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LLM-Powered Business Process Modelling in Small and Medium Enterprises

Benefits, Success Factors and Implementation Challenges

Information System Science
Master's thesis

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Small and Medium Enterprises (SMEs) face significant barriers in adopting traditional Business Process Modelling (BPM) due to resource constraints, expertise requirements, and complex notation systems. Large Language Models (LLMs) offer potential solutions by generating process models from natural language descriptions, yet empirical evidence of their effectiveness in real SME contexts remains limited. This research investigates the benefits, success factors, and failure factors when implementing LLM-powered BPM in SMEs. Existing literature demonstrates clear BPM organizational benefits but identifies expertise requirements and resource constraints as primary SME adoption barriers (Papademetriou & Karras, 2017; Viegas & Costa, 2022). Recent AI-powered BPM research shows technical feasibility for generating BPMN-compliant models from textual descriptions (Grohs et al., 2023; Kourani et al., 2024) but lacks empirical investigation of organizational adoption factors in real business contexts. The study employs the Technology-Organization-Environment (TOE) framework to analyse adoption factors, combined with established BPM quality assessment frameworks (SEQUAL for multi-dimensional quality evaluation, 7PMG for objective diagram assessment) to create a comprehensive evaluation approach for AI-generated process models. A qualitative multiple case study approach examines three French SMEs across different industries (IT consulting, manufacturing, perfume production) with varying digital maturity levels. Using GPT-4 mini, BPMN 2.0 compliant process models were generated from organizational documentation and evaluated using the established quality frameworks. Semi-structured interviews with key stakeholders captured organizational perceptions, adoption challenges, and value recognition patterns. The technical assessment revealed consistent strengths in activity labelling and gateway selection, alongside universal weaknesses including multiple start/end event violations and excessive element proliferation. Stakeholder evaluation demonstrated a fundamental dichotomy between communication effectiveness and operational completeness. While all participants recognized value for external communication and training purposes, semantic gaps rendered models insufficient for internal process management. The most significant finding involved universal requirements for human verification despite AI accessibility benefits, creating capability demands that potentially exceeded SME resources. The research contributes a Multi-Factor Alignment Framework organizing success factors across technical, organizational, and environmental dimensions. The study concludes that LLM-powered BPM represents a transformation from operational tool to communication medium, requiring hybrid approaches leveraging AI for communication while maintaining traditional methods for operational requirements.

Key words: Business Process Modelling, Large Language Models, SME Digital Transformation, AI Adoption, Process Management, BPMN.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 Introduction

1.1 Contextualisation of the Research Topic

Nowadays, with the quick pace of transformation of Information Systems (IS) and Information Technology (IT), organizations, of all sizes and across every sector, are experiencing unprecedented pressure to leverage those technological transformations to improve their efficiency and effectiveness, while driving innovation. It has brought more light on how businesses see, design and execute their core processes. However, this change has been happening at a different pace for big and small enterprises. Indeed, while large corporations have successfully harnessed these technological opportunities to scale operations and optimize efficiency, Small and Medium Enterprises (SMEs) face distinct challenges in navigating this digital landscape (Bamidele Micheal Omowole et al., 2024; Samuel Omokhafe Yusuf et al., 2024).

The emergence of Enterprise Resource Planning (ERP) systems from the 1990s marked the starting point for process-oriented thinking in organizations, demonstrating the critical importance of understanding and documenting business workflows before implementing technological solutions. Business Process Modelling (BPM) serves to translate complex business processes into visual notations, enhancing understanding, analysis, and improvement of organizational workflows (Kourani et al., 2024). BPM has proven essential not only for operational optimization but also as a prerequisite for successful technology implementations, particularly during the blueprint phases of ERP and other information system projects (Daclin et al., 2024).

However, the specialized nature of BPM expertise has created significant barriers for SMEs. Traditional process modelling approaches have relied heavily on manual processes, requiring extensive manual effort including data entry, task assignment, and approval processes (Kokala, 2024). The stakeholders handling BPM tasks need specialized expertise, as specific modelling languages are complex, and the lack of specialized expertise hinders adoption of process modelling in the smaller companies (Daclin et al., 2024). As SMEs often operate with constrained budgets and face a shortage of skilled technical personnel (Papademetriou & Karras, 2017), they do not have the financial and human resource commitments that many SMEs cannot readily accommodate. Hence, organizations that could benefit the most from process clarity, face the greatest barriers to achieving it.

The recent evolution in Artificial Intelligence (AI), particularly the development of Large Language Models (LLMs), presents opportunities to democratize business process modelling. Even before the widespread awareness of LLMs like ChatGPT, Language Models were used in BPM for tasks such as process extraction from text, and the introduction of LLMs has led to significant changes in this field (Busch et al., 2023; Kampik et al., 2024). LLMs bring transformative capabilities to BPM through automation, extraction from unstructured data sources, and comprehension that enables natural language interaction (Bernardi et al., 2024). Recent studies have demonstrated that LLMs can be prompted to generate BPMN process diagrams from natural language descriptions, with state-of-the-art LLMs able to produce process models from textual inputs as accurately as or even better than specialized algorithms (Grohs et al., 2023).

For SMEs specifically, LLM-powered approaches offer potential solutions to traditional BPM barriers. The increasing accessibility and affordability of AI technologies, with substantial cost reductions and availability of general-purpose generative AI tools in free or low-cost versions, allows SMEs to experiment with AI without substantial initial investment (Hussain & Rizwan, 2024; Oldemeyer et al., 2024). This technological advancement suggests the possibility of transforming how organizations approach process documentation, potentially enabling SMEs to create sophisticated process models without requiring extensive technical expertise or significant resource investments and benefiting from the advantages of understanding and transforming their processes.

However, despite this potential, empirical research on LLM-powered BPM within SMEs remains limited, with existing models often lacking prescriptive guidance tailored to SME constraints such as limited digitalization, infrastructure, or expertise (A'yun & Prihartono, 2025; Viegas & Costa, 2022). As LLMs become increasingly sophisticated and accessible, questions arise about their effectiveness in supporting business process modelling, the quality and reliability of AI-generated process models, and the organizational factors that influence successful adoption of these technologies in SME contexts.

This research employs a qualitative exploratory case study design to investigate LLM-powered BPM adoption in SMEs. The case study approach enables in-depth exploration of contemporary phenomena within their real-world contexts (Yin, 2018), making it particularly suitable for examining how SMEs evaluate and implement emerging AI technologies. The interpretative philosophy recognizes that stakeholder views on technology adoption are deeply influenced by their specific organizational contexts (Walsham, 1995). This combination of case study methodology with interpretative analysis allows for rich understanding of both the technical capabilities of LLM-generated models and the organizational factors that influence their adoption in SME settings.

The setting for this research is to uncover how LLM-powered BPM can address SME-specific challenges in process modelling while identifying the conditions that enable or hinder successful its adoption. Understanding the practical benefits, implementation requirements, and quality considerations can help SME leadership make informed decisions about AI-powered process modelling tools and recognize their organizational readiness for such technologies.

The research begins with a comprehensive literature review covering business process modelling foundations and AI applications in BPM. The methodology section describes the empirical approach including case study selection, LLM-generated model creation using LLM frameworks, and semi-structured interview protocols. Results are presented along with discussion points, followed by conclusions with practical implications, limitations, and future research directions.

1.2 Research Gap

The convergence of Business Process Modelling (BPM) and Artificial Intelligence (AI) in Small and Medium Enterprises (SMEs) presents both opportunities and challenges, yet empirical research in this domain remains critically limited. While systematic literature reviews highlight potential benefits (Oldemeyer et al., 2024), existing models often lack prescriptive guidance tailored to SME constraints such as limited digitalization, infrastructure, or expertise (A'yun & Prihartono, 2025; Viegas & Costa, 2022). Moreover, traditional BPM evaluation metrics prove inadequate for assessing LLM-generated diagrams, which may introduce hallucinations, structural inconsistencies, or bias (De Meyer & Claes, 2018; Kampik et al., 2024). The variability of LLM output, driven by model parameters, presents additional risks in standardization and interpretability (Grohs et al., 2023). These challenges, combined with the lack of validation in real SME environments, reinforce the need for experimental studies and case-based evaluations that examine LLM-enabled BPM

Emerging trends such as prompt engineering and AI-enhanced interfaces (Busch et al., 2023), suggest promising directions, but adoption remains low, up to 90% of SMEs have yet to implement AI tools (Oldemeyer et al., 2024). Factors like cultural differences, technical literacy, and data governance continue to influence perceptions of BPM maturity in smaller enterprises (Cetindamar et al., 2024; Viegas & Costa, 2022).

In summary, while LLM-powered BPM offers strong potential for SMEs, research gaps persist around empirical validation, evaluation frameworks, and SME-specific adoption strategies. Bridging these gaps requires interdisciplinary approaches involving AI, BPM, and SME-focused transformation research.

1.3 Research Problem, Purpose, and Main Question

The central problem addressed by this research lies in the persistent gap between SMEs' critical need for effective business process understanding and the barriers they face in accessing traditional BPM methodologies. Traditional BPM requires specialized knowledge of complex notations, significant time investments, and financial resources for training or external consulting that many SMEs cannot readily accommodate (Daclin et al., 2024; Papademetriou & Karras, 2017). This creates a paradoxical situation where organizations that could benefit most from process clarity face the greatest barriers to achieving it.

Research on BPM adoption barriers in SMEs consistently identifies three primary constraint categories: (1) technical accessibility: Traditional BPM requires specialized knowledge that exceeds typical SME capabilities, with steep learning curves competing with operational priorities (Ivanchikj et al., 2020; Kokala, 2024), (2) resource constraints: SMEs operate under financial and human resource limitations that restrict investment in BPM training, tools, or consulting expertise (Papademetriou & Karras, 2017), and (3) quality and reliability: While LLMs offer potential solutions to accessibility challenges, questions remain about the quality and completeness of AI-generated process models compared to traditional expert-created models (Bernardi et al., 2024; Grohs et al., 2023).

The motivation for this research stems from the transformative potential of Large Language Models to make business process modelling accessible to organizations without specialized expertise. Early research suggests that LLMs can interpret textual process descriptions and generate formal process models, potentially eliminating specialized technical knowledge requirements while dramatically reducing time and cost (Grohs et al., 2023; Kourani et al., 2024). However, the practical application of these technologies in real SME contexts remains largely unexplored, with limited empirical evidence regarding their effectiveness, reliability, and organizational adoption factors.

To answer the previously cited problem, this research addresses the following main research question:

What are the benefits, success and failure factors when implementing LLM-powered Business Process Modelling (BPM) in Small and Medium Enterprises?

This question encompasses several critical dimensions that address fundamental gaps in AI-BPM adoption research.

- **Technical feasibility** is essential because SMEs require evidence that AI-generated models meet basic quality standards before investing limited resources, as implementation failures could prove costly for resource-constrained organizations (Daclin et al., 2024).
- **Organizational adoption factors** represent a critical dimension because SMEs face distinct challenges including financial limitations and expertise gaps that differ from large enterprise contexts (Hussain & Rizwan, 2024).
- **Implementation guidance** constitutes the third dimension because current research lacks practical SME-specific recommendations regarding input preparation and quality assurance procedures, yet poor implementation could undermine the accessibility benefits that motivate AI-BPM adoption (Kourani et al., 2024).

The urgency of this investigation is heightened by the rapid pace of AI development and increasing competitive pressures facing SMEs. Understanding how to effectively leverage LLM-powered BPM tools could prove crucial for SME competitiveness and digital transformation in an increasingly AI-enabled business environment.

1.4 Research Significance

This research addresses a critical gap at the intersection of artificial intelligence, business process management, and small enterprise digital transformation. The investigation offers contributions to both academic knowledge and practical applications.

From a theoretical perspective, this research contributes to the emerging field of AI-powered business process management by providing empirical evidence in an area dominated by technical demonstrations and conceptual frameworks. While existing literature extensively covers the computer science dimension of LLM-Powered BPM methodologies (Bernardi et al., 2024), limited research examines their practical integration in real organizational contexts, particularly within resource-constrained SME environments (Grohs et al., 2023).

From the practical implications, the investigation addresses a pressing practical need within the SME community. Traditional BPM approaches often require investments in specialized expertise or external consulting that many SMEs cannot afford, yet process understanding remains crucial for operational efficiency, regulatory compliance, and digital transformation initiatives. By evaluating whether LLM-powered alternatives can effectively address these needs, this research has direct implications for SME competitiveness and growth, while covering advice on how to implement it.

1.5 Boundaries of the Research

To ensure focused investigation and meaningful conclusions, this research operates within several clearly defined boundaries:

Concerning the geographical and organizational scope, the empirical investigation focuses on French SMEs meeting European Union criteria (10-250 employees), providing cultural and regulatory consistency while acknowledging that findings may require adaptation for other national contexts. The research includes SMEs from different sectors to ensure broader applicability without attempting industry-specific guidance.

This research also adopts a technology and modelling language focus. Indeed, the investigation centers specifically on Large Language Model applications for business process modelling, particularly using GPT-4 technology, with Business Process Model and Notation (BPMN) as the target output format. Other AI approaches and modelling notations are excluded to maintain research depth and focus.

Finally, the research represents a snapshot of current LLM capabilities and SME contexts, focusing on initial adoption and evaluation rather than long-term organizational change management or comprehensive digital transformation strategies. Quality assessment emphasizes immediate process model quality and stakeholder perceptions rather than long-term operational impacts.

1.6 Expected Results

The research expects to reveal specific strengths and limitations of LLM-generated BPMN models when evaluated against established quality criteria. Findings regarding model accuracy, completeness, and syntactic correctness are anticipated to provide empirical evidence about the practical viability of AI-powered process modelling for SME use. Moreover, interview analysis is expected to uncover SME-specific perspectives on AI-generated process models, including perceived benefits such as reduced modelling complexity and potential concerns about accuracy and control. These findings will illuminate the gap between technical capabilities and organizational acceptance. Finally, the research is likely to identify practical requirements for successful LLM-powered BPM implementation, including optimal input formats, prompt engineering best practices, and organizational readiness factors specific to SME contexts.

1.7 Definition of Key Concepts and Central Terminology

To ensure clarity and consistency throughout this research, the following key concepts and terminology are defined:

Small and Medium Enterprises (SMEs): Organizations meeting European Union criteria for SME classification, specifically employing between 10 and 250 people and meeting established revenue or balance sheet thresholds. This definition excludes micro-enterprises (fewer than 10 employees) and larger organizations with different resource profiles and needs (European Commission, 2003).

Business Process Modelling (BPM): The activity of creating formal, structured representations of organizational processes to enable analysis, improvement, and automation. This encompasses both the creation of process models and their use for organizational development purposes (Weske, 2024).

Large Language Models (LLMs): Advanced artificial intelligence systems trained on extensive text datasets to understand and generate human-like text, with demonstrated capabilities in complex reasoning and structured output generation (OpenAI et al., 2023). For this research, the focus is primarily on GPT-4 and similar transformer-based models.

These definitions provide the conceptual basis for understanding and interpreting the research findings, ensuring consistency in terminology usage throughout the investigation.

The next chapters explore existing research literature relevant to Business Process Modelling and its application in Small and Medium Enterprises, with particular focus on AI-powered approaches. The primary aim of this literature review is to establish the theoretical foundation for understanding how organizations adopt process modelling practices, the specific challenges faced by SMEs, and how AI technologies might address these barriers. The first chapter examines business process modelling fundamentals and traditional adoption barriers to understand why SMEs struggle with conventional BPM approaches and what benefits they might gain from process understanding. The second chapter focuses on SME-specific contexts and BPM challenges to identify the unique organizational, financial, and capability constraints that adoption in smaller organizations. Finally, the review examines AI applications in BPM to understand how LLMs might address traditional barriers while introducing new technical and organizational challenges.

2 Business Process Modelling: Foundations and Adoption

This section establishes why business process modelling matters for organizational effectiveness while identifying the systematic barriers inherent in traditional BPM approaches. The analysis begins with BPM fundamentals and organizational benefits (2.1) to demonstrate the value proposition and strategic importance of process understanding. The examination then covers modelling artifacts and notations (2.2) to understand the technical complexity and expertise requirements of traditional approaches. Finally, the section analyses traditional BPM practices and their limitations (2.3) to reveal the challenges that organizations face when attempting to implement conventional process modelling methodologies.

2.1 BPM Fundamentals and Organizational Benefits

Business Process Modelling (BPM) refers to the activity of representing an organization's processes to enable the analysis of current practices ("as-is") and the design of improved future processes ("to-be") (Muehlen & Recker, 2008). It is a fundamental step in understanding and enhancing the internal operations of organizations, especially in the context of information systems implementations, where it typically serves as a foundation for digital transformation initiatives by providing the process clarity needed before implementing new technologies (Daclin et al., 2024).

BPM is a subpart of Business Process Management. Business Process Management (BPMa) is recognized as a comprehensive discipline that transcends the boundaries of traditional methodologies, toolsets, or software types. It emphasizes the separation of process definition, design, analysis, and refinement from their execution. This distinction allows organizations to focus on optimizing workflows independently of operational constraints, fostering adaptability and continuous improvement. BPM's holistic nature is particularly relevant for SMEs, where resource limitations necessitate streamlined processes to enhance efficiency and competitiveness (Papademetriou & Karras, 2017)

The core activities of Business Process Management are defined by Viegas & Costa, 2022 as (1) Modelling/ Design; (2) Analysis; (3) Execution/ Implementation; (4) Monitoring and Control/ Measurement; (5) Improvement/ Optimization/ Refinement; and (6) Planning and Strategy Alignment.

The modelling of processes plays a crucial role in visualizing, analysing, and improving organizational activities. It facilitates a shared understanding among stakeholders, supports decision-making, and enables organizations to manage change effectively. As such, process models are often used not only to comprehend operations but also to support automation, simulate future scenarios, or serve as blueprints for software development (Kourani et al., 2024).

Beyond supporting operational clarity, process modelling is integral to strategic IT planning and compliance. It provides the foundation for formal models that can be verified or simulated, which is increasingly vital in dynamic business environments subject to frequent regulatory updates (Claes, 2018). Moreover, modelling allows organizations to align their processes with business goals, adapt to change, and ensure quality and efficiency across functions (Gonçalves et al., 2011).

Lack of in-house BPM expertise in organizations often leads to confusion regarding the distinct meanings of business processes, business process management, and business process modelling. A business process (BP) is defined as a collection of interrelated activities, resources, events and decisions executed in a predetermined order to achieve a specific organizational objective. Those activities involve actors fulfilling roles that are completing some organizational value (Moreira et al., 2024). These processes may operate within a single department or span across multiple organizational boundaries. However, collaboration across several departments often faces challenges due to inconsistent terminologies and standards (Bernardi et al., 2024). Business Process Management (BPMa) refers to the governance of these processes to improve an organization's agility, efficiency, and overall performance. It is important to differentiate BPMa as a broad management approach, not a specific technology nor simply the act of creating process diagrams. Business Process Modelling (BPM), often confused with BPMa, is the activity of digitally defining, representing, or modifying process descriptions in order to analyse and improve them. Typically performed by business analysts and managers, modelling supports efforts to enhance process efficiency, clarity, and quality. The term itself dates back to the 1960s, but gained significant traction in the 1990s, when organizations began shifting away from terms like "procedures" or "workflows" toward more process-oriented thinking (Kraljic et al., 2014).

Business Process Modelling (BPM) can help achieve multiple strategic and operational purposes across organizations. Its core foundation is to enable companies to understand and improve their internal operations by providing a representation on how activities are engineered (Daclin et al., 2024). It serves to enhance understanding, providing a comprehensive view from architectural levels, catering to the perspectives of stakeholders and representing logical depictions of process architectures (Shivhare, 2024).

Analysis of BPM literature reveals several key ways that process modelling assists organizations in achieving their objectives:

Enhancing understanding and communication: BPM creates comprehensible visual representations of complex process dynamics. This modelling enables a common understanding and analysis of business processes, which is the first step in many improvement methodologies. Improved business process understanding, including knowing "what" and "how" related to processes, supports positive outcomes. The standardized languages and graphical notations, facilitates clear communication and knowledge sharing among different stakeholders (Shivhare, 2024).

Supporting assessment ("As-Is" modelling): BPM helps organizations understand their current state ("as is") by documenting existing processes. This documentation is crucial for assessing the organization's current capabilities, which can be the starting point of Process Automation projects (Kraljic et al., 2014).

Identifying Areas for Improvement (Analysis): Business process models are used for analysis purposes. By modelling the current processes, organizations can identify bottlenecks, inefficiencies, and constraints. This analysis reveals weaknesses that need to be addressed to increase capabilities and progress towards higher maturity levels (Papademetriou & Karras, 2017).

Defining improvement goals and roadmaps ("To-Be" modelling): Modelling is also used to design improved processes ("to-be"). By comparing the "as is" and "to be" models, organizations can define the necessary changes and improvements (Grube & Wynn, 2019).

Structuring Capabilities: Business process models show the interactions between tasks, operations, and processes, providing a foundation for improving efficiency, effectiveness, and the overall business process. They also specify roles involved. Understanding and defining these components and their interactions is directly related to building the capabilities measured by maturity models (Grube & Wynn, 2019).

Facilitating Process Reuse and Optimization: A business process model can be used repeatedly for similar processes. The primary goal of modelling a business process is often to improve system performance through the optimization of activities (Grube & Wynn, 2019).

To leverage these advantages, BPM employs a defined set of practices, established norms, and standardized languages. The research now examines the technical artifacts and notations through which this understanding is created and communicated

2.2 Business Process Modelling Artifacts

BPM creates organizational value through structured artifacts that serve different stakeholder purposes. Process models typically employ standardized constructs to depict business logic and execution semantics. The specific set of these constructs varies depending on the modelling language used, with Business Process Model and Notation (BPMN) being the most common (Daclin et al., 2024; Lopes & Guerreiro, 2023). Some shared rules about the key aspects of Business Process Modelling across the different languages is that (1) they represent structure and behavior of an organization (Kokala, 2024), (2) they depict both the activities and constraints faced by the organization (Bernardi et al., 2024), (3) by using graphical core elements and constructs (Daclin et al., 2024).

Elements of a model are represented differently depending on the specific process modelling language and the business rules defined by the organization. A diagram of a business process can be referred to by several terms, including a process map, workflow diagram, a business process model, or an activity diagram (Kraljic et al., 2014).

The following are core elements commonly found in various process models languages:

Table 1. Elements of process models language (derived from Kraljic et al., 2014)

FLOW OBJECTS	These define the behavioural flow of a process	
	Events	Instantaneous triggers such as start, end, or intermediate occurrences.
	Activities	Work performed during the process, including tasks and sub-processes.
	Gateways	Control the divergence and convergence of flow; for example, exclusive (XOR) gateways for decision paths and parallel (AND) gateways for concurrent activities.
CONNECTING OBJECTS	These illustrate the dependencies and communication between process elements	
	Sequence Flows	Show the execution order
	Message Flows	Indicate communication between different participants or pools.
DATA OBJECTS	Represent data created, read, updated, or deleted during process execution. Process models support the association of data objects but do not constitute data models.	
SWIMLANES	Used to group and organize activities by participant or role:	
	Pools	Represent independent participants in a process.
	Lanes	Subdivisions within pools that denote responsibilities.
ARTIFACTS	Provide additional contextual or explanatory information:	

	Text Annotations, Groups, and other visual elements that enhance understanding without affecting process flow.

This structured modelling approach not only promotes clarity and consistency in process documentation but also enables formal verification, simulation, and automation of business operations.

A wide variety of process modelling notations have been developed to support the design, analysis, and communication of business processes. These notations differ in their syntax, the extent they express the processes, target users, and areas of application. Selecting the appropriate notation depends on the modelling purpose, the organizational context, and the expertise of the stakeholders involved.

2.2.1 Business Process Model and Notation (BPMN)

Business Process Model and Notation (BPMN) stands as the most widely adopted and comprehensive graphical language for modelling business processes. Developed by the Business Process Management Initiative (BPMI) and later standardized by the Object Management Group (OMG), BPMN is designed to bridge the gap between business users and technical developers. Its objective is to provide a common visual language that is both expressive and understandable across diverse stakeholder groups (Ivanchikj et al., 2020).

BPMN's strength lies in its comprehensive notation system that can represent complex business scenarios while maintaining visual clarity. The notation uses standardized symbols organized into the four main categories described above: Flow Objects (Events, Activities, Gateways), Connecting Objects (Sequence Flows, Message Flows), Swimlanes (Pools, Lanes), and Artifacts (Annotations, Groups, Data Objects). This systematic approach allows BPMN to capture intricate process logic including parallel execution, conditional flows, exception handling, and inter-organizational process interactions (Vega, 2015).

BPMN 2.0, the current standard, provides enhanced capabilities for process execution and automation. The notation supports both descriptive modelling for communication and analysis purposes, and prescriptive modelling for process automation and workflow systems. This dual capability makes BPMN particularly valuable for organizations pursuing digital transformation, as models can serve both documentation and implementation purposes (Vega, 2015).

However, despite its comprehensiveness, BPMN is often criticized for its steep learning curve, especially for users in small and medium-sized enterprises (SMEs) with limited modelling experience (Daclin et al., 2024). Its full utility is typically realized in large-scale or IT-intensive projects where precise process specification is required. The complexity of BPMN's full notation set can overwhelm novice users, with studies showing that many organizations use only a subset of BPMN elements in practice. Nonetheless, BPMN remains the de facto standard in business process modelling and automation literature.

BPMN's standardization by OMG ensures interoperability between different modelling tools and process engines, making it the preferred choice for organizations requiring vendor-neutral process representations. This standardization is particularly important for SMEs that may need to change tools or collaborate with partners using different BPM platforms (Lopes & Guerreiro, 2023).

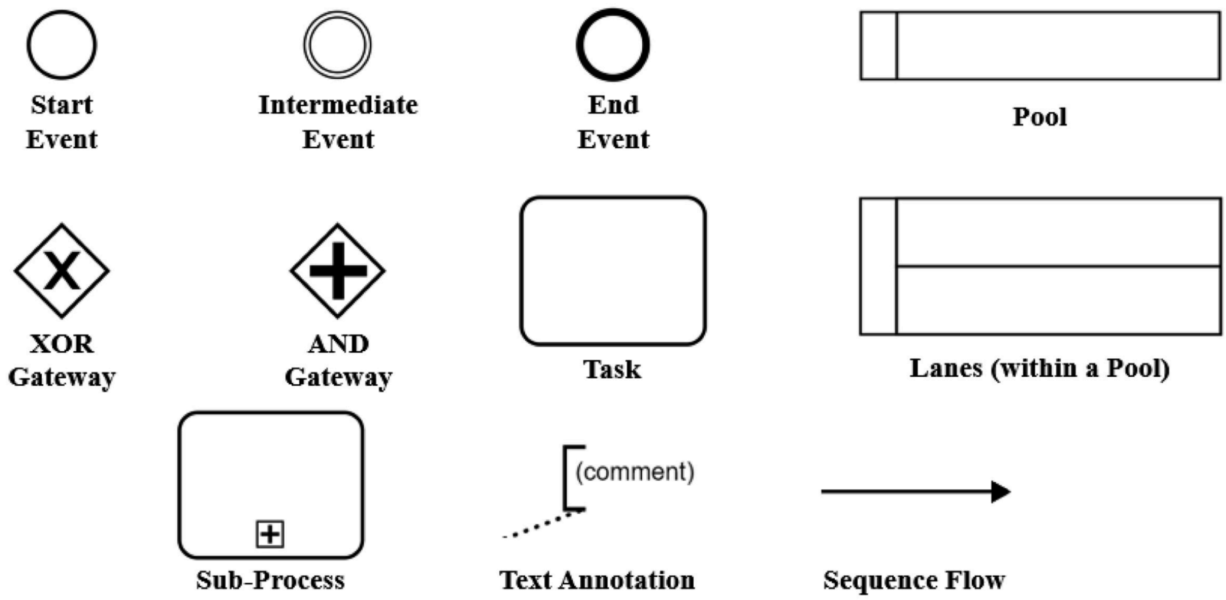

Figure 1. BPMN elements (from Lopes & Guerreiro, 2023, adapted from Object Management Group, 2010)

2.2.2 Alternative Modelling Notations

While BPMN dominates business process modelling, several alternative notations serve specific contexts and requirements. Unified Modelling Language (UML) Activity Diagrams, originally developed for software engineering, are sometimes applied in business process modelling due to their familiarity in IT departments and capacity to represent workflows and decision points. However, UML lacks several business-specific semantics provided by BPMN, limiting its adoption in purely business-driven modelling initiatives (Moreira et al., 2024).

Event-Driven Process Chains (EPC), developed within the ARIS framework, model processes as alternating sequences of events and functions connected via logical operators. EPC remains popular in SAP-centric environments but has increasingly limited use outside organizations with historical ARIS methodology adoption (Kraljic et al., 2014).

The Integrated DEFinition (IDEF) family, particularly IDEF0 and IDEF3, provides structured approaches for systems engineering and manufacturing contexts, emphasizing functional decomposition and clarity. However, these methods are generally less flexible and intuitive than BPMN, making them less common in contemporary business process initiatives (Kraljic et al., 2014).

2.3 Traditional Business Process Modelling Practices & Limitations

While BPM provides significant organizational value, traditional approaches face substantial limitations that particularly impact resource-constrained organizations. Historically, BPM approaches have relied heavily on manual processes (Kokala, 2024), with techniques evolving from diagrammatic and mathematical models to business process languages. This activity is often performed by business analysts and managers who aim to enhance process efficiency and quality (Papademetriou & Karras, 2017).

However, the literature points to several notable drawbacks associated with these traditional practices, as resumed by Kokala, 2024 in Table 2. First, traditional process modelling methods require extensive manual effort. This includes tasks like data entry, task assignment, and approval processes. Manually converting textual descriptions of processes into formal models, such as BPMN, is highlighted as a time-consuming and laborious task. Furthermore, process models require ongoing updates to reflect changes, which adds to the manual load (Daclin et al., 2024). Moreover, the actors that are handling BPM tasks need to have specialized expertise. Indeed, modelling languages like BPMN or Petri Nets are complex, and the lack of specialized expertise hinders the widespread adoption of process modelling (Daclin et al., 2024). Finally, manually converting text to models is prone to errors. Ensuring the correctness and compliance of business processes through testing and formal verification is crucial (Lopes & Guerreiro, 2023).

Table 2. Challenges of traditional Business Process Modelling (from Kokala, 2024)

CHALLENGE	DESCRIPTION	IMPACT ON BPM
HIGH MANUAL EFFORT	Relies on human intervention, leading to errors and inefficiencies.	Increased cycle times, high costs.
LACK OF SCALABILITY	Inability to handle large Reduced volumes of data and complex tasks efficiently.	Operational efficiency.
LIMITED FLEXIBILITY	Difficulty adapting to new business needs or changes in workflow structure.	Reduced responsiveness and agility.

In conclusion, while traditional business process modelling provides a foundation for understanding and improving organizational workflows, its reliance on manual effort, deep expertise, and its limitations in handling complexity and flexibility pose significant challenges, particularly in dynamic contexts and for resource-constrained entities like SMEs. These drawbacks motivate the exploration of newer approaches, potentially leveraging advancements in areas like Artificial Intelligence.

This analysis of BPM foundations reveals a fundamental tension: while process understanding provides clear organizational benefits including enhanced communication, operational efficiency, and strategic alignment, traditional BPM approaches create significant adoption barriers through complexity, resource requirements, and expertise demands. These barriers affect organizations of all sizes but become particularly constraining for resource-limited environments, establishing the need for alternative approaches that maintain BPM benefits while addressing accessibility constraints. These drawbacks motivate the exploration of newer approaches, potentially leveraging advancements in areas like Artificial Intelligence.

3 BPM Adoption in SMEs

Having established general BPM principles and challenges, this section focuses specifically on SME contexts to understand how resource constraints, organizational characteristics, and digital maturity levels create adoption challenges that differ fundamentally from large enterprise experiences. Finally, the section examines SME adoption patterns and modelling practices (3.1-3.2) to understand current approaches and benefits recognition, then analyses implementation challenges and risks (3.3-3.4) to identify SME specific barriers that AI technologies might address.

SMEs occupy a significant role in the global economy (Bamidele Micheal Omowole et al., 2024). They are widely recognized as key drivers of economic growth, innovation, and employment (Samuel Omokhafe Yusuf et al., 2024), making substantial contributions to national economies, and accounting for a large portion of employment and economic activity in both developed and developing nations (Bamidele Micheal Omowole et al., 2024).

However, despite their importance, SMEs face a distinct set of challenges when it comes to embracing digital technologies and undertaking digital transformation compared to larger organizations. The literature reviewed highlights several pervasive barriers. (Bamidele Micheal Omowole et al., 2024; Hussain & Rizwan, 2024; Samuel Omokhafe Yusuf et al., 2024). These barriers operate across three primary dimensions: financial constraints that limit investment in technological infrastructure and training due to prohibitive implementation costs; human resource challenges including shortage of skilled personnel and difficulties retaining talent amid rapid technological change; and organizational resistance stemming from traditional business models, fear of change, and leadership lacking digital literacy to enable transformation.

Despite these general digital transformation challenges, business process modelling presents both significant opportunities and specific adoption barriers for SMEs. While process understanding can serve as a foundation for overcoming broader digital transformation challenges, the complexity of traditional BPM approaches often conflicts with SME resource constraints and organizational characteristics.

3.1 BPM Adoption Patterns and Modelling Practices in SMEs

Research on BPM adoption in SMEs reveals distinct patterns that differ significantly from large enterprise implementations. Studies examining BPM adoption in SMEs show that implementation success varies by organizational culture type, with the highest level of adoption success occurring in organizations with adhocracy culture compared to market and hierarchy culture types (Pejić Bach et al., 2019).

SME process modelling adoption demonstrates pragmatic preferences for simplicity over methodological sophistication. Organizations face significant challenges in selecting appropriate modelling methodologies from the extensive range of available options, with key selection factors including readability, tool support availability, purpose alignment, and organizational context fit (Entringer et al., 2021). SMEs typically prioritize ease of understanding and immediate applicability over comprehensive notation features.

The modelling adoption process in SMEs frequently follows a maturity progression from informal to formal documentation, consistent with the low BPM maturity levels observed in SMEs (Viegas & Costa, 2022) and their preference for iterative, gradual implementation approaches (Pejić Bach et al., 2019). Organizations often begin with simple flowcharts or text-based process descriptions before advancing to structured modelling notations. This evolutionary approach reflects SME learning preferences and resource constraints, with organizations adopting more sophisticated modelling tools only as their process management capabilities develop.

Recent empirical research confirms these patterns while highlighting the systemic nature of digital transformation in SMEs. Analysis of 201 Chinese SMEs reveals that digital drive fully mediates the relationship between digital adoption and innovation performance, with digital culture serving as a critical moderator in adoption decisions Digital Transformation and Innovation Performance in Small- and Medium-Sized Enterprises: A Systems Perspective on the Interplay of Digital Adoption, Digital Drive, and Digital Culture (Li et al., 2025). This systemic perspective suggests that successful process modelling adoption requires coordinated organizational transformation rather than isolated technology implementation.

The implementation of modelling practices in SMEs often occurs through informal knowledge transfer rather than structured training programs. Research on process modelling acceptance shows that social influence from different stakeholder reference groups affects adoption, with SMEs particularly influenced by peer organizations and industry examples rather than formal best practices (Muehlen & Recker, 2008). This peer-driven adoption pattern results in varied modelling quality and consistency but enables rapid knowledge diffusion within SME communities.

The decision-making process for modelling adoption in SMEs is characterized by centralized ownership involvement and practical evaluation criteria. Research shows that owner's attitude towards IT and owner's knowledge serve as key determinants in SME technology adoption decisions, with leadership commitment being crucial for successful implementation (Hussain & Rizwan, 2024). Unlike larger organizations where modelling may be mandated (Recker et al, 2009), SME adoption decisions typically focus on immediate problem-solving needs and clear return on investment expectations, reflecting their resource constraints and voluntary adoption context. This pragmatic decision-making can accelerate adoption when clear benefits are evident but may result in inconsistent modelling standards across the organization.

3.2 Benefits of Business Process Modelling for SMEs

Small and Medium Companies are generally at a low level of Business Process Management maturity. This low maturity level is reported in comparison to companies in general and is especially pronounced in SMEs (Viegas & Costa, 2022). They have not yet advanced beyond the initial stages of the model. While they recognise the importance of operational efficiencies, they do not yet have a process-aware mindset and have not yet established intra-process automation and control (Moreira et al., 2024).

Business Process Modelling is a core activity that can efficiently help SMEs reach a higher maturity level by addressing limited process understanding, providing a foundation for improvement (Claes, 2018), facilitating communication and knowledge sharing (Papademetriou & Karras, 2017), supporting structured initiatives and identifying opportunities for automation and control.

Given the digital transformation challenges SMEs face, business process understanding becomes particularly crucial as a strategic enabler. Understanding business processes (BPU) becomes particularly vital for SMEs as it can enable and improve their overall technology acceptance. BPM offers a means to achieve this understanding, outlining organizational activities and providing a framework for improvement (Papademetriou & Karras, 2017). An improved understanding of processes can lead to more informed business decisions and the achievement of strategic goals, ultimately contributing to enhanced operational efficiency, greater innovation, and a strengthened competitive edge (Susanty et al., 2025).

According to (Moreira et al., 2024), the existence of BPM within an organization can positively influence Business Process Automation (BPA). BPA is a direct form of digital technology adoption, automating routine tasks to streamline processes. Having a solid understanding of business processes through BPM makes it easier for SMEs to identify that could be automated and implement BPA effectively.

Another significant benefit is the improvement in customer experience. BPM enables SMEs to deliver consistent and personalized services by standardizing processes that directly impact customer interactions, thereby increasing satisfaction and loyalty (Ibrahim et al., 2024).

Finally, the financial benefits of BPM implementation are also important. By using process models to optimize processes to reduce operational costs, SMEs can achieve higher profit margins without compromising on quality or service delivery. This cost-effectiveness is particularly interesting for smaller enterprises that operate under tight budget constraints. (Kokala, 2024).

Despite its numerous advantages, research indicates that the adoption of BPM in SMEs remains underdeveloped compared to larger corporations. This gap underscores the need for tailored approaches that address the unique challenges faced by smaller enterprises

3.3 SME Challenges in Process Modelling Adoption

SMEs face multifaceted barriers in adopting process modelling practices, with challenges operating across technological, organizational, and socio-political dimensions. The Technology Acceptance Model (TAM) provides insight into these barriers, suggesting that SMEs' adoption decisions are primarily influenced by perceived usefulness and perceived ease of use of modelling tools and methods (Velasquez et al., 2023).

However, SME adoption challenges extend beyond individual perceptions to encompass structural organizational constraints. These barriers can be systematically categorized into three primary areas: resource limitations, technical barriers, and organizational factors.

Financial constraints are one of the most significant obstacles for SMEs, as they often lack the capital required to invest in BPM tools and technologies. The limited financial resources available to these enterprises can restrict their ability to acquire advanced systems or hire specialized personnel needed for BPM initiatives. Furthermore, the absence of skilled personnel exacerbates this issue, as SMEs frequently struggle to attract and retain employees with expertise in process modelling and digital transformation (Papademetriou & Karras, 2017).

Technological challenges also represent a significant barrier for SMEs. Many enterprises lack access to robust infrastructure or face difficulties integrating BPM tools with existing systems. This technological gap can lead to inefficiencies and limit the potential benefits of process modelling efforts (Samuel Omokhafe Yusuf et al., 2024).

The complexity of traditional modelling notations, particularly BPMN, creates additional barriers for SMEs that lack specialized modelling expertise, with the time and resource investments required for modelling training often preventing smaller organizations from realizing process visualization benefits (Ivanchikj et al., 2020).

Anotther dimension of the acceptance of process modelling is the stakeholder perceptions of the modelling activity's value and necessity. Research shows that social influence from different stakeholder reference groups should be analyzed separately to reveal their influence on process modelling acceptance, as different groups (management, IT staff, process participants) may have varying motivations and concerns about modelling initiatives.

3.4 Traditional Modelling Adoption Risks

Empirical research on BPM adoption identifies several recurring pitfalls in business process modelling initiatives (Mendling & Mandelburger, 2013). These include insufficient stakeholder involvement in model development, lack of clear modelling standards within organizations, and failure to connect modelling activities to concrete business improvements. Organizations often underestimate the change management aspects of introducing process modelling practices, leading to resistance and poor adoption rates.

The complexity of traditional modelling notations, particularly BPMN, creates barriers for SMEs that lack specialized modelling expertise. This technical complexity, combined with the time and resource investments required for modelling training and implementation, often prevents smaller organizations from realizing the benefits of process visualization and analysis (Kraljic et al., 2014).

As seen, within SMEs, the perceived usefulness of process modelling often conflicts with immediate operational pressures and resource or technical constraints. Unlike larger organizations where modelling may be mandated, SMEs typically make voluntary adoption decisions based on clear Return On Investments (ROI) expectations. The perceived ease of use becomes particularly critical given limited access to specialized modelling expertise and training resources (Hussain & Rizwan, 2024).

In conclusion, while a strong understanding of business processes is crucial for SME success in the digital economy, the literature indicates that traditional, often manual, BPM practices are frequently ill-suited to their unique characteristics. The high complexity and resource intensity of these methods, coupled with the specific limitations SMEs face regarding finances, technical skills, and organizational resistance, significantly hinder their effective adoption and application. This suggests a need for alternative, less resource-intensive approaches to process understanding for SMEs.

The examination of BPM adoption in SMEs confirms that resource constraints, organizational characteristics, and change management challenges create systematic barriers that differ fundamentally from large enterprise contexts. While SMEs recognize process understanding benefits, traditional implementation approaches prove misaligned with their operational realities, pragmatic decision-making patterns, and capability limitations. These findings establish the specific organizational context and constraints that any alternative BPM approach must address to achieve successful SME adoption.

3.5 Technology Adoption Theoretical Framework for SME BPM Implementation

Understanding technology adoption in SMEs requires theoretical frameworks that systematically organize the complex factors influencing adoption decisions. While multiple technology adoption models exist, including the Technology Acceptance Model (TAM) and Diffusion of Innovation Theory, the Technology-Organization-Environment (TOE) framework proves particularly suited for analysing organizational-level technology adoption in SME contexts (Oliveira & Martins, 2011; Tornatzky & Fleischer, 1990).

The TOE framework was specifically developed to explain technology adoption at the organizational level, distinguishing it from individual-focused models like TAM (Tornatzky & Fleischer, 1990). The framework posits that technology adoption decisions result from the interaction of three contextual factors: technological characteristics, organizational capabilities, and environmental influences. This multi-dimensional approach recognizes that technology adoption extends beyond individual user acceptance to encompass organizational processes, resources, and external pressures that particularly constrain SME decision-making.

Technological Context encompasses the characteristics of available technologies, including their perceived advantages, complexity, compatibility with existing systems, and accessibility (Tornatzky & Fleischer, 1990). For SMEs, technological factors often center on cost-effectiveness and ease of implementation rather than sophisticated feature sets (Ramdani et al., 2009). Organizational Context includes structural characteristics such as firm size, management structure, human resources, and available resources for innovation (Tornatzky & Fleischer, 1990). SMEs typically exhibit distinct organizational characteristics including resource constraints, centralized decision-making, and limited technical expertise that fundamentally influence technology adoption patterns compared to larger enterprises (Oliveira & Martins, 2011). Finally, Environmental Context comprises external factors including industry characteristics, regulatory environment, and competitive pressures (Tornatzky & Fleischer, 1990). SMEs often face greater environmental constraints than larger firms, including limited access to technical support and competitive pressures from digitally advanced competitors (Ramdani et al., 2009).

The framework's comprehensive approach makes it particularly valuable for analysing emerging technologies like AI-powered BPM, where technical capabilities interact with organizational constraints and environmental pressures to determine adoption outcomes. Unlike individual-focused models, TOE captures the multi-level complexity of organizational technology adoption decisions that characterize SME contexts (Oliveira & Martins, 2011).

4 Artificial Intelligence (AI) in Business Process Modelling

This section examines how AI technologies, particularly Large Language Models, might address the SME-specific BPM barriers identified in previous sections while introducing new implementation considerations. The analysis begins by examining how AI capabilities directly address traditional BPM barriers (4.1) to establish the theoretical foundation for AI-powered solutions. The review then covers current LLM-generated process modelling methods and applications (4.2) to understand technical capabilities and implementation approaches. Finally, the section examines quality assessment frameworks and technical limitations (4.3-4.4) to identify the gaps and challenges that this research investigates empirically.

Artificial intelligence, particularly natural language processing (NLP) and large language models (LLMs) is emerging as a powerful tool in business process modelling activities. LLMs can convert textual process descriptions into formal process models, lowering the expertise barrier for creating diagrams - directly addressing one of the primary barriers to traditional BPM adoption identified in section 2.1. Those advancements are answering to the high requirements needed to use BPM in a company setting, especially for SMEs.

The literature on this subject delves into the technical side rather than organizational benefits. For example, (Kourani et al., 2024) propose a framework that uses GPT-4 to automatically generate and refine process models, with mechanisms to enforce modelling rules and correct errors. Early results show that generative AI can streamline process modelling tasks without extensive manual effort. LLMs have also been used to converse with process models and answer questions about process logic. This capability could improve understanding and management of complex processes.

However, output quality remains a concern. Indeed, ensuring the LLM-generated models are correct and useful requires careful prompt engineering and manual post-processing. Overall, AI and its subsets like NLP and LLM offer new ways to model and analyse processes, moving BPM toward more intelligent and interactive systems. This area is rapidly evolving, with experimental systems being introduced but not yet widely tested in real business settings (Bernardi et al., 2024).

4.1 How AI Addresses Traditional BPM Barriers

Building on this foundation, AI brings transformative capabilities that specifically address the traditional BPM barriers through three primary mechanisms.

Large Language Models (LLMs) represent the most significant advancement in AI-powered Business Process Modelling, offering transformative capabilities that address traditional BPM barriers. LLMs are advanced Natural Language Processing (NLP) systems trained on extensive datasets that can resolve many issues linked to the complexity of mapped processes. These models can be fine-tuned to obtain process-specific knowledge, enabling them to support a wide range of process mining tasks (Berti et al., 2024; Rebmann et al., 2024).

LLMs serve as flexible assistants for process modelling, capable of automating the drafting of process flows, classifying tasks, and conversing with users to refine models. Recent studies demonstrate that LLMs can be prompted to generate BPMN process diagrams from natural language descriptions, identify process steps and decisions, and suggest process improvements. In experimental evaluations, state-of-the-art LLMs have produced process models from textual inputs as accurately as or even better than specialized algorithms, with minimal prompting (Grohs et al., 2023).

These capabilities build upon foundational Natural Language Processing (NLP) techniques that have been transforming process modelling by automating and enhancing various aspects of business workflows. Even before the widespread awareness of LLMs like ChatGPT, Language Models were used in BPM for tasks such as process extraction from text or activity recommendation, typically using fine-tuning approaches (Busch et al., 2023; Grohs et al., 2023). The introduction and rapid advancement of LLMs have led to a significant paradigm shift, with researchers now switching from fine-tuning to prompt engineering, using natural language specifications to give instructions without changing the underlying model.

NLP techniques enable BPM systems to extract processes from unstructured data sources, such as emails, contracts, and customer interactions, enabling process discovery in document-heavy environments (Bernardi et al., 2024). These techniques are enhanced through prompt engineering and domain knowledge integration, leading to more accurate and contextually relevant process models (Ayad & Alsayoud, 2024; Bernardi et al., 2024). By setting up pipelines that systematically search through organizational knowledge silos, NLP can convert scattered information into actionable models and queries (Kampik et al., 2024).

The integration of these AI technologies offers several key advantages for BPM: (1) Extraction: LLMs can autonomously generate process models from natural language input, reducing the need for manual diagramming or technical expertise. For example, ProMoAI and similar frameworks automate the translation of textual descriptions into formal models (Kourani et al., 2024). This automation directly addresses the time-consuming and laborious nature of traditional process modelling identified in section 2.1. (2) Extraction: NLP techniques empower BPM systems to extract processes from unstructured data sources, such as emails, contracts, and customer interactions, enabling process discovery in document-heavy environments (Bernardi et al., 2024). This capability makes process modelling accessible to organizations without specialized modelling expertise. (3) Comprehension and Interaction: LLMs enable systems to “understand” process logic and interact with users via natural language. This has led to the emergence of conversational BPM assistants capable of answering questions about a process or recommending redesigns (Bernardi et al., 2024).

However, implementing these AI technologies effectively within BPM practices presents notable challenges. The complexity of LLMs necessitates robust evaluation frameworks to ensure outputs align with organizational goals and maintain high-quality standards. For SMEs, the risk associated with deploying sophisticated AI systems is particularly concerning, given potential limitations in technical expertise required to manage these tools effectively.

The application of AI techniques in BPM also raises questions about data privacy, security, and applicability across different business contexts. While AI excels at automating repetitive tasks and analysing textual data, its effectiveness may vary depending on the complexity of the processes being modelled. Certain industries may require more specialized adaptations of AI techniques to address domain-specific challenges effectively (Velasquez et al., 2023).

Despite these challenges, the evolution from traditional NLP approaches to advanced LLMs represents a fundamental shift toward more accessible and powerful process modelling capabilities, potentially democratizing BPM for organizations with limited technical expertise.

Looking ahead, the concept of Large Process Models (LPMs) is proposed as a central conceptual framework for software-supported BPM in the era of generative AI. An LPM is envisioned as a software system that combines expert knowledge, real-life business data, and advanced AI tools to help organizations better understand and manage their processes. By blending human expertise with AI processing capabilities and data analysis, LPMs could automatically suggest useful insights and actions to improve organizational operations (Kampik et al., 2024).

The LPM vision represents a potential solution to many current limitations of both traditional BPM and current AI approaches. LPMs could integrate multiple AI technologies (NLP, machine learning, knowledge graphs) with organizational data and human expertise to create comprehensive process management systems that learn and adapt over time. This integration could address current challenges around model quality, organizational context, and continuous improvement that limit both traditional BPM adoption and current AI implementations.

For SMEs, the LPM vision offers promise by potentially providing enterprise-level process management capabilities through cloud-based, AI-powered platforms that require minimal technical expertise to deploy and maintain. However, realizing this vision requires addressing current limitations in AI reliability, organizational readiness, and integration with existing business systems.

The evolution of BPM has transitioned from initial manual and symbolic process depictions to an era where advanced AI, including LLMs, can comprehend, create, and engage with process models and data via natural language, potentially paving the way for more automated and unified BPM systems such as the proposed LPMs. This evolutionary trajectory suggests that the barriers to BPM adoption identified in traditional approaches may be fundamentally addressable through AI technologies, though significant research and development challenges remain, particularly in understanding how these technologies can be successfully adopted and implemented in resource-constrained SME environments.

4.2 LLM-Generated Process Modelling: Methods and Applications

The deployment of Large Language Models (LLMs) in Business Process Modelling (BPM) necessitates an understanding of how to generate reliable, structured models from natural language inputs. While LLMs offer unprecedented capabilities in interpreting and generating process logic, their effectiveness depends heavily on how they are prompted and the tools used to manage their output. This section examines the formulation of inputs, toolchain configurations, and methodological guidelines drawn from recent academic and practical developments.

4.2.1 Inputs best practices and prompt engineering

The effectiveness of LLM-generated process models depends heavily on prompt engineering and input design. Prompt engineering has emerged as a critical skill because LLMs operate on probabilistic language generation rather than deterministic rule execution. Several studies highlight that providing clear, structured, and context-rich prompts leads to more accurate and complete process models (Kourani et al., 2024).

To start, prompts should clearly instruct the model on the goal and follow some notation rules if possible. For example, “Generate a BPMN diagram that describes the following order fulfillment process…” is more effective than vague or implicit instructions (Grohs et al., 2023). Moreover, including clear associations between activities and responsible roles (e.g., customer service, finance) enhances the model's ability to assign tasks appropriately, thereby improving semantic accuracy. Furthermore, describing the order of tasks and their dependencies using connectors such as “if”, “then”, or “after” improves coherence. This is essential for modelling gateways and control flow logic accurately. Finally, setting the scope of the model (e.g., excluding external interactions or focusing only on internal handoffs) reduces ambiguity and ensures the LLM focuses on the relevant subprocess.

When it comes to the input given to the LLMs with the content about the processes, semi-structured or unstructured data are some possibilities, however, according to (Pisoni & Moloney, 2024), besides textual descriptions, LLMs perform better when structured data such as tables, checklists, or documents are included. They emphasize that semi-structured inputs (e.g., labeled task lists, documents with headers) increase the LLM's ability to distinguish activities, roles, and dependencies. Recent developments have also explored few-shot prompting, where one or two example inputs and outputs are included to guide the model. This technique helps calibrate the LLM's responses, especially for less common process types (Brown et al., 2020; OpenAI et al., 2023).

Effective LLM implementation also requires domain-specific knowledge integration. Successful AI-augmented BPM systems are knowledge-intensive systems that depend on contextual data and metadata about processes, users, and industry standards (Bernardi et al., 2024). The literature recommends basing inputs and prompts on the Seven Process Modelling Guidelines (7PMG) framework (Mendling et al., 2010a; Claes, 2018) to ensure understandable models with lower chances of syntactic errors.

4.2.2 Seven Process Modelling Guidelines (7PMG) Framework for LLM Prompts

As a general ruling, the literature agrees to base inputs and prompts on the principles of the 7PMG framework. 7PMG stands for Seven Process Modelling Guidelines. They were proposed by (Mendling et al., 2010). 7PMG are intended provides best practices for creating comprehensible process models with reduced technical errors. These guidelines function as recommended practices rather than mandatory rules, supporting modellers in developing high-quality representations that balance clarity with syntactic accuracy. The framework's emphasis on structured modelling approaches makes it particularly suitable for evaluating AI-generated process model. After listing the guidelines for the first time, authors weighed their importance for prioritizing them [add the table name and link]. The 7PMG are (1) model as structured as possible, (2) decompose a model with more than 50 elements, (3) use as few elements in the model as possible, (4) use verb-object activity labels, (5) minimize the routing paths per element, (6) use one start and one end event, and (7) Avoid OR routing elements. Those guidelines allow the designer to keep a high understandability on the designed model and can be applicable to prompts used for LLM-generated models (Claes, 2018).

The application of 7PMG principles to LLM prompt design offers several advantages: (1) Quality Assurance - incorporating established modelling best practices into AI generation; (2) Consistency - ensuring LLM outputs follow proven guidelines for understandable models; (3) Error Reduction - minimizing syntactic errors through structured guidance; (4) SME Accessibility - producing models that are more easily understood by non-expert users (Mendling et al., 2010).

For SME contexts, 7PMG-guided prompts are particularly valuable because they help ensure that AI-generated models follow principles of simplicity and clarity that are essential for organizations with limited modelling expertise. By incorporating these guidelines into prompt engineering, organizations can leverage AI capabilities while maintaining the quality and understandability benefits that traditional expert modelers would provide (De Meyer & Claes, 2018).

Table 3. 7PMG guidelines, prioritized (from Mendling et al., 2010)

PRIORITY	NR.	EXPLANATION
1	G4	Model as structured as possible
2	G7	Decompose a model with more than 50 elements
3	G1	Use as few elements in the model as possible
4	G6	Use verb-object activity labels
5	G2	Minimize the routing paths per element
6	G3	Use one start and one end event
7	G5	Avoid OR routing elements

4.2.3 Toolchains and Interfaces Supporting LLM Modelling

LLM-generated process models can be produced using several architectures, typically involving three layers: input interface (user prompt), intermediate model (LLM + optional rules or retrieval), and output interface (diagram generation).

Other approaches, such as those used in Conversational BPM Tools (Papademetriou & Karras, 2017), integrate LLMs directly into modelling platforms, allowing users to iteratively build models via a chat interface. These tools often include visual validation and error feedback mechanisms that help guide non-expert users. According to (Busch et al., 2023), organizations should prioritize working with pre-trained and fine-tuned models, as they will lower the initial investment needed.

Researchers such as (Kampik et al., 2024) advocate for hybrid human-AI modelling approaches, where AI generates the base model and human experts provide refinement and domain-specific corrections. This collaborative method balances automation with oversight and has shown strong results in pilot deployments across small and medium-sized enterprises.

Moreover, a common pattern adopted in academic prototypes such as ProMoAI (Kourani et al., 2024) involves the use of a domain-specific language (DSL) as an intermediate representation. The use of DSLs offers two advantages: (1) structure enforcement which ensures outputs follow BPMN semantics before rendering, and (2) separation of concerns which allows developers to refine model logic independently from the natural language output.

In essence, LLM-based modelling is a multilayered effort that combines prompt engineering, structured toolchains, and iterative human feedback. Although LLMs represent a transformative step in democratizing business process modelling, their effectiveness hinges on carefully designed inputs, intermediate control layers such as DSLs, and robust post-generation validation practices. With emerging frameworks and increasingly refined prompt strategies, LLM-generated modelling is rapidly becoming viable in environments where modelling expertise is scarce, but process documentation is rich.

While LLMs offer potential solutions to traditional BPM barriers, evaluating the quality of AI-generated process models presents new challenges that existing literature has not adequately addressed. Understanding how to assess whether LLM-generated models meet organizational requirements is essential for SME adoption decisions, as poor-quality models could undermine the accessibility benefits that motivate AI-BPM adoption.

4.3 Quality Assessment and Technical Limitations

Several frameworks and models have been developed to theoretically support the notion of process model quality. Among the most prominent and relevant discussed in the sources is the SEQUAL (semiotic quality) framework. This recognized framework is based on semiotic theory. By considering conceptual models as sets of statements in a language, evaluation in linguistic and semiotic terms becomes possible (Krogstie et al., 2006). The three main dimensions of quality the SEQUAL framework measures are (1) syntactic quality, (2) semantic quality and (3) pragmatic quality.

The SEQUAL framework has been adapted and extended multiple times. More recent efforts build upon these frameworks, such as the CMQF (Conceptual Modelling Quality Framework), which synthesizes the SEQUAL extension and the Bunge-Wand-Weber (BWW) framework, incorporating a process-oriented viewpoint on quality (Claes, 2018). Another framework, GoM (Guidelines of Modelling), specifically centers on process model quality and is grounded in general accounting principles, bundling six principles influencing model quality (Schuette & Rotthowe, 1998). The SIQ framework also builds on the three SEQUAL dimensions: syntactic, semantic, and pragmatic quality. The BPMQ framework presented by Van Mersbergen (2013) also positions the three SEQUAL dimensions as preferred dimensions for the 'WHAT' component of process model quality. The MAQ model (Model for Assessing Quality of business process models in BPMN) was built based on the ISO/IEC 1926 standard for software quality. The IQ-CC-EQ framework proposes a model to objectively judge the quality of process models, based on the idea that internal quality aspects can predict external quality dimensions (Claes, 2018).

It is important to note that there is a lack of consensus about which dimensions constitute process model quality. This makes it difficult to decide how a certain dimension should be measured, and which dimensions are relevant. Many quality dimensions are abstract or practically impossible to measure objectively, requiring personal assessment (Claes, 2018). The quality measures to prioritize are those that resonate with the expected results of the models and their usage.

To effectively evaluate LLM-generated business process models, quality assessment must address multiple dimensions that determine both technical accuracy and practical organizational utility. These dimensions can be systematically organized into three fundamental categories that capture the essential requirements for successful SME adoption (Papademetriou & Karras, 2017) : usability, correctness, and completeness.

4.3.1 Usability

The first area of quality is the usability. Indeed, one consensus across the frameworks is the “fit-for-purpose” dimension. Process models are considered high quality if they are suitable for achieving their intended goal(s) (Claes, 2018). According to Krogstie et al., 2006, this corresponds to the pragmatic (use) quality (is the model understandable and useful?). Undeniably, usability (understandability) is primordial: models should be clear and not overly complex for end users. Recent research on process model comprehension underscores that factors like model size, complexity, and layout have measurable impacts on how well humans can interpret a diagram (Velasquez et al., 2023). For example, a study found that reducing the number of nodes and using a clean layout significantly improved stakeholders' understanding of a BPMN, which is a dimension you can find for example in the 7PMG framework (Mendling et al., 2010b). In addition, recent studies on BPM Understandability (BPMU) highlight that both personal factors (such as modelling expertise and domain knowledge) and model factors (such as graph diameter or number of branches) influence how users interpret diagrams (Velasquez et al., 2023). Therefore, usability is not only about how the model looks but also about how well it matches the cognitive profile of its stakeholders. However, according to (Claes, 2018), measuring pragmatic quality/understandability is less investigated compared to syntactic quality.

4.3.2 Correctness

Correctness, specifically referred to as syntactic quality in frameworks like SEQUAL, focuses on how well the process model adheres to the rules and vocabulary of the modelling language being used. It concerns the structural correctness of the model according to the rules and vocabulary of the language. Syntactic quality is considered a fundament that supports other dimensions, as syntax errors can obscure the intended message and impact the assessment of semantic and pragmatic quality (Claes, 2018). Syntactic quality/correctness is one of the most investigated and measured quality dimensions.

A key criterion for syntactic correctness in workflow-nets is the soundness property. Soundness ensures that the process model is free from common grammatical irregularities. The requirements for soundness include the ability to reach the end state from any state, ensuring that each end state is a full end state with no active branches left, and the absence of branches that can never be executed. Tools are available that can automatically assess whether a model meets these soundness requirements (De Meyer & Claes, 2018).

Factors influencing syntactic correctness include the size of the model, with larger models tending to have a higher probability of containing errors. The structure of the model also plays a significant role; models that are structured (where every split connector matches a corresponding join connector of the same type) are less likely to include errors. Avoiding the use of certain problematic routing elements, such as OR gateways, can also contribute to reducing errors. Guidelines like the Seven Process Modelling Guidelines (7PMG) focus on organizing the structure of a process model while preserving its content, thereby complementing concerns about model validity. It is important to note that errors introduced at the requirements definition level, where modelling often occurs, are significantly more costly to correct in later phases like maintenance (Mendling et al., 2010).

4.3.3 Completeness

Completeness, known as semantic quality, refers to the extent to which the process model accurately reflects the real world or the domain it intends to represent. This includes ensuring the model's correctness and completeness in relation to that reality (Claes, 2018). (Papademetriou & Karras, 2017) states that the resources, organizational units, idle time and operating time and everything related to the process should be stated. And that, while a distinction is made between the factual domain ('as is' models) and the optimal domain ('to be' models) to properly describe semantic quality, the model is complete if it enables some capacities to achieve the transformation for the as-is to the to-be models. Techniques exist to assure semantic quality, referred to as truthfulness-by-design.

Compared to syntactic quality, the measurement of semantic quality is less frequently evaluated and can be inherently abstract, making objective measurement hard to achieve. Subjective evaluations of semantic quality, such as perceived difficulty by users, may not always accurately correlate with objective measures. Achieving semantic quality is closely tied to the principle of construction adequacy or reality adequacy, which requires establishing a consensus between the modelers and users regarding the problem being represented and the form of its representation (Schuette & Rotthowe, 1998). This involves the explicit definition of information objects, ensuring context-invariant modelling of problems, and using standardized naming conventions and consistent application of the modelling language. The appropriateness of the model is influenced by the selection of relevant information objects based on the goals of the intended model audience, which in turn impacts the model's level of abstraction and its usability. The principle of minimalism, related to construction adequacy, suggests that a model is minimal when no information objects can be removed without losing essential information for the user. Similar to syntactic quality, using the same information objects in structural and behavioral models contributes to semantic correctness through systematic design (Schuette & Rotthowe, 1998).

In summary, a high-quality business process model should satisfy the following criteria:

- Syntactic correctness (no notation errors),
- Semantic completeness and precision (faithful to the domain reality),
- Pragmatic usability (clear, readable, and fit-for-purpose),

Balancing these dimensions is particularly important in non-technical settings where intuitive designs must coexist with rigorous standards for process representation (Kourani et al., 2024; Lopes & Guerreiro, 2023).

Models generated by AI bring additional challenges to quality measurements, which must involve checking if the generated model accurately identifies relations and entities described in the source text (e.g., using recall as a metric). The soundness and executability of the generated models are highlighted as indicators of quality (Kourani et al., 2024). Evaluating frameworks for generating models considers the quality of the models generated, efficiency in error handling, and integrating user feedback.

The probabilistic nature of LLMs introduces risks like hallucination (where the model invents, steps, actors, or relations not grounded in the source material). This undermines the accuracy and reliability of BPM outputs and complicates validation (Bernardi et al., 2024). Furthermore, beyond structural quality, ethical and responsible AI considerations are also critical. As outlined by (Pisoni & Moloney, 2024), four core dimensions should guide AI-driven BPM tools: (1) fairness (outputs should not reinforce biases or lead to discriminatory process decisions, even when patterns exist in data), (2) accuracy (the model must avoid speculation instead of relying on verified input), (3) confidentiality (generated models should not leak sensitive business logic or data embedded in training sets), and (4), transparency (Explanations of generated outputs must be interpretable and meaningful for business users).

In practice, organizations evaluate LLM-generated BPM models using a mix of these criteria. For example, one might check an AI-produced BPMN diagram for syntactic validity, validate its steps against the actual business procedure (semantic check), ensure it doesn't introduce extraneous activities (precision), and then perform user reviews or usability tests to gauge if it's understandable to business users.

4.4 LLM-generated Models challenges

While the previous sections demonstrate significant potential for LLM-powered BPM, successful implementation faces substantial challenges that must be understood and managed. These challenges operate across technical, organizational, and ethical dimensions and may limit the benefits identified above.

4.4.1 Technical Challenges

One major limitation is the ambiguity in natural language inputs, which affects the model's ability to generate precise and usable process representations. Inputs often suffer from structural ambiguity, where the logical flow of the process is unclear; lexical ambiguity, where terms have multiple interpretations; under description, where key elements are missing; and over description, where unnecessary details are included (Bernardi et al., 2024; Claes, 2018). Moreover, the level of precision in users' requests impact the results (Kunstmann et al., 2024). These ambiguities challenge the model's ability to construct a faithful and useful process representation.

Moreover, LLMs encounter challenges with representation and scalability. They often struggle to generate complete BPMN diagrams in a single response due to output length limitations. LLMs are prone to generation inconsistencies, such as introducing new actors which are not present in the original process (Bernardi et al., 2024; Kokala, 2024). Additional difficulties arise in modelling complex BPMN structures such as exclusive gateways, parallel paths, loops, and swimlanes, which are not natively understood by LLMs without structured guidance. The BPLLM framework explicitly highlights these representation issues, noting that key constraints such as event-based gateways or boundary events are often misrepresented or omitted by the model (Bernardi et al., 2024).

Furthermore, success with AI-powered workflows is influenced by reduced flexibility and adaptability during dynamic business processes. SMEs often operate under resource constraints that demand agile solutions capable of handling diverse scenarios. However, LLMs may struggle with adaptability due to their reliance on pre-trained knowledge bases rather than real- time learning mechanisms (Kokala, 2024; Kunstmann et al., 2024)

Finally, SMEs face integration barriers when attempting to incorporate LLM-generated models into existing BPM infrastructures. Legacy systems, low-quality input data, and fragmented organizational knowledge hinder seamless adoption (Claes, 2018; Kraljic et al., 2014). Moreover, most tools are designed for tech-savvy users, requiring a level of modelling or prompt engineering expertise that may be lacking in small and medium-sized enterprises (SMEs). Even when tools lower the technical barrier, users may struggle to understand or validate the models, particularly when outputs contain errors or use domain-inconsistent language (Daclin et al., 2024; Kourani et al., 2024).

4.4.2 Organizational Barriers

While AI presents potential solutions to BPM adoption challenges, it introduces its own adoption barriers. Research using the Technology-Organization-Environment (TOE) framework identifies that organizational factors like top management support and employee skills, along with technological factors such as perceived relative advantage, play critical roles in SME AI adoption (Badghish & Soomro, 2024). SMEs are more likely to embrace AI solutions when they perceive clear benefits, possess necessary skills, and face market pressures.

Key enablers include increasing accessibility and affordability of AI technologies, making applications viable for resource-constrained SMEs (Oldemeyer et al., 2024), along with fostering digital-first mindsets and securing leadership commitment (Zavodna et al., 2024). However, significant barriers persist: cost barriers where initial investment remains prohibitive (Muminova et al., 2024); expertise gaps in AI development and maintenance (Oldemeyer et al., 2024); and trust concerns including data privacy requirements and employee resistance (Hussain & Rizwan, 2024).

Building on that, the socio-organizational context within SMEs further amplifies these challenges. Many small companies face resource constraints, lack of internal expertise, and a low level of digitalization, which prevents them from effectively using advanced AI tools (Bernardi et al., 2024). SMEs often lack the technical expertise required to fully leverage LLMs for BPM. This includes skills in prompt engineering, process mining, and the integration of LLMs into existing systems (Oldemeyer et al., 2024; Zavodna et al., 2024). In addition, the performance of LLMs in BPM is heavily dependent on the quality and availability of data. Smaller organizations often face challenges in providing high-quality training data, which can limit the effectiveness of LLMs in process modelling (Berti et al., 2024). Many BPM tools are designed for large enterprises, making them too complex for SMEs. These tools often require specialized skills and resources that SMEs lack (Papademetriou & Karras, 2017).

Another challenge lies in evaluating the quality of BPM outputs generated by LLMs. SMEs often lack established evaluation frameworks for assessing whether AI-generated diagrams meet organizational standards or align with strategic goals (Kampik et al., 2024).

Furthermore, cultural factors play a significant role in shaping how non-technical organizations perceive and adopt AI technologies. Learning and knowledge creation are integral components of BPM capabilities within people-centric areas like culture (Samuel Omokhafe Yusuf et al., 2024). However, fostering a culture that embraces technological innovation requires deliberate efforts to align organizational values with AI-driven methodologies (Bamidele Micheal Omowole et al., 2024). Finally, the adoption of LLMs in SMEs is often hindered by cost and resource constraints. While LLMs can reduce operational costs in the long run, the initial investment in tools and training can be prohibitive for many SMEs (Muminova et al., 2024; Rajaram & Tinguely, 2024)

Beyond technical and organizational challenges, LLM-powered BPM implementation raises broader ethical and security concerns that SMEs must navigate carefully.

4.4.3 Ethical Concerns

Finally, ethical and security concerns surrounding LLM-powered BPM systems are multi- faceted and demand attention across technical, organizational, and societal dimensions (Cetindamar et al., 2024; Kokala, 2024; Kunstmann et al., 2024). SMEs must navigate these challenges carefully by investing in both technological solutions and human strategies that promote fairness, transparency, and resilience against emerging threats.

Integrating LLMs into BPM systems raises concerns about accountability and transparency in decision-making processes. The inability of LLMs to consistently justify their outputs or provide traceable reasoning can lead to mistrust among users, especially in non-technical settings where stakeholders lack expertise in AI technologies (Kokala, 2024). This issue is exacerbated by the potential for biased or incomplete outputs stemming from training data limitations which reflect societal prejudices or incomplete representations of diverse populations (Cetindamar et al., 2024; Kokala, 2024).

Many organizations express discomfort with sharing internal processes with external APIs, raising questions about confidentiality and data protection (Moreira et al., 2024). Transparency in LLM operations is also a pressing issue. According to (Cetindamar et al., 2024), many employees in digital workplaces lack sufficient AI literacy, which limits their ability to understand how decisions are made by these systems. This opacity can erode trust among users and stakeholders, as they may perceive LLM-generated BPM diagrams as "black boxes" with unclear logic or reasoning. These limitations erode user trust, especially when LLMs produce outputs that are plausible but factually inaccurate, or when outputs reflect biases or inconsistencies in the training data (Bernardi et al., 2024).

The analysis of AI applications in BPM demonstrates significant potential for addressing traditional adoption barriers through automation, accessibility improvements, and reduced expertise requirements. However, these multi-dimensional challenges demonstrate that successful LLM-powered BPM adoption requires more than technical capability. It demands understanding of organizational factors, implementation strategies, and quality management approaches. This complexity motivates the empirical investigation that follows, examining how real SMEs evaluate and adopt AI-generated process models in practice.

5 Methodology

This methodology chapter establishes the research approach designed to investigate LLM-powered BPM adoption in SMEs through systematic empirical investigation. The research design (5.1) explains the qualitative case study approach and theoretical foundations that enable in-depth exploration of contemporary technology adoption phenomena. The data gathering and analysis sections (5.2-5.3) detail the multi-stage process to connect with interviewees, collect data, process combining AI model generation with stakeholder evaluation to capture both technical capabilities and organizational perceptions. Finally, the section addresses research quality assurance, ethical considerations, and AI technologies used in the process (5.4-5.6) to ensure methodological rigor and participant protection.

5.1 Research Design

This study employs a qualitative exploratory multiple case study approach to investigate the benefits, success factors, and failure factors associated with the implementation of Large Language Model (LLM)-powered Business Process Modelling (BPM) within Small and Medium Enterprises (SMEs). The research integrates a practical demonstration of LLM capabilities in generating BPMN diagrams with qualitative insights obtained through semi-structured interviews, offering a comprehensive understanding of technological impact and stakeholder perceptions. The choice of this research design aligns with the principles of qualitative case study research, which emphasizes contextual depth and real-world exploration (Yin, 2018). The AI-generated models combined with interview feedback enable the study to capture how SMEs perceive and interact with LLM-generated models in practice, highlighting both the perceived value and contextual limitations of such technologies.

This research equally adopts an interpretative research philosophy (Walsham, 1995), which considers human interpretations and meanings surrounding complex constructs like the use of computer-based IS. It is particularly well-suited for examining socially constructed perceptions and context-dependent interpretations, recognizing that stakeholders' views on technology adoption, for example, are not neutral but are deeply influenced by their specific organizational and individual contexts. It is important to understand the different technological reactions of people with different experiences with BPM and working in companies where BPM and digital maturity are different.

The research process is structured into three sequential phases. Initially, for the LLM model generation, textual process descriptions are gathered from SMEs, subsequently transformed into formal BPM diagrams using LLM technology. Following this, semi-structured interviews are conducted to qualitatively evaluate the quality, accuracy, and perceived utility of these AI-generated diagrams. Finally, findings are analysed and synthesized into a framework outlining, success factors, and failure factors, thus providing actionable insights tailored specifically to SME contexts.

Following Yin (2018) guidance on case study research, this study employs a multiple case study strategy involving three French SMEs with varying levels of digital maturity, from different activity sector. This approach enables an in-depth investigation of LLM-powered BPM adoption within real-life contexts while allowing for comparison across cases to identify patterns of success and failure factors. The multiple case study design enhances the robustness of the findings through replication logic, whereby findings that replicate across different cases carry stronger validity. With (Stake, 2006) multiple case analysis method, the design enables cross-case comparison to identify convergent and divergent adoption factors across different organizational characteristics, industries, and digital maturity levels, strengthening the validity and transferability of findings beyond individual organizational contexts. The exploratory approach follows Stebbins' (2001) guidelines for investigating emerging phenomena where existing theory provides limited predictive frameworks.

To support the empirical investigation, a tool was needed to generate BPMN diagrams from natural language descriptions. This research hence uses the framework developed by (Kourani et al., 2024) as it provides a clear, validated approach to translating textual process descriptions into BPMN-compliant models, and it aligns with the BPMN 2.0 specification, ensuring generated diagrams meet industry standards. In addition, the integration of the framework enhances the construct validity of the study by grounding the data collection process in a repeatable and standards-based procedure.

To evaluate the applicability and perceived usefulness of LLM-generated BPMN models, semi-structured interviews were conducted with key stakeholders from each participating SME. The interview approach was informed by the qualitative research methodology outlined by (Schultze & Avital, 2011), focusing on eliciting rich descriptions of participants' experiences and perceptions, as it allows to combine the interviewer’s knowledge about prior research to the interviewees' decisions about what is important and relevant to talk about, and how they choose to express themselves. This is a fundamental characteristic distinguishing them from more rigid structured interviews. Case study research is a suitable method for novel topics lacking rigorous prior knowledge or when existing theories are inadequate (Eisenhardt, 1989). Consequently, a case study employing semi-structured interviews is an appropriate approach for this paper's research.

To ensure empirical validity, the research follows established case study protocols including systematic case selection, multiple data sources, and cross-case analysis as outlined in Table 4.

Table 4. Case Study Research Process (adapted from Yin, 2018; Eisenhardt, 1989)

PHASE	DESCRIPTION	ACTIVITIES	OUTPUTS
CASE SELECTION	Identifying and selecting appropriate SME cases for the study	• Define selection criteria (size, digital maturity, BPM experience) • Contact potential participants • Confirm participation and access	Three SME cases with varying organizational characteristics
DATA COLLECTION	Gathering multiple sources of evidence from each case	• Collect existing process documentation • Generate LLM-powered BPMN models • Conduct semi-structured interviews	• Process documentation • AI-generated BPMN diagrams • Interview transcripts
WITHIN-CASE ANALYSIS	Analysing each case individually to understand unique contexts	• Apply quality assessment frameworks (SEQUAL, 7PMG) • Conduct thematic analysis of interviews • Evaluate model accuracy and completeness	• Individual case reports • Quality assessment scores • Case-specific themes
CROSS-CASE ANALYSIS	Identifying patterns and variations across all three cases	• Compare quality assessment results • Identify common themes and divergences • Map success and failure patterns	• Cross-case patterns • Common success factors • Shared barriers
SHAPING HYPOTHESES	Synthesizing findings into practical guidance	• Integrate findings across dimensions • Develop Multi-Factor Alignment Framework • Validate against existing literature	• Multi-Factor Alignment Framework • Implementation recommendations

5.2 Data analysis

The analysis of qualitative data collected through semi-structured interviews employs a systematic hybrid approach combining Framework Analysis and Thematic Analysis, following established methodological guidelines for rigorous mixed-methods research in information systems (Venkatesh et al., 2016). This analytical strategy is specifically designed to address the multi-dimensional nature of AI-BPM adoption factors while maintaining theoretical grounding through pre-existing frameworks and additional insights as it is an emergent field.

The primary analytical structure follows the Framework Method originally developed by Ritchie and Spencer (1994) for applied policy research, which has proven particularly effective for research contexts presenting organization of diverse qualitative data (Gale et al., 2013). It was selected as it enables the analysis across multiple cases, while keeping the connection to existing theoretical knowledge and constructs. More particularly to our research as we validate the LLM generated model against TOE, SEQUAL and 7PMG frameworks.

The Framework Analysis process follows the five-stage approach outlined by (Gale et al., 2013):

1. Familiarization: The researcher immerses in the raw data through reading and listening of the interview transcripts and recording, to gain an initial understanding of content and content.

2. Identification of a Thematic Framework: Development of an initial analytical framework based on the study's theoretical foundations (TOE framework, SEQUAL dimensions, 7PMG guidelines) combined with issues emerging from the data. This ensures an both inductive and deductive approach.

3. Indexing: The researcher applies the thematic framework to all data through line-by-line coding, identifying portions of data that correspond to particular themes or concepts within the framework.

4. Charting: Creation of thematic matrices for each case and across cases, organizing summarized data by theme and case to enable systematic comparison and pattern identification.

5. Mapping and Interpretation - Analysis of the charted data to identify patterns, associations, concepts, and explanations, drawing on both the original theoretical frameworks and emergent insights from the data.

Within the Framework Analysis structure, Reflexive Thematic Analysis following (Braun & Clarke, 2006) is employed to identify, analyse, and interpret patterns of meaning within and across the framework categories, allowing inductive research for emergent themes.

Moreover, in alignment with mixed-methods research principles the analysis integrates quantitative assessments of BPM diagram quality (using 7PMG and SEQUAL measures) with qualitative stakeholder perceptions (Venkatesh et al., 2016). This integration follows a convergent parallel design where quantitative and qualitative data are analysed separately and then merged during interpretation to provide comprehensive understanding of AI-BPM effectiveness and adoption potential.

5.2.1 Theoretical Frameworks

The study utilizes the SEQUAL framework by (Krogstie et al., 2006) to comprehensively evaluate the quality of conceptual BPM models (technical evaluation). SEQUAL was chosen because it systematically assesses multiple quality dimensions, including semantic accuracy, stakeholder comprehensibility, social agreement, visual clarity, and syntactic adherence to BPMN standards. The Technology-Organization-Environment (TOE) framework by (Tornatzky & Fleischer, 1990) is employed to categorize and analyse contextual factors influencing the adoption of LLM-powered BPM (organizational evaluation). This framework is particularly suitable because it covers technological characteristics, organizational capabilities, and external environmental pressures. Additionally, the Seven Process Modelling Guidelines (7PMG) framework by (Mendling et al., 2010) is integrated to objectively assess technical aspects of BPM diagrams, ensuring clarity, simplicity, structured modelling, and compliance with established best practices (objective assessment).

5.2.2 Quality Assessment Methodology

The technical quality evaluation of AI-generated BPMN models employed two established frameworks applied through systematic scoring procedures to ensure rigorous and consistent assessment across all cases.

Each generated model was evaluated against the seven guidelines established by Mendling et al. (2010) detailed in Section 4.2.2. The assessment employed a standardized 5-point compliance scale: 1 = Poor compliance (significant violations of the guideline), 2 = Below average (multiple violations with some adherence), 3 = Average (moderate compliance with some violations), 4 = Good (strong compliance with minor violations), 5 = Excellent (full compliance with guideline requirements). The researcher systematically examined each BPMN diagram against specific criteria including element count (G1), routing complexity (G2), start/end event usage (G3), structural organization (G4), gateway types (G5), activity labelling conventions (G6), and model decomposition (G7).

For the SEQUAL Framework Assessment, models were evaluated across three quality dimensions established by Krogstie et al. (2006) and detailed in Section 4.3, using the same 5-point scale. Syntactic quality (correctness) assessed adherence to BPMN 2.0 notation rules and structural requirements. Semantic quality (completeness) evaluated the accuracy and comprehensiveness of process representation compared to actual organizational workflows. Pragmatic quality (usability) measured model comprehensibility, visual clarity, and practical utility for stakeholder communication and decision-making.

All assessments were conducted by the researcher through structured analysis combining visual diagram examination, process logic evaluation. Each guideline and quality dimension were scored independently to prevent bias between assessments. Detailed scoring rationales were documented to ensure consistency and transparency. The scoring was conducted immediately following model generation and prior to stakeholder interviews to prevent interview insights from influencing technical assessments.

Inter-rater reliability assessment was not feasible due to resource constraints and the specialized nature of both BPM expertise and organizational process knowledge required for accurate evaluation. This represents a potential source of bias, mitigated through systematic application of established frameworks and transparent documentation of scoring criteria. The single-evaluator approach is acknowledged as a limitation addressed in Section 7.6.

5.2.3 Software-Assisted Analysis

Qualitative data analysis is helped by NVivo 12 software to manage large volumes of interview data systematically and maintain data integrity. The software facilitates the creation of framework matrices, coding consistency checks, and visual mapping of relationships between themes and cases. However, software is used as a tool to support rather than replace analytical thinking and interpretation (Gale et al., 2013).

The analytical approach outlined above provides a robust foundation for addressing the study's research objectives while maintaining methodological rigor. The combination of framework and thematic Analysis ensures both systematic organization of findings according to established theoretical constructs and sensitivity to emergent insights that may inform future research and practice in AI-powered business process modelling.

5.3 Data gathering

5.3.1 Case study selection

For participant selection, the researcher working as an ERP implementation consultant for SMEs, invitations were sent to the 9 (out of 12) customers of the company, who were respecting the criteria to be part of the case-study selection. Some of the criteria considered were the following:

1. Size (employees): the company must be between 10 and 250 employees to be considered an SME
2. Digital Maturity: the criteria was defined according to the technology readiness of the company: low (basic IT), medium (some digital tools), high (integrated systems). The participating companies should have low or medium digital maturity to ensure alignment with the research problem.
3. BPM Experience: the criteria were defined according to the adoption readiness of the organizations: low (no, or informal tools), medium (formal processes developed by non-specialists), high (formal processes produced by specialized staff). Only companies with low or medium BPM experience were selected to ensure alignment with the research problem focusing on early-stage digitalisation

Many companies were interested in the research, however, did not have enough documentation to provide, and did not have the time resources to provide them. Out of the 9 companies, 3 accepted to be part of the research. Interview participants within each SME were selected based on their direct involvement in process management and decision-making roles, ensuring that insights captured reflect both operational and strategic perspectives. To preserve anonymity, the research will refer to the interviewees by pseudonyms (SME A, SME B, SME C) They are listed in the Table 5.

Table 5. Overview of interviewees

SME	PARTICIPANT ROLE	INDUSTRY	COMPANY SIZE	DIGITAL MATURITY	BPM EXPERIENCE	INTERVIEW DURATION
A	Project Manager	IT Consulting	15-25 employees	Medium	Low	50 minutes

B	Operations Manager	Manufacturing (Footwear)	150-200 employees	Medium	Medium	45 minutes
C	Operations Manager	Manufacturing (Perfume)	10-15 employees	Medium	Low	104 minutes

Following (Eisenhardt, 1989) guidance for theory-building case studies, this research employs three SME cases, which falls within the recommended range of 4-10 cases but is justified by the exploratory nature of AI-BPM research and time constraints typical in master research. The heterogeneous nature of SME contexts and the structured framework analysis approach support the adequacy of three diverse cases for initial theory development.

The following case descriptions establish the organizational contexts that shape stakeholder perspectives and adoption capabilities. These diverse SME environments, spanning consulting services and manufacturing industries, provide the empirical foundation for understanding how different organizational characteristics influence AI-BPM evaluation and implementation potential.

SME A is an IT consulting firm representing a knowledge-intensive service organization with 15-25 employees specializing in ERP implementation. The organization possesses medium digital maturity through regular project management tools but lacks formal process documentation, operating through informal, expert-centric knowledge transfer. This creates dependency risks and inconsistent service delivery that are common SME challenges. Their client-facing role in digital transformation provides unique perspectives on process modelling value propositions, as they regularly encounter other SMEs struggling with similar documentation challenges. The participant, serving as Project Manager, brings direct experience with ERP implementation processes and project coordination, offering insights into both internal process management needs and client communication requirements.

SME B is a traditional footwear manufacturing company with 150-200 employees, representing the larger end of the SME spectrum. This family-owned business combines traditional craftsmanship with modern production techniques, creating high-end leather shoes through omnichannel distribution including owned boutiques, e-commerce, and wholesale networks.

The organization demonstrates medium digital maturity with enterprise systems in place but faces adoption challenges due to system complexity and inadequate training. Uniquely among the three cases, SME B has previous experience with formal process modelling, having invested approximately 40 hours in comprehensive process mapping exercises. The participant, serving as

Operations Manager, oversees production, logistics, and quality management, providing operational perspectives on process accuracy requirements.

SME C is a perfume and fragrance manufacturer representing a creative manufacturing organization with 10-15 employees operating in the luxury fragrance sector. The company creates custom olfactory products for both B2B and B2C markets, emphasizing flexibility, customization, and rapid response to client requirements. The organization faces significant regulatory complexity due to dangerous materials handling, safety data sheet management, and international shipping regulations. SME C demonstrates the highest organizational dynamism among the three cases, with frequent role changes, high staff turnover, and constantly evolving structures that challenge traditional process standardization approaches. The participant, serving as Operations Manager, has attempted process mapping initiatives that became obsolete due to organizational changes, providing insights into the relationship between organizational stability and process modelling effectiveness.

5.3.2 Data collection process

Process data collection was conducted through structured documentation requests, explicitly justified by the need to obtain comprehensive, accurate, and context-rich descriptions of SME business processes. These data included textual narratives, existing documentation, and detailed organizational context information. Knowing that the data would be structured for optimal LLM input (Kourani et al., 2024), and to capitalize on existing documentation, organizations procured existing descriptions of their processes. Internal interviews, excel documentation and audit specifications were transmitted by the companies.

The LLM-powered BPM generation process utilized diverse input documents from the three participating SMEs, varying significantly in structure, format, and content clarity. Appendix A provides a comprehensive overview of all input documents categorized by case, type, content, and structural quality rating.

5.3.3 LLM-generated model creation

The AI-powered BPM generation utilized a structured approach adapted from Kourani et al. (2023), justified by its rigor in ensuring BPMN 2.0 compliance and maximizing the accuracy of LLM-generated diagrams through precise prompt engineering. Here are the steps of the framework:

1. Data preparation: Structuring the collected process information for optimal LLM input

2. Prompt engineering: Developing precise prompts that guide the LLM to generate accurate BPMN 2.0 compliant diagrams

3. Model generation: Using the LLM to generate the BPM diagrams

4. Post-processing: Converting the LLM output into formal BPM notation using specialized BPM software

The prompt design followed principles that improve the accuracy of structured outputs from LLMs. This prompt was iterated base on pilot testing and the consistency was tested across 5 sample processes.

- The LLM-generated models generation employs GPTo4-mini with the following configuration:

- Temperature setting: 0.1 (to ensure consistency and reduce randomness)

- Top-p: 0.9 (balance between creativity and determinism)

- BPM visualization software used: Camunda

The parameters were selected based on preliminary testing to optimize for accuracy and consistency in BPMN generation while minimizing hallucinations or structural errors. Some excerpts of the prompt can be found in the table 6, and the example of input and output can be found in the Appendix B.

Table 6. Prompt used for BPM generation

Task: You are a BPM consultant with 10 years of experience. Generate a BPMN 2.0 compliant business process model from the following process description. Process name: [Process Name] INSTRUCTIONS: 1. Follow BPMN 2.0 notation standards precisely. 2. Identify all actors/roles involved and create appropriate swimlanes. 3. Create a single start event and appropriate end event(s). 4. Identify all activities and represent them as tasks or sub-processes as appropriate. 5. Identify decision points and represent them using appropriate gateways (exclusive, parallel, inclusive). 5.b. For each main activity identified, consider and model possible exceptions or error paths that might occur, including how the process handles these exceptions. 6. Follow the Seven Process Modeling Guidelines (7PMG): - Use as few elements as possible

- Minimize routing paths per element
- Use one start and one end event
- Model as structured as possible
- Avoid OR routing elements when possible
- Use verb-object activity labels
- Decompose the model if it has more than 50 elements

7. Ensure semantic correctness (the model accurately represents the process described)
8. Ensure syntactic correctness (the model follows BPMN 2.0 rules)
9. Output the model as a text-based representation that can be directly imported into BPMN software.

PROCESS DESCRIPTION:
Before generating the complete BPMN diagram, identify and list all potential sub-processes in this business process that could be modeled separately.
[Insert detailed process description here]

PROCESS CONTEXT:
- Key stakeholders: [List stakeholders]
- Systems used: [List systems]
- Organizational context: [Brief organizational context]

OUTPUT FORMAT:
Provide the output in a format that represents BPMN elements with their properties and connections, maintaining proper sequence flows, message flows, and gateway logic.

VALIDATION AGAINST ERRORS:
Check the generated model for the following common errors and correct if found:
- Disconnected elements
- Missing end events
- Improper gateway matching (splits without corresponding joins)
- Ambiguous decision logic
- Unclear activity labels

5.3.4 Semi-structured Interviews

Following the generation of BPM diagrams, semi-structured interviews were conducted with key stakeholders from each participating SME. The interview approach was informed by the qualitative research methodology outlined by Schultze & Avital (2011), focusing on eliciting rich descriptions of participants' experiences and perceptions. The semi-structured format allows participants to express their perspectives in their own terms while maintaining sufficient structure to enable cross-case comparison and analysis.

Semi-structured interviews were selected for data collection method as they provide the flexibility to explore emerging themes (inductive research), while ensuring that all the dimensions from the frameworks were covered (deductive research) ((Bryman, 2016). This approach is suited to case study research, as it enables rich, contextual data collection essential for understanding complex phenomena in their natural settings (Yin, 2018; Eisenhardt, 1989).

The interview guide (Appendix C) was structured around three main thematic sections, each designed to address specific research objectives: (1) an opening section to gather contextual information, and introducing definitions to ensure the interviewer and interviewees were on the same page, (2) a section that assessed organizational context and current practices, (3) participants were asked to review the diagrams and provide detailed feedback on accuracy, completeness, clarity, and usability, and finally (4) a section on perceived benefits, and utility assessment for future implementation.

All the interviews were recorded with the interviewees' consent and took place physically and through video conferencing. Each interview lasted between 45-100 minutes (average 65 minutes), to allow sufficient time to cover all the thematic areas, while respecting time constraints of the interviewees. Moreover, the interview questions, and the produced process diagram were sent prior to the interviews to let the interviewees get familiar with the questions.

5.3.5 Data Analysis Methods

Thematic analysis, following Braun and Clarke's (2006) structured approach, was employed to systematically identify and refine themes from interview data. This analytical method is justified for its clarity, replicability, and flexibility in capturing complex qualitative data. Cross-case analysis, as recommended by Miles and Huberman (1994) and Stake (2006), was performed to uncover broader patterns and variations across different SME contexts, justified by its capacity to enhance the explainability of the phenomenon and robustness of findings. The quality assessment of BPM diagrams combined elements from SEQUAL and 7PMG frameworks, justified by the comprehensive and structured evaluation provided through these combined frameworks.

5.4 Research Quality

Research quality was ensured through multiple strategies designed to enhance the validity and reliability of findings. Triangulation of data sources was achieved through the integration of documentary evidence (existing process descriptions), AI-generated models, and stakeholder interviews, providing multiple perspectives on the same phenomena and confirming the validity of findings. Interview transcripts were provided to participants for review and validation, allowing them to clarify, correct, or expand upon their responses. This member checking process ensures accurate representation of participant perspectives and reduces researcher misinterpretation (Lincoln, 1995).

The case study design followed established protocols including systematic case selection, structured data collection procedures, and cross-case analysis to enhance the robustness and transferability of findings (Yin, 2018).

5.5 Ethical Considerations

Ethical considerations were addressed through comprehensive data protection and participant confidentiality measures. All participating organizations were assigned pseudonyms (SME A, SME B, SME C) used consistently throughout data collection, analysis, and reporting. Organizational identifying information was removed from process descriptions and BPM diagrams, while location and industry details were generalized to prevent identification while maintaining analytical relevance.

Interview recordings, transcripts, and analytical files were stored on encrypted, password-protected devices with restricted access. Participants provided informed consent for both interview participation and audio recording. Data will be retained for a maximum duration of 5 years, following university research data management policies, after which it will be securely destroyed.

Having established the research approach and data collection procedures, the next section presents the empirical findings that address the research question about benefits, success factors, and failure factors of LLM-powered BPM implementation in SMEs.

5.6 AI Tools and Technologies Used

This research utilized GPT-4 mini for generating BPMN process models from organizational descriptions (detailed in Section 5.3.3), GPT-4 and Claude 3.5 Sonnet for writing enhancement and structural improvements, NotebookLM for literature analysis, and SciSpace for a first article discovery. All AI tools served as research assistance rather than content generation, with the author maintaining full responsibility for analysis, interpretation, and conclusions.

6 Results

This chapter presents findings organized to directly address the research question about benefits, success factors, and failure factors of LLM-powered BPM in SMEs. The structure moves from technical capability assessment to organizational adoption insights, to allow understanding of both technological performance and stakeholder acceptance. The analysis begins with technical quality assessment of AI-generated models (4.1) to establish baseline capabilities using established frameworks (7PMG, SEQUAL). The chapter then presents stakeholder perceptions and experiences through detailed case studies (4.2) to understand how SMEs evaluate AI-generated models in practice. The input quality impact analysis (4.3) explains variation in technical results, while cross-case analysis identifies patterns and variations across different organizational contexts. This progression from technical assessment to organizational insights provides the empirical foundation for answering the research question.

6.1 LLM-Generated Model Overview and Technical Quality Assessment

Using the structured prompt engineering framework adapted from Kourani et al. (2024), three BPMN 2.0 compliant process models were generated corresponding to each SME's core business processes:

- **SME A**: ERP Implementation Process (Appendix D)
- **SME B**: Raw Materials Reception Process (Appendix E)
- **SME C**: Custom Product Development Process (Appendix F)

This technical assessment establishes the baseline capabilities of LLM-generated process models using objective quality frameworks. The 7PMG evaluation (4.1.1) measures compliance with established modelling guidelines, while the SEQUAL assessment (4.1.2) evaluates syntactic, semantic, and pragmatic quality dimensions. These assessments provide the technical foundation for understanding AI capabilities and limitations that influence organizational adoption decisions.

6.1.1 Seven Process Modelling Guidelines (7PMG) Evaluation

The technical assessment of AI-generated BPM models reveals consistent patterns across all three cases. Table 7 summarizes the 7PMG compliance scores for each case.

Table 7. 7PMG compliance assessment summary

GUIDELINE	SME A SCORE	SME B SCORE	SME C SCORE	AVERAGE	KEY FINDINGS

G1: USE AS FEW ELEMENTS AS POSSIBLE	2/5	2/5	2/5	2.0	Consistent over-complexity with ~21-35 elements; redundant intermediate events
G2: MINIMIZE ROUTING PATHS PER ELEMENT	3/5	2/5	3/5	2.7	Some gateways with 3-4 paths; message flows increase cognitive load
G3: ONE START AND ONE END EVENT	1/5	1/5	1/5	1.0	Universal violation with multiple start/end events per swimlane
G4: MODEL AS STRUCTURED AS POSSIBLE	3/5	2/5	2/5	2.3	Cross-lane flows break structure; limited subprocess decomposition
G5: AVOID OR ROUTING ELEMENTS	5/5	5/5	5/5	5.0	Perfect compliance: only XOR and parallel gateways used
G6: USE VERB-OBJECT ACTIVITY LABELS	5/5	5/5	5/5	5.0	Excellent labelling consistency across all models
G7: DECOMPOSE IF >50 ELEMENTS	5/5	5/5	1/5	3.7	Models under 50 elements except SME C (>70 elements)

6.1.1.1 Universal Strengths Across All Cases

The technical assessment revealed two areas where AI-generated models consistently achieved excellence across all three organizational contexts, demonstrating reliable LLM capabilities that transcend industry differences and input document variations. Most notably, every model achieved perfect compliance with verb-object activity labelling conventions, creating task descriptions that followed clear, professional patterns such as "Review Macro-Process," "Receive Delivery Note and Materials," and "Qualify Lead.". The systematic application of this naming convention represents a substantial improvement over traditional process documentation approaches that often suffer from vague or inconsistent terminology.

Gateway type selection emerged as another universal strength, with the LLM consistently demonstrating disciplined routing element choices that avoided common semantic pitfalls. All models exclusively employed XOR (exclusive) and AND (parallel) gateways while completely avoiding problematic OR-routing elements that typically create implementation challenges and semantic ambiguities in traditional process modelling efforts. This selective approach eliminates the confusion often associated with inclusive gateways, where process executors struggle to determine appropriate pathway selection criteria, representing a significant technical achievement that enhances both model clarity and implementation feasibility.

6.1.1.2 Universal Weaknesses Across All Case studies

Despite these strengths, the assessment identified two systematic deficiencies that affected every AI-generated model regardless of organizational context or input quality, suggesting fundamental limitations in current LLM process modelling capabilities. The most significant technical deficiency involved consistent violation of the single start/end event principle, with each model containing 4-6 separate start/end event pairs distributed across individual swimlanes rather than maintaining unified process boundaries. This pattern fundamentally contradicts BPMN best practices and creates substantial confusion about overall process scope, triggering conditions, and completion criteria that participants consistently noted during evaluation sessions.

Element proliferation represented the second universal weakness, manifesting as systematic over-specification that generated unnecessary complexity throughout all models. This tendency appeared as excessive intermediate events that added no semantic value, redundant message flows that complicated visual interpretation, and tasks that could have been logically consolidated into simpler activity groupings. Particularly concerning, this pattern emerged regardless of input document structure or organizational complexity, suggesting a systematic LLM bias toward detailed specification rather than elegant simplification. The consistency of this over-specification tendency across diverse contexts indicates that current AI approaches may inherently struggle with the abstraction and consolidation judgments that characterize effective process modelling, requiring human intervention to achieve optimal model complexity levels.

6.1.2 SEQUAL Framework Assessment

The SEQUAL evaluation assesses AI-generated models across three established quality dimensions (Krogstie et al., 2006): syntactic quality (correctness: adherence to BPMN notation rules), semantic quality (completeness: accuracy in representing real-world processes), and pragmatic quality (usability: understandability and usability for stakeholders). These dimensions provide a comprehensive framework for evaluating both technical correctness and organizational utility of AI-generated process models. Table 8 summarizes the SEQUAL scores across all three cases.

Table 8. SEQUAL compliance assessment summary

QUALITY DIMENSION	SME A SCORE	SME B SCORE	SME C SCORE	AVERAGE	KEY CHARACTERISTICS
SYNTACTIC QUALITY	2/5	3/5	2/5	2.3	Multiple start/end events; inconsistent flow notation; some gateway misuse
SEMANTIC QUALITY	3/5	2.5/5	3/5	2.8	Good high-level accuracy; missing exception paths and role nuances

PRAGMATIC QUALITY	3/5	2/5	3/5	2.7	Clear labelling aids understanding; complexity hinders usability

6.1.2.1 *Syntactic Quality (Correctness) Assessment*

The technical assessment revealed systematic BPMN compliance challenges that affected all three AI-generated models despite their different organizational contexts and input document structures. Most significantly, every model violated fundamental process boundary principles by generating multiple start and end events rather than the single process initiation and termination points prescribed by BPMN 2.0 standards. This pattern manifested as 4-6 separate start/end event pairs distributed across swimlanes, creating confusion about overall process scope and triggering conditions that participants consistently noted during evaluation sessions.

Message flow notation presented another recurring challenge, with approximately 60% of inter-swimlane communications exhibiting inconsistencies that compromised model interpretability. These issues ranged from completely unlabelled arrows to ambiguously placed directional indicators that left stakeholders uncertain about information exchange patterns between organizational roles. Gateway pairing violations further complicated the syntactic landscape, as exclusive and parallel splits frequently lacked corresponding join gateways, creating incomplete control flow logic that fundamentally contradicts BPMN structural requirements.

Within this pattern of universal challenges, SME B's raw materials reception process emerged as the relative technical leader, achieving a syntactic quality score of 3/5 compared to the 2/5 scores recorded for SME A and SME C. This superior performance stemmed primarily from more consistent application of core BPMN elements and reduced visual complexity in message flow arrangements. However, even this highest-performing model exhibited the universal start/end event violation, reinforcing the conclusion that these issues reflect systematic LLM limitations rather than input-specific problems that individual organizations might address through improved documentation strategies.

6.1.2.2 Semantic Quality (Completeness) Assessment

The semantic evaluation revealed a nuanced quality profile characterized by strong macro-level process capture coupled with systematic gaps in operational detail and exception handling. All three models demonstrated remarkable capability in extracting and representing primary process logic from textual descriptions, successfully identifying approximately 90% of major process steps and sequencing them according to actual organizational workflows. This high-level accuracy extended to stakeholder role identification, where the AI achieved perfect recognition of primary organizational functions and assigned them to appropriate swimlanes that reflected genuine responsibility distributions within each SME.

However, this macro-level success masked significant deficiencies in representing the operational complexity that defines real-world business execution. Exception handling and error management processes were systematically under-represented, with critical operational procedures either completely omitted or oversimplified to the point of misrepresenting actual business reality. SME B's model particularly illustrated this limitation by excluding quality control rejection workflows and supplier non-compliance procedures that typically represent 15-20% of actual operational activity, while SME C's regulatory compliance requirements, including mandatory safety data sheet generation and transport documentation, were entirely absent despite their legal necessity for business operations.

The role representation challenges extended beyond simple omission to fundamental misunderstanding of organizational dynamics. While major functional areas were correctly identified, the models consistently collapsed detailed responsibility hierarchies and decision-making authorities into broad functional swimlanes, losing critical organizational nuances that affect actual process execution. Decision-making authority distinctions between operational staff and management approval levels were inadequately captured, while the informal communication channels and cross-functional collaboration patterns that characterize SME operations were reduced to formal message flows that may not reflect authentic organizational behaviours.

6.1.2.3 Pragmatic Quality (Usability) Assessment

The pragmatic quality evaluation revealed a fundamental tension between individual element clarity and overall model complexity that significantly influenced stakeholder comprehension and utility perceptions. AI-generated models achieved strong baseline comprehensibility through consistent structural organization and exceptionally clear element labelling, with perfect compliance with verb-object activity naming conventions creating unambiguous task descriptions that enhanced stakeholder understanding across all organizational levels. The swimlane organization proved particularly effective, providing intuitive role-responsibility mapping that participants immediately recognized and appreciated, with SME B's participant describing the models as "clear and accessible" for general process understanding purposes.

Despite these comprehensibility strengths, overall model complexity created significant barriers to detailed understanding and practical implementation. The combination of excessive element counts, ranging from 21-35 elements per model, and multiple start/end events generated cognitive overload that participants across all cases identified as obstacles to thorough comprehension. This complexity manifested in practical ways, with SME A's participant specifically requesting "a legend to know what the difference was between solid arrows and dotted arrows," indicating that BPMN notation complexity exceeded non-expert stakeholder capabilities for detailed process analysis. The proliferation of intermediate events and crossing message flows further reduced model effectiveness as communication tools, creating visual clutter that participants noted obscured rather than clarified process understanding for operational implementation purposes, despite the clarity of individual process elements.

While technical quality assessment provides objective baseline capabilities, stakeholder perceptions reveal how these capabilities translate into organizational value and adoption potential.

6.2 Stakeholder Perceptions and Experiences

Moving from technical assessment to organizational perspectives, this section presents stakeholder evaluation of AI-generated models within real SME contexts. The analysis examines traditional documentation experiences (4.2.1) to establish baseline process management approaches, then analyses stakeholder evaluation of AI-generated models (4.2.2) to understand accuracy and completeness perceptions. The examination of perceived benefits and challenges (4.2.3-4.2.4) reveals adoption drivers and barriers, while future adoption considerations (4.2.5) indicate implementation potential. Cross-case analysis (4.2.6) identifies patterns across diverse organizational contexts.

6.2.1 Traditional Documentation and Modelling Experience

The three participating SMEs demonstrate different process documentation maturity that reflects the diverse approaches and challenges characterizing small and medium enterprises in their attempts to formalize organizational knowledge. These varied approaches reveal both the adaptive strategies SMEs employ to manage operational complexity and the fundamental constraints that limit their adoption of traditional BPM methodologies.

SME A represents the informal end of the process documentation spectrum, operating through what can be characterized as expert-centric knowledge transfer. The participant's description captures this approach:

> Everyone does their own thing with [Project Director]'s expertise. So, it's a bit [Project Director]'s method, but with each person's touch for their own processes.

According to Participant A, this approach generates significant vulnerabilities during staff transitions and creates inconsistent service delivery as individual interpretations of processes diverge over time. The organization's struggle with newcomer integration, described as learning *"drop by drop when we need them"*, illustrates the scalability limitations of purely informal knowledge transfer systems.

SME B occupies the middle ground with attempted formal documentation that faces sustainability challenges. The organization's investment of approximately 40 hours with multiple stakeholders in comprehensive process mapping demonstrates both capability and commitment to formal process documentation. However, their experience reveals critical maintenance challenges that limit the long-term value of traditional BPM investments. The participant acknowledged that time consumption to produce a model covering only one subprocess, was too demanding that they need to keep documentation current amid organizational changes and staff turnover proves difficult.

SME C represents the most complex documentation challenge, operating in an environment where traditional process standardization conflicts with operational requirements. The participant's observation:

> "We have more exception cases than rules... the organizational chart changes really very often"

It illustrates how dynamic business environments can fundamentally undermine static process documentation approaches. The participant's attempts at process mapping, which became obsolete as soon as organizational structures changed, demonstrate the fundamental mismatch between traditional BPM assumptions of stable organizational structures and the reality of many SME operating environments.

6.2.2 AI-Generated Model Evaluation

6.2.2.1 Semantic Quality Assessment by Stakeholders

Stakeholder evaluation across all three SMEs revealed a fundamental dichotomy in semantic quality: while AI-generated models demonstrated strong capability in capturing macro-level process flows and organizational structures, they systematically failed to represent the operational complexity that defines real-world business execution.

All participants immediately recognized their core business processes within the generated models, confirming the AI's ability to extract and represent primary process logic from textual descriptions. SME A's participant noted the accuracy of basic project management sequences, SME B acknowledged correct material reception workflows, and SME C identified accurate high-level custom product development stages. However, this surface-level recognition masked profound gaps in operational detail. Furthermore, the messages and their nature were not covered in enough depth for SME B and SME C. SME C's participant most succinctly captured this limitation:

> "It seems much simpler to me than it is in reality [...] looking at the model, I have the impression there aren't so many interactions between the different services, whereas in real life there are more than that."

At the macro level, some processes disappeared completely. For example, while the basic project management flow was captured for SME A, essential elements such as training phases, detailed communication protocols and iterative development cycles were absent. This was especially evident for SME C, where regulatory and compliance requirements were completely omitted.

> "There's a whole info transfer flow for the regulatory part missing. Once we have our validated concentrate BAT, we're supposed to send a sample to the subcontractor who will do the filling, who himself makes the concentrate safety data sheet"

For all the participants, exception handling and error recovery processes were universally absent from all models. SME A highlighted missing iterative development cycles and rework loops essential for ERP implementation, while SME B identified absent quality control exception paths that represent significant operational risks in manufacturing environments, with some processes entirely absent due to lack of exception handling representation.

> "For example, there's a missing link between accounting and the purchasing service when there are - when there are RNCs, so these are returns for non-compliance, because we find it from the supplier to accounting when they send an invoice, but if there's a return for non-compliance, it must generate a credit note"

Finally, SME A found that temporal relationships and process timing were inadequately represented:

> "It lacks a temporality dimension... we have the impression that everything is done in parallel when that's not true."

These semantic gaps reveal that while LLMs can process textual process descriptions effectively, they lack the domain-specific knowledge and operational understanding necessary to capture the full complexity of business process execution. The models represent idealized, linear interpretations of processes that may satisfy documentation requirements the main processes but fall short of operational reality and completeness.

6.2.2.2 Pragmatic Quality Assessment by Stakeholders

All participants found the AI-generated models relatively easy to understand at a surface level, with consistent recognition of their visual effectiveness compared to traditional documentation approaches. SME A's participant stated the models are "*quite simple to understand*" due to their streamlined presentation. SME B's participant noted that "*the diagram is clear, honestly*" and appreciated that "*it's distributed by service, which when you do flow mapping behind to see how information circulates is relevant*." The visual representation received particularly positive feedback compared to text-based alternatives. The following quotes support this notion:

> "This model of presentation, it's clear, it's accessible and easily understandable... I find it's better than in text, because it allows to have visibility that's really a view from above."

> "Much more efficient in diagram form like that than if it were a note to read where there would necessarily be many things to evoke, and so I think there would be many diagonal readings and so... oversights due to skimming the information note."

While participants B1 and C1 could understand the overall process flow, Participant A1 struggled with specific BPMN notation elements - arrows, symbols, gateways. This created a gap between general comprehension and technical precision.

> "I looked for a legend to know what the difference was between solid arrows and dotted arrows... the circles, I didn't know what they corresponded to."

Participants generally agreed that colleagues would understand the basic process representations, though with varying degrees of confidence about consensus-building potential. SME B assessed that the models provide sufficient information for general understanding:

> "I think it's sufficient because not everyone needs the same degree of information. If there the objective is just to understand in broad lines what are the main flows... well, actually yes, it's somewhat sufficient."

However, a clear distinction emerged between the models' effectiveness for communication purposes versus operational implementation. All participants made this distinction, with SME A providing the most explicit assessment. When asked if the model would be sufficient for internal process consensus-building, SME A stated:

> "As is, no. If it's for internal use, no, it's good for explaining to clients what's going to happen, but in internal functioning, no, there are too many things missing."

To conclude, the high-level abstraction that makes models easy to understand also makes them insufficient for detailed operational guidance. SME B particularly, questions the abstraction of the model:

> "It's quite clear because it's quite macro, we don't go into detail. I really go on the big steps of a classic ERP integration. […] it's quite clear, but it is not what I need.

The cognitive load assessment showed mixed results. Participants appreciated the reduction in complexity compared to comprehensive process documentation, but several noted that the oversimplification created false impressions of process ease and linearity. This could potentially mislead stakeholders about actual implementation requirements and operational challenges.

6.2.3 Perceived Benefits and Value Propositions

The stakeholder interviews revealed significant perceived benefits that could fundamentally transform how SMEs approach process understanding and organizational communication. Despite technical limitations, participants identified compelling value propositions that address core SME challenges in process management and knowledge transfer.

The most significant perceived benefit centered on accelerating organizational learning and reducing the steep learning curves that characterize SME environments. All participants recognized the potential for dramatically improving newcomer integration and reducing the time required to achieve operational autonomy. SME A's participant articulated this transformative potential:

> "If it were more exhaustive, I think we'd be less lost when arriving. We'd be more autonomous more quickly... we would maybe also lose less time when you arrive, you take a ticket you don't know."

This benefit addresses a critical SME challenge where informal knowledge transfer creates bottlenecks and inconsistencies in operational capability development.

The communication enhancement dimension revealed particularly strong value recognition for external stakeholder management. Participants across all SMEs identified significant potential for improving client confidence and project transparency through visual process communication. SME B emphasized how process visualization could transform client relationships:

> "It would also increase client confidence, I think, because if we have regular exchanges, understanding, alignment of what the project should be, how we do it."

This capability addresses a fundamental SME competitive disadvantage compared to larger organizations with established process communication protocols.

Beyond external communication, participants recognized internal governance benefits that could address persistent SME challenges in decision-making coordination and project management effectiveness. SME C identified how process modelling could fundamentally improve organizational coordination:

> "Thanks to all these milestones that are specified, we could more easily say OK, there I know I must make an instance for this subject, that will unblock this step for me. This would […] allows us to be efficient, to stay close, to be efficient in managing this just-in-time."

This structured approach could replace the ad-hoc decision-making that characterizes many SME operations with more systematic, milestone-driven project governance. Moreover, participant A recognized that process standardization could provide operational advantages:

> "If there's a real framework in place and all people know the framework and apply it, actually, standardizing will simplify processes."

This could lead to time and energy savings through reduced ad-hoc decision-making.

6.2.4 Implementation Challenges and Barriers

6.2.4.1 Technical and Quality Concerns

The stakeholder evaluation revealed profound concerns about AI reliability and accuracy that represent the most significant barrier to LLM-powered BPM adoption in SMEs. These concerns extend beyond simple technical scepticism to fundamental questions about organizational risk management and quality assurance capabilities within resource-constrained environments.

All participants expressed deep reservations about trusting AI-generated models for critical business processes, with concerns intensifying when considering operational decision-making applications. SME A's participant captured the fundamental trust challenge:

> "Trust in AI today, it's quite weak, unless it's quite simple things, but process modelling in the company, I think we'd need to go verify because there are maybe things that aren't square on paper and that aren't really in real life."

This scepticism reflects legitimate concerns about the potential consequences of process modelling errors in operational environments where mistakes can directly impact customer relationships, regulatory compliance, and financial performance.

The human verification requirement emerged as a universal finding that potentially undermines the efficiency value proposition of AI-generated modelling. SME C's participant emphasized this necessity:

> "Human verification and editing of models before implementation... It must be done, it's an obligation."

This requirement creates additional resource demands that may offset the time and cost savings that represent primary motivations for AI adoption in SME contexts. The verification burden becomes particularly challenging for SMEs lacking specialized process modelling expertise, potentially requiring external consulting support that negates cost advantages.

Quality assurance capabilities represent a critical organizational barrier that emerged across all cases. Participants questioned their organizations' ability to systematically evaluate AI-generated models and identify critical errors or omissions. This limitation could result in implementing flawed process models that create operational disruptions or compliance failures, representing unacceptable risks for resource-constrained SMEs operating in competitive markets.

6.2.4.2 Organizational and Cultural Barriers

The interviews revealed sophisticated understanding of organizational change challenges that extend well beyond technical implementation issues. Participants recognized that successful AI-powered BPM adoption requires comprehensive organizational transformation that may exceed many SMEs' change management capabilities.

To conclude, SME C noted that while stakeholders had previously invested significant time in process clarification, there remained some uncertainty about universal adoption.

> "I don't know if everyone adheres to this way of doing things... But on the other hand, the majority would want to tend toward process follow-up like that anyway."

Indeed, cultural resistance and process adherence challenges emerged as significant barriers that AI-generated modelling alone cannot address. SME A's participant identified a fundamental limitation:

> "Even having documentation, we see that processes aren't necessarily respected."

This finding suggests that process modelling represents only one component of broader organizational development requirements, with process adoption and enforcement representing equally critical challenges that require sustained management attention and organizational culture development.

The organizational stability requirement revealed challenges for SMEs experiencing rapid growth, staff turnover, or market volatility. SME C's participant highlighted how organizational dynamism undermines process standardization efforts:

> "Since the organizational chart being constantly rediscussed, the process... it doesn't really have a reason to be... we have more exception cases than rules."

This reality suggests that AI-generated process modelling may provide limited value in highly dynamic SME environments where processes must continuously adapt to changing circumstances and role definitions.

Finally, change management resource requirements represent another significant barrier that could challenge SME implementation capacity. SME C emphasized the comprehensive stakeholder engagement necessary for successful adoption:

> "It would need to be built with decision-making stakeholders... so everyone agrees and there's no longer ignorance and misunderstanding."

This requirement implies substantial time investments for consensus building, training, and organizational alignment that may strain SME management resources already focused on operational demands and growth management.

6.2.5 Future Adoption Considerations

All participants expressed conditional interest in continued exploration of AI-powered BPM, contingent on addressing identified limitations. SME A captured this sentiment:

> "I think it's interesting because AI is going to compile enormous amounts of data to provide us this type of schema... It's a form of collective intelligence but that we need to go verify behind."

Participants consistently requested more detailed models that could support operational decision-making rather than just high-level communication. Better representation of error paths, quality failures, and rework loops was identified as essential for operational utility across all cases. SME A specifically emphasized temporal requirements: "Communication and temporality dimension. Because there, we have the impression that everything is done in parallel when that's not true." These requirements reflect the gap between current AI capabilities focused on macro-level process visualization and SME needs for operationally viable process models that could guide daily business execution and decision-making.

6.2.6 Cross-Case Analysis and Pattern Identification

6.2.6.1 Convergent Findings Across SMEs

Despite operating in different industries (IT consulting, footwear manufacturing, perfume manufacturing) and having varied organizational characteristics, several convergent patterns emerged across all three SMEs that suggest systematic rather than context-specific phenomena.

All AI-generated models exhibited identical structural issues, particularly multiple start/end events (7PMG G3 violations) and excessive element counts (7PMG G1 violations). This consistency across diverse input types and organizational contexts suggests systematic LLM limitations rather than input-specific issues. The universal failure to properly handle process boundaries indicates a fundamental gap in current AI capabilities for holistic process understanding. Additionally, semantic accuracy at macro levels was consistently strong across all cases. The AI successfully captured primary process flows and major stakeholder roles regardless of industry complexity, indicating reliable capability for high-level process understanding. However, exception handling gaps appeared universally, with all models consistently under-representing error handling, rework loops, and quality control procedures. This pattern suggests a fundamental limitation in LLM process modelling for operational completeness rather than industry-specific challenges.

Universal stakeholder perceptions emerged across cases. All participants acknowledged the potential utility of visual process representations for communication and training purposes despite technical limitations. Quality scepticism was equally universal, with all participants expressing concern about AI accuracy for critical business decisions and emphasizing human verification requirements. Implementation interest was consistently conditional on addressing identified technical and organizational barriers.

6.2.6.2 Divergent Findings and Context-Specific Variations

Context-specific variations revealed important differences influencing adoption potential. SME C identified significantly more regulatory compliance requirements that were completely absent from the AI-generated model, suggesting that highly regulated industries may require domain-specific AI solutions. SME B emphasized complex supplier relationships requiring more detailed external stakeholder modelling than captured by the AI. SME A required sophisticated iteration and testing cycles that the linear AI-generated model failed to represent adequately.

Organizational maturity influenced evaluation capabilities and adoption readiness. SME B, with existing formal process documentation experience, demonstrated greater ability to evaluate model accuracy compared to SME A and SME C. SME C, experiencing high staff turnover and organizational instability, expressed the greatest scepticism about implementing standardized processes, while SME A and SME B showed more openness to process standardization.

The convergence of technical limitations across diverse contexts indicates that current AI-powered BPM tools face systematic challenges requiring technological advancement. However, universal recognition of potential value suggests that addressing these limitations could unlock significant benefits for SME process management. The consistent gap between communication value and operational utility suggests that current tools are most appropriately positioned as process communication aids rather than operational management systems.

6.3 Input Quality Impact Analysis

The relationship between input document structure and LLM-generated model quality reveals significant patterns that directly explain the technical assessment findings. Input preparation represents a critical success factor for effective LLM-powered BPM adoption.

SME A's Excel-based process definitions and structured Word documents enabled the LLM to reliably extract process steps, role definitions, and sequential dependencies. The tabular format proved particularly effective, allowing the AI to map structured data directly into BPMN elements with minimal interpretation errors. This correlation explains why SME A achieved relatively high semantic quality scores despite organizational informality, structured input documents compensated for process documentation gaps.

SME B's reception process, generated from medium-structure PDFs, exhibited syntactic complexity and semantic gaps identified in the SEQUAL evaluation. The LLM occasionally conflated separate process steps or omitted contextual information when processing these less structured inputs, resulting in moderate quality scores across multiple evaluation dimensions.

SME C's unstructured narrative descriptions produced the most significant quality challenges. The LLM struggled to extract clear process boundaries, role definitions, and sequential relationships from prose-heavy documents, resulting in models that required substantial manual correction. PDF-based inputs across all cases consistently led to more interpretation challenges compared to native digital formats, contributing to syntactic errors and semantic gaps.

Generally, PDF-based inputs across all cases consistently led to more interpretation challenges compared to native digital formats. Even well-organized PDF documents required additional LLM processing to extract structured information, contributing to the syntactic errors and semantic gaps identified in the technical assessment.

These findings establish input quality as a primary determinant of LLM-generated models' success, with direct implications for SME preparation strategies and realistic expectation setting regarding AI-generated model quality.

7 Discussion

This study investigated the benefits, success factors, and failure factors associated with implementing Large Language Model (LLM)-powered Business Process Modelling (BPM) in Small and Medium Enterprises (SMEs). The findings reveal a complex landscape where technological capabilities intersect with organizational realities to create both significant opportunities and substantial challenges for AI-powered process management adoption.

> What are the benefits, success and failure factors when implementing LLM-powered Business Process Modelling (BPM) in Small and Medium Enterprises?

The implementation of LLM-powered BPM in SMEs reveals a complex interplay of technological capabilities, organizational readiness, and contextual factors that fundamentally challenges traditional technology adoption models. Rather than simple benefit-barrier calculations, successful implementation depends on understanding three critical dynamics: the transformation of BPM from operational tool to communication medium, the emergence of new organizational capabilities requirements, and the conditional nature of value realization.

7.1 Benefits of LLM-Powered BPM for SMEs

The following benefits represent empirical findings from the case study investigation, organized by their immediacy and implementation requirements. These benefits demonstrate how AI-powered BPM addresses specific SME challenges while revealing the conditions under which value realization occurs.

The empirical findings demonstrate clear benefits that directly address SME-specific challenges identified in existing literature. Most immediately, **rapid process visualization** emerged across all cases, with SMEs obtaining visual process representations within hours rather than the weeks or months typically required for traditional consultant-led process modelling. SME B participant noted their previous manual effort: "*We spent about forty hours because there were about ten interlocutors*." This capability directly addresses the time and cost barriers that prevent SME BPM adoption (Papademetriou & Karras, 2017).

Accessibility for non-experts represents a fundamental shift from traditional BPM requirements. The AI-generated models provided process visualization capabilities to organizations lacking specialized BPM expertise, with SME A noting: "It's a form of collective intelligence but that we need to go verify behind." This finding confirms recent projections about AI democratizing BPM access (Grohs et al., 2023) while revealing the unmentioned verification dimension absent from the literature.

Communication enhancement emerged as the most significant realized benefit across all cases, supported by the 7PMG evaluation revealing perfect verb-object activity labelling and disciplined gateway selection. This finding extends Kourani et al.'s (2024) suggestion that LLMs excel at creating understandable process representations by demonstrating practical stakeholder acceptance. The foundational documentation benefit addressed a critical gap identified across SME literature: the absence of formal process documentation in resource-constrained organizations (Viegas & Costa, 2022). Even with technical limitations, the models provided starting points for process discussion and refinement, addressing the complete absence of process documentation in SMEs A and C.

Beyond these demonstrated benefits, the research identified significant potential benefits conditional on technological improvements. **Onboarding acceleration** emerged as a transformative possibility, with all participants recognizing potential for newcomer integration enhancement. This addresses a critical SME challenge where informal knowledge transfer creates bottlenecks (Viegas & Costa, 2022). **Standardization enablement** could support operational efforts through more accurate models, potentially delivering time and cost savings through reduced ad-hoc decision-making." Enhanced models with proper temporal dimensions and milestone clarity could **improve governance and project management effectiveness**.

Understanding benefits provides the value proposition foundation, but successful implementation requires systematic attention to enabling factors and barrier management.

7.2 Success Factors for Implementation

This analysis organizes implementation success factors using the TOE framework to provide systematic guidance for SME adoption decisions. Technical factors (7.2.1) focus on documentation and process characteristics that predict successful outcomes. Organizational factors (7.2.2) address capability requirements and cultural readiness that enable effective adoption. Environmental factors (7.2.3) consider external constraints and opportunities that influence implementation viability.

7.2.1 Technical Success Factors

Technical factors proved foundational to implementation viability, with specific characteristics consistently predicting success across all three SME cases. **Input document quality** emerged as the strongest predictor of technical success across all SEQUAL and 7PMG evaluations. The correlation between document structure and output quality was remarkably consistent: structured Excel spreadsheets achieved average SEQUAL scores of 3.2/5, well-organized Word documents scored 2.8/5, while unstructured PDFs consistently scored below 2.0/5. SME A's superior technical outcomes through structured Excel-based process definitions compensated for organizational informality, supporting Pisoni & Moloney's (2024) findings about structured input requirements for effective LLM performance.

The technical dimension encompasses two critical subcategories. **Document structure and format** proved decisive, with tabular formats enabling direct mapping to BPMN elements while narrative descriptions required complex interpretation that frequently introduced errors, which validates what has been said by Ivanchikj et al., 2020. **Information completeness** significantly influenced semantic quality, with comprehensive role definitions, clear process boundaries, and explicit decision points producing models that stakeholders immediately recognized as accurate representations of their operations, building on what Daclin et al., 2024 recommended.

Process complexity matching proved critical for successful modelling outcomes, as theorized by Daclin et al., 2024. The SEQUAL semantic quality assessment revealed 90% accuracy for macro-level process flows but systematic failures in exception handling across all cases. Linear processes with clear sequential dependencies achieved consistently high technical quality scores, while processes involving parallel activities, complex decision trees, or iterative cycles challenged current LLM capabilities. SME B's raw materials reception process, with its straightforward sequential flow, achieved superior technical scores compared to SME C's custom product development process involving multiple iterative refinement cycles.

Finally, **technology infrastructure readiness** influenced ongoing sustainability, confirming the AI-barrier to implementation being valid for BPM implementation (Zavodna et al., 2024). Organizations with modern document management systems, standardized file formats, and reliable internet connectivity expect a better ongoing model maintenance capability.

7.2.2 Organizational Success Factors

Organizational capabilities proved equally crucial for sustainable implementation, with human factors often determining whether technical capabilities translated into operational value. **Leadership commitment** proved essential for successful adoption across all cases, extending beyond simple approval to active engagement in implementation processes. This commitment manifested in three specific ways: resource allocation for verification activities, change management support for process standardization initiatives, and sustained engagement through implementation challenges to enforce the defined processes, which is supported by Claes, 2018, Kraljic et al., 2014 and Moreira et al., 2024.

Active leadership engagement enables resource allocation for verification activities and changes management processes necessary for implementation success

Existing process awareness significantly influenced evaluation capabilities and adoption readiness, creating a capability paradox where organizations most needing process clarity often lacked the capabilities necessary for effective AI-BPM evaluation. SME B, with 40 hours of previous formal process documentation experience, demonstrated superior ability to evaluate model accuracy and identify specific improvement requirements compared to SME A and SME C. This evaluation sophistication enabled more effective human verification, faster error identification, and better integration with existing organizational practices. Within the process awareness, **documentation maturity** influenced both input preparation capabilities and output evaluation skills, with organizations possessing formal documentation practices achieving better implementation outcomes regardless of their technical sophistication, validating findings by Velasquez et al., 2023.

Quality assurance capabilities emerged as mandatory rather than optional requirements across all cases. The universal requirement for human verification challenges assumptions about AI democratizing BPM access and suggests that AI-BPM may increase rather than decrease organizational capability demands. Organizations must be able to evaluate whether AI-generated models accurately represent their actual processes, identify technical errors in the diagrams, and recognize when important business requirements are missing from the models. SME A's request for a legend illustrates how organizations lacking these evaluation capabilities face implementation risks that could exceed their operational tolerance, potentially leading to flawed process implementations with negative organizational consequences. This contradicts AI democratization projections by Grohs et al., 2023 while confirming that specialized expertise remains essential (Daclin et al., 2024).

Finally, **organizational stability** proved critical for sustainable implementation, with dynamic environments undermining the value proposition of process standardization efforts. High staff turnover, frequent role changes, and organizational restructuring created fundamental incompatibility with process standardization approaches that assume stable operational structures. This stability requirement encompasses **role stability** (frequent changes requiring constant model updates that negated efficiency benefits), **process stability** (dynamic processes requiring flexibility that current AI-BPM tools cannot accommodate), and **strategic stability** (strategic uncertainty undermining long-term process improvement investments).

7.2.3 Environmental Success Factors

Environmental factors significantly influenced implementation success through external constraints and opportunities that organizations could influence but not fully control. **Industry regulatory requirements** created substantial variation in implementation feasibility across the three cases, as previously identified in the literature. Lower regulatory complexity industries like IT consulting (SME A) and footwear manufacturing (SME B) experienced greater success with standard LLM-generated models, while highly regulated industries like perfume manufacturing (SME C) required additional domain-specific modelling that was completely absent from AI outputs.

The regulatory dimension proved more complex than simple compliance requirements, encompassing several specific factors that influenced implementation outcomes. **Compliance documentation requirements** affected both input preparation needs and output validation criteria, with highly regulated industries requiring specialized expertise that exceeded typical SME capabilities. **Regulatory change frequency** influenced the sustainability of process documentation investments, with dynamic regulatory environments requiring frequent updates that could negate initial efficiency gains. And finally, **industry standards** determined whether AI-generated models met sector-specific requirements, with specialized industries requiring adaptations that generic tools could not provide.

Moreover, **stakeholder collaboration needs** affected modelling success through the complexity of external coordination requirements. Processes involving primarily internal stakeholders showed better modelling success than those requiring complex external partner coordination. SME A's ERP implementation process, while complex, remained largely internal and achieved better modelling outcomes than SME C's supply chain processes involving multiple external subcontractors and message flows.

Finally, **market and competitive pressures** influenced both implementation motivation and sustainability, with external pressures creating both drivers and constraints for AI-BPM adoption. Organizations facing competitive pressure for process transparency and standardization found stronger value propositions for AI-BPM implementation, while those operating in stable markets with established practices experienced less implementation urgency. This pattern aligns with broader SME digital transformation challenges around external integration and competitive positioning (Bamidele Micheal Omowole et al., 2024).

While success factors establish the conditions for effective implementation, failure factors reveal the systematic challenges that must be anticipated and managed.

7.3 Failure Factors and Implementation Barriers

Understanding failure factors and implementation barriers is essential for realistic adoption planning and risk management. These barriers are organized using the same TOE framework structure to enable systematic assessment of implementation challenges that SMEs must address or avoid.

7.3.1 Technical Failure Factors

Technical limitations proved most persistent across all organizational contexts, suggesting systematic rather than correctable constraints in current AI capabilities. **Complex exception handling** represented a universal limitation across all cases, with LLM inability to model error paths, quality failures, and rework loops essential for operational completeness. This limitation manifested differently across industries but proved consistently problematic: SME A's missing iterative development cycles and client feedback loops, SME Bs absent quality control exception paths and supplier non-compliance procedures, and SME C's missing regulatory compliance workflows and safety protocol deviations.

The exception handling limitation encompasses several specific technical deficiencies that proved insurmountable with current technology. **Error pathway modelling** consistently failed across all cases, with AI-generated models representing idealized linear flows that ignored the reality of operational failures and recovery procedures. **Quality control integration** remained absent despite being essential for manufacturing contexts. **Iterative process cycles** proved particularly challenging, with AI consistently linearizing processes that inherently require cyclical refinement and stakeholder feedback integration.

Multiple process boundaries emerged as a systematic technical failure with universal violation of single start/end event principles (7PMG G3). This limitation appeared consistently across all cases regardless of industry context or input document quality, indicating fundamental LLM limitations in understanding overall process scope and boundaries. This boundary definition failure created several specific implementation problems: process scope confusion when stakeholders couldn't determine where processes began and ended (undermining the clarity benefits that motivated adoption), and measurement difficulties from inability to define clear process performance metrics when start and end points remained ambiguous.

Temporal relationship modelling limitations significantly reduced operational utility across all cases. This finding extends Bernardi et al.'s (2024) concerns about LLM structural limitations by demonstrating their persistence across diverse organizational contexts. The temporal modelling deficiency encompasses several specific limitations: **sequencing accuracy** where AI failed to capture essential ordering requirements between activities, **duration estimation** where time requirements remained absent despite operational importance, and **scheduling constraints** where resource availability and timing dependencies were ignored.

Finally, industry-specific requirements proved systematically under-represented across all cases, with lack of domain expertise in specialized regulatory or technical requirements creating significant semantic gaps, validating the need for domain experts and stakeholders (Ivanchikj et al., 2020). SME C's missing safety data sheet generation and transport documentation illustrate this limitation's operational impact most clearly, but similar gaps appeared across all industries. SME A lacked essential project management protocols specific to ERP implementations, while SME B missed footwear-specific quality standards and material handling requirements.

7.3.2 Organizational Failure Factors

Organizational constraints created implementation barriers that technology improvements alone could not address, revealing fundamental misalignment between AI-BPM requirements and typical SME characteristics. **Insufficient digital maturity** created evaluation and implementation challenges that exceeded many organizations' adaptation capabilities. While medium digital maturity proved sufficient for basic adoption, organizations lacking evaluation capabilities faced implementation risks exceeding their operational tolerance (Oldemeyer et al., 2024).

Moreover, **organizational instability** fundamentally undermined standardization value propositions, particularly evident in SME C's frequent role changes and structural modifications. This suggests that AI-BPM implementation requires minimum organizational stability thresholds that may exclude organizations most needing process clarity.

Change resistance persisted regardless of documentation quality or creation methodology, revealing cultural and behavioural barriers above technological considerations. It highlights implementation challenges that technology alone cannot address (Samuel Omokhafe Yusuf et al., 2024). This resistance manifested through cultural attachment to informal coordination mechanisms, scepticism about standardization benefits in dynamic environments, and implementation fatigue from previous unsuccessful change initiatives.

Finally, **resource allocation limitations** emerged despite reduced initial modelling costs, with ongoing requirements for verification, and maintenance exceeding SME capabilities and negating efficiency advantages. These limitations encompassed time availability constraints for verification activities, expertise access requirements that exceeded internal capabilities, and financial sustainability concerns for ongoing maintenance that could exceed initial cost savings.

7.3.3 Environmental Failure Factors

Environmental constraints created implementation barriers through external factors that organizations could neither control nor easily adapt to accommodate. **Regulatory complexity** proved particularly constraining for specialized industries, with compliance requirements that exceeded AI capabilities creating fundamental implementation limitations. SME C's extensive regulatory demands, safety data sheet generation, transport documentation, dangerous materials handling procedures, were completely absent from AI-generated models despite representing essential operational requirements.

The regulatory complexity barrier encompasses several specific challenges that proved difficult to address through organizational adaptation. **Compliance completeness** requirements meant that partial process models could create legal risks rather than operational benefits, making incomplete AI-generated models potentially harmful rather than helpful. **Regulatory change frequency** in dynamic regulatory environments required constant model updates that could exceed organizational maintenance capabilities. **Specialized expertise** requirements for regulatory compliance often exceeded both AI capabilities and organizational resources, creating dependencies on external expertise that negated cost advantages.

The **stakeholder coordination complexity** created implementation barriers when processes involved multiple external parties with different standards, expectations, and coordination mechanisms. SME C's supply chain processes involving multiple subcontractors, regulatory agencies, and distribution partners proved particularly challenging for AI modelling, with coordination requirements that exceeded current technological capabilities.

Finally, **market and competitive pressures** sometimes created constraints rather than drivers for AI-BPM adoption, particularly when competitive advantages depended on process flexibility and adaptation rather than standardization. Organizations operating in rapidly changing markets or requiring high customization capabilities found that process standardization could reduce rather than enhance competitive positioning, creating environmental resistance to AI-BPM implementation regardless of technical capabilities or organizational readiness.

The comprehensive analysis of benefits, success factors, and failure factors provides the empirical foundation for theoretical and practical contributions that advance both academic understanding and organizational guidance.

7.4 Theoretical Contributions

This research contributes to the emerging understanding of AI adoption in SME contexts by extending existing BPM implementation research with AI-specific insights. While prior BPM adoption studies focus primarily on traditional barriers such as resource constraints and expertise requirements (Papademetriou & Karras, 2017), this study reveals that AI-powered BPM introduces fundamentally different adoption dynamics that require new theoretical considerations.

The Technology-Organization-Environment (TOE) framework analysis reveals that AI adoption introduces dynamic interactions between technological, organizational, and environmental dimensions that change throughout implementation rather than remaining static (Tornatzky & Fleischer, 1990). In practice, this means that SMEs cannot simply apply traditional BPM readiness assessments to AI-powered approaches. The findings demonstrate that organizations must simultaneously address technical input preparation, develop new verification capabilities, and manage stakeholder expectations about AI limitations, requirements absent from conventional BPM adoption frameworks.

The research reveals that AI-BPM adoption requires developing entirely new organizational capabilities rather than enhancing existing ones. Traditional BPM builds upon existing documentation practices and analytical skills (Papademetriou & Karras, 2017), but AI-BPM demands quality assurance and verification capabilities that don't exist in most SME contexts. Specifically, SMEs should develop quality assurance capabilities to evaluate AI-generated model accuracy, completeness, and business relevance. This capability transformation requirement suggests that SMEs should invest in verification training or external expertise rather than assuming AI democratizes BPM access.

The SEQUAL framework's application to AI-generated models reveals new quality dimensions around verification requirements, trust development, and hybrid utility that weren't anticipated in traditional conceptual modelling evaluation (Krogstie et al., 2006). These additions suggest that AI-generated organizational models require expanded quality assessment frameworks addressing reliability, transparency, and organizational confidence alongside traditional semantic, syntactic, and pragmatic criteria.

Moreover, the research contributes a Multi-Factor Alignment Framework that provides practical guidance for SME AI-BPM adoption decisions. This framework synthesizes the empirical findings into an actionable assessment tool that organizations can use to evaluate their implementation readiness and select appropriate strategies based on their specific context and capabilities.

7.4.1 Multi-Factor Alignment Framework for AI-BPM Implementation

The empirical findings reveal that successful LLM-powered BPM implementation requires simultaneous alignment across multiple dimensions rather than meeting isolated criteria. This Multi-Factor Alignment Framework synthesizes the research findings into a practical assessment tool that enables SMEs to evaluate their implementation readiness and identify specific areas requiring development before adoption.

Table 9 Multi-Factor alignment framework for AI-BPM implementation

DIMENSION	HIGH READINESS (+)	MEDIUM READINESS (±)	LOW READINESS (-)
TECHNICAL READINESS	• Structured documents (Excel, organized Word) • Simple, linear processes • Clear role definitions • Stable process boundaries	• Semi-structured documents • Moderate process complexity • Some documentation gaps • Mixed format inputs	• Unstructured narratives • Complex exception handling • Unclear stakeholder roles • Dynamic process boundaries
ORGANIZATIONAL CAPABILITY	• Active leadership commitment • Existing process awareness • Quality assurance skills • Organizational stability	• Limited leadership support • Basic process consciousness • Some evaluation capability • Moderate stability	• Passive leadership • No formal processes • Insufficient QA skills • High staff turnover
ENVIRONMENTAL COMPATIBILITY	• Low regulatory complexity • Internal stakeholder focus • Clear communication needs • Competitive advantage from standardization	• Medium regulatory requirements • Mixed internal/external processes • Some standardization benefits • Moderate competitive pressure	• High regulatory complexity • Complex external coordination • Competitive advantage from flexibility • Dynamic market conditions

This multi-factor alignment framework enables organizations to assess their position across the three critical dimensions identified through the empirical analysis of SME A, SME B, and SME C, helping them understand the likelihood of successful AI-BPM implementation based on their specific organizational context and capabilities.

7.5 Practical contributions

The findings provide actionable insights for SME practitioners considering AI-powered BPM adoption for supporting successful implementation. Organizations should approach implementation with realistic expectations about current AI capabilities, focusing on communication and documentation applications rather than operational process management. The consistent gap between communication utility and operational completeness indicates that hybrid approaches leveraging AI for specific applications while maintaining traditional methods for operational requirements may be most effective.

Investment in input preparation and quality assurance capabilities represents a critical success factor that may require external consulting support for organizations lacking internal expertise. The correlation between input structure and output quality suggests that preparation costs may significantly impact overall implementation economics, potentially shifting the value proposition from AI automation to AI-assisted documentation. The emphasis on human verification requirements suggests that SMEs should budget for ongoing validation activities rather than expecting fully automated solutions. This requirement may favour collaborative adoption approaches where multiple SMEs share verification expertise or engage specialized consultants for quality assurance activities.

7.6 Research Limitations

This study faces several methodological and contextual limitations that constrain the generalizability and interpretation of findings while revealing important considerations for future research design and implementation.

7.6.1 Methodological Limitations

The three-case study design, while appropriate for exploratory research in an emerging field, inherently limits statistical generalizability of findings. Although case selection followed theoretical sampling principles to maximize variation across industry sectors and organizational characteristics, the small sample size prevents robust pattern identification that would emerge from larger-scale studies. This limitation is particularly significant given the heterogeneity of SME contexts across different cultural, economic, and regulatory environments (Eisenhardt, 1989).

Furthermore, the temporal constraints of master's thesis research created significant limitations in longitudinal analysis capabilities. The cross-sectional design captured stakeholder perceptions and technical quality assessments at a single point in time, preventing observation of how adoption patterns, organizational learning, and technology adaptation evolve over extended implementation periods. Finally, the researcher's dual role as ERP implementation consultant and academic investigator introduced potential bias in case selection, data collection, and interpretation processes, despite systematic analytical frameworks.

7.6.2 Technological Limitations

The selection of GPT-4 mini as the primary LLM platform reflected practical accessibility and cost considerations rather than comprehensive technology evaluation, limiting the generalizability of technical findings to AI-powered BPM more broadly. Different LLM architectures, specialized BPM-trained models, or enterprise AI solutions might yield significantly different technical quality profiles and implementation requirements (Grohs et al., 2023).

The static evaluation approach, focusing on single-iteration model generation, failed to capture the potential benefits of iterative refinement processes that might emerge through human-AI collaboration over extended periods. Real-world implementation scenarios typically involve multiple revision cycles and gradual improvement processes that this research design could not accommodate.

Moreover, the research timing, conducted during a period of rapid AI advancement and heightened organizational interest in digital transformation, may limit the temporal generalizability of findings. The specific technological capabilities, cost structures, and market conditions present during the study period may not persist, potentially altering the fundamental value propositions and adoption barriers identified.

7.6.3 Contextual and Cultural Limitations

The exclusive focus on French SMEs operating under European Union regulatory frameworks significantly constrains transferability to different cultural, legal, and economic contexts. Cultural factors influencing technology adoption, organizational change readiness, and stakeholder collaboration patterns vary substantially across national and regional contexts (Bamidele Micheal Omowole et al., 2024; Samuel Omokhafe Yusuf et al., 2024). The industry selection excluded several important SME categories including healthcare, financial services, and professional services that might exhibit different adoption patterns due to specific regulatory requirements or professional standards.

7.6.4 Data Collection and Analysis Limitations

The reliance on single-informant interviews from each organization, while justified by SME resource constraints, introduces potential bias through individual perspective limitations and incomplete organizational representation. The interview duration variations differences may have influenced data quality and depth across cases, while the analytical approach relied heavily on researcher interpretation of qualitative data despite systematic frameworks. Additionally, the technical quality assessment of AI-generated models relied on single-evaluator scoring using 7PMG and SEQUAL frameworks, preventing inter-rater reliability validation that would strengthen the objectivity of quality measurements

7.7 Future Research Directions

The limitations identified above, combined with the exploratory nature of this investigation, point toward several critical research priorities that could advance understanding of AI adoption in organizational contexts.

7.7.1 Long-term Studies and Technology Evolution

Longitudinal research examining how AI-BPM capabilities and SME adoption patterns evolve over extended periods represents the highest priority for future investigation. Such studies should track organizations through complete implementation cycles to understand how the success factors and failure barriers identified change over time. The finding that stakeholders initially expected operational benefits but ultimately recognized communication value suggests that longitudinal analysis could reveal important adaptation patterns that cross-sectional studies cannot capture.

7.7.2 Cross-Cultural and Comparative Studies

Comparative studies across different cultural, regulatory, and economic contexts represent essential next steps for establishing boundary conditions. Research should systematically examine how cultural dimensions influence stakeholder acceptance, verification requirements, and implementation approaches. Cross-national studies comparing SME adoption patterns in highly regulated sectors such as healthcare, financial services, and pharmaceuticals could investigate domain adaptation requirements and specialized quality assurance approaches.

7.7.3 Technology Architecture and Capability Studies

Cross-technology studies comparing different AI architectures, specialized BPM-trained models, and hybrid human-AI systems could establish more comprehensive understanding of AI capabilities and limitations. The systematic technical limitations identified, particularly around process boundaries and exception handling, suggest that architectural research could address fundamental constraints through alternative approaches.

Research should examine domain-specific language models trained on BPM datasets, few-shot learning approaches, and retrieval-augmented generation systems that could address the semantic completeness gaps identified across all cases. Studies examining different verification and quality assurance technologies could address the capability transformation requirements that currently limit SME adoption.

7.7.4 Implementation Strategy and Support Systems

Intervention studies examining different implementation strategies represent crucial practical research priorities. Controlled comparisons of consultant-supported deployment, collaborative multi-SME adoption, and gradual rollout approaches could provide evidence-based guidance for organizations attempting AI-BPM adoption. Research should investigate support system designs that address the capability transformation requirements identified as barriers to successful adoption.

8 Conclusion

The rapid advancement of Large Language Models presents unprecedented opportunities to address longstanding barriers in business process modelling adoption among Small and Medium Enterprises. While SMEs represent critical drivers of economic growth and innovation, they face distinct challenges in implementing traditional BPM approaches due to resource constraints, lack of specialized expertise, and complex notation requirements that favour larger organizations. The emergence of AI technologies capable of generating process models from natural language descriptions offers potential solutions to these accessibility barriers, yet empirical evidence regarding real-world implementation effectiveness, organizational acceptance, and practical viability in SME contexts remained largely absent from existing literature. This research addressed the critical gap by investigating: What are the benefits, success and failure factors when implementing LLM-powered Business Process Modelling in Small and Medium Enterprises?

Existing research established strong theoretical foundations across business process modelling benefits and SME adoption barriers (Papademetriou & Karras, 2017; Viegas & Costa, 2022), while emerging AI-powered BPM studies demonstrated technical feasibility for generating BPMN-compliant models (Grohs et al., 2023; Kourani et al., 2024). However, empirical investigation of organizational adoption factors and practical implementation challenges in real business contexts remained absent.

This study employed a qualitative exploratory research design integrating multiple case studies with interpretative approaches to investigate LLM-powered BPM adoption across three French SMEs representing different industries and digital maturity levels. The theoretical framework combined the Technology-Organization-Environment (TOE) model for adoption factor analysis, the SEQUAL framework for technical quality assessment, and the Seven Process Modelling Guidelines (7PMG) for objective diagram evaluation. The empirical investigation involved generating BPMN models using GPT-4 mini to generate BPMN models from organizational process descriptions, followed by comprehensive quality assessment and semi-structured interviews with key stakeholders to capture adoption perceptions, implementation challenges, and value recognition patterns.

The empirical investigation revealed systematic patterns across technical capabilities and organizational adoption factors. Technical quality assessment using 7PMG and SEQUAL frameworks demonstrated consistent strengths in activity labelling and gateway selection, alongside universal weaknesses including multiple start/end event violations and excessive element proliferation. Stakeholder evaluation revealed a fundamental dichotomy between communication effectiveness and operational completeness, with all participants recognizing value for external communication while identifying semantic gaps that rendered models insufficient for internal process management. The most significant finding involved universal requirement for human verification despite AI accessibility benefits, creating capability demands that potentially exceeded SME resources and negated primary adoption advantages.

The research confirmed several predictions from existing literature. Rapid process visualization capabilities emerged as anticipated, with organizations obtaining visual representations within hours rather than weeks (Kourani et al., 2024). Accessibility for non-expert users proved consistent with democratization projections, though revealing verification requirements not anticipated in technical literature (Grohs et al., 2023). Resource constraint challenges manifested precisely as SME literature predicted, with financial limitations and expertise gaps creating implementation barriers (Hussain & Rizwan, 2024). Quality and accuracy concerns emerged as expected, with stakeholders expressing deep scepticism about trusting AI-generated models for critical decisions (Bernardi et al., 2024).

The research identified several findings absent from existing literature. The transformation of BPM from operational tool to communication medium represents a fundamental shift not anticipated in prior research, suggesting AI-powered BPM creates new organizational capabilities rather than enhancing existing ones. Input quality as the primary determinant of success emerged as more critical than traditional digital readiness measures, with structured documentation predicting outcomes more reliably than organizational technology sophistication.

To synthetize, the multi-factors alignment framework presents empirical findings into an actionable assessment tool that enables organizations to evaluate implementation readiness across technical, organizational, and environmental dimensions. This framework provides both theoretical contribution to AI adoption research and practical guidance for organizational decision-making in emerging technology contexts, representing a novel integration of technology adoption factors with AI-specific implementation requirements.

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10 Appendices

Appendix A. List of inputs used for model generation

CASE	DOCUMENT NAME	DOCUMENT TYPE	CONTENT SUMMARY	STRUCTURE RATING	JUSTIFICATION
A	Diagnostic Gestion Projets	PowerPoint (pptx)	Diagnostic of ERP project management: roles, tools, communication bottlenecks, prioritization issues, testing phases.	Medium	Slides mix text and visuals; headings are inconsistent, making navigation uneven.
A	Outils Gestion Projets	PowerPoint (pptx)	Overview of project-management toolset (Mantis, Redmine, Google), process inefficiencies and coordination objectives.	Medium	Bullet-point format lacks deep hierarchy; sections flow but without clear sub-grouping.
A	Process Projet ERP	Word Document (docx)	Step-by-step ERP implementation: workshop prep, macros-processes, development, testing, training, delivery stages.	High	Well-structured with clear headings, numbered lists, and distinct phases.
A	Les bonnes pratiques.xlsx	Excel spreadsheet (xlsx)	Tabulated best practices for ERP/process management, checklists and guidelines across multiple dimensions.	High	Columns and rows clearly labeled; filters and grouping aid quick lookup.
A	Process Projet – format Excel.xlsx	Excel spreadsheet (xlsx)	Process definitions in spreadsheet form: tasks, roles, inputs/outputs per step.	High	Uniform tabular layout with dedicated columns for each attribute.
A	Questions_réponses_préliminaires_État_des_lieux.xlsx	Excel spreadsheet (xlsx)	Q&A log capturing stakeholder preliminary questions and clarifications on current “as-is” processes.	Medium	Mixed free-text entries; lacks consistent categorization or column constraints.
B	Standardisation Process et Flux Réception MP.pdf	PDF	Tabular swimlane-style flows for purchasing, reception, QC, storage, accounting, exchange modes and handoffs.	Medium	Swimlanes clear, but textual annotations are dense and not uniformly placed.
B	Process Affects Transact V2.pdf	PDF	Detailed transactional map: service	Medium	Comprehensive but densely

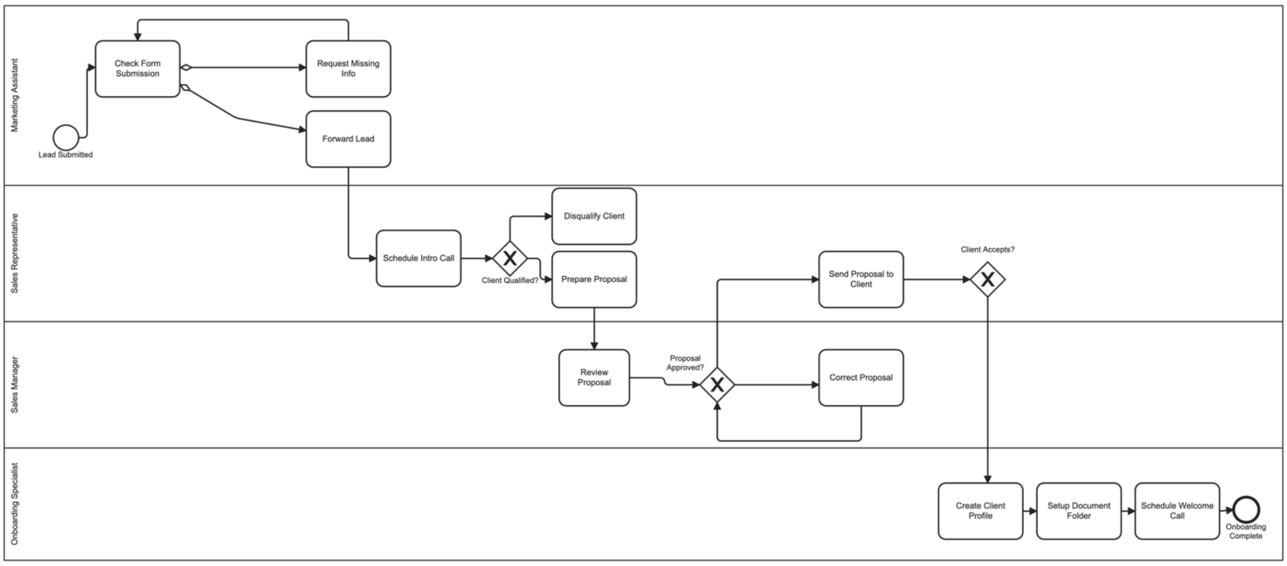
			assignments, actions, transaction types, remarks, procedural steps in Excel-export style.		formatted; inconsistent use of fonts and indentation.
C	ANNEXES – Macro-process.pdf	PDF	High-level macro-process diagram of the custom-order lifecycle: stages, tools, timelines, roles.	High	Clean diagrammatic layout with numbered phases and concise labels.
C	ERP-Grille comparative.pdf	PDF	Comparative grid of ERP functional domains with descriptions and priorities for each.	High	Tabular format with distinct columns for domain, description, and priority.
C	Process – Offre sur-mesure.pdf	PDF	Detailed process flow for the “sur-mesure” order lifecycle, outlining steps from briefing to delivery.	Medium	Structured sections and bullet lists but lacks a formal TOC and consistent subheadings.
C	XXX Paris - ERP - Cahier des charges.pdf	PDF	Full ERP specification document with comprehensive TOC, covering company overview, functional requirements, budget, timeline.	High	Well-organized with a detailed table of contents and clear section hierarchies.
C	XXX Paris - ERP - Use Case_21.10.24.pdf	PDF	Use-case scenarios depicting phases of client engagement, development, production, and billing for a custom-order project.	High	Numbered phases and bullet points clearly delineate sequential steps and requirements.

Appendix B. Pilot-study : Input/Output

One of the inputs used for the pilot study was the following:

> When a potential client expresses interest via the website form, the marketing assistant receives a notification and checks the submission for completeness. If the form is incomplete, the assistant contacts the client for missing information. Once all required details are available, the assistant forwards the lead to the sales representative.
>
> The sales representative then schedules an introductory call to understand the client's financial needs. After the call, if the client is qualified, the representative prepares a proposal. If not, the client is marked as disqualified and archived.
>
> The proposal is reviewed and approved by the sales manager. If it is rejected, it is sent back to the representative for correction. If approved, the proposal is sent to the client. Once the client accepts the proposal, the onboarding specialist creates a client profile in the CRM, sets up a client folder in the secure document management system, and schedules a welcome call.
>
> The process ends when the welcome call is completed, and the onboarding checklist is marked as done.

Here is the generated output:



Appendix C. Semi-Structured Interview Guide for AI-Generated BPM Evaluation in SMEs

Semi-Structured Interview Guide for AI-Generated BPM Evaluation in SMEs

Pre-Interview Preparation
- Ensure AI-generated BPMN diagrams are ready for presentation
- Test recording equipment and obtain consent
- Review participant's submitted process documentation
- Prepare diagram sharing capabilities (screen share/printed copies)

Introduction Script
Thank you for participating in this research interview. As discussed, I've used the process information you provided to generate formal Business Process Models using Large Language Model technology. Today, I'd like to show you these models and gather your feedback on their accuracy, utility, and potential application in your organization.

This interview will take approximately 60 minutes. Your participation is entirely voluntary. With your permission, I'd like to record this interview to ensure I capture your responses accurately. All information will be kept confidential and used solely for research purposes.

Part 1: Organizational Context (15 minutes)

Current Business Operations
1. Could you briefly describe your company's main business activities and primary value proposition
2. How many different roles/departments do you identify in your company to deliver this value proposition?
3. How would you characterize the complexity of your company's key business processes?
   - Probe: Simple vs. complicated, and why?
4. How important is process efficiency and standardization for your competitive advantage?

Current Process Management Practices
5. How does your organization currently document and manage its business processes?
   - Probe: Formal documentation, informal knowledge, dedicated tools*
6. How do you communicate process information to newcomers or between departments?
7. What challenges do you face in maintaining accurate and up-to-date process documentation?

Part 2: AI-Generated Model Evaluation (30 minutes)
[Present AI-generated BPMN diagrams, explaining notation briefly if necessary]

Initial Reaction
8. What was your first reaction when you saw this diagram? What stood out to you immediately?

Semantic Quality (Correspondence to Reality)
9. To what extent do these models accurately capture your real business processes?
10. What aspects of your processes are well represented in these models?
11. What important elements or nuances are missing or inaccurately represented?
   - Probe: Decision points, exceptions, roles, system interactions
12. Are there process variations or exceptions that these models don't account for?

Pragmatic Quality (Comprehensibility)
13. How easy or difficult is it to understand these process models?
14. Would someone unfamiliar with your processes be able to understand them from these models?
15. Are there aspects of the model that are more difficult to interpret than others?

Visual Efficiency
16. How effective are these diagrams for communicating process flows?
17. Are the symbols and connections used in the diagram intuitive and clear?
18. Does this visual representation help or hinder your understanding of the processes?

Social Quality (Stakeholder Agreement)
19. Do you think your colleagues would agree with this process representation?
20. How useful would these models be for reaching consensus on current or desired process functioning?

<u>Part 3: Utility and Implementation Considerations (15 minutes)</u>

Perceived Benefits
21. What potential benefits do you see in using AI-generated process models in your organization?
   - Probe: Training, standardization, improvement identification
22. How could these models facilitate communication about your processes internally or with external stakeholders?

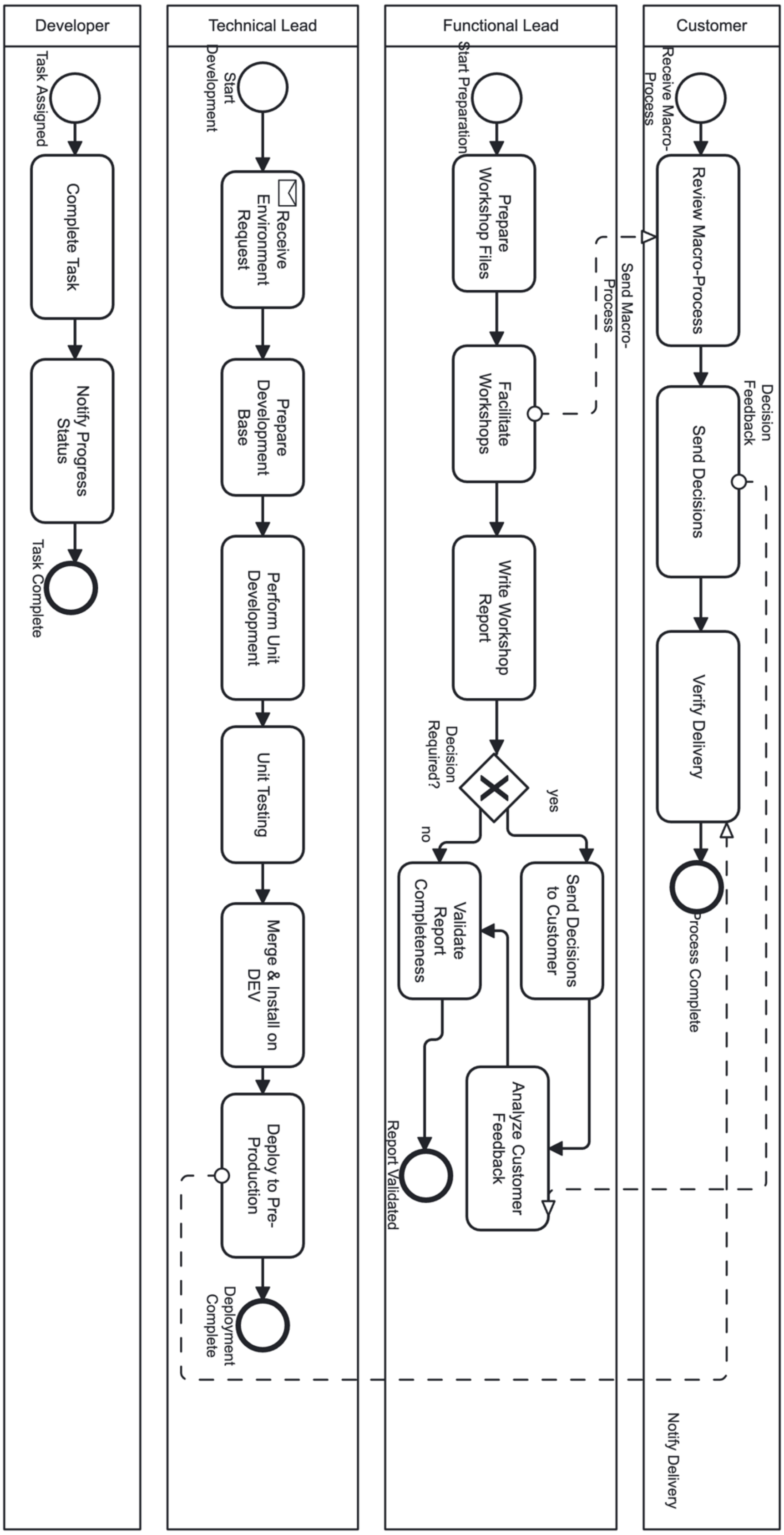
Implementation Factors
23. What organizational resources (time, budget, personnel) would be needed to implement this approach?
24. What would be the main barriers to adopting this type of AI-assisted process modelling?

Trust and Quality Assurance
25. To what extent do you trust the accuracy and comprehensiveness of these AI-generated process models?
26. What importance would you place on human verification and editing of models before implementation?

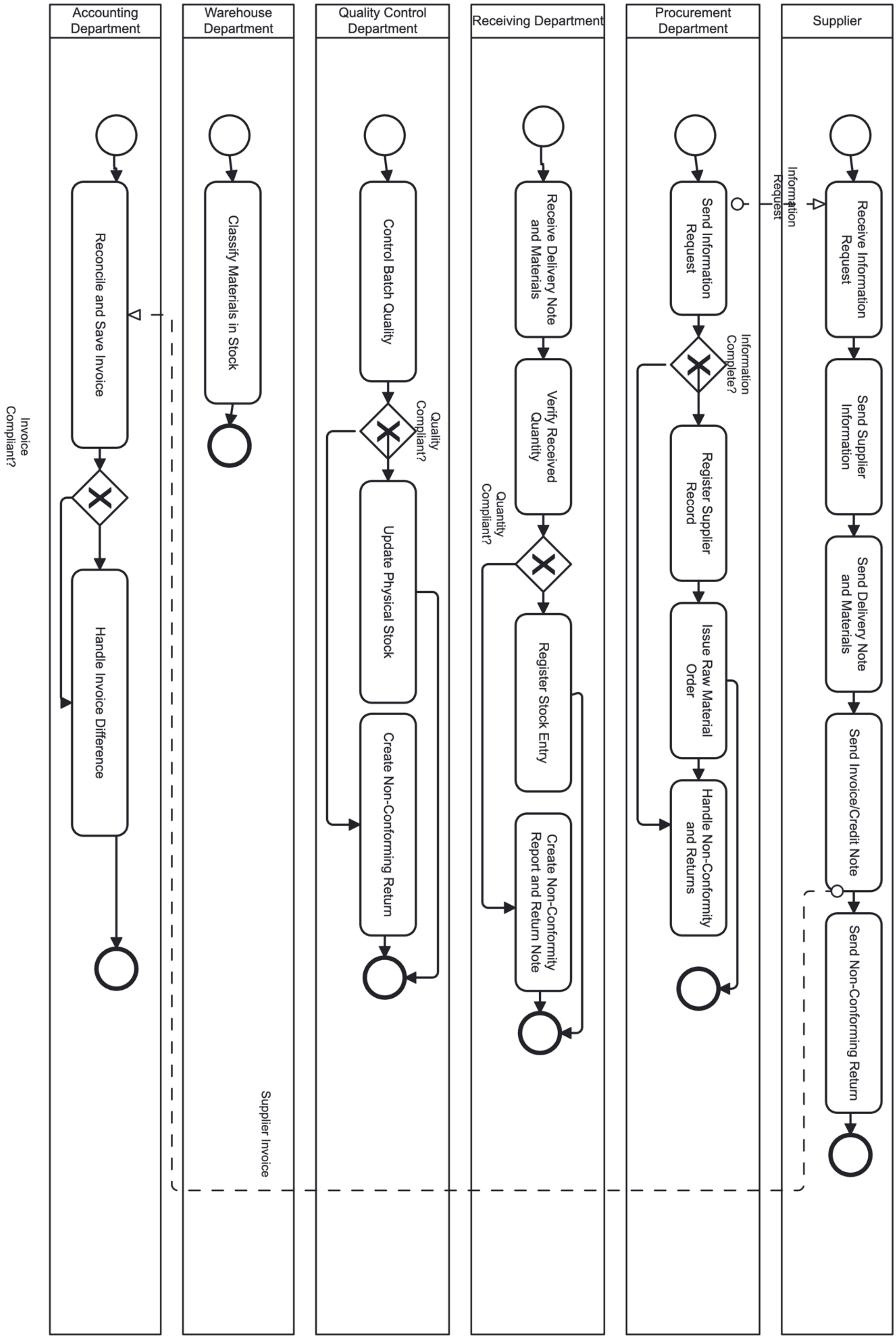
Future Potential
27. If we were to generate these models again, what feedback would you provide to improve the results?
28. Would you be interested in exploring further or implementing AI-assisted BPM approaches?

<u>Closing</u>
"Thank you for your time and insights. Your feedback will be valuable for understanding the potential and limitations of AI-assisted Business Process Modelling for SMEs. I'll share a summary of the research findings with you once the study is completed."

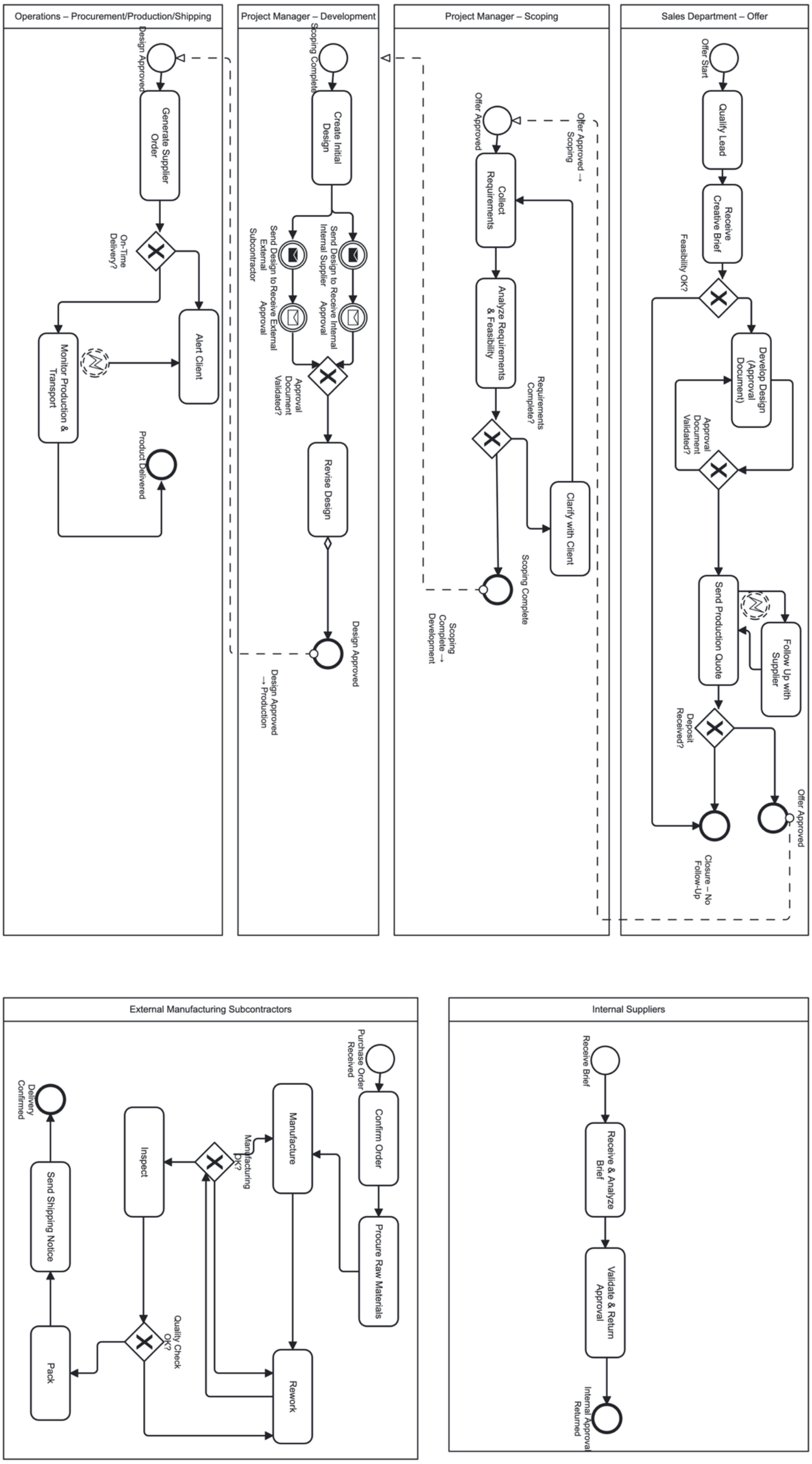
Appendix D. Case Study A - ERP Implementation Process Model



Appendix E. Case Study B - Materials Reception Process Model



Appendix F. Case Study C - Custom Product Development Process Model



Appendix G. Data Management Plan

This document will help you plan how to manage your research data. More detailed instructions for each section are available online in the Research Data Management Guide for Students.

1. Research data

Research data refers to all the material with which the analysis and results of the research can be verified and reproduced. It may be, for example, various measurement results, data from surveys or interviews, recordings or videos, notes, software, source codes, biological samples, text samples, or collection data.
In the table below, list all the research data you use in your research. Note that the data may consist of several different types of data, so please remember to list all the different data types. List both digital and physical research data.

Research data type	Contains personal details/information*	I will gather/produce the data myself	Someone else has gathered/produced the data	Other notes
Data type 1: Interview recordings and transcripts	x	x		Audio recordings of semi-structured interviews with SME stakeholders
Data type 2: Process documentation from SMEs			x	Excel files, Word documents, PDFs containing business process descriptions provided by participating organizations
Data type 3: AI-generated BPMN models		x		Business process models generated using GPT-4 mini from organizational process descriptions
Data type 4: Research notes and analysis		x		Field notes, coding sheets, thematic analysis documentation

* Personal details/information are all information based on which a person can be identified directly or indirectly, for example by connecting a specific piece of data to another, which makes identification possible. For more information about what data is considered personal go to the [Office of the Finnish Data Protection Ombudsman's website]

2. Processing personal data in research

If your data contains personal details/information, you are obliged to comply with the EU's General Data Protection Regulation (GDPR) and the Finnish Data Protection Act. For data that contains personal details, you must prepare a Data Protection Notice for your research participants and determine who is the controller for the research data.
I will prepare a Data Protection Notice** and give it to the research participants before collecting data ☒
The controller** for the personal details is the student themself ☒ the university ☐
My data does not contain any personal data ☐
** More information at the university's intranet page, [Data Protection Guideline for Thesis Research]

3. Permissions and rights related to the use of data

Find out what permissions and rights are involved in the use of the data. Consult your thesis supervisor, if necessary. Describe the use permissions and rights for each data type. You can add more data types to the list, if necessary.

3.1. Self-collected data

You may need separate permissions to use the data you collect or produce, both in research and in publishing the results. If you are archiving your data, remember to ask the research participants for the necessary permissions for archiving and further use of the data. Also, find out if the repository/archive you have selected requires written permissions from the participants.
Necessary permissions and how they are acquired

Data type 1 (Interviews): Verbal informed consent obtained before each interview, with explicit permission for audio recording. Participants informed of anonymization procedures and voluntary participation.

Data type 3 (AI-generated models): Created using publicly available AI technology (GPT-4 mini) based on process descriptions provided with organizational consent.

Data type 4 (Research notes): Original analysis and notes created by researcher.

3.2 Data collected by someone else

Do you have the necessary permissions to use the data in your research and to publish the results? Are there copyright or licencing issues involved in the use of the data? Note, for example, that you may need permission to use the images or graphs you have found in publications.
Rights and licences related to the data

Data type 2 (Process documentation): **Provided voluntarily by participating SMEs with explicit permission for research use. All organizational identifying information removed to ensure confidentiality.**

4. Storing the data during the research process

Where will you store your data during the research process?

In the university's network drive ☐
In the university-provided Seafile Cloud Service ☐
Other location, please specify: ☒ Encrypted external hard drive and password-protected personal computer

The university's data storage services will take care of data security and backup files automatically. If you choose to store your data somewhere other than in the services provided by the university, please specify how you will ensure data security and file backups. Remember to make sure you know every time where you are saving the edited/modified data.
If you are using a smartphone to record anything, please check in advance where the audio or video will be saved. If you are using commercial cloud services (iCloud, Dropbox, Google Drive, etc.) and your data contains personal data, make sure the information you provide in the Data Protection Notice about data migration matches your device settings. The use of commercial cloud services means the data will be transferred to third countries outside the EU.

5. Documenting the data and metadata

How would you describe your research data so that even an outsider or a person unfamiliar with it will understand what the data is? How would you help yourself recall years later what your data consists of?

5.1 Data documentation

Can you describe what has happened to your research data during the research process? Data documentation is essential when you try to track any changes made to the data.
To document the data, I will use:
A field/research journal ☐
A separate document where I will record the main points of the data, such as changes made, phases of analysis, and significance of variables ☒
A readme file linked to the data that describes the main points of the data ☐
Other, please specify: ☐

5.2 Data arrangement and integrity

How will you keep your data in order and intact, as well as prevent any accidental changes to it?

I will keep the original data files separate from the data I am using in the research process, so that I can always revert back to the original, if need be. ☒

Version control: I will plan before starting the research how I will name the different data versions and I will adhere to the plan consistently. ☒

I recognise the life span of the data from the beginning of the research and am already prepared for situations, where the data can alter unnoticed, for example while recording, transcribing, downloading, or in data conversions from one file format to another, etc. ☒

5.3 Metadata

Metadata is a description of you research data. Based on metadata someone unfamiliar with your data will understand what it consists of. Metadata should include, among others, the file name, location, file size, and information about the producer of the data. Will you require metadata?

I will save my data into an archive or a repository that will take care of the metadata for me. ☐

I will have to create the metadata myself, because the archive/repository where I am uploading the data requires it. ☐

I will not store my data into a public archive/repository, and therefore I will not need to create any metadata. ☒

6. Data after completing the research

You are responsible for the data even after the research process has ended. Make sure you will handle the data according to the agreements you have made. The university recommends a general retention period of five (5) years, with an exception for medical research data, where the retention period is 15 years. Personal data can only be stored as long as it is necessary. If you have agreed to destroy the data after a set time period, you are responsible for destroying the data, even if you no longer are a student at the university. Likewise, when using the university's online storage services, destroying the data is your responsibility.
What happens to your research data, when the research is completed?

I will store all data for 5 years.

If you will store the data, please identify where: Encrypted external hard drive stored securely by researcher

Remember to keep the data management plan updated throughout the research project.