DEGREE PROJECT

Systematic Process Selection for LLM-Based AI Implementation

An Operations Management Perspective on Efficiency in Administrative and Knowledge Work

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An Operations Management Perspective on Efficiency in Administrative and Knowledge Work

Master's Thesis in Industrial Engineering and Management

Operations Management

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Abstract

Organizations are adopting LLM-based AI rapidly, yet most struggle to translate adoption into real value. This thesis examines how operations management frameworks can explain where and under what conditions LLM-based AI improves administrative and knowledge work processes. The study is based on twelve semi-structured interviews across twelve organizations in the Swedish energy and utilities sector, in collaboration with Intric AB. The theory that is used combines Lean waste analysis, Task-Technology Fit theory and organizational condition assessment. LLM-based AI primarily reduces the lean wastes skills underutilization and motion by freeing qualified staff from routine execution and making information directly accessible, addressing inefficiency within individual process steps rather than between processes. The four process-fit dimensions examined in this study each influence a different aspect of implementation, and the four organizational conditions help explain varying results between organizations. These findings are synthesized into a practical selection framework where organizational readiness functions as a boundary condition. Beyond efficiency, capability expansion emerged as a distinct outcome where AI enables previously infeasible work rather than effectivizing existing tasks. The main theoretical contribution is the extension of Task-Technology Fit logic from the individual to the process level. The main practical contribution is a selection guidance framework offering organizations a structured alternative to unstructured experimentation.

Keywords: LLM, artificial intelligence, operations management, process improvement, lean, task-technology fit, administrative work, knowledge work, efficiency

Sammanfattning

Organisationer implementerar LLM-baserad AI i allt snabbare takt, men de flesta har svårt att omvandla användningen till verkligt värde. Denna studie undersöker hur teorier från operations management kan förklara var och under vilka förutsättningar LLM-baserad AI förbättrar administrativa processer och kunskapsarbete. Studien bygger på tolv semistrukturerade intervjuer med tolv organisationer inom den svenska energi-, vatten- och avfallsbranschen, i samarbete med Intric AB. Teorin som används kombinerar Lean-slöserier, Task-Technology Fit-teori och en bedömning av organisatoriska förutsättningar. LLM-baserad AI minskar främst Lean-slöserierna outnyttjad kompetens och rörelse genom att frigöra kvalificerad personal från rutinuppgifter och göra information mer lättillgänglig, vilket åtgärdar ineffektivitet inom enskilda processteg snarare än mellan processer. De fyra processdimensioner som undersöks i denna studie påverkar var och en olika aspekter av implementeringen, och de fyra organisatoriska förutsättningarna bidrar till att förklara varför resultaten skiljer sig åt mellan organisationer. Dessa resultat sammanfattas i ett ramverk för beslutsstöd där organisatorisk beredskap fungerar som ett gränsvillkor. Utöver effektivitet framträdde nya förmågor som ett tydligt utfall där AI möjliggör arbete som tidigare inte utfördes snarare än att effektivisera befintliga processer. Det huvudsakliga teoretiska bidraget är att Task-Technology Fit-logiken utvidgas från individnivå till processnivå. Det huvudsakliga praktiska bidraget är ett vägledande ramverk för beslutsstöd som erbjuder organisationer ett strukturerat alternativ till ostrukturerad experimentering.

Nyckelord: LLM, artificiell intelligens, operations management, processförbättring, lean, task-technology fit, administrativt arbete, kunskapsarbete, effektivitet

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This research has deepened my understanding of current AI adoption and the many different ways people and organizations are putting this technology to use.

Luleå, June 2026
Jonas Nordlander

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1 Introduction

Artificial intelligence (AI) has rapidly transitioned from emerging technology to widespread adoption. Survey data from Internetstiftelsen (2025) show that 40 percent of Swedes aged eight years or older now use AI tools regularly, such as ChatGPT or Copilot, demonstrating the acceptance of the technology in everyday life. However, this widespread adoption has not resolved fundamental questions about how organizations can systematically translate AI capabilities into operational value in administrative and knowledge work.

1.1 LLM-Based AI

The current wave of AI adoption is driven by *large language models* (LLMs). LLMs are pre-trained language models of significant scale that can process natural language input and generate contextually relevant output, exhibiting capabilities not present in smaller models (Zhao et al., 2023). Unlike traditional automation which requires predefined rules for specific tasks, LLMs can process unstructured information, interpret context and generate responses across diverse activities (Kumar, 2025). This capability makes LLMs particularly relevant for administrative and knowledge work. These are processes that involve information processing and decision support rather than physical production. *Administrative work* here refers to structured, recurring information tasks such as reporting, documentation and regulatory compliance. *Knowledge work* here refers to less structured information tasks where inputs and outputs are less defined and where interpretation and understanding are central (Davenport, 2005, p. 15). Some implementations studied in this thesis use multimodal inputs such as images, but the LLM remains the core technology in all observed cases. The thesis therefore uses the term *LLM-based AI* rather than the broader label *generative AI*. As illustrated in Figure 1, LLMs are a subset of generative AI.

LLM-based AI implementations vary considerably in autonomy and complexity, from simple chat-based assistance to multi-step configurations involving autonomous reasoning and tool use (Wang et al., 2024). The appropriate level of autonomy depends on the process, since different levels of autonomy influence process fit, risk and outcomes differently. The specific autonomy configurations used in the analysis are developed in section 3.3.2.

In the studied organizations, a common implementation pattern is the configuration of dedicated *AI assistants*. An assistant here means a conversational AI interface configured with curated information sources and instructions to serve a specific function. The term is used throughout this thesis to describe such configurations.

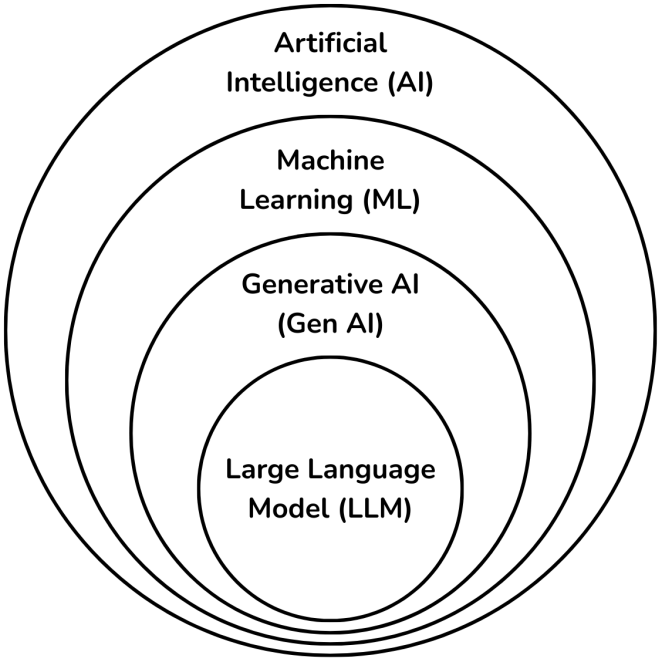

Figure 1: Hierarchical relationship between artificial intelligence, machine learning, generative AI and large language models.

Many established *Operations Management* (OM) activities, from demand forecasting and inventory analysis to quality control and process mapping, involve information processing and judgment that constitute knowledge work. This thesis examines where AI generates value at the process level, using OM methods such as waste analysis and process evaluation to identify which administrative processes are suitable for LLM-based AI implementation. OM is here understood as the activity of managing the resources and processes that create and deliver services and products (Slack et al., 2022, p.5).

1.2 Problem Background

According to a recent global survey covering 1,993 participants across different industries, the share of organizations regularly using generative AI rose from 33 percent in 2023 to 79 percent in 2025, yet most organizations remain in the experimenting or piloting phase of their AI programs rather than scaling (McKinsey & Company, 2024, 2025). With rapid diffusion, organizations face increasing pressure to implement AI in order to maintain competitiveness, yet the gap between expectations and realized operational value remains. Empirical evidence suggests that many initiatives stall in pilot phases with little or no economic return, reflecting gaps in deployment capabilities such as system integration, organizational change management and talent availability (Benbya et al., 2020). This is described as a value paradox in which adoption becomes widespread while organizations report no significant improvements

in revenue or cost performance (Sawaya et al., 2025). Whether this reflects limited actual impact or the difficulty of attributing outcomes to AI specifically remains an open question.

From an OM perspective, the core problem is therefore not adoption itself, but selection and prioritization. Organizations often lack methods for identifying which processes are suitable for LLM based support and which implementations are likely to improve efficiency and quality. Davenport and Ronanki (2018) argue that AI value creation is closely linked to process choice and implementation approach rather than the inherent capabilities of the technology. They emphasize the importance of prioritized portfolios and disciplined scaling. Without structured evaluation criteria, implementation decisions risk being shaped by available tools, local initiatives, or convenience. This can lead to investment in processes where AI yields limited impact and missed opportunities where high-potential processes are overlooked. LLM-based AI can also actively degrade output quality through errors such as hallucinations, a problem examined further in section 3.5. These dynamics are consistent with findings that the scaling of AI requires a coordinated development of both technical infrastructure and organizational conditions, underscoring the need for deliberate process selection early in the implementation journey (Haefner et al., 2023).

A further challenge concerns measurement. Efficiency improvements from LLM-based AI are often claimed based on perceived time savings or local productivity gains, but these effects do not necessarily translate into noticeable financial benefits at the organizational level (Sawaya et al., 2025). For OM, this creates a methodological challenge that is examined further in section 3.6. This study therefore reports perceived outcomes, rather than measured, a distinction that shapes how its findings should be read.

1.3 Empirical Context

This research has been conducted in collaboration with Intric AB, a platform provider for LLM-based AI in enterprise B2B settings. This collaboration enabled access to organizations implementing LLM-based AI in administrative and knowledge work processes within the Swedish energy and utilities sector.

Swedish energy and utilities organizations operate under regulatory frameworks, including emerging sustainability reporting requirements under the Corporate Sustainability Reporting Directive (European Parliament and Council of the European Union, 2022). The EU AI Act further classifies the management of critical infrastructure for electricity, gas, heating and water supply as high-risk (European Parliament and Council of the European Union, 2024), which may influence how these orga-

nizations approach AI adoption even in administrative processes that fall outside the high-risk classification. These regulatory pressures generate administrative complexity in areas such as compliance documentation, environmental reporting, and permit management, where process efficiency improvements can generate operational value. The sector's organizational characteristics, including large-scale operations, cross-functional coordination, and complex operating models, make it suitable for examining challenges related to scaling AI implementations beyond pilot phases.

1.4 Research Gap

Academic research has not fully kept up with the rapid evolution of LLM-based AI implementations, particularly regarding how organizations select and deploy these tools in practice. Research on AI implementation is spread across multiple fields, and OM research in particular lacks a consolidated understanding of which process contexts produce performance outcomes and which do not.

Existing OM research has established the relevance of AI in operations and supply chain contexts (Fosso Wamba et al., 2024; Helo & Hao, 2022). Empirical work documenting benefits, barriers, and capability requirements for AI in operations is also growing (Cannas et al., 2024; Peretz-Andersson et al., 2024). However, these studies primarily describe where AI has been applied and what outcomes resulted, rather than explaining what makes a process suitable for AI in the first place. Consequently, it remains unclear from an OM perspective what process characteristics and organizational conditions determine whether a process is likely to benefit from LLM-based support.

There is limited guidance on how OM concepts such as waste identification, process characteristics, and efficiency evaluation can guide process selection for LLM-based AI implementations. This thesis addresses this gap by examining twelve organizations in the Swedish energy and utilities sector at various stages of LLM-based AI implementation.

1.5 Theoretical Positioning

This thesis combines three complementary analytical perspectives. Lean waste analysis provides a classification logic to identify inefficiency in administrative processes (Melara et al., 2017; Womack & Jones, 2003). Task-technology fit examines alignment between process characteristics and technology capabilities (Goodhue & Thompson, 1995). Organizational conditions capture the enabling factors that determine whether an implementation can succeed in practice. These perspectives are supplemented by quality and risk constraints and efficiency categories to evaluate results. The strategic

relevance of process improvement as part of operations capability development is addressed through the Hayes and Wheelwright (1984) model in section 3.2.

1.6 Research Purpose and Questions

The purpose of this thesis is to examine how OM frameworks can explain where and under what conditions LLM-based AI improves administrative and knowledge work processes. The focus is on identifying process inefficiency through Lean waste analysis, examining which process characteristics and organizational conditions shape efficiency outcomes after AI implementation and how these can guide process selection.

RQ1 What types of process inefficiency does LLM-based AI reduce in administrative and knowledge work?

RQ2 Which process characteristics and organizational conditions help shape outcomes following LLM-based AI implementation and how?

RQ3 How can the identified characteristics and conditions guide process selection for LLM-based AI implementation?

1.7 Delimitations

The focus of this research is on administrative and knowledge work processes. The primary outcome of interest is process efficiency, assessed through perceived metrics related to time, resources and quality. Because the study is empirically situated in the Swedish energy and utilities sector, a direct generalization to other industries is not claimed. However, the analytical framework builds on OM concepts that are not sector-specific, meaning the results are intended as analytically transferable insights about process selection guidance and fit.

2 Method

The research questions require both empirical data on how organizations use AI and an analytical framework to interpret that data. This chapter describes how both were obtained.

2.1 Literature Review

A literature review was conducted in English using Google Scholar and the Luleå University of Technology library database. The review served to identify publications relevant to the research questions. Search terms included ”artificial intelligence”, ”AI”, ”AI implementation”, ”large language model”, ”lean”, ”lean office”, ”task-technology fit”, ”process efficiency”, ”knowledge work”, ”organizational readiness” and ”AI agents”, often combined with terms such as ”operations management” and ”administrative processes”.

Foundational operations management works form the basis of the analytical framework, identified in part through previous course literature. No strict time period was applied. Recent empirical studies on AI implementation published from 2020 onward were prioritized, while foundational theoretical works were included regardless of publication date.

Additional sources were identified through reference-based searching, using reference lists of key articles or related works. Emphasis was placed on peer-reviewed journal articles and frequently cited studies, while acknowledging that citation count alone does not reflect scientific quality. Industry reports were included where they provided empirical data not available in academic sources.

2.2 Research Design

The study adopts a qualitative exploratory research design based on semi-structured interviews in twelve organizations, consistent with methodological recommendations for contexts where prior theory is still developing (Edmondson & McManus, 2007, p. 1160). The unit of analysis is the administrative or knowledge work process in which LLM-based AI has been implemented, following Yin (2018) on defining units of analysis in qualitative research. Since individual interviews may surface multiple relevant processes within a single organization, each process is treated as a distinct unit of analysis.

A comparative design was chosen to allow cross-organization comparison and pattern identification. The comparison between organizations applies the cross-case

logic described by Eisenhardt (1989), where recurring patterns between independent accounts strengthen the analytical claims. The breadth of comparison across twelve organizations provides variation in process types and organizational contexts, but necessarily limits the depth of individual analysis. The sector context ensures comparability, as similar administrative processes recur across the studied organizations and are grouped into process types in section 4.2.

2.3 Sampling

Organizations were selected to capture variation in organizational size, a purposive sampling strategy recommended by Patton (2015). After twelve interviews the empirical information was deemed sufficient. This exceeds the four to ten cases recommended by Eisenhardt (1989, p. 545), and the sample captures polar types and fills theoretical categories.

Organizations were identified through two channels. The first consisted of Intric customer organizations, with access facilitated through the collaboration with Intric AB. The second channel consisted of organizations identified through the SNI codes listed in Table 1 in public business registers. All organizations regardless of channel belong to the Swedish energy and utilities sector.

Table 1: SNI codes used to identify energy and utilities sector organizations.

SNI code	Description
35.110	Production of electricity from non-renewable sources
35.120	Production of electricity from renewable sources
35.130	Transmission of electricity
35.140	Distribution of electricity
35.150	Trade of electricity

Including both Intric customers and non-customers serves an analytical, rather than comparative, purpose. All organizations are analyzed through the same theoretical framework and coding scheme, with the two groups providing complementary variation in implementation context, tool choice and organizational maturity. For each organization, an interviewee was selected based on their knowledge of AI implementation within the organization. Interviewing multiple respondents per organization could have provided richer accounts but was not feasible within the scope of the study. A detailed overview is presented in section 4.1.

2.4 Data Collection

Semi-structured interviews were used as the primary data source. The semi-structured format combines the thematic consistency needed for cross-organization comparison with the flexibility to pursue unanticipated topics (Bell et al., 2022, p. 13).

Two interview guides were developed to account for differences in implementation approach while covering the same underlying topics, one for Intric customers and one for non-customers. Both guides were organized around the organization's processes and implementation experience. They also covered perceived effects on efficiency and quality, as well as organizational conditions. In practice, interviews followed a conversational flow with the guide serving as a checklist rather than a strict sequence. Where evaluative claims were made, follow-up questions explored the basis for those assessments. The interview guides are provided in Appendix A & Appendix B.

All interviews were conducted individually by the author, lasted approximately 20 to 40 minutes and were transcribed with informed consent. Individual rather than group interviews ensured that interviewees could describe their own experiences without being influenced by colleagues (Bell et al., 2022, p. 214).

The interviews were conducted in Swedish, as both the author and all the interviewees are native Swedish speakers. The transcripts were reviewed and corrected by the author, converting conversational speech into proper written Swedish and removing speech artifacts while preserving the meaning of all statements. This follows the principle that transcription involves a transformation from oral to written language where some degree of interpretation is unavoidable (Brinkmann & Kvale, 2009, pp. 177–178). The thesis is written in English while interviews were conducted in Swedish. van Nes et al. (2010) note that translation between languages constitutes an additional interpretive act. To manage this, coding and analysis were performed on the original Swedish transcripts. Direct quotes were translated by the author with attention to preserving meaning rather than producing literal translations.

The empirical material is based on self-reported accounts, which means efficiency outcomes reflect perceived rather than measured changes. To manage potential bias, organizations where AI produced limited or negative effects are presented alongside positive outcomes, and follow-up questions were used to explore the basis for evaluative claims.

2.5 Data Analysis

The analysis followed a thematic approach that combined deductive and inductive elements. Braun and Clarke (2006) describe thematic analysis as a flexible method

that can be applied across different theoretical and methodological approaches. Deductive categories from the theoretical framework provided the initial coding structure. When interviewee descriptions introduced patterns not captured by these categories, such as capability expansion, these were developed inductively from the material. The complete coding framework with definitions is provided in Appendix D.

The analysis was carried out in three stages. The first stage involved repeated reading of all transcripts to identify the processes described by each interviewee, consistent with the familiarization phase described by Braun and Clarke (2006). The second stage compiled within-organization summaries of each organization's AI implementation context, identified processes and perceived outcomes (Miles et al., 2014). The third stage compared patterns across organizations, grouping processes into types based on functional similarity. This follows the logic of Eisenhardt (1989) where understanding individual cases precedes cross-case pattern search. The patterns from RQ1 and RQ2 were then synthesized into selection guidance for RQ3.

The analysis also involved developing analytical tools from the qualitative material. Waste categories were assigned to each process type based on the coded interview accounts and then counted to identify which types of waste AI most frequently addressed. Organizational conditions were rated on a three-level scale with scoring criteria documented in Appendix D. The ratings are based on the author's interpretation of the interview accounts and are intended to make cross-organization comparison easier to follow. A condition was rated present or absent when the interview account provided a clear basis for the assessment. When evidence existed but did not clearly indicate either, the condition was rated partial. The scores indicate relative standing between organizations rather than precise measurements. Organizations were then grouped based on their organizational conditions and process-fit patterns and interpreted through the Hayes and Wheelwright (1984) four-stage model.

2.6 Research Quality

Research quality is assessed using the four qualitative concepts proposed by Lincoln and Guba (1985), namely credibility, transferability, dependability, and confirmability.

Credibility is strengthened through the data collection procedures described in section 2.4. The analysis relies on the author's interpretation, as interviewees did not review the findings. Transferability is supported by describing each implementation in sufficient detail for readers to assess relevance to their own context. The analytical framework is based on general OM concepts rather than sector-specific theory, which supports application beyond the energy and utilities sector. Dependability is

addressed through the interview guides, coding framework, and analytical procedures. Deductive categories were derived from the theoretical framework before analysis began. Confirmability is strengthened by presenting both positive outcomes and cases where AI produced limited or negative effects.

As a single researcher conducted all interviews, coding, and analysis, inter-coder reliability checks were not possible. This is mitigated by the structured coding framework and documented procedures described in section 2.5.

2.7 Ethical Considerations

The study was conducted according to the principles of good research practice outlined by Vetenskapsrådet (2024). All interviewees were informed about the purpose of the study, that participation was voluntary and that they could withdraw at any time. Confidentiality was ensured through anonymization of organizations and interviewees.

The study was conducted in collaboration with Intric AB, creating a potential conflict of interest as findings could reflect positively or negatively on Intric's product. To maintain academic independence, the purpose, questions, and analytical framework of the investigation were defined independently of Intric. The analysis treats Intric customers and non-customers equivalently through the same analytical dimensions and no distinction is made that would serve a commercial rather than analytical purpose (Vetenskapsrådet, 2024, pp. 12–13). LLM-based language tools were used to assist with editing and proofreading during the writing process, in accordance with current guidance on AI disclosure in scholarly work (Resnik & Hosseini, 2026).

3 Theoretical Framework

No single framework covers the full scope of process selection for AI implementation. This chapter combines perspectives from several fields into an integrated analytical framework.

3.1 Lean Wastes

Lean is a systematic approach to identifying and eliminating activities that consume resources without creating value for customers. Womack and Jones (2003, p. 15) describe it as "a way to do more and more with less and less ... while coming closer and closer to providing customers with exactly what they want." This principle applies beyond manufacturing. Melara et al. (2017) confirm that lean has been successfully applied in office and administrative settings, although the evidence base remains limited to thirteen included studies.

The concept of *waste* describes the gap between current performance and the ideal state. Ohno (1988) distinguishes seven forms of production waste, including overproduction, waiting, transporting, over-processing, inventories, unnecessary movement and making defective products. Liker (2004) added an eighth category, underutilization of people, arguing that "losing time, ideas, skills, improvements and learning opportunities by not engaging or listening to your employees" represents waste of human potential. The eight waste categories applied in this study are shown in Table 2.

Table 2: Lean waste categories applied to administrative and knowledge work contexts, adapted from Ohno (1988) and Liker (2004).

Waste type	**Definition**
Transport	Unnecessary movement of information between systems, departments or approval stages.
Inventory	Backlogs of tasks or queued requests.
Motion	Time spent searching for information, switching between applications or navigating systems.
Waiting	Time spent awaiting information, approvals or handoffs between process stages.
Overproduction	Outputs generated without clear demand or usefulness.
Overprocessing	Redundant steps or manual work beyond what the output requires.
Defects	Errors requiring rework or corrections.
Skills underutilization	Employees performing tasks below their expertise or judgment level.

3.2 Process Perspective

In OM, a *process* is commonly defined as a structured, measured set of activities that transforms inputs into outputs through a sequence of coordinated tasks for an internal or external customer (Davenport, 1993, p. 5). vom Brocke and Rosemann (2015, pp. 113–114) add that process performance requires a coherent process architecture, clear ownership and performance indicators tied to strategic objectives. Compared with manufacturing processes, administrative processes are often less physically observable and depend more on information quality and professional judgment, yet they can still be analyzed through OM methods.

The performance of processes is also strategically relevant. Hayes and Wheelwright (1984) position the cumulative performance of processes as a potential source of competitive advantage, distinguishing between reactive operations that merely avoid negative impact and strategic operations that actively drive competitive advantage, as illustrated in Figure 2. The model is used in OM to assess how far an organization's operations function has developed from a reactive role toward a strategic one. Administrative and knowledge work performance fits this logic because it shapes responsiveness, reliability, and quality in the same way that manufacturing performance does. In this study, the model motivates systematic process selection as strategically relevant and provides a lens for interpreting the empirical patterns identified in section 5.4.

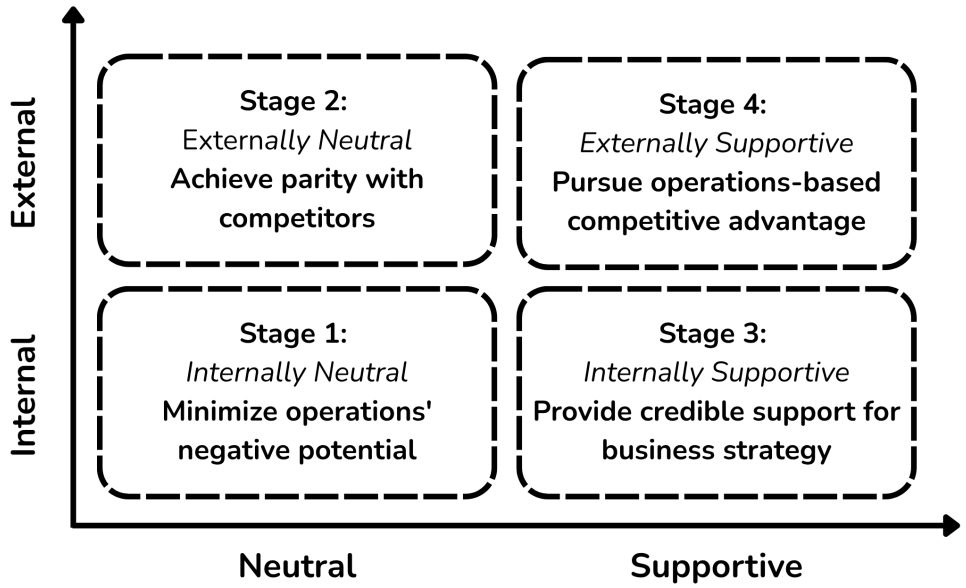

Figure 2: Visualization of the Hayes and Wheelwright four-stage model of operations contribution to competitive advantage (Hayes & Wheelwright, 1984)

3.3 Task-Technology Fit

Goodhue and Thompson (1995) propose *Task-Technology Fit* (TTF) theory and the Technology-to-Performance Chain to explain why similar tools may produce different outcomes depending on what they are used for. The core argument is that a technology must not only be used, but also fit the tasks it supports in order to improve performance. *Fit* here means the match between what the task requires, what the technology can do, and what the user is capable of. Goodhue and Thompson (1995, p. 218) note that a more precise name would be task-individual-technology fit, to underscore the importance of individual capabilities.

The original TTF framework was formulated at the individual level to explain information system utilization and performance outcomes. Alternative frameworks such as the Technology Acceptance Model (Davis, 1989) focus on adoption intentions, but TTF is preferred here because the research questions concern performance outcomes rather than adoption. In this study, the logic is extended from individual tasks to administrative processes by assessing fit across sequences of tasks rather than isolated activities. The specific dimensions through which fit is assessed are developed in the following section.

3.3.1 Process-fit Dimensions

Since all studied implementations use LLM-based AI, process characteristics become the primary source of variation in process fit. Building on TTF (Goodhue & Thompson, 1995), four dimensions were developed to capture the characteristics most relevant for evaluating fit with LLM-based AI. *Input characteristics* reflect the TTF premise that process input constrains which technologies can support it. *Standardization* reflects where a process falls on the volume-variety continuum (Slack et al., 2022), and captures how reliably AI can operate within it. *Judgment complexity* captures what type of decision-making is required. *Domain expertise* here means the specialist knowledge of the field in which a process operates. This connects to the automation model of Parasuraman et al. (2000), developed further in section 3.3.2. *Error sensitivity* connects to the quality and risk logic in section 3.5, reflecting the consequences of incorrect output. These dimensions are assessed qualitatively through interview accounts rather than numerical scales. Table 3 summarizes the four dimensions.

Table 3: Process-fit dimensions used in the analysis.

Dimension	Definition
Input characteristics	Type, format and source of information the process requires.
Standardization	Predictability of the process versus frequency of exceptions or ambiguous inputs.
Judgment complexity	Decision requirements from routine rule-following to contextual interpretation requiring domain expertise.
Error sensitivity	Consequences when the process produces incorrect outputs.

3.3.2 Autonomy Configurations

Parasuraman et al. (2000, p. 286) describe automation decisions as questions of "which system functions should be automated and to what extent". They propose that automation applies to four distinct function types, namely information acquisition, information analysis, decision selection and action implementation. Each function type can be automated at different levels independently.

For LLM-based AI, information acquisition and analysis are consistently automated at high levels because natural language processing, retrieval and summarization are core capabilities of the technology. The meaningful variation lies in how much decision authority and action execution is delegated to the tool. Applying the model of Parasuraman et al. (2000, p. 288), three autonomy configurations can be distinguished based on where this boundary is set. An *informational* configuration retrieves information while the user makes decisions. An *advisory* configuration recommends outputs that a human executes. An *agentic* configuration selects and executes actions, corresponding to what Wang et al. (2024) characterize as autonomous agents capable of multi-step planning and tool use. Table 4 summarizes the three configurations and Figure 3 illustrates how they map onto the four function types.

Table 4: Autonomy configurations describing the degree of human oversight in AI-supported processes.

Configuration	Definition
Agentic	Actions are selected and executed with limited human oversight.
Advisory	Actions or outputs are recommended or drafted, human reviews before execution.
Informational	Information is retrieved and presented, human makes decisions.

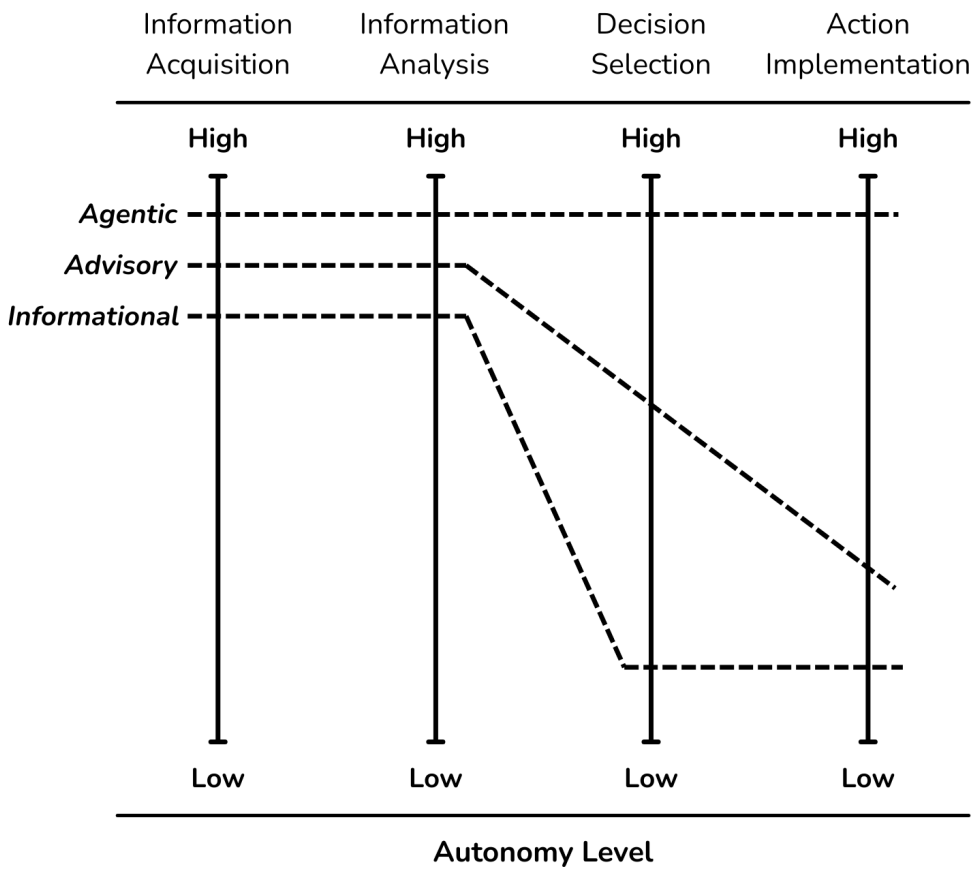

Figure 3: Three LLM autonomy configurations mapped onto the automation function types of Parasuraman et al. (2000).

Serrano and Karahanna (2016) add that performance also depends on how well human and technology capabilities complement each other, with humans compensating for technology limitations through their knowledge and skills. As autonomy increases from informational toward agentic, human verification decreases and the risk of undetected errors rises, connecting directly to the quality constraints discussed in section 3.5. Parasuraman et al. (2000) further argue that low-risk decisions are strong candidates for higher autonomy, while decision and action automation should remain at lower levels when errors carry serious consequences.

3.4 Organizational Conditions

Implementation success depends on organizational conditions, not just process fit. Without supporting conditions, implementations risk never moving beyond early experiments. Weiner (2009, p. 1) describes *readiness for change* as ”organizational members’ shared resolve to implement a change and shared belief in their collective capability to do so”, arguing that both must be present for implementation to succeed.

However, readiness is tied to the specific change being implemented rather than being a permanent organizational property. This motivates examining conditions that are specifically relevant to AI implementation.

Research consistently finds that organizational conditions are what separates successful AI implementations from those that stall. Haefner et al. (2023) identify data pipelines, technical infrastructure and organizational structure as necessary components for achieving broader organizational use. According to Ransbotham et al. (2020), technological foundations alone are insufficient to realize financial benefits with AI. What separates successful organizations is their investment in mutual learning between humans and machines. Asatiani and Penttinen (2016) reinforce this, showing that value depends on assessing suitable processes for automation and clearly communicating to employees how their work will change.

Building on these findings, the analysis examines four conditions. *Process ownership* reflects the emphasis of vom Brocke and Rosemann (2015, pp. 113–114) on clear roles and cross-functional coordination as prerequisites for process performance. *Process documentation* follows the same logic, since documented procedures and quality criteria provide a reference for how the process should be performed and what acceptable output looks like. *Data infrastructure* reflects the finding of Haefner et al. (2023) that technical elements such as data access and pipeline maturity are important enablers of AI implementation. *Technical capability* reflects the finding of Ransbotham et al. (2020) that organizational investment in building human-AI competence is what separates successful implementations from those that stall. These conditions are assessed qualitatively through interview accounts rather than numerical scales. Table 5 summarizes the four conditions, which describe the organizational context of each implementation.

Table 5: Organizational condition dimensions used in the analysis.

Dimension	**Definition**
Process ownership	Clear responsibility and decision authority for AI in a process, assigned to specific individuals or teams.
Process documentation	Documented procedures, templates or quality criteria that provide a baseline for execution and evaluation.
Data infrastructure	Access to required information sources, including system integration and security constraints.
Technical capability	Individuals or roles with knowledge to configure tools and handle implementations.

3.5 Quality and Risk

Quality can be understood as conformance, defined by Crosby as ”conformance to requirements” (Crosby, 1979, p. 15) and by ISO 9000 as the ”degree to which a set of inherent characteristics of an object fulfils requirements” (International Organization for Standardization, 2015, clause 3.6.2). In administrative work, these requirements are set in part by the users, customers and regulatory frameworks that receive the output. When AI-generated output fails to meet these requirements, the resulting errors carry a cost. The concept of *cost of poor quality* (American Society for Quality, n.d.) captures this, and when AI implementations require additional verification to catch errors, these costs can offset perceived efficiency gains. Quality and risk therefore constrain which processes can be supported by AI and how much autonomy the AI can be given.

The success of AI implementation can be limited by quality requirements. In OM, quality is one of the five fundamental performance objectives alongside speed, dependability, cost and flexibility (Slack et al., 2022, pp. 45–46). Quality receives particular attention in this study because AI can introduce new errors and if output quality is insufficient, improvements in speed or cost become irrelevant. In administrative and knowledge work this matters especially because the output of one process often serves as input to the next, meaning poor coordination or inefficiency in one step affects downstream work (Davenport, 1993). If AI reduces processing time but introduces errors, the time saved may simply shift to rework and correction rather than being eliminated (Hopp & Spearman, 2008, p. 390)

LLM-based AI is commonly associated with quality risks, three of which are described here. *Hallucinations* are outputs that appear plausible but are incorrect representations of the provided source content, whether through direct contradiction or unverifiable additions (Ji et al., 2023). *Automation bias* describes a tendency from users to over-rely on automated output as a substitute for independent judgment (Goddard et al., 2012, p. 121). *Confirmation bias* describes a pattern where LLM-based AI affirms the user's existing assumptions rather than challenge them, which can reinforce rather than correct a mistaken view. A common organizational response is to require that a human reviews AI output before it is used. However, automation bias suggests that the effectiveness of such verification depends on how the review process is designed, because reviewers may otherwise default to accepting the output rather than critically evaluating it.

3.6 Efficiency Measurements

Measuring process efficiency in administrative and knowledge work differs from manufacturing because outputs are often intangible rather than physical. Indicators such as machine utilization or output volumes are not meaningful when the work involves information processing or human judgment. In this study, reported outcomes from interviews are grouped into the three categories shown in Table 6.

Table 6: Efficiency metric families used in the analysis.

Metric family	**Examples**
Time metrics	Lead time, cycle time and waiting time.
Resource metrics	Labor cost, number of employees and utilization of resources.
Quality metrics	Perceived output quality, customer satisfaction, error rates, error severity and user experience.

These categories assume a comparable baseline where the process was performed before and after implementation. When AI enables work that was previously not performed at all, this baseline does not exist. In such cases, the outcome may be better understood as *capability expansion*, where AI makes previously infeasible work possible rather than performing existing work more efficiently. The value lies in what becomes possible, which means it cannot be assessed against a prior level of performance.

Attributing observed changes to AI alone is difficult because multiple factors influence outcomes at the same time. The study captures perceived rather than measured outcomes, based on how interviewees describe their processes before and after AI was introduced. The emphasis is therefore on understanding which process and organizational characteristics accompany the outcomes interviewees describe, rather than on quantifying the outcomes themselves.

3.7 Theoretical Synthesis

The preceding sections present several theoretical perspectives that are combined here into an analytical framework for understanding where and under what conditions LLM-based AI improves administrative and knowledge work processes, illustrated in Figure 4.

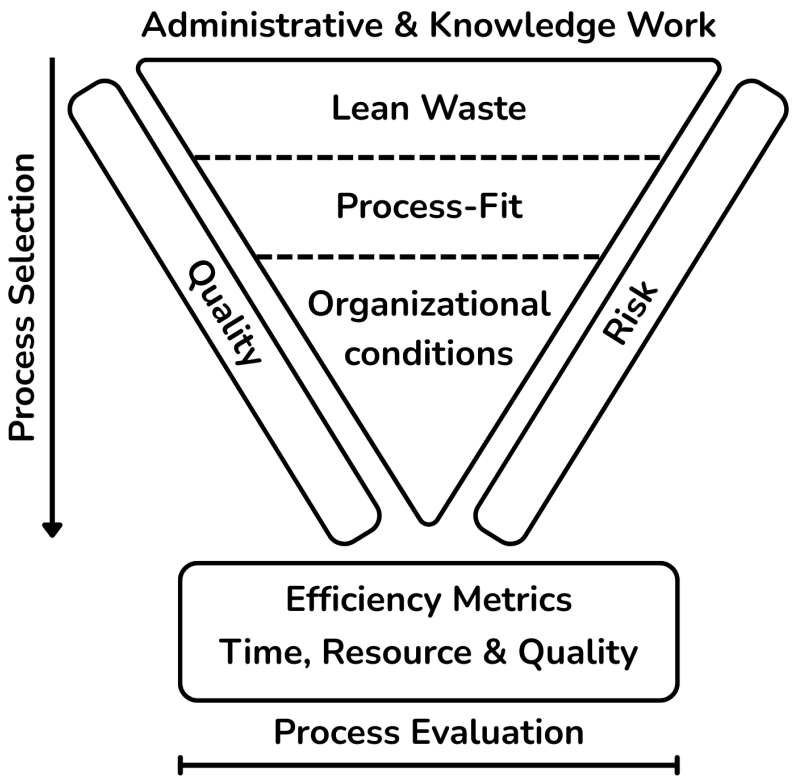

Figure 4: Analytical funnel for systematic process selection in LLM-based AI implementation.

The framework is developed for this study by integrating existing theoretical perspectives rather than adopting an existing model. The perspectives form an analytical funnel, where each layer narrows the analysis from identifying inefficiency to evaluating outcomes. Lean waste analysis categorizes the types of inefficiency present. Process-fit dimensions describe the characteristics that shape how well a process aligns with LLM-based AI. Organizational conditions describe the environment in which implementation takes place. Quality and risk constraints limit what implementations are feasible, and outcome categories capture the reported effects of AI use.

4 Results

This chapter presents what interviewees reported about their AI implementations, organized by process type and followed by the perceived outcomes and emergent effects.

4.1 Overview

The empirical material consists of twelve semi-structured interviews with representatives from twelve organizations in the Swedish energy and utilities sector. Table 7 shows each organization with labels A to L throughout the thesis.

Table 7: Overview of organizations and interviewees

Org.	Organization type	Employees	Interviewee	AI Tool
A	Municipal energy & waste	100-500	Head of Digital Development	Intric
B	Municipal water & waste	0-100	Business Developer	Intric
C	International energy	500-1000	Teamleader Data Science	Microsoft 365 Copilot, Github Copilot
D	Municipal energy	1000+	Development Strategist	Microsoft 365 Copilot
E	Municipal energy	0-100	COO	Intric
F	Municipal energy	100-500	Head of Business Support	Microsoft 365 Copilot
G	Municipal energy & waste	100-500	OT Strategist	Intric
H	International energy	1000+	P2P Accountant	Microsoft 365 Copilot, undisclosed LLM tool
I	Energy association	0-100	IT Security Coordinator	Intric
J	Municipal energy	100-500	IT Strategist	Microsoft 365 Copilot
K	Private energy	100-500	Head of Process & IT Support	Microsoft 365 Copilot
L	Municipal energy	500-1000	Finance IT Specialist	Microsoft 365 Copilot

Implementation maturity varies considerably across the sample. Organizations E and G have deployed AI across multiple processes with dedicated platforms, while organizations F and J remain at the level of individual experimentation with general-purpose tools. Five organizations use Intric as their primary platform, six rely

primarily on Microsoft Copilot and organization H uses an undisclosed LLM tool for structured data processing.

4.2 Identified Processes

Across the organizations, seven process types were identified. These emerged inductively by grouping the processes described by interviewees according to what purpose the AI served, as documented in the coding framework in Appendix D. Process types are described in Table 8.

Table 8: Identified process types and descriptions.

Process type	Description	Example
Internal information retrieval	Querying internal information sources and documentation.	Searching technical manuals for maintenance instructions.
External information retrieval	Searching information from internet or external sources.	Looking up an industry standard online.
Document generation	Generating, drafting or proofreading written content.	Drafting an annual report from several data sources.
Operational support	Reasoning about technical data, diagnosing problems or generating code.	Recommending sensor settings from historical data.
Customer service	Automated responses to external customer queries through chatbots.	A chatbot answering questions about invoices.
Business analysis	Research, interpretation or analysis for strategic or specialist tasks.	Comparing old and new regulations for a feasibility study.
Structured data processing	High-volume structured data classification or transformation.	Matching tax codes to incoming invoices.

Figure 5 shows which process types are present in each organization. The following subsections present the specific implementations in each organization by process type. Direct quotes are translated from Swedish by the author.

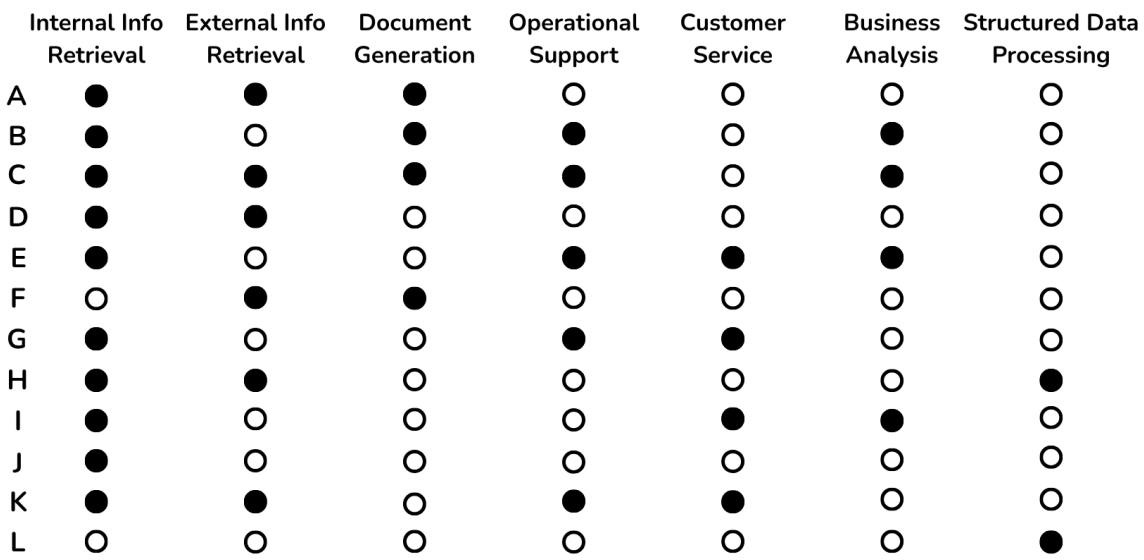

Figure 5: Identified process types in studied organizations.

4.2.1 Internal Information Retrieval

Internal information retrieval is the most consistently observed process, appearing in ten organizations. The common pattern involves using AI to query internal information conversationally rather than searching manually. Some organizations configure dedicated assistants with curated documentation while others rely on general-purpose tools with access to internal files. Table 9 summarizes the implementations across organizations.

Table 9: Internal information retrieval implementations across organizations.

Org.	Application
A	Documentation and legal search
B	Operational and regulatory documentation search
C	Internal document search
D	Internal document search
E	Technical documentation search
G	Technical documentation, legal and accounting search
H	Internal document search
I	Personnel documentation, handbook and legal search
J	Internal document search
K	Internal document search

Organization A has built assistants across its water, waste and recycling operations. The most developed is a water and sewage assistant drawing on extensive technical documentation. A separate legal assistant cross-references between laws and flags when a question falls under a regulation different from the one being queried, replacing what the interviewee described as a tendency to "just guess rather than look things up."

At organization B, the business developer built a process-focused assistant for his own work. Other employees have since built their own assistants, including one for water and sewage project managers that is based on an industry standard the interviewee described as being of "bible-like thickness," replacing what was previously manual browsing. Strategists have also built assistants that monitor trade organization publications and track current and upcoming legislation in their domain.

At organization C, Copilot is used for general internal document search and topic summarization, but without domain-specific configurations.

Organization D uses Copilot similarly, for summarizing and interpreting documents such as research reports, though data classification restrictions keep sensitive material outside the tool.

Organization E has built an assistant for the combined heat and power plant that draws on around 360 documents, including equipment manuals, research articles and industry reports. Operators query by equipment identifier across the plant's thousands of equipment objects and receive maintenance instructions directly, replacing binders of instructions the interviewee described as capable of filling an entire room. The union is developing a separate assistant to interpret collective agreements and extend the retrieval pattern to new organizational domains.

At organization G, the AI searches technical documentation, laws and regulations and charts of accounts for invoicing.

Organization H uses Copilot, which is connected to the internal cloud network, to search for documentation the interviewee has previously written. The interviewee described documents as being "scattered everywhere" and uses Copilot to retrieve specific instructions and information across these sources rather than searching manually.

Organization I searches across legal references, industry handbooks and personnel documentation, cited as examples of content that existed but went unused because searching it was too cumbersome.

Organization J has experimented with agents built by individual employees for

legal references, meeting room instructions, troubleshooting and manufacturer user manuals, but none have spread beyond individual use. The organization lacks SharePoint synchronization, restricts access to some data classification levels, and has no coordinated effort to scale individual experiments.

Organization K runs a Copilot agent with access to the management system that directs employees to the correct procedures, reducing reliance on locally stored copies of instructions.

4.2.2 External Information Retrieval

External search appears in six organizations, used to retrieve and summarize information from open internet sources. Table 10 summarizes the observed usage.

Table 10: External information retrieval across organizations.

Org.	Application
A	General research
C	General research and summarization
D	General research and summarization
F	General research and summarization
H	Troubleshooting and community search
K	Standards search

In organization A, general AI tools are used for external queries on topics outside the organization's internal knowledge base. The interviewee describes AI as the first step in a broader information-seeking pattern, stating that "first you check AI, if that does not work, you turn to Google, then to specialist databases, and then you start asking colleagues."

In organization C, Copilot is also used for external research and topic summarization, based on open internet content alongside the internal document search described in the previous section.

In organization D, Copilot is also used for external research and summaries, with open internet content that does not carry usage restrictions, unlike internal material.

Organization F relies entirely on Copilot Chat for external internet content because license limitations prevent access to internal data. The interviewee uses it for research and summarizing external content on specific topics.

In organization H, Copilot is used to search for external content, such as online SAP community resources, when troubleshooting error messages, described as a shortcut before consulting colleagues.

In organization K, Copilot is used to search external content, particularly ISO and IMS standards, providing quick access to relevant information with links to the source documents.

4.2.3 Document Generation

Document generation appears in four organizations, ranging from occasional proofreading to structured report production. Table 11 summarizes the observed usage.

Table 11: Document generation implementations across organizations.

Org.	Application
A	Image and text generation
B	Structured document drafting
C	General document drafting
F	Proofreading

In organization A, AI is used to generate images and content for presentations. Employees also use it to rephrase text or translate between languages.

Organization B has the most structured use, with assistants producing content for what the interviewee described as ”annual reports, business reports, and material for meetings with owners and the board.”

In organization C, AI is used to produce initial drafts of new material. It also helps to create documentation and to prepare reports that combine multiple data sources.

In organization F, the interviewee uses AI primarily for proofreading and quality checking documents that he has already written.

Organization J experimented with generating marketing copy in the communicator's tone but found the effort required to configure the prompts and formatting ”very cumbersome,” describing it as ”interesting, but nothing I am continuing with.”

4.2.4 Operational Support

Operational support appears in five organizations where AI supports technical and production work, from interpreting sensor data to generating code for production systems. Table 12 summarizes the implementations.

Table 12: Operational support implementations across organizations.

Org.	Application
B	Image analysis and system parameter anomaly detection
C	Code generation
E	Sensor data diagnostics and regulator troubleshooting
G	Technical classification and code generation
K	Inspection assessment analysis

In organization B, AI analyzes microscope images of bacterial cultures against reference images of what good and bad states look like to assess how the wastewater treatment plant is performing. A separate assistant scans historical system parameter data for anomalies and relationships, replacing what the interviewee described as ”a lot of manual work to look through these tables and search for anomalies.” Engineers review the output from both assistants and decide which parameters to adjust. Technicians then carry out the changes, such as chemical dosing, temperature or pressure.

In organization C, GitHub Copilot supports developers in producing software for operational applications such as forecasting and production planning.

In organization E, a boiler operator uploaded historical data from a control sensor on the superheater that had been unstable for five to six years. The AI asked clarifying questions and recommended specific regulator settings, which the operator applied and which stabilized the signal. The interviewee described the operator as ”shocked at how well it worked” and noted that he now uses the same assistant regularly for other sensor and equipment problems in the production environment.

In organization G, AI helps engineers assign the correct technical classification to equipment in the production environment. Equipment is classified based on what it measures rather than what type of device it is, a distinction the interviewee described as easy to get wrong under the previous manual process. Additional assistants generate code for production control systems.

Organization K uses AI to interpret the completed inspection forms from its large network of substations and cable cabinets. Staff first worked with the AI to calibrate how the written inspector assessments should be interpreted, and the AI now classifies forms at scale to flag which assets need attention.

4.2.5 Customer Service

Customer-facing chatbots appear at four organizations and are deployed on company websites to handle routine customer queries. All four limit what the chatbot can access to curated public information. Table 13 summarizes the implementations.

Table 13: Customer service implementations across organizations.

Org.	Application
E	Customer-facing chatbot
G	Customer-facing chatbot
I	Customer-facing chatbot
K	Customer-facing chatbot

At organization E, a chatbot on the website handles simple customer queries such as contract questions, trained on website content and FAQ material. More complex questions are routed to customer service staff. The admin interface allows staff to review past conversations and adjust answers to improve future responses.

At organization G, a chatbot built on the Intric platform has been deployed on the organization's website. The interviewee has limited direct involvement with it.

At organization I, chatbots are deployed for customer interaction, narrowed to work with public information and suited for customers who prefer quick digital answers over speaking with a person. Administrators review past conversations and adjust answers to improve future responses.

At organization K, chatbots are operated by the external customer service provider on the organization's behalf, with the aim of handling simple customer questions that would otherwise accumulate as incoming calls so that customer service staff can focus on more complex cases. The organization actively works with the provider to configure the chatbots so that they provide the correct and relevant information.

4.2.6 Business Analysis

Business analysis appears in four organizations where AI supports decision-making and strategic reasoning, such as regulatory interpretation, feasibility assessment and legal review. Table 14 summarizes the implementations.

Table 14: Business analysis implementations across organizations.

Org.	Application
B	Regulatory change analysis
C	Natural language interface to forecasting tools
E	Feasibility studies and legal review
I	Legal review and analysis

At organization B, the AI was given old and new versions of local regulations and extracted the differences between them. The output was used for internal verification that the intended changes were correctly implemented and for explaining the changes to external audiences.

At organization C, a prototype LLM interface layered on forecasting tools allows non-technical users to query production and market forecasts conversationally.

At organization E, the business developer uses AI for feasibility studies. One assistant does background research, another handles economic analysis, another drafts a project plan, with output manually fed from one to the next. A separate legal assistant is configured with access to the organization's own law list, the Swedish parliament's legal database and web search, used for tasks such as preparing appeals to the administrative court.

At organization I, a legal assistant helps staff interpret incoming legal claims and regulatory references. The interviewee frames this as enabling "amateurs in law" to prepare better input for a professional lawyer, explicitly not replacing the lawyer's final judgment.

4.2.7 Structured Data Processing

Structured data processing appears in two organizations where AI handles repetitive classification, matching or transformation tasks at volume. Table 15 summarizes the implementations.

Table 15: Structured data processing implementation.

Org.	Application
H	Tax code prediction and invoice scanning
L	Financial data restructuring and reconciliation

In organization H, two AI systems support a high-volume invoice flow. A tax code predictor recognizes suppliers and matches correct VAT codes by country and transaction type, pre-filling invoice information. A scanning system extracts data from paper invoices received by post and routes them to the correct subsidiary and supplier contract in the ERP system.

In organization L, the finance function has built Copilot agents for several structured data tasks. An agent restructures data from shared internal Excel reports into a format suitable for external customers. A second agent reconciles the bank files with the general ledger to identify discrepancies. A third transfers data from external reports to the accounting system. As the interviewee summarized it, ”what we gain is that all the manual keying is eliminated.”

4.3 Perceived Outcomes

This section presents what the interviewees reported about the effects of AI implementation on time, resources and quality. Organizations that did not describe a perceived outcome in a given category are omitted from the table.

4.3.1 Time and Resource Effects

Although no organization has established systematic measurement of efficiency outcomes, interviewees describe a range of perceived effects on time and resource use. Table 16 summarizes the outcomes described by each organization.

The most concrete outcomes come from organizations E and H. At organization H, AI increased the processing rate of the invoice flow, reducing staffing from three half-time positions to one while handling the same volume. At organization E, the interviewee estimated that preparatory research that previously would have taken six months can now be completed in days, and a specialized legal assistant has replaced the use of external lawyers. Both H and E have a prior state clear enough for the change to be obvious without measurement. Most other organizations describe more diffuse effects, and staff save time on individual tasks while acknowledging that organizational-level effects are harder to assess. Organization F captures this distinction directly. The interviewee described feeling ”personally a bit more efficient” but added, ”I do not know if the company as a whole gets better from it.”

Several interviewees resist quantification entirely, pointing out that a simple before-and-after comparison misses what actually changes with AI. Several instead describe benefits that fall outside time and resource metrics, such as increased confidence in decisions, broader consideration of available information, and greater self-sufficiency. Organization A argues that behavior itself has changed, and organization I adds

that while AI will save personnel effort it will also create new types of work. These outcomes are explored in more detail in section 4.3.3. Apart from organization H's staff reduction, no organization has reallocated resources as a result of AI implementation.

Table 16: Time and resource outcomes described across organizations.

Org.	Described outcome	Type
A	Comparison is inherently complicated because behavior has changed; people now ask questions they would previously have guessed at, framed as individual empowerment rather than time saved	Perceived
B	Organization believes it saves time but has no way to provide evidence	Perceived
C	Staff save time on individual tasks; no formal measurement conducted	Perceived
D	Staff save time on individual tasks; organizational effects not yet visible due to restricted scope of permitted use	Perceived
E	Preparatory research that previously would have taken around half a year can now be completed in days; specialized legal assistant has eliminated the use of external lawyers that previously charged approximately 5,000 SEK per hour	Estimated
F	Personally feels more efficient but questions whether the organization as a whole benefits	Perceived
G	Engineers arrive faster at correct signal designations and understand better why a given designation applies	Perceived
H	Staffing required for physical mail handling and data entry reduced from three half-time positions to one	Quantified
I	Interviewee thinks AI will save personnel effort but also create new types of work	Anticipated
K	Customer service chatbots have reduced telephone traffic, though the interviewee is not directly involved with the numbers	Perceived
L	Staff save time on individual tasks; real value of restructured customer reports may lie in downstream time savings for customers rather than time saved internally	Perceived

4.3.2 Quality Effects

Interviewees describe quality effects as both improvements and risks, often within the same organization. Table 17 summarizes the outcomes described by each organization.

Table 17: Quality outcomes described across organizations.

Org.	Described outcome	Type
A	Contextualized legal answers with cross-referencing between laws; improved relevance compared with keyword search; hallucinations rare because the knowledge base is narrowed; trust in AI output has shifted, people relying on answers they would previously have verified	Mixed
B	Image analysis catches anomalies engineers might miss; described as ”works shockingly well”	Positive
C	Users who encounter errors early dismiss AI as useless, while engaged users develop strategies for catching and limiting errors	Mixed
E	Sensor diagnostics and legal assistant produce reliable output with configured inputs; explicit policy that nobody may treat AI output as truth without understanding the subject	Positive
F	Proofreading improves document quality; AI tends to confirm the user’s existing position rather than challenge it; people without domain knowledge can present unrealistic conclusions	Mixed
G	Signal designations more consistent than under the manual process with better understanding of why a designation applies; domain knowledge required to catch hallucinations; customer chatbot struggles with dates and dynamic information	Mixed
H	Tax code predictor matches correct VAT codes reliably; scanning system processes invoices at volume once master data was corrected; incomplete master data during rushed implementation caused worse performance than the manual process initially	Mixed
I	Legal assistant enables non-lawyers to produce better analytical input; chatbot quality managed through administrator review; when the AI is ”creative”, the output fails	Mixed
K	Inspection classifier produces reliable results after calibration with staff; management system agent directs employees to correct procedures; legacy data inconsistencies from merged companies propagate into AI output	Mixed
L	Restructured customer reports are clearer and reduce errors; every output is checked as standard practice	Positive

The positive outcomes at organizations A, B, E and G share a common feature in that they all come from AI implementations configured with curated, domain-specific information sources. Hallucinations are reported at organizations G and I, with organization A noting these are rare when the knowledge base is narrowed. Confirmation bias is described at organization F, where the interviewee illustrates that AI tends to accommodate the questioner rather than challenge them. The broader risk of automation bias, where users over-rely on AI output, is reinforced by the recurring

emphasis on domain expertise as a prerequisite for safe use. Organization G's customer chatbot struggles with dates and dynamic information, showing limitations in handling content that changes over time.

Data quality emerges as a separate category of risk. Organization H states that AI is only as good as the data you give it, while organization K describes inconsistent legacy data as their biggest problem.

A recurring observation across interviewees is that domain expertise is a prerequisite for safe use of AI output. Organizations E, F and G state this directly, and organizations L and C reinforce it through practice, with organization L checking every output and organization C describing how engaged users develop their own methods for catching and limiting errors.

4.3.3 Emergent Outcomes

Four interviewees from four organizations independently described AI benefits not as doing existing work more efficiently, but as enabling work that was previously not done at all. Table 18 summarizes these descriptions.

Table 18: Personal capability expansion outcomes described across organizations.

Org.	Described outcome
A	Empowerment and increased self-sufficiency where employees look things up instead of guessing, framed as doing things today that were not done before
C	Time saving may not be dramatic, but users can do things that were not possible before
E	Chained assistants, enabling preparatory research a sole business developer could never complete alone
I	AI enables non-lawyers to produce better analytical input for a professional jurist; analyses that would today be too personnel-intensive to perform at all become feasible

The descriptions come from people in different roles across organizations of different sizes using different tools, suggesting an empirical pattern rather than isolated anecdotes. As the interviewee at organization A put it, "...we do things today that we did not do before." At organization E, the sole business developer used AI assistants to conduct feasibility studies the organization previously lacked the capacity to perform at all. Organization C similarly noted that "...the time saving may not be dramatic, but you do things you could not do before." The analytical implications of this pattern are examined in section 6.1.

5 Analysis

This chapter applies the theoretical framework to the empirical material presented in the results chapter. The analysis maps the observed processes to Lean waste categories for RQ1, examines the process-fit dimensions and organizational conditions for RQ2 and combines these patterns into process selection guidance for RQ3.

5.1 Lean Wastes

The eight Lean waste categories of section 3.1 were applied to the process descriptions in the results chapter. The following subsections present the analysis for each waste category. Waste categories identify non-value-added activities that consume resources without contributing to the output. Figure 6 and Table 19 at the end of the section show the mappings and the prevalence in the data.

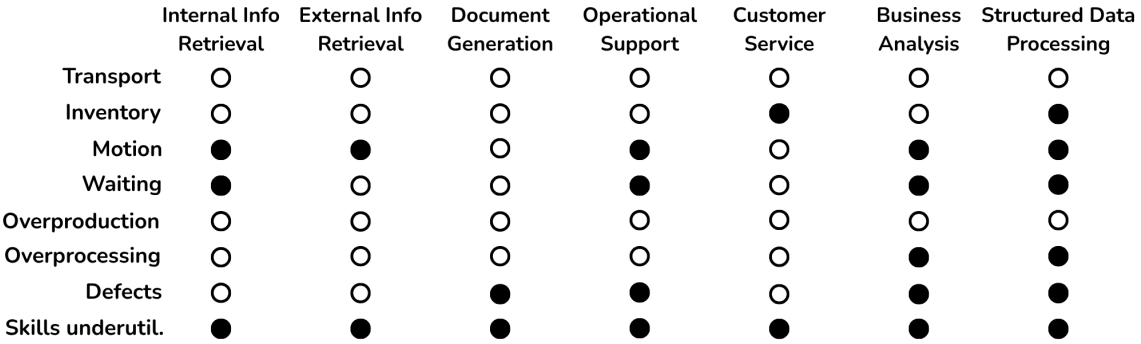

Figure 6: Identified waste categories by process type.

Motion and skills underutilization are the most common waste types addressed. In practical terms, AI makes information directly accessible and frees qualified personnel from routine execution. Transport and overproduction are entirely absent. The absence of both suggests that LLM-based AI primarily addresses inefficiencies within process steps rather than between them and that its value comes from responding to user needs rather than acting autonomously. This is because transport describes movement of information between steps, which AI leaves unchanged, and overproduction would require AI to generate output without a triggering demand, which none of the observed implementations do. Both absences reflect the nature of the technology rather than the deployment choices. The material also shows that current AI use appears to free up time at the task level without translating into structural changes like reallocation of resources.

Which waste types are addressed appears to depend on the autonomy configuration. Informational configurations primarily reduce motion because they replace manual search with direct retrieval. Advisory configurations also address defects and over-

processing because they draft or recommend outputs that collapse multiple manual steps. Agentic configurations address inventory and waiting because they process items independently, removing both backlogs and dependencies on manual capacity.

Table 19 summarizes the prevalence of each waste category across the number of process types affected and the total number of organizations where that waste was observed. For each type of waste w, the prevalence of the type $T(w)$ and the total appearance $A(w)$ are calculated as follows:

$$T(w) = \text{number of process types where } w \text{ is addressed} \tag{1}$$

$$A(w) = \sum_{p \in M(w)} n_p \tag{2}$$

where $M(w)$ is the set of process types that address waste w and n_p is the number of organizations assigned to process type p.

Table 19: Prevalence of Lean waste types across process types and organizations.

Waste type	**Process types** $T(w)$	**Appearances** $A(w)$
Skills underutilization	7	35
Motion	5	27
Waiting	4	21
Defects	4	15
Overprocessing	2	6
Inventory	2	6
Transport	0	0
Overproduction	0	0

The following subsections discuss where AI addresses each waste category, but the empirical material also shows AI introducing new inefficiency. Hallucinations, confirmation bias, and data quality issues documented in section 4.3.2 represent new forms of waste that can offset the reductions described below. Absent waste types are excluded.

5.1.1 Inventory

Inventory appears where unprocessed items accumulate in queues. Organizations E and K show this with customer queries waiting for staff and organization H with invoices awaiting manual handling. AI clears these backlogs by handling routine items directly.

5.1.2 Motion

Motion is addressed where AI replaces manual search, lookup, or navigation with direct retrieval or reasoning over the relevant sources. Organizations A, B, E, and G illustrate this with the search for physical documents in binders and reference tables, organization H with the manual lookup in the country and combination of transaction types for tax codes, and organization I with the search for internal standard documents. The common mechanism is to remove the need to find and read through the source material before using it.

5.1.3 Waiting

Waiting appears where handoffs or bottlenecks cause work to wait on a specific person or team. Organizations E, G, and I illustrate this where staff previously waited on knowledge from colleagues, organization E also with an unresolved sensor problem, and organization H with invoices waiting on manual handling. AI removes these dependencies either by letting the person who needs information obtain it directly or by replacing the manual step that other work depended on.

5.1.4 Overprocessing

Overprocessing appears where work can be achieved with fewer steps once AI is applied. Organizations B, E, H, and L illustrate this with comparing document versions, reasoning through legal material, and handling structured data. AI reduces overprocessing by collapsing multiple manual steps into a single operation.

5.1.5 Defects

Defects are addressed through two mechanisms. AI either corrects existing errors, as at organization F where it targets mistakes in written documents, or catches them earlier through more consistent review than manual handling provides. Organizations E, G and B show AI reducing inconsistencies in technical and operational work, organizations B and I show fewer errors in material that feeds into further analysis, and organizations H and L show AI detecting discrepancies in structured data that manual handling would miss.

AI can also introduce new defects in the form of hallucinations and confirmation bias, discussed in section 4.3.2. Whether the net effect is fewer total errors or simply different types of errors depends on the verification effort applied and is not something that the organizations studied have measured.

5.1.6 Skills Underutilization

Skills underutilization is addressed in all seven process types. The pattern is consistent regardless of context. Engineers at organizations E, B, and G previously performed

document lookup below their expertise. Professionals at organizations A, C, D, F, H, and K spent time on research and summarization. The finance staff of organizations H and L handled deterministic data tasks. AI now absorbs these routine tasks, freeing qualified staff for work that matches their expertise. In organization K, customer service now focuses on more complex cases, and in organization E, the boiler operator shifted from manual lookup to active sensor diagnosis. Although no organization has formally redirected freed capacity, the shift toward more qualified work appears to happen naturally as routine tasks are handled by AI.

5.2 Process-fit Dimensions

This section examines how the four process-fit dimensions from section 3.3.1 help explain the variation in described outcomes across process types. The following assessments are based on the author's interpretation of the interview accounts using these dimensions.

As the following sections demonstrate, no single dimension determines whether a process is suitable for AI. Instead, each shapes a different aspect of the implementation. Input characteristics guide what is feasible, standardization shapes the type of outcome that emerges, judgment complexity determines the human role required, and error sensitivity determines the safeguarding strategy applied. Together, judgment complexity and error sensitivity in part explain the autonomy configurations observed in the dataset. Low judgment and low sensitivity allow agentic autonomy, while high judgment or high sensitivity push toward advisory configurations. Judgment complexity does so through the need for interpretation and error sensitivity through the cost of failure.

5.2.1 Input Characteristics

The scope and curation of input sources shapes both the type of process that AI can support and the quality of the outcome. Organizations A, B, E and G all invested in curating domain-specific inputs and also support more advanced process types as a result. Organizations D, F and J rely on generic Copilot access without domain-specific input and none have moved beyond basic retrieval or experiments.

The input format also differentiates the results. Structured inputs in organizations H and L enable the most concrete efficiency outcomes in the dataset, and organization B demonstrates that multimodal inputs can be effective when paired with clear reference material.

Input characteristics function as a necessary first step since organizations cannot implement more advanced process types without first scoping their inputs.

5.2.2 Standardization

Standardization shapes the type of outcome AI produces. Highly standardized processes at organizations H and L produced the most concrete and measurable efficiency outcomes in the dataset. Customer service at organizations E, G, I and K follows the same pattern, with organizations deliberately limiting AI scope to routine queries.

Less standardized processes show a different outcome profile. Business analysis at organizations E and I and sensor diagnostics at organization E involve unique problems that vary each time, yet these organizations report some of the strongest perceived value. The difference is that outcomes appear as capability expansion rather than perceived efficiency gains. Organization J's abandoned marketing copy experiment illustrates the boundary, where the low standardization of matching a communicator's tone made the preparation effort exceed the benefit.

Highly standardized processes yield efficiency outcomes that are easier to observe and quantify, while less standardized processes yield capability expansion that is harder to measure.

5.2.3 Judgment Complexity

Judgment complexity determines the human role in relation to AI. In processes where decisions follow clear rules, such as structured data processing at organizations H and L, output can be verified against objective criteria. Organization L currently checks every output but expects that this will not continue indefinitely. In processes where decisions require interpretation, such as business analysis at organizations E and I and operational support at organizations B, E and G, the human role shifts from verification to interpretation and domain expertise becomes the requirement for safe use.

This connects directly to the quality risks in section 4.3.2. The recurring finding that domain expertise is needed for safe AI use reflects the role of judgment complexity. When a process requires interpretation rather than routine verification, only someone with domain knowledge can assess whether the output is correct. Hallucinations in rule-based processes produce detectable errors, whereas in processes requiring interpretation, they produce plausible-sounding output that requires expertise to evaluate.

Judgment complexity determines what safeguards are required for a process. Processes with routine decisions can move toward agentic autonomy, while processes requiring interpretation appear to require advisory autonomy with domain-qualified reviewers.

5.2.4 Error Sensitivity

Error sensitivity determines how organizations control AI output. Processes with financial or regulatory consequences maintain the strictest review. At organization H, misrouted invoices trigger debt collection, organization E's legal assistant supports court appeals, and organization L's finance function checks every output. In contrast, internal and external retrieval in organizations D and F carry low organizational stakes, where an incorrect answer simply prompts another search.

Customer service presents a distinct challenge. Organization C argues that customer-facing applications cannot include human review without defeating the purpose of automation, forcing organizations to narrowly scope chatbots rather than verify each response. This explains the pattern observed at organizations E, G, I and K where chatbots are limited to routine queries with a real human answering for anything beyond their scope.

Error sensitivity also varies within the same organization. Organization E uses AI for both internal research and court appeals, with different levels of oversight applied to each. This suggests that error sensitivity should be evaluated per process rather than per organization and that organizations adjust their autonomy configuration based on risk in each specific use. Where error sensitivity and judgment complexity diverge, as in organization H where judgment is low but financial consequences are high, organizations rely on the detectability of errors rather than restricting autonomy. This illustrates that the dimensions must be considered together.

5.3 Organizational Conditions

This section examines how the four organizational conditions from section 3.4 help explain variation in outcomes across organizations. Where the process-fit dimensions in the previous section describe properties of the process itself, organizational conditions describe properties of the environment in which AI is implemented.

Process-fit dimensions vary primarily between process types and not between organizations. Organizational conditions vary between those implementing the same process type. This makes organizational conditions interesting for structured cross-organization comparison. To make the cross-organization comparison explicit, each condition was rated as present (2), partial (1) or absent (0) based on the interview accounts. These ratings are qualitative assessments assigned by the author. Table 20 summarizes the results. Table 30 in Appendix D defines the criteria used for each rating level.

Table 20: Organizational condition ratings by organization. P.O. = process ownership, P.D. = process documentation, D.I. = data infrastructure, T.C. = technical capability. Rated as present (2), partial (1) or absent (0).

Org.	P.O.	P.D.	D.I.	T.C.	Total
A	1	1	2	1	**5**
B	2	1	2	2	**7**
C	1	1	1	2	**5**
D	0	1	1	0	**2**
E	2	2	2	2	**8**
F	0	1	0	0	**1**
G	2	2	2	2	**8**
H	2	1	1	2	**6**
I	1	1	1	1	**4**
J	0	0	0	1	**1**
K	1	1	1	2	**5**
L	2	1	1	1	**5**

As the following sections will show, these conditions each shape a different aspect and interact to support implementations. Organizations E and G are strong on all four and produced the most diverse implementations and the clearest described outcomes. Organizations D, F and J have not progressed beyond basic use. All three lack process ownership, though they are also weak on other conditions, making it difficult to isolate any single condition as decisive. Organization A has strong technical capability and process ownership, but concentrates both in one person, creating fragility. Organization K made a top-down strategic decision, but without supporting infrastructure or distributed capability, leaving adoption individually driven. The pattern in the dataset suggests that organizational readiness for AI implementation requires alignment between conditions, rather than focusing on a single one.

5.3.1 Process Ownership

Organizations where process owners take direct responsibility for AI use in their domains show more focused implementations and clearer outcomes. In organization E, designated administrators per business area coordinate AI use. Organization G established an ambassador program with a dedicated coordinator, and organization

L built a core AI team. In organization B, the engineer who built the operational support solutions owns that process directly and the strategists built assistants for their own domains. In organization H, the process specialist has clear authority over the invoice flow where AI operates.

Organizations A, C, I, and K show partial ownership. Organization A concentrates all AI coordination on a single person, creating a dependency on that individual. In organization C, the data science team steers AI within its own domain but not across the organization. Organization I has planned an ownership structure with administrators per member company that is not yet operational. In organization K, inspection and customer service personnel engage with AI but without coordination across the organization. Organizations D, F, and J lack process-level ownership. All three describe AI use driven by individual curiosity, and none report outcomes beyond vague productivity impressions.

Process ownership shapes whether AI use becomes organized. It does not determine whether people use AI, but whether that use accumulates into process-level change rather than remaining scattered personal experimentation.

5.3.2 Process Documentation

Process documentation shapes AI implementation in two ways. First, documented procedures serve as both reference material that AI can draw on and as a baseline against which AI-supported work can be evaluated. Organizations E and G had the most structured process documentation. Organization G maintained standardized designation manuals and procedures for signal classification. Organization E combined operational documentation with an explicit policy that governs how staff should evaluate AI output. Most other organizations had some form of process documentation that was not related to AI use. Organizations A, B, and F have documented routines and templates for underlying work processes, but none governing AI use. Organizations C, D, and I have documented policies for data classification or information security but not for the processes AI supports. In organizations H and K, documented procedures exist, but legacy inconsistencies from system migrations or rushed implementations limit their effectiveness. Organization L has just begun to build procedures through its AI core team. Organization J did not have documented procedures relevant to AI use.

Second, most organizations have documented what information may go into AI systems, but not how staff should evaluate the output. This gap between input governance and output governance is a recurring pattern across the dataset. Organization E remains a rare exception. In most other organizations, safe and effective AI use depends on individual knowledge among early adopters rather than documented

procedures. This represents a growing risk as implementations scale beyond the individuals who developed them, a point examined further in section 6.3.

5.3.3 Data Infrastructure

Data infrastructure shapes what inputs the AI can access and, therefore, what processes it can support. Organizations A, B, E, and G configured dedicated platforms with curated domain-specific sources which enabled the widest range of process types. Organizations E and F are both small energy companies with similar process needs, but organization E configured AI with access to curated internal sources while organization F's Copilot license limits AI to external information only. Organization C illustrates a different constraint, where data infrastructure built for traditional analytics did not readily support LLM-based AI, despite the organization's technical maturity in other areas.

Where data infrastructure is lacking, the constraints vary. The cost of Copilot licenses limits access in organization F, where it was considered too expensive and data is disconnected in different systems. Information security restricts what data AI may process at organizations D, J and H. Organization J is limited to entirely public data, and organization H's had delayed data upload due to a security, causing quality deterioration at launch. Organizations I, K and L have infrastructure in place or under development but with limited scope. Organization I is implementing Intric but the full deployment is not yet complete. Organization K has a management system agent but data inconsistencies constrain output quality. Organization L has just started building Copilot agents for structured data tasks. Organization I identifies a risk, noting that employees who are not given adequate tools will use private AI and expose sensitive information.

Data infrastructure limits the scope of what can be implemented. Even when other organizational conditions are favorable, limited data access constrains what AI can do in practice.

5.3.4 Technical Capability

Every organization that moved beyond basic AI use to more advanced configurations has identifiable individuals or teams who can configure tools, build solutions, and connect data sources. At organization E, the business developer builds most assistants while the boiler operator independently configures their AI for sensor diagnostics. Organization B's engineer combines domain expertise with technical capability, building operational support solutions himself. In organization C, a data science team has a deep technical capability, including cloud-based LLM platforms, although this has not yet translated into broad LLM adoption. Organization G brought in

external consultants to build an ambassador program that distributes capabilities throughout the organization. Organization H implemented two AI systems for invoice processing, which required technical capability to integrate with the ERP system. Organization K built AI for the prediction of outages and trained an assessment classifier for inspection protocols.

Organizations A, I, J, and L have partial technical capability. Organization A concentrates all AI configuration on a single person, producing results quickly but creating dependency. Organization L established a core AI team with training planned through AI Sweden but is still early in building capability. Organization I is selecting platforms and planning administrator structures but has not yet fully deployed. At organization J, the IT strategist has built AI agents but organizational constraints prevent broader use.

In the studied organizations, implementations did not move beyond basic tool use when technical capability was absent, even when other conditions were in place. This suggests that technical capability is a necessary condition for more advanced implementations to develop.

5.4 Implementation Clusters

The organizations cluster into four groups when implementations and organizational conditions are considered together. As illustrated in Figure 7, these groups broadly correspond to the Hayes and Wheelwright (1984) four-stage model introduced in section 3.2. The mapping builds on the role AI plays in each group and the strategic effect that Hayes and Wheelwright associate with each stage. In the weakest cluster, organizations adopt AI reactively to avoid falling behind. In the strongest, AI-enabled process improvement actively supports business strategy.

Organizations D, F, and J lacked multiple organizational conditions simultaneously and none progressed beyond basic use. These organizations can be considered to operate at stage 1 of the Hayes and Wheelwright (1984) model. Here AI adoption is motivated by avoiding negative impact rather than systematic process analysis. In these organizations AI use remains an IT initiative rather than a response to identified process needs, since the demand does not come from the operations that would benefit. The interviewee at organization J captured this, noting that ”the demand needs to come from the business side for it to create real value.”

Organizations A, C, I and K have functional implementations but each faces a specific constraint that limits scope or depth. Organization A depends on a single person, Organization C lacks active leadership engagement, Organization I faces

coordination complexity across member companies, and Organization K lacks process-level ownership. These organizations approximately represent stage 2, where AI use keeps pace with peers but does not yet produce a distinct advantage.

Organizations H and L form their own cluster but can also be considered to operate in stage 2. Both focused on highly standardized processes where strong process fit compensated for narrower organizational capability, achieving concrete outcomes in a limited scope rather than broad implementation.

Organizations E, B and G can be considered to operate in stage 3. They combined strong organizational conditions with curated inputs and successfully implemented more complex processes with concrete outcomes. At this stage, process improvement through AI begins to support business strategy rather than simply improving individual tasks.

No organization described implementations in terms consistent with stage 4. The organizational condition scores in Table 20 align broadly with these clusters, with the strongest group scoring 7–8 and the basic-use group scoring 1–2.

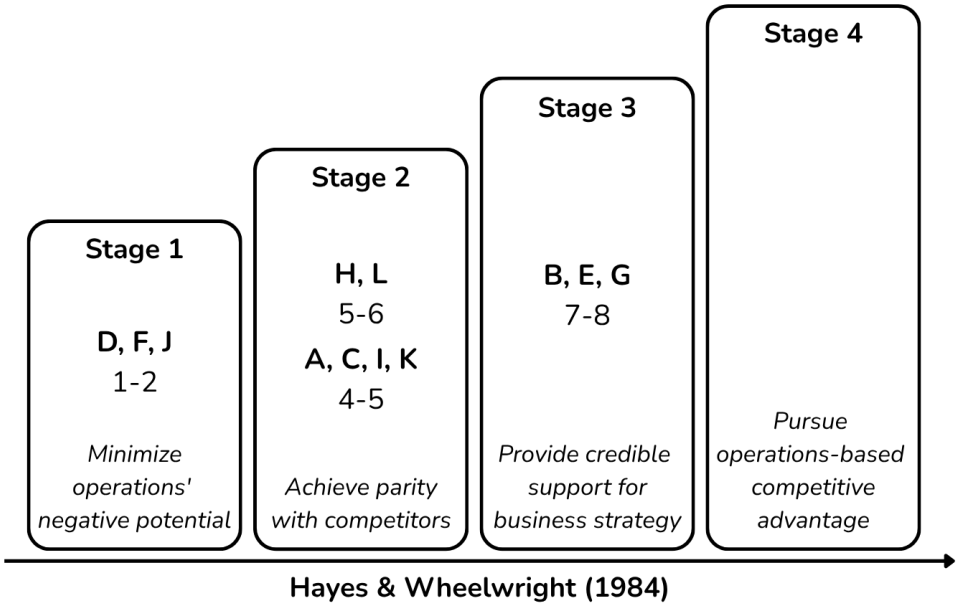

Figure 7: Implementation clusters mapped to the Hayes and Wheelwright (1984) four-stage model. Numbers indicate total organizational condition ratings from Table 20.

What separates the groups is primarily the combination of organizational conditions surrounding the technology rather than the technology itself. The organizations that advanced furthest were consistently those where ownership, documentation, data access and technical capability were in place together.

5.5 Process Selection Guidance

The analysis points to organizational readiness as a boundary condition with four criteria that distinguish processes where AI produced positively described results from those where it did not. Figure 8 summarizes the framework.

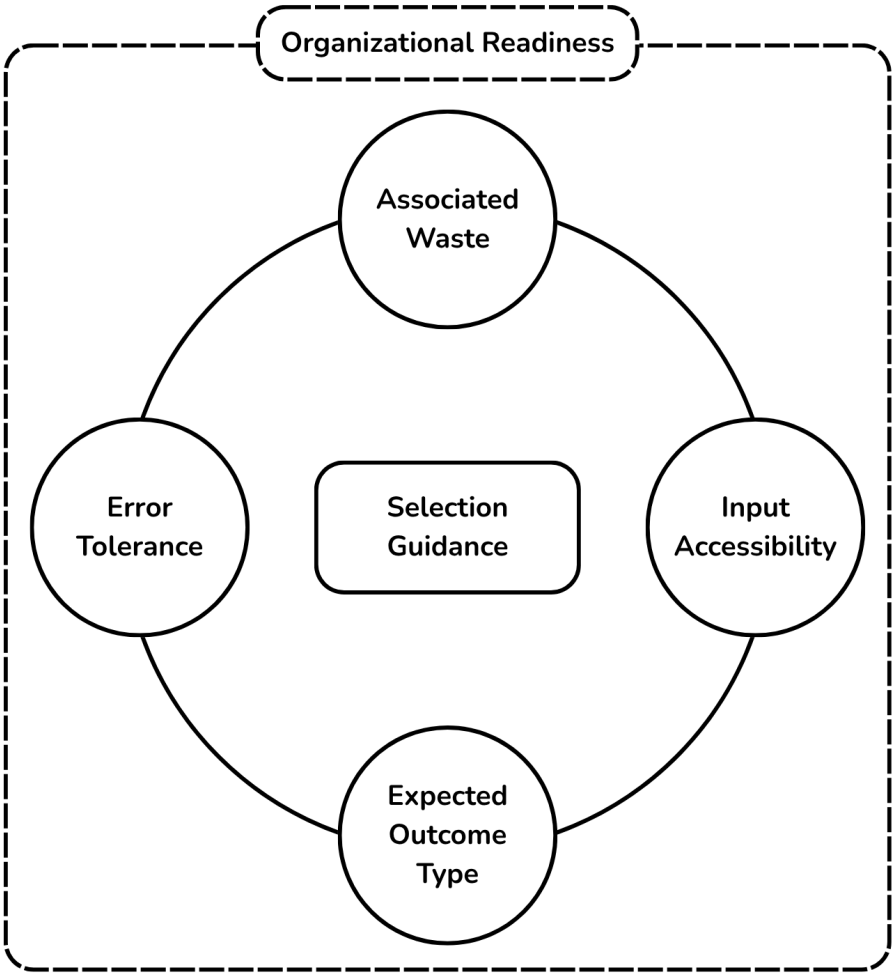

Figure 8: Selection guidance framework for LLM-based AI implementation

Organizational readiness. Readiness refers to whether the organizational conditions defined in this thesis are in place. Organizations that were weak across multiple conditions never progressed beyond basic tool use. Organizational readiness therefore functions as a necessary first step that must be achieved before the remaining four process-level criteria become relevant.

Associated waste. Processes where qualified staff spend time searching for information or performing routine tasks below their expertise are among the strongest candidates, since motion and skills underutilization are the waste types LLM-based AI most directly addresses. Other waste types such as waiting and defects are also addressed but less consistently across the dataset.

Input accessibility. Where data infrastructure describes the organization's overall capability, input accessibility asks whether the specific information a given process requires can be made available to the AI system. Even a well suited process will stall if its inputs are inaccessible, making this a feasibility question that should be assessed early and per process.

Expected outcome type. Highly standardized processes tend to produce efficiency gains, while less standardized processes tend to result in capability expansion where previously infeasible work becomes possible. Recognizing which outcome type to expect helps set appropriate evaluation criteria before implementation begins.

Error tolerance. Processes where errors carry more serious consequences require either someone with enough domain knowledge to review the output or a narrowly defined scope that limits what the AI can produce. This shapes both the domain expertise expected of the user and the level of autonomy that is feasible, since higher consequences push toward closer review and away from agentic configurations.

This framework applies to existing processes in the organization's operations. However, the studied organizations also show that AI implementation can give rise to entirely new processes that were not performed before, as described in section 6.1. These outcomes emerged through use rather than selection, which means that structured process selection can identify where to start but not fully predict what new work AI will enable.

6 Discussion

The research gap identified in the introduction concerned a lack of structured methods for selecting administrative processes suitable for LLM-based AI implementation. The following sections discuss what the findings contribute to this gap from both theoretical and practical perspectives.

6.1 Capability Expansion

The capability expansion reported in section 4.3.3 is analytically distinct from the waste reduction described in section 5.1. Waste reduction improves how existing work is performed while capability expansion enables work that was previously not performed at all. The four organizations that reported this result described fundamentally new capabilities rather than faster execution of known tasks. All four cases involve less standardized processes, consistent with the pattern identified in section 5.2.2.

The examples of capability expansion vary but share a common structure. In organization A, legal cross-referencing across regulations is now possible where employees previously guessed rather than looked things up. In organization E, business analyses are now conducted by a single person where the organization previously lacked the staff to perform them at all. In organization I, legal cases are now being pursued that were previously left unaddressed because the preparatory analysis was too resource-intensive to undertake. At organization C, non-technical staff can now use forecasting tools that were previously accessible only to the data science team, enabling people to perform analyses they could not conduct independently before.

In each case, the relevant comparison is not how long the work took before but whether it was done at all. Traditional efficiency metrics, Lean waste analysis and TTF all assume a stable baseline, and none can fully account for outcomes where that baseline is absent. When AI enables previously infeasible work, the analytical logic shifts from evaluating process fit to evaluating whether a new capability is worth pursuing at all. More broadly, efficiency is not the only basis for evaluating AI use. Quality improvements and previously infeasible work represent legitimate evaluation criteria alongside time and resource savings.

6.2 Theoretical Contributions

TTF theory was originally formulated at the individual level to explain how alignment between tasks and technology affects performance (Goodhue & Thompson, 1995).

This study applies the same logic at the process level, evaluating fit across entire administrative processes rather than single tasks. The four process-fit dimensions are based on TTF, OM and automation theory as described in section 3.3.1 and are assessed through the interview accounts. The dimensions each shape a different aspect of implementation. A process can present challenges on one dimension and strengths on another while still benefiting from LLM-based AI support. Serrano and Karahanna (2016) reinforce this by arguing that performance depends on the interaction between user capabilities and technology capabilities rather than on the technology alone. In the studied organizations, this user capability often took the form of domain expertise. LLM-based AI did not remove the need for that expertise but relied on it, since staff used their domain knowledge to judge whether the output was correct. This indicates that technical capability should be understood to include not only the ability to configure AI tools but also the domain knowledge required to evaluate what they produce.

The finding that organizational readiness functions as a boundary condition aligns with existing literature. Weiner (2009) argues that implementation success depends on both shared commitment and shared confidence in the collective capability to execute, while Haefner et al. (2023) similarly find that social alignment and technical infrastructure must develop together. The four organizational conditions identified in this study help describe what that readiness looks like in the context of LLM-based AI. Across the dataset, technology appears to be a minor limiting factor compared to these conditions. Although Intric and Microsoft Copilot differ as products, both allow users to configure assistants with access to curated information sources. Organizations using both platforms produced vastly different results, which suggests that the limiting factor lies in how AI is implemented rather than in what the tools can do. However, the most advanced organizations all chose to invest in a dedicated AI platform, and that decision itself likely reflects a pre-existing commitment to AI and a more active approach to implementation. This attitude toward AI may be a more relevant explanation for the advanced implementations than the difference in tools.

The four-stage mapping of Hayes and Wheelwright (1984) shows most organizations at stage 1 or 2, approaching AI reactively rather than as a strategic capability. Haefner et al. (2023) describe a similar progression at the firm level, identifying what organizations need to build to implement and scale AI, but their framework does not address which processes to target. The selection framework in section 5.5 helps address this gap by offering process-level criteria for deciding where to direct LLM-based AI efforts once the organizational foundations are in place. This suggests that researchers studying AI implementation should examine organizational conditions

before evaluating the technology itself. For organizations where these conditions are lacking, building them should come before selecting which processes to target with LLM-based AI.

No organization has formally measured AI results, including those that described positive efficiency improvements. This likely reflects a structural challenge rather than a lack of effort. AI changes how people work in ways that make it difficult to separate the effect of technology from the broader changes in behavior that accompany it. One perspective on this may be found in Parkinson's Law, which holds that work expands to fill the time available for its completion (Parkinson, 1957). When AI reduces the time needed for a task, the freed capacity may be absorbed into other activities rather than accumulating as a measurable improvement at the organizational level. The capability expansion described in section 6.1 follows a related pattern but with different consequences. There, freed capacity is redirected toward work that was previously infeasible rather than dissipating unnoticed. Regardless of whether the freed capacity is absorbed passively or deliberately redirected, both patterns make individual time savings difficult to detect in organizational metrics. From an OM perspective, this means that these organizations cannot close the improvement cycle such as PDCA on their AI implementations. Without evaluation of outcomes, the iterative improvement that structured process development depends on does not occur.

6.3 Practical Implications

The output governance gap concerns how most organizations have documented what information may enter AI systems but not how staff should evaluate or use what comes out. This creates risk since AI can produce incorrect answers despite sufficient input control. Organizations should consider establishing guidelines for how staff review AI output, clarifying who is responsible for verifying results in different process types and defining which situations require domain expertise before AI output is used. Without such guidelines, hallucinations represent new defects introduced by the same technology intended to reduce waste. If the verification effort required to catch these errors exceeds the time saved by automation, the net effect on process efficiency is negative. This asymmetry between input governance and output governance is likely to cause problems as AI use scales.

The practical recommendations differ depending on where an organization stands. Organizations with low readiness should focus on building organizational conditions before selecting processes. This means establishing process ownership, documenting procedures, securing access to relevant data sources and developing technical capa-

bility to configure and maintain AI tools. Organizations with stronger conditions in place can apply the full set of process-level criteria and pursue both efficiency gains in standardized processes and capability expansion in less standardized ones. These organizations are also better positioned to move from informational toward advisory and agentic configurations where the process characteristics allow it. When starting to implement LLM-based AI, internal information retrieval is a natural starting point, as it carries low risk while building familiarity with the technology.

Table 21 provides a set of evaluation questions based on the framework in section 5.5 that practitioners can use when assessing whether a process is suitable for LLM-based AI implementation.

Table 21: Evaluation questions for LLM-based AI process selection.

Criteria	Evaluation questions
Organizational readiness	Has a specific role or person been designated as responsible for this process, with the authority to coordinate AI implementation within it? Are the procedures, input, output and quality expectations for this process documented? Does the organization have the technical infrastructure to connect AI tools to relevant information sources? Is there someone with the technical capability who can set up, configure and maintain the AI tool?
Associated waste	Are employees performing tasks below their expertise level? Does this process involve time spent searching for or gathering information?
Input accessibility	Can the information this process requires be made available to the AI system? Are there security or format constraints that prevent access?
Expected outcome type	Does this process follow a predictable pattern with consistent steps? Would success mean doing the same work faster or with fewer resources? Would the main value be enabling something that no one currently has time, resources or capability to do?
Error tolerance	What happens if this process produces an incorrect result? Does the person responsible for using the output have enough knowledge of the subject to judge whether results are correct? If no one is able to verify the output, can the process be designed so that the AI only handles a limited and well-defined part?

6.4 Limitations

Each organization is represented by a single interviewee whose account may not reflect how AI is used across all departments and functions, particularly in larger

organizations. The process type mapping may therefore underestimate actual AI use. All reported results are self-reported and subject to recall bias and social desirability, and no organization provided baseline measurements against which changes could be verified. Interviewees were also selected for their insight into AI implementation, which means they are often driving adoption in their organization rather than typical end users. Their accounts may present a more favorable view of AI than would emerge from staff who use the tools only occasionally.

The organizational condition ratings in table 20 are qualitative assessments by the author rather than validated scales. Finally, the study captures a snapshot of implementations that several organizations described as still developing, meaning the patterns identified may not be stable over time.

6.5 Future Research

A natural next step would be to apply the selection framework within an organization and evaluate whether the criteria identify suitable processes when used as a decision guidance tool rather than an analytical lens after the fact. Future studies should also interview multiple respondents within the same organization to capture AI use that falls outside any single person's visibility. Capability expansion needs further conceptual development along with methods for evaluating outcomes where the baseline is absent. Future studies could also examine user experience within specific processes, complementing the process-level analysis presented here while providing insights relevant to platform providers.

7 Conclusion

This study examined how OM frameworks can explain where and under what conditions LLM-based AI improves administrative and knowledge work processes, based on twelve interviews from the Swedish energy and utilities sector.

RQ1. LLM-based AI primarily reduces skills underutilization and motion waste by freeing qualified staff from routine execution and making information directly accessible. The technology eliminates non-value-added activities within individual process steps rather than restructuring the flow between them.

RQ2. Outcomes are shaped by four process-fit dimensions that each influence a different aspect of implementation. Input characteristics determine feasibility, standardization shapes outcomes, judgment complexity determines human roles, and error sensitivity determines safeguards. Together, judgment complexity and error sensitivity help explain autonomy configurations. Four organizational conditions also shape implementations. These are process ownership, process documentation, data infrastructure and technical capability. Strong organizational conditions can compensate for moderate process fit, but processes without supporting organizational conditions did not produce comparable outcomes.

RQ3. The analysis suggests five criteria for implementations of LLM-based AI, presented as a practical selection framework. Organizational readiness functions as a boundary and first step. Within that boundary, associated waste identifies processes, input accessibility determines feasibility, expected outcome type sets appropriate expectations and error tolerance determines safeguard requirements.

A central theoretical contribution is the extension of TTF logic from the individual level to the process level, which required new dimensions to capture how entire processes align with LLM-based AI. Beyond the research questions, capability expansion emerged as a distinct finding with implications for how AI value is assessed in OM, since traditional efficiency metrics cannot account for work that was not performed before. The study also identified a recurring gap across the studied organizations where input governance is established while output governance remains largely absent. The introduction described a value paradox where widespread AI adoption produces limited operational improvements. Within the studied organizations, this is explained mostly by how AI is implemented rather than by the technology itself.

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Appendices

A Interview Guide: Organizations using Intric platform

B Interview Guide: Organizations without Intric platform

C List of all interviews conducted

D Coding framework for thematic analysis

A Interview Guide: Organizations using Intric platform

Introduction and consent

- Present the study purpose and confirm voluntary participation, confidentiality, expected duration and permission to record.

Background and role

- What is your role in the organization?
- How long have you worked in this role?

AI use and process identification

- Which processes or tasks do you use the Intric platform for?
- How did you identify and select those processes? Were there processes you considered but decided against?
- How many assistants have you created and how are they used across roles?
- Do employees also use other AI tools?

Process before AI

- How did this process work before AI was introduced? What were the main steps and handoffs?
- What were the main inputs and outputs?
- How standardized was the process and was it documented with procedures or based on individual knowledge?
- Who was responsible for the process?
- How often was it performed and what was the typical lead time?
- What were the main inefficiencies?
- What constituted good quality and what happened when something went wrong?

Implementation and organizational conditions

- Why was AI introduced for this process and who initiated the change?
- How was the information organized for the platform's data rooms and who decided what to include? Were there data sensitivity restrictions?

- Who is responsible for maintaining assistants and their knowledge bases?
- What training or support did users receive and how did usage develop over time?
- Has there been resistance to adoption and if so from whom?
- What factors made implementation easier or more difficult, such as data access, documentation, internal expertise or management support?

Current process with AI

- How does the process work today with AI and what has changed?
- Which activities are handled by AI and which remain with people?
- How much do people review AI output before using it and how much domain knowledge is needed to evaluate it?
- Has usage evolved since initial implementation, for example through new use-cases or refined configurations?
- Where do delays or bottlenecks remain?

Outcomes and quality

- What changes have you observed in time, workload or resource use?
- Has output quality changed and in what way?
- Does the AI make errors? What kind, how often and how are they handled?
- Has anything become worse since AI was introduced?
- Are there things you can do now with AI that were not feasible before?
- Where do you see further potential that has not been applied yet and what prevents it?

Closing

- What has been the greatest benefit and the greatest limitation?
- Looking back, would you do anything differently?
- Is there anything else relevant to this study?

B Interview Guide: Organizations without Intric platform

Introduction and consent

- Present the study purpose and confirm voluntary participation, confidentiality, expected duration and permission to record.

Background and role

- What is your role in the organization?
- How long have you worked in this role?

AI tools and current state

- Which AI tools are available in the organization and which do you use?
- What restrictions exist for AI use, such as information classification or data sensitivity rules?
- Is AI use organized centrally or driven by individual initiative?
- Do employees use private AI tools for work?

Process landscape

- What are the most recurring administrative or knowledge work processes in your role?
- Where do you see the main waste or inefficiency?
- How standardized and documented are these processes and who is responsible for them?

AI use in specific processes

- For processes where AI is used: what is it used for and where in the process?
- How do you decide which processes to use AI for and what makes a process suitable or unsuitable?
- What information does the AI rely on?
- Which activities are handled by AI and which remain with people?
- How is AI output validated and how much domain knowledge is needed to evaluate it?

- Has usage evolved over time, for example through new use-cases or refined approaches?
- In which situations do people avoid using AI?

Quality and errors

- What does good quality mean in these processes and how serious are the consequences of errors?
- What kinds of mistakes occur with AI and how are they discovered and handled?

Outcomes

- What changes have you observed in time, workload, resource use or quality?
- Has anything become worse since you started using AI?
- Are there things you can do now with AI that were not feasible before?

Barriers and readiness

- Who initiated AI adoption and was the drive top-down or bottom-up?
- Has there been resistance and if so from whom?
- What has made AI use easier or more difficult, such as data access, system integration, expertise or management support?
- How is the organization building AI capability, for example through training, ambassador networks or dedicated teams?
- Where do you see further potential and what would need to be in place to expand AI use?

Closing

- What has been the greatest benefit and the greatest limitation?
- Is there anything else relevant to this study?

C List of Interviews

Table 22: List of interviews conducted.

Org.	Organization type	Date	Duration
A	Municipal energy	2026-02-12	37 min
B	Municipal water & waste	2026-02-12	38 min
C	International energy	2026-02-13	27 min
D	Municipal energy	2026-02-13	23 min
E	Municipal energy	2026-02-17	26 min
F	Municipal energy	2026-02-20	23 min
G	Municipal energy & waste	2026-02-25	26 min
H	International energy	2026-03-05	34 min
I	Energy association	2026-03-11	24 min
J	Municipal energy	2026-03-12	29 min
K	Private energy	2026-03-31	29 min
L	Municipal energy	2026-04-08	26 min

D Coding Framework

This following is the coding framework used in the thematic analysis. Deductive codes were derived from the theoretical framework before data analysis began and inductive codes emerged from the empirical material during analysis. Each code includes a definition and one illustrative example quote translated from Swedish by the author.

Table 23: Coding framework: Lean waste categories (deductive).

Code	Definition	Example quote
Transport	Unnecessary movement of information between systems, departments or approval stages.	Not addressed by AI in studied organizations.
Inventory	Backlogs of tasks or queued requests.	"Remove the incoming phone call flow to our customer service group" (E)
Motion	Time spent searching for information, switching between applications or navigating systems.	"Today it is not very easy to find information in a register" (I)
Waiting	Time spent awaiting information, approvals or handoffs between process stages.	"I use Copilot 100% before I look further to others who might have more knowledge" (H)
Overproduction	Outputs generated without clear demand or usefulness.	Not addressed by AI in studied organizations.
Overprocessing	Redundant steps or manual work beyond what the output requires.	"Cutting and pasting and sorting" (L)
Defects	Errors requiring rework or corrections.	"It is easy to get different answers each time" (G)
Skills underutilization	Employees performing tasks below their expertise or judgment level.	"Customer service can instead focus on the more difficult cases" (K)

Table 24: Coding framework: Process-fit dimensions (deductive).

Code	Definition	Example quote
Input characteristics	Type, format and source of information the process requires.	"Our own law list connected to parliament's legislation database and web search" (E)
Standardization	Predictability of the process versus frequency of exceptions or ambiguous inputs.	"The template does not change, only the values change" (H)
Judgment complexity	Decision requirements from routine rule-following to contextual interpretation requiring domain expertise.	"You really have to know a lot beforehand so that you can interpret the answer" (G)
Error sensitivity	Consequences when the process produces incorrect outputs.	"An invoice meant for subsidiary A ends up in subsidiary B, it sits there unpaid and goes to debt collection" (H)

Table 25: Coding framework: Organizational conditions (deductive).

Code	Definition	Example quote
Process ownership	Clear responsibility and decision authority assigned to identifiable roles rather than left to individual discretion.	"I am the main administrator, and then we have one administrator for each business area" (E)
Process documentation	Documented procedures, templates or quality criteria that provide a baseline for execution and evaluation.	"There are thousands of pages of manuals, and we have our designation manual" (G)
Data infrastructure	Access to required information sources, including system integration and security constraints.	"We lack this central database where you could feed in data from different systems" (F)
Technical capability	Individuals or roles with knowledge to configure tools and handle implementations.	"I created my own assistant with a process focus" (B)

Table 26: Coding framework: Autonomy configurations (deductive).

Code	Definition	Example quote
Informational	Information is retrieved and presented, human makes all decisions.	"You use the AI service more as guidance to answer questions" (I)
Advisory	Actions or outputs are recommended or drafted, human reviews before execution.	"We check everything it produces, we never dare to take chances" (L)
Agentic	Actions are selected and executed with limited human oversight.	"It inputs all the information on the invoice, validates it, and sends it to our ERP system" (H)

Table 27: Coding framework: Efficiency outcome metrics (deductive).

Code	Definition	Example quote
Time effects	Lead time, cycle time and waiting time.	"Would take me half a year to figure out, but it has it ready in a moment" (E)
Resource effects	Labor cost, number of employees and utilization of resources such as knowledge bases or reference materials.	"There were three half-time workers who opened and sorted the mail, now we have cut two of those positions" (H)
Quality effects	Perceived output quality, customer satisfaction, error rates, error severity and user experience.	"You can never fully trust the result" (C)

Table 28: Coding framework: Capability expansion (inductive).

Code	Definition	Example quote
Capability expansion	AI enables work that was previously not performed rather than accelerating existing processes.	"We may very well be doing things today that we did not do before" (A)

Table 29: Coding framework: Process types (inductive).

Code	Description	Example quote
Internal information retrieval	Querying internal information sources and documentation.	"The most common use is searches, looking up legislation and large volumes of information" (A)
External information retrieval	Searching information from internet or external sources.	"If I want to read about an ISO or IMS standard, I use Copilot" (K)
Document generation	Generating, drafting or proofreading written content.	"A large number of different data sources and summarizes them in a report" (C)
Operational support	Reasoning about technical data, diagnosing problems or generating code.	"Engineers receive information that tells them how the plant is doing and which parameters need adjusting" (B)
Customer service	Automated responses to external customer queries through chatbots.	"Remove these very simple questions that otherwise take an email or a phone call to answer" (E)
Business analysis	Multi-step research, interpretation or analysis for strategic or specialist tasks.	"It does desk research for me, then I feed that into the next assistant for economic analysis, and then into another for a project plan" (E)
Structured data processing	High-volume structured data classification, matching or transformation.	"It recognizes which supplier sent the invoice and matches the correct tax code to the correct invoice" (H)

Table 30: Scoring criteria for organizational condition ratings.

Condition	Absent (0)	Partial (1)	Present (2)
Process ownership	No designated owner	Ownership concentrated in one person or limited in scope	Clear ownership with authority across relevant processes
Process documentation	No documented procedures	Documentation exists but not connected to AI use	Documented procedures and quality criteria used as baseline for AI execution
Data infrastructure	AI cannot access relevant data	Partial access with security, cost or format constraints	Curated domain-specific sources accessible to AI
Technical capability	No person with technical ability to configure AI tools	Capability exists but limited or concentrated	Identified individuals or teams who build and maintain AI implementations