agentic AI usage. LLM has high potential within the other categories, which could be of interest in the future, but these are areas where management thinks AI implementations don't have the most potential and are not critical at the moment. However, as mentioned by Microsoft (2026a), the LLM Copilot can be used to create an agentic AI model which will then cover all categories identified in this study.

In table 4.5 agentic AI is the most suitable AI-model in the categories where automaton is possible. This type of AI-model is able to work with minimum amount of interaction and therefore it is more feasible in those types of processes. On the other side, the LLM is an AI-model that needs interaction and therefore would it be more feasible to use in categories where human interaction is critical.

Table 4.5: List of process categories, respective score, and suitable AI model

Score	Area	Category	Suitable AI
11,5	Data Management & Accessibility	Convert/move data between systems	Agentic AI
11,5	Data Management & Accessibility	Validate data between systems	Agentic AI
9	Data Management & Accessibility	Data accessibility	Agentic AI
9	Optimization Problems	Logistics	Agentic AI
9	Optimization Problems	Sales Forecast	Agentic AI
6,5	Optimization Problems	Production Planning	LLM
6	Admin Tasks	Information summarization	LLM
4,5	Admin Tasks	Communication	LLM
4	Admin Tasks	Coordination	LLM
4	Analysis	Performance analysis	LLM
2	Analysis	Decision making	LLM
1	Optimization Problems	Procurement	LLM
0	Analysis	Strategy	LLM

4.5 Implementation Process Framework

Depending on AI model and application, the implementation differs. This section covers how the implementation strategy for the recommended AI model is to be designed to fulfill the identified needs from employees, and connect it to the literature study.

4.5.1 Internal Training

This section covers the type of training required to optimize the effects of LLMs. The large-scale brewery's current training and usage, along with wishes for future training and usage, are discussed and connected to AI literature and SDT.

The interviews showed a vast amount of different opinions on the current integrated AI tool training at the large-scale brewery. Today they offer an online training with the basics of using the integrated AI tool, which is mandatory if one is to use it at work. Although some interviewees thought it was a rewarding education, others thought it was too basic and redundant. However, they all thought it was good to have some kind of training. The fact that different interviewees had different opinions on the training shows a varying understanding of the basics of using LLMs. When implementing more AI applications, this must be considered so that the need for *relatedness* and *competence* in SDT is not ignored. To facilitate the different employees' needs, different training approaches should be provided to enable all employees to learn in a way that's suitable for them.

The interviews showed that all employees wanted to participate in exploring AI usages within their work processes, regardless of prior AI knowledge. This engagement of employees can be used to drive the development of internal knowledge of the integrated AI tool. Some interviewees expressed explicit needs for practical AI use cases to be provided, one interviewee from *PCM* said during the interview *"could be that the prompt is not good enough, but then I might need help or instructions with how to write them"* (*this thesis translation*) which shows that there is motivation but not the correct training.

Haddud (2024) discuss the implementation of LLMs in supply chain and suggest a few recommendations. He explains the benefits of implementing the LLM and enabling usage and testing of applications, something the large-scale brewery has already done with an integrated AI tool. Haddud (2024) also explains the importance of training employees, broad or within a more niche function. This is something that could possibly benefit the large-scale brewery. Supplementing the existing training course with more advanced training for employees who are interested could benefit the organization in its entirety. This enthusiasm should be encouraged by allocating more time towards training them. Facilitating internal education toward specific employees who show interest will increase the SDT need for *competence*, and motivate them to learn more. During the focus group, Mgmt showed a vision of having *"influencers"* or *"ambassadors"* within their teams that explore AI usage and share their findings. This vision can be achieved by enabling internal education.

4.5.2 Responsible Usage

In this section, the findings related to trust in AI output will be analyzed. Both interviewed employees and Mgmt during the focus group raised concerns about accuracy of AI output. One interviewee from *PCM* claimed:

"It (the output from AI) sounded too good to be true" (this thesis translation)

This was further discussed during the interview and concerns were raised regarding AI usage from new employees. The interviewee in question had experience within the company and could therefore identify the error. The employee from *PCM* argues that similar errors would be difficult to identify without experience:

"I don't believe I would have noticed it at that time" (the time when the employee was new) (this thesis translation)

This aligns well with Mgmt's perspective on responsibility for output. They mean that the one using AI is responsible for its output, and that in the future there will be a greater need for business acumen among employees. Understanding the business itself to evaluate whether an output is reliable or not is a key characteristic in the future. Mgmt claim that:

"Perhaps now, more than ever, it will be extra important to have a high level of business acumen. That is, to have a good intellectual understanding of how the business works because that is usually when you can quite

simply understand: Is this reasonable? Is it unreasonable? How relevant is it? How can it be tweaked? Can I ask control questions?" (this thesis translation)

This means that Mgmt and employees share the vision of responsibility, but there are still uncertainties related to how unrestricted they can use it. Mgmt means that:

"You must be able to understand the content yourself to be able to use it, otherwise there could be a risk of bringing something that was incorrect." (this thesis translation)

Connected to the acumen among employees, Mgmt highlights the importance of understanding the concept before being able to evaluate an AI response. This could be something that new employees would focus on in their introduction to the company, so they afterwards could work more efficient with AI.

4.5.3 Management's Role

The findings showed how AI is not discussed among employees.

"It's almost like you keep it (usage of the integrated AI tool) to yourself. [...] When I reconciled with them, it seemed like we used it the same way." (this thesis translation)

Although the integrated AI tool usage for this *PCM* interviewee didn't differ that much compared to their colleagues, the lack of discussion among employees is an issue. One wish connecting to this from the *PCM* interviews was a community where applications are shared with the purpose of inspiring. The interviewee also meant that it's important to:

"Dare to start using it and get a basic understanding of how it can be used or how it can improve efficiency" (this thesis translation)

Therefore, management needs to show the direction and support the exploration of AI usage within S&OP. The effect will likely be that more employees feel comfortable trying others' solutions and potentially find inspiration to discover their own applications. This would likely require a culture change that encourage usage and sharing of applications of AI. By facilitating this need, employees will have higher motivation of trying to find efficiency improvements. By giving directions and listening to employees' needs, managers can enable the SDT need for *autonomy* as employees feel safe to explore their own solutions when they know that they are allowed to. This requires management to clearly determine the limitations of what is okay and not okay.

Following this, supporting the learning and usage of AI requires time resources. Employees in the *PCM* department doesn't feel that they have enough time to explore AI applications to the extent they wish. One *PCM* employee says:

"I would like to use it more, but it feels like it takes time to get up to speed with how to use it, and it doesn't really feel like that time is available" (this thesis translation)

Allocating specific time towards teaching AI usage could be a first initiative to "get the ball moving". Enabling employees to find some "easy fixes" could strengthen their SDT need for *competence*, as they feel competent after identifying and implementing new AI applications. Gstettner et al. (2024) explains how using AI, results in learning more about AI and its application areas. This can be achieved, or at least mediated, through managerial direction and time allocation.

Another finding from the interviews with PCM was:

"If I make my work more efficient, what does that actually give me as an individual?" (this thesis translation)

Management clarified during the focus group and interviews that the purpose of AI implementation is not to replace employees, but to streamline work tasks and free up time for more value-adding activities. This vision aligns well with employees' own expressed desire to contribute more to meaningful and value-adding work. The findings therefore highlight the importance of clearly communicating that AI-driven improvements are intended to enable employees to focus on higher-value activities, rather than reduce workforce needs.

During the focus group, Mgmt said that:

"In the beginning, it's important to start with an introduction — what does AI mean in our workplace?" (this thesis translation)

This aligns well with the wishes from PCM employees who wants more directions from management. Trying to break down improvement efforts into smaller feasible objectives could possibly mediate this. Finding incremental efficiency improvements using the integrated AI tool could help employees understand that improvements can also be small.

The focus group found that implementing AI depends on the solution. It's good to have a shared start, but depending on the process' change and AI effect, the implementation differs, for example, it can be a workshop or an online meeting. This way of thinking aligns with Haddud (2024) who argues that the best training could be broad, or more specific towards a certain function. The interviewees vary in their opinions about workshops being beneficial. Whereas some see a risk of a workshop being inefficient due to less learning through practical trial and errors, others might benefit from this. Management can create the possibilities for workshops and more personalized training sessions, and allow employees to decide their best way of learning. This would further benefit their SDT need of *autonomy* as well.

4.5.4 Enabling Usage

The analysis of the most suitable AI model showed that agentic AI had great potential. Since an integrated AI tool is already in the large-scale brewery's IT-system and agentic AI models can be designed through this tool, the technical implementation is easier compared to a solution that would require deeper integration.

For many of the processes, especially those connected to the process area of *data management & accessibility*, technical integration is crucial. API integration, explained by IBM (n.d.), must be prioritized before applying AI applications within this area. AI has the potential to make processes more efficient, but it needs access to the different systems within the large-scale brewery to accomplish that.

In the interview with the company Alice Labs the interviewee mediated one of the founders that highlighted the importance of keeping the language and demonstrations basic in the beginning. He said that:

"As soon as you get too technical you loose 90% of them" (this thesis translation)

"them" in this situation are the employees who will learn to use AI in their work. Another important thing that he mentioned was that:

"A common misunderstanding is that they believe that AI is the solution to everything" (this thesis translation)

This second statement is of high relevance, since some processes identified at the large-scale brewery can be optimized without AI.

4.5.5 Proposed Implementation Process Framework

There are many different approaches for implementing AI at the large-scale brewery. This subsection covers a proposed approach with the purpose of highlighting and structuring important aspects when implementing agentic AI. The 8 step framework for transformations, described by Kotter (2007), is used to motivate a suitable approach based on the findings of this report. The presented approach covers different periods in the implementation at different organizational levels. Figure 4.1 shows the general overview of the implementation strategy based on the framework derived from Kotter (2007).

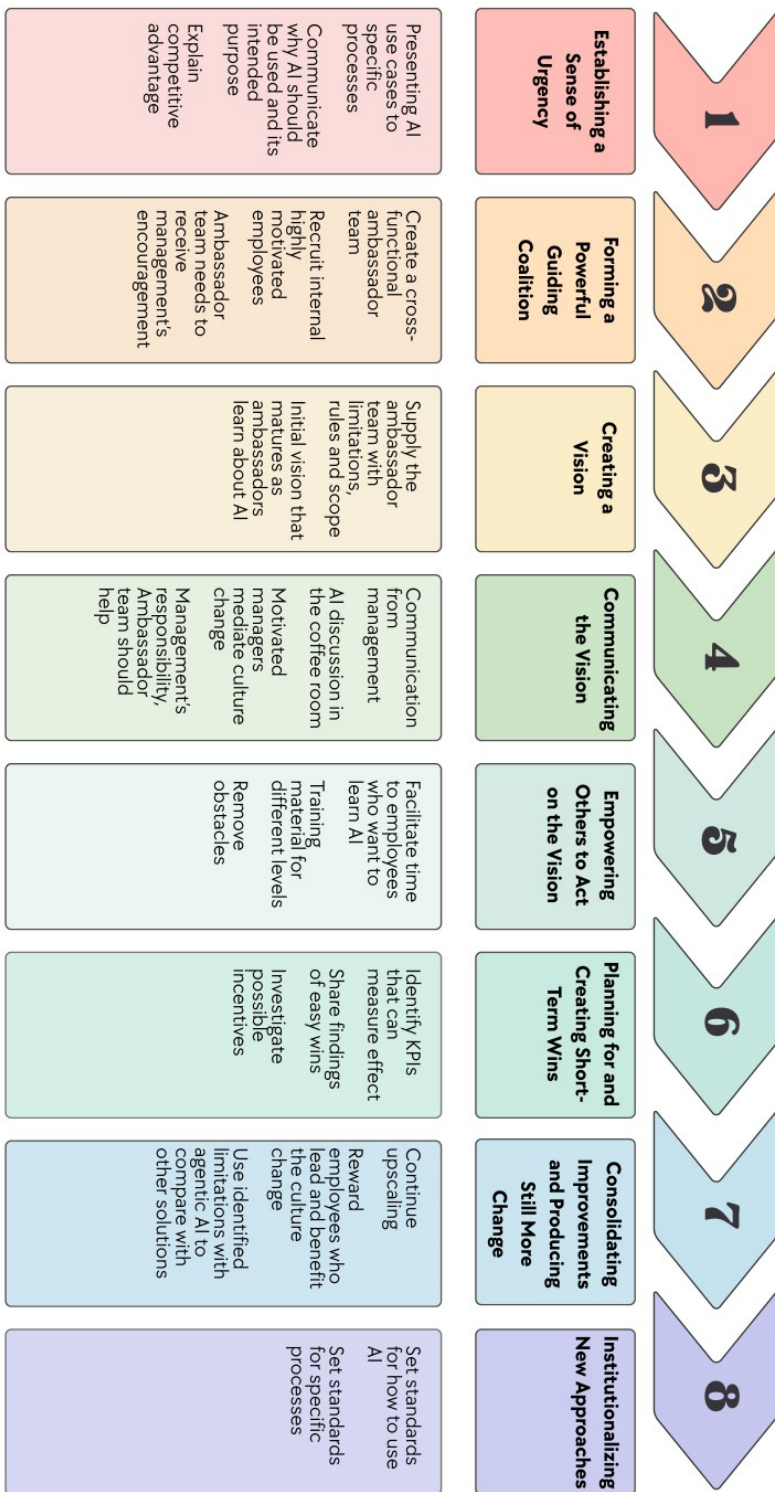


Figure 4.1: Proposed implementation strategy, broad perspective

1. Establishing a Sense of Urgency

The large-scale brewery's AI transformation is a great opportunity that needs urgency. Employees have participated through interviews and shadowings to this thesis, meaning there is an initial understanding of managerial focus on AI improvements. The findings from this thesis regarding ranked process categories, suitable AI applications, and AI models can act as a base for highlighting the potential of change. Understanding the AI use cases provides an understanding for usage of agentic AI, and combined with transparent managerial communication and goals, a sense of urgency can be created.

Mgmt also needs to create some urgency that motivates employees as to why an AI implementation is needed. Both from a strategic perspective, but also considering employees' needs for allocating more time to valuable activities. There needs to be a clear communication about the intended purpose of AI usage. Everyone has to receive the message that AI is to be used to streamline work tasks and free up time for more value-adding activities, not replace employees. Finally, It can be argued that the emerging AI development will be utilized by competitors, meaning the large-scale brewery has a sense of urgency as to not fall behind.

2. Forming a Powerful Guiding Coalition

The findings from the thesis suggests that this step will be a less complex issue compared to other ones. The interviews showed that all interviewees wanted to be ambassadors, meaning the motivation from employees are high. A cross-functional team would mediate the vast amount of AI use cases, and they could together support each other in the learning process. Management needs to provide the team with encouragement and large amount of training material so they can understand applications at a deeper level.

3. Creating a Vision

The ambassador team will, together with Mgmt envision the direction for the AI implementation. Ambassadors need clear limitations and scope as their task is not to develop an AI strategy, but rather find use cases and actual solutions. In order to try, they need to be given all required resources for successful change. Finding API issues beforehand would make their scope smaller by only focusing on the integrated AI tool for example. The initial vision doesn't need to be absolute but can change during time. Ambassadors do need a common vision to ensure a common goal. To achieve this, Mgmt has to support in helping setting boundaries. The empirical findings showed uncertainties as to what extent and what ways AI was allowed to be used. Ambassadors can not have a feeling that using AI is cheating, but should rather have a feeling of accomplishment for finding more efficient approaches.

The vision also has to consider the limitations of agentic AI and the large-scale brewery's internal IT systems. These limitations are partly covered in this thesis, but the ambassadors have to identify the limits to a more measurable extent. AliceLabs claims that AI doesn't solve everything. The vision will likely change as ambassadors

learn the AI model's limits, and that enables a future comparison for other solutions. One approach could be that the process categories with highest scoring in this thesis act as projects, but it's not the *vision*. The vision needs to take the ambassador team into consideration as they find limitations, but also opportunities. This can result in a realistic vision. Gstettner et al. (2024) discussed how they used ChatGPT and identified limitations with its capabilities, and a similar approach is needed for the large-scale brewery, but using their integrated AI tool.

4. Communicating the Vision

This part of the implementation needs extensive focus from Mgmt. There is a need for culture change regarding AI usage at the large-scale brewery to encourage more AI usage. During previous steps, the "rules" for AI usage have been set, and they need to be communicated clearly. Mgmt needs to feel motivated about the transformation and vision. Today, there is no talk about AI in the coffee room which is something Mgmt can initiate and encourage. Adding to this, Mgmt needs to facilitate educational efforts, and show themselves as motivated for the change. Finally, encouraging ambassadors to help drive the cultural change would strengthen their SDT need for *competence*.

5. Empowering Others to Act on the Vision

In this step, Mgmt needs to encourage people who dare to test AI applications. The vision and improved culture allows employees to test and learn more about AI, which they need time resources to do. The employees that dare to try applications need encouragement and the bar for trying should be as low as possible. Mgmt needs to identify possible obstacles that's holding back the change. Time resources is one obstacle that is identified in this thesis, and another one is the level of the training material. More advanced training material should be facilitated in earlier steps to the ambassador team, but it should be clear and easily accessible for everyone as the transformation goes on. More obstacles will likely be identified during the transformation by either ambassadors or Mgmt, and they need to be solved as the emerge.

6. Planning for and Creating Short-Term Wins

During this step, some improvement efforts need identified measurements to show tangible results. Measuring AI improvements was discussed during the focus group and although no definite KPI for all cases were identified, different KPIs could be appointed to different cases. Time and quality of work was brought up as KPIs but these are not relevant for all processes. During the focus group, Mgmt meant that it can be beneficial to have measurements to incentivize why AI should be used, especially in the beginning. However, they agreed that not all applications required measured KPIs. Ambassadors can also identify some easy wins that colleagues can replicate in their AI usage that facilitates the broad AI usage among the S&OP department.

To further encourage change efforts, Kaizen, explained by Kaizen Institute (n.d.), can be used as inspiration for initiatives that can be used. Showcasing employees' AI achievement enables clearer application areas, decreases the uncertainty for how it is allowed to be used, and encourage employees to identify efficiency applications. Adding to this, incentives can be investigated and whether they would have a positive effect.

7. Consolidating Improvements and Producing Still More Change

Continuous development within the team is crucial, as well as sharing the knowledge and culture among other employees. The AI transformation needs to continue with its upscaling to ensure that the culture is sustainable. Continuing distribution of training material of various levels and rewarding employees that show leadership in this culture change could facilitate this. Limits might become more clearly identified in the integrated AI tools applications as the internal knowledge develops, and then the need for more advanced ML solutions could be investigated. Since there are clearly defined limitations to the usage of agentic AI, a factual comparison can be conducted between models as there are two more clearly defined options. Real KPIs can be used to enable an objective comparison for specific processes.

8. Institutionalizing New Approaches

Sustainable change needs leaders that embrace the new culture. Rewarding the employees that show leadership traits in the transformation, and engagement in the internal development among themselves and others are therefore of importance. When a new and better way of conducting a process is identified, it needs to be shared, tried, and standardized if appropriate. The way AI is used within S&OP will be possible to redefine as employees tries its limitations and applications. As the organization learns more about the usage, future guidelines for usage could become even more developed.

4.5.6 Ambassador Team

The ambassador team is a crucial part of the implementation strategy and effect. Figure 4.2 illustrates the important aspects connected to this ambassador team, showing their needs, and expected findings. The ambassador team is crucial for the success of an AI implementation shown in Figure 4.1. Figure 4.2 shows what is needed from management, and what the effect of an ambassador team could be.

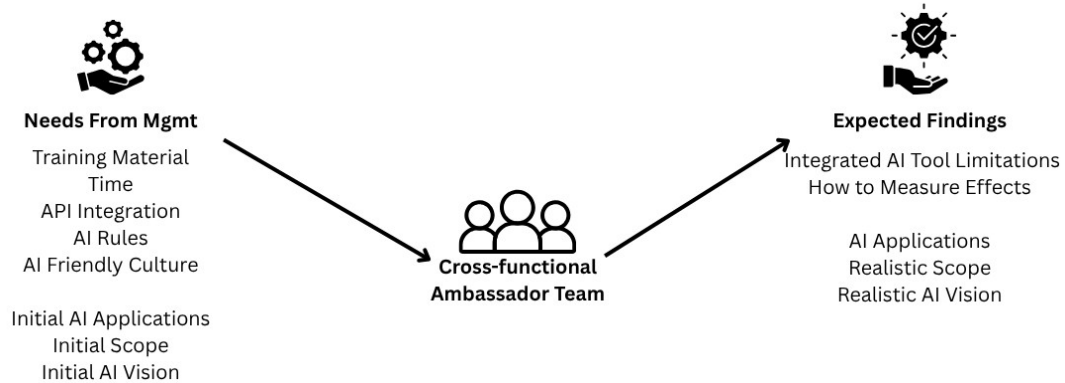


Figure 4.2: Ambassador team needs from Mgmt and expected findings

The findings from this thesis suggests that training material and time is important for an ambassador team and that the chosen material is dependent on the receiver. To set a more tangible initial scope, the API integration needs to be clarified to the ambassador team. Ambassadors need a clear understanding of how information between systems are managed and accessed. Another need that Mgmt needs to provide is AI rules. This can potentially be conducted in collaboration with IT security to ensure that internal information is not leaked and that an agentic AI is used in a secure way. Finally, Mgmt needs to provide an AI friendly culture within the S&OP department.

Apart from the needs above, Mgmt needs to provide the ambassador team with initial AI use cases. The initial AI use cases will act as support for the processes identified in this thesis, along with use cases provided through external training material. More AI use cases is the most important expected finding from the ambassador team in later stages, but there is a need for initial AI use cases. There is also a need for an initial scope. Enabling the ambassador team to understand their expectations and encouraging them is crucial. This scope will, in later stages, become more realistic as suitable AI use cases are identified. The scope that sets the boundary of only using the integrated AI tool already available can then be instigated and evaluated as other, more complex solutions, can be compared to actual results from the ambassador team. Finally, there is a need for an initial AI vision. There is a need to have a clear answer to why AI should be used and transparent communication that the usage is to become more efficient, not replace employees. Adding to this, the AI vision has to include expected outcomes in the initial stage. This is further enabled by setting clear rules connected to what applications are acceptable, and which ones are not. The vision will likely mature and become more realistic with support of the ambassador team as they identify limitations and measure the effects of AI applications.

5

Conclusion

This chapter concludes this thesis by discussing the overall approach and alternative choices, followed by a recommendation to the large-scale brewery about what type of AI that would be most suitable in their case and how they should think when implementing it into the company.

5.1 Answers to Research Questions

RQ1: Which processes within S&OP at the large-scale brewery have the greatest potential for efficiency improvements through AI implementation?

The findings showed how processes within the area of *Data Management & Accessibility* had great potential for efficiency improvements. The reason for their high potential was the expected time savings from AI, and their feasibility. These processes are beneficial to focus on when deciding on investments for AI. The process area *Optimization Problems*, apart from the procurement category, was also highly valued when scoring process categories to their potential. This area received a lower score than *Data Management & Accessibility* since the effects were not as tangible. Table 4.3 shows the scoring for all process categories, and the conclusion is that the ones with highest scores have highest potential.

RQ2: What type of AI is most suitable in this case?

The most suitable AI model is dependent on what processes have the highest potential. Table 4.5 shows the most suitable AI model for every process category, and the conclusion is based on this. Agentic AI is the most appropriate AI model for the five highest scoring process categories. Therefore, the conclusion is that agentic AI is most suitable in this case. It is strengthened by the possibility of fulfilling needs that LLMs provide as well since agentic AI systems can provide both.

RQ3: How can the implementation of AI be designed and executed within the S&OP process?

This thesis concludes that an implementation of agentic AI requires thorough planning and the framework shown in Figure 4.1 acts as a broad planning with consideration to both short- and long term aspects. Within this implementation process, an ambassador team with highly motivated employees is crucial. Figure 4.2 shows the needs of an ambassador team, and its expected results.

5.2 Reflection on Research Process

This section is an open discussion of the thesis, what the thesis students are pleased with and what could have been done differently.

5.2.1 Reflections

The general approach and methodology for the thesis have been well thought through, and the thesis students think that it was easy to work according to the plan to get to the final result. The time-plan was close to the actual time spent on each task, and the thesis followed it almost exactly as planned.

One conclusion that could be drawn is the fact that the more you use AI, the more you understand where you can use it. This was something that was shown in the interviews where employees who used AI could come up with more wishes and ideas than employees who did not. This information is something that could be taken into regard when deciding whom to interview. In this thesis, it was neglected since the students conducted interviews with everyone that offered their time.

The thesis students could also have had this in mind after the empirical study was conducted, and at that point decide to conduct some more benchmarking to further understand different AI models before starting to analyze the results. This would lead to better understanding of AI capabilities connected to different AI models, which would lead to better recommendations for the employees who already use AI in their work. This is something that would be recommended to future work within the same subject.

The thesis students consider that the RQs have been answered in this thesis and that the result is pleasing. There has been a thorough investigation into each RQ and the answers have been analyzed to ensure the inclusion of legitimate information. The result of this is a recommendation to the large-scale brewery that will be of value.

The thesis students consider that the purpose of the study has been fulfilled and that the findings can be used to support decisions regarding future investments in AI. By identifying suitable AI applications and providing implementation recommendations, this thesis offers guidance on how large-scale breweries can utilize AI effectively. This thesis also filled the gap for AI usage and implementation in S&OP departments for large-scale breweries.

Furthermore, the students are satisfied with the structure of the report and the ease of reading the thesis.

5.2.2 Difficulties and Uncertainties

The most important difficulty was the need to separate different AI models to be able to compare them against each other. Separating AI models turned out to be a complicated task because of the integration of AI models into each other, meaning,

an LLM today consists of ML and to some extent generative AI as well and are therefore hard to isolate. This could have been avoided if the thesis had instead focused on what AI as a whole could do and only recommended where to implement AI. However, this would result in a broader and less tangible result.

An uncertainty encountered by the thesis was the amount of data from DP. This uncertainty was something that could not be improved in an easy way, since DP department has their office in another city and they have limited people working in the department at the current time. The amount of data from interviews could not have been increased since the thesis interviewed all the employees at the DP department. A site visit to shadow one or two employees was not an option either, since the thesis did not have any budget for a trip to another city.

Another uncertainty is the identified processes that have been collected from interviews, focus group, and shadowings. There could have been processes that exist that were not identified for reasons such as, not enough empirical data collected or that the employees did not understand where AI could be implemented and therefore chose to neglect that information during interviews. The answers could also be bias because of the interviewees' views on AI. The large-scale brewery has already implemented an integrated AI tool to some extent, and therefore interviewees might only think of AI use cases that they believe are possible with that type of AI model.

5.3 Limitations and Future Research

This thesis has not quantified effects of AI adaptations. Future research could potentially measure time spent on specific processes without AI, and then implement AI usage to find how the amount of time spent on the process change. All processes are not suitable for this sort of time measurement, and the research could instead focus on perceived quality and efficiency improvements from employees. For example, this can be done by conducting an empirical study before an internal AI transformation, and following up after a few months with both qualitative and quantitative data. These approaches would build upon findings in this thesis.

The thesis does not cover data and cyber security which is crucial when managing data in IT-systems. This needs consideration when implementing AI within an organization, and needs future research for the large-scale brewery's case.

The thesis finds that employees and management does not fully trust AI output since there is a risk of it being wrong. The thesis discuss how this has to be considered during implementation, but there is no tangible guideline as to what extent AI output can be trusted. This needs future research where agentic AI applications are studied and KPIs are measured. The measured KPIs for this should likely be quality and time. How much supervision, if any, is needed to ensure reliable output from the agentic AI? Adding to this, the trust could differ depending on the studied process. Therefore, future research is needed to create a framework covering what processes require supervision and to what extent.

5.4 Practical Recommendations

The following section is this thesis recommendations to the large-scale brewery regarding *Improving Operational Efficiency and Performance in Large-Scale Brewery With the Use of AI*.

Processes and AI Model

The process categories that have been identified and weighted against each other answer RQ1 *Which processes within S&OP at the large-scale brewery have the greatest potential for efficiency improvements through AI implementation?*. The different types of AI models identified and matched is used to answer RQ2 *What type of AI is most suitable in this case?*. The final score of the weighting for the categories and the suitable corresponding AI models are shown in Table 4.5.

The recommendation for the large-scale brewery is to focus on the five processes that received the highest score in Table 4.5. Focusing on those five categories will create the most value for the company according to this thesis analysis. The AI model the large-scale brewery should focus on is an agentic AI since that is the AI model suitable for the categories they should focus on. The agentic AI model will also be suitable in many other categories, even if it's not the most suitable, and can therefore become increasingly useful for the company the more they learn to use it. This can then create arguments to continue to implement more AI models into more categories. The thesis recommends the large-scale brewery to use the AI model they already have in their system and build AI agents. This is to minimize the cost of new technological implementations, and at the same time facilitate usage for employees who have already started to use the integrated AI tool in their work.

Implementation

This thesis recommends that the framework in Figure 4.1 is used as a general strategy. This approach will likely fit the studied large-scale brewery since the content in the strategy is based on their needs. One important part of the practical implementation is the usage of an ambassador team. For a sustainable implementation, it is recommended to use an ambassador team depicted in Figure 4.2. The expected outcome is a strong and competitive AI strategy that evolves as the AI culture strengthens, and employees learn more about AI.

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A

Appendix

Pairwise comparison

Table A.1: Relationship matrix (Data Management and Admin Tasks)

	Data Management and Accessibility				Admin Tasks		
	Convert/move data between systems	Validate data between systems	Data accessibility	Communication	Information summari-sation	Coordi-nation	
Data Management and Accessibility	Convert/move data between sys- - tems	0,5	1	1	1	1	
	Validate data between systems	0,5	-	1	1	1	
	Data accessibility	0	0	-	1	1	
Admin Tasks	Communication	0	0	0	-	0	
	Information summarisation	0	0	0	1	-	
	Coordination	0	0	0	0,5	0	
Optimization Problems	Procurement	0	0	0	0	0	
	Logistics	0	0	0,5	1	1	
	Production Planning	0	0	0	0,5	1	
Analysis	Sales Forecast	0	0	0,5	1	1	
	Performance analysis	0	0	0	0,5	0	
	Decision making Strategy	0	0	0	0	0	

Table A.2: Relationship matrix (Optimization Problems and Analysis)

	Optimization Problems				Analysis			SUM	Rank
	Procurement	Logistics	Production Planning	Sales Forecast	Performance analysis	Decision making	Strategy		
Data Management and Accessibility	Convert/move data between sys-tens	1	1	1	1	1	1	11,5	1
	Validate data between systems	1	1	1	1	1	1	11,5	1
	Data accessibility	1	0,5	1	0,5	1	1	9	3
Admin Tasks	Communication	1	0	0,5	0	0,5	1	4,5	8
	Information summarisation	1	0	0	0	1	1	6	7
	Coordination	1	0	0	0	0,5	1	4	9
Optimization Problems	Procurement	-	0	0	0	0	0	1	12
	Logistics	1	-	1	0,5	1	1	9	3
	Production Planning	1	0	-	0	1	1	6,5	6
	Sales Forecast	1	0,5	1	-	1	1	9	3
Analysis	Performance analysis	1	0	0	0	-	1	4	9
	Decision making	1	0	0	0	0	-	2	11
	Strategy	0	0	0	0	0	-	0	13

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