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Artificial Intelligence Adoption Across Firm Sizes: A Systematic Review of Drivers, Barriers, and Strategies

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Table of contents

Chapter 1
Introduction

1.1 Background and Context

Artificial intelligence (AI) is profoundly reshaping the global economic landscape, with its applications proliferating across an ever-widening array of industries and fundamentally altering corporate operations. There is a broad consensus that AI possesses the capacity to significantly transform how businesses function, compete, and generate value (Cho et al., 2025; Li et al., 2024). Key AI technologies, including machine learning (ML), natural language processing (NLP), computer vision, and the more recent advancements in generative AI (Gen-AI), are unlocking novel opportunities for organizations. These technologies empower companies to automate a diverse range of tasks, derive sophisticated insights from vast datasets, personalize products and services for enhanced customer experiences, and ultimately improve the quality and efficacy of their decision-making processes (Ardito et al., 2024; Ojeda et al., 2024; Perifanis & Kitsios, 2023).

The contemporary business environment is characterized by the increasing integration of AI, not as a distant futuristic concept, but as a tangible and impactful reality (Glebova et al., 2024; Yen et al., 2024). Studies demonstrate AI's role in shaping data analysis for business decisions (Godbless Ocran et al., 2024; Sullivan & Fosso Wamba, 2024), its transformative effect on knowledge, innovation, and efficiency within the Industry 4.0 paradigm (Ciampi et al., 2021; Weber, 2023), its ability to bolster firm performance and innovation through enhanced adaptive responses to market dynamics (Mateev, 2023; Wang & Zhang, 2025), its significant influence on overall business value in the current digital era (Falahat et al., 2020; Yang et al., 2024), and its broad and growing market impact (Arranz et al., 2023; Tummalapalli et al., 2025). Consequently, the adoption of AI has transitioned into a competitive necessity for businesses aiming to maintain relevance and foster continuous innovation (Tominc et al., 2024; Yen et al., 2024).

However, the journey of AI adoption is not uniform across all enterprises. The specific approaches taken, the challenges encountered, and the benefits realized can vary substantially (Bhatia & Diaz-Elsayed, 2023; Maroufkhani et al., 2020). A primary determinant of these variations is the size of the company. Small and medium-sized enterprises (SMEs) and large corporations (LCs) operate with distinct strategic objectives, possess disparate levels of financial and human resources, and exhibit different organizational capabilities (Maroufkhani et al., 2023; Ridho, 2023; Zheng et al., 2025). These intrinsic differences dictate that their engagement with AI will inherently follow unique trajectories, a phenomenon that warrants a closer, comparative examination. The rapid evolution of AI technologies further complicates this landscape, as emerging AI forms may be adopted differently by firms of varying sizes and agility, making continuous comparative research not only essential but also increasingly complex (Farmanesh et al., 2025; Sipos et al., 2024; Xin et al., 2024).

1.2 Research Gap and Relevance

Despite the burgeoning discourse surrounding AI adoption, a comprehensive and nuanced comparative analysis of how SMEs and LCs are navigating this technological shift remains relatively underdeveloped in the existing literature (Bianchi & Stoian, 2024; Limpeeticharoenchot et al., 2022; Zhang & Peng, 2025). A significant portion of current research tends to concentrate either on the AI adoption experiences of SMEs (Agarwal et al., 2025; Grashof & Kopka, 2023; Zairis & Zairis, 2022) or, conversely, on those of LCs (Arranz et al., 2023; El Hilali et al., 2020; Regona et al., 2022). This bifurcated focus creates a knowledge void concerning direct, in-depth comparisons of their respective methodologies, encountered obstacles, and achieved outcomes.

Even in studies that encompass both SMEs and LCs, detailed comparative insights are often peripheral to the main research objectives or presented implicitly rather than as a central analytical theme (Limpeeticharoenchot et al., 2022; Mateev, 2024; Park & Lee, 2024). Preliminary data analysis for this thesis, reviewing the "Differences (SMEs vs. large)" column in the master data compilation, frequently revealed entries such as "Not specified" or "Implicit" (Adwan, 2024; Mantri & Mishra, 2023). This observation empirically substantiates the assertion that comprehensive comparisons are typically not the primary focus of individual studies, thus underscoring the existing research gap. This thesis aims to address this lacuna by systematically consolidating and synthesizing dispersed information to construct a coherent comparative narrative.

Bridging this research gap is crucial. AI adoption strategies effective for one type of company may prove unsuitable for another. SMEs, often characterized by agility but constrained by limited resources, are likely to require different AI adoption paradigms than LCs, which typically command greater financial and technological resources but may face organizational inertia or the complexities of integrating AI with extensive legacy systems (Chen et al., 2021; Lemos et al., 2022; Siregar et al., 2024; Sommer, 2023). Understanding these distinctions is essential for designing effective firm-level strategies and informed public policies (Grimaldi et al., 2023; Muto et al., 2024). The identified research gap also reflects a potential "comparability challenge": SMEs and LCs operate on vastly different scales of resources, complexity, and strategic intent, making the development of equivalent metrics for comparison methodologically demanding (Kulkov et al., 2024).

1.3 Research Questions and Objectives

This thesis addresses the following two main research questions:

- **RQ1.** What are the main drivers that lead small and medium-sized enterprises (SMEs) and large corporations (LCs) to adopt artificial intelligence (AI) technologies?
- **RQ2.** What are the main similarities and differences between SMEs and LCs in terms of enabling factors and challenges during AI implementation?

The specific goals of this thesis are:

- To systematically review and synthesize the existing body of research on AI adoption in both SMEs and LCs.
- To identify, categorize, and analyze the principal drivers, barriers, types of AI technologies employed, application areas, and observed benefits for each firm size.

- To conduct a rigorous comparative analysis that highlights the key differences and similarities in AI adoption approaches.
- To provide a clear, evidence-based understanding of the structural and contextual factors contributing to these differences.

1.4 Why This Thesis Matters

Academic Contribution: This thesis contributes a synthesized, evidence-based understanding of a rapidly evolving topic. By consolidating fragmented literature, it provides a comprehensive overview and identifies underexplored areas in the comparative study of AI adoption across firm sizes (Y. Liu et al., 2024; Schwaeke et al., 2025; Zhang & Peng, 2025).

Practical Contribution:

- For **SMEs**: The research offers actionable insights on navigating AI adoption, drawing from peer experiences and adaptable strategies (Huang et al., 2023; Mantri & Mishra, 2023).
- For **LCs**: It highlights the agile and focused adoption models of SMEs, which may inspire innovation within more structured environments (Duan et al., 2025; Rehman et al., 2024).
- For **Policymakers**: The findings support the development of tailored AI support programs. Numerous reviewed articles underscore the need to address SME-specific challenges, promote equitable access to AI, and shape responsible AI ecosystems (Gupta & Khan, 2024; S. Liu & Cheng, 2025; Ricci et al., 2021).

1.5 How the Thesis is Organized

The thesis is structured into six chapters:

- Chapter 2: Defines AI in business, outlines theoretical frameworks, reviews AI adoption in SMEs and LCs, and identifies comparative dimensions.

- Chapter 3: Details the SLR methodology, including search strategy, inclusion/exclusion criteria, study selection, data extraction, quality appraisal, and synthesis.
- Chapter 4: Presents descriptive statistics and thematic synthesis, comparing SMEs and LCs across key themes.
- Chapter 5: Discusses results using theoretical lenses and explores implications for research, management, and policy.
- Chapter 6: Summarizes findings, answers the research questions, outlines contributions, and suggests future research directions.

This structure provides a logical foundation for understanding and evaluating the differences in AI adoption between SMEs and LCs.

Chapter 2
Theoretical Background

his chapter establishes the core conceptual foundations and theories for my thesis. First, I'll explain what Artificial Intelligence (AI) means in the business world and talk about the key AI technologies that companies are looking at. After that, I'll explore some important theories that you often see in the literature when people try to understand how new technologies get adopted. The chapter then gives a general look at how AI is being adopted, what's driving it, and what problems companies are facing, especially Small and Medium-sized Enterprises (SMEs) and Large Corporations (LCs), using what other researchers have already found. Finally, I'll point out the main aspects I'll use to compare AI adoption between these two types of companies in the next chapters. Having a solid conceptual background is really important to make sure the comparison is based on good theory and clear definitions, which makes the thesis more academically sound. Choosing the right theories is a big deal here, because frameworks like TOE, RBV, Dynamic Capabilities, and DOI naturally let us look at factors (like technology, organization, environment, resources, and capabilities) that are quite different between SMEs and LCs (Sipos et al., 2024; Zhang & Peng, 2025; Zheng et al., 2025). Also, since AI systems are getting more complex and companies (SMEs and LCs) are very different from each other, this chapter also tries to connect basic understanding with real-world differences. Setting up a common language and theoretical view isn't just for keeping things consistent in the thesis, but it's also needed to put into context the various empirical findings I'll review later (Ojeda et al., 2024).

2.1 SMEs and LCs: Characteristics and Differences

For this thesis, Artificial Intelligence (AI) is defined as a set of advanced technologies that let computer systems do tasks that usually need human intelligence. These tasks include things like learning from data, reasoning, solving problems, seeing things, understanding and using human language, and making decisions on their own or with some help (Ardito et al., 2024; Bianchi & Stoian, 2024; Ojeda et al., 2024).

In the business world, AI shows up in many forms and uses. The articles I've reviewed for this thesis keep pointing to several main types of AI technologies that organizations are actively using (Falahat et al., 2020; Perifanis & Kitsios, 2023; Siregar et al., 2024).

- **Machine Learning (ML):** This is a part of AI with algorithms that let computers learn from data and make predictions or decisions, without someone having to program them for every single task (Csordás & Füzesi, 2023).
- **Deep Learning (DL):** A special bit of ML that uses deep neural networks to look at complex data (Yang et al., 2024).
- **Natural Language Processing (NLP):** This helps computers interact with human language and is used in things like chatbots and checking out customer sentiments (Godbless Ocran et al., 2024).
- **Computer Vision:** Used for quality control, recognizing faces, and in self-driving cars (Mateev, 2023).
- **Generative AI (Gen-AI):** This can create new content (like text, images, or code) and is being used more and more for automation and design(Duan et al., 2025).
- **Predictive Analytics:** Often used for forecasting, keeping customers, and checking risks (Grimaldi et al., 2023).
- **Robotic Process Automation (RPA):** This automates tasks that follow set rules, often in back-office work (Mantri & Mishra, 2023).
- **Expert Systems:** These try to copy the decision-making of human experts (Ricci et al., 2021).

How we define and categorize AI directly influences which companies adopt which technologies and why they do it strategically (Cho et al., 2025; Ciampi et al., 2021; Limpeeticharoenchot et al., 2022). The fact that Gen-AI is becoming easier to access has also given new opportunities for SMEs to get started (Farmanesh et al., 2025). It's important to say that these definitions change fast, and what's considered AI today might just be normal IT tomorrow. This just shows we need flexible ways to classify these things.

2.2 Frameworks for Interpreting AI Adoption

The academic research on how organizations adopt AI often uses well-known theoretical frameworks to analyze and understand all the complex stuff going on. For this thesis, since I'm comparing SMEs and LCs, these theories are particularly useful:

- **Technology-Organization-Environment (TOE) Model:** This explains adoption based on technological, organizational, and environmental factors (Regona et al., 2022; Schwaeke et al., 2025; Zairis & Zairis, 2022). This model is really helpful to see how SMEs and LCs are different in their internal setups and what influences them from the outside.

- **Resource-Based View (RBV):** This focuses on how companies get an edge by getting and managing strategic resources, like AI (Kolková & Ključnikov, 2022; Kulkov et al., 2024; Siregar et al., 2024). Since companies of different sizes have very different amounts of resources, this framework fits well.

- **Dynamic Capabilities Framework:** This describes how firms change, integrate, and reorganise their capabilities in environments that change quickly (Lemos et al., 2022; Maroufkhani et al., 2020; Muto et al., 2024). The framework gives us a look into how well companies can change when AI is shaking up the market.

- **Diffusion of Innovations (DOI) Theory:** Introduced by Rogers, this explains how technologies like AI spread through organizations based on how much advantage they seem to offer, if they fit well, how complex they are, if they can be tried out, and if their results are visible (El Hilali et al., 2020; Sullivan & Fosso Wamba, 2024, 2024). It's especially good for understanding how SMEs and LCs see the balance of costs and benefits of adopting AI.

While these models give some structure, the fact that AI can be a bit of a 'black box' and has ethical issues often means we need to adapt these models or use them together (Bhatia & Diaz-Elsayed, 2023; Y. Liu et al., 2024; Rehman et al., 2024). Frameworks like TOE and RBV might not fully cover things like how transparent algorithms are, bias, or if we can explain their decisions – and these issues are getting more and more critical when companies use AI systems.

2.3 AI Adoption in SMEs: General Overview from Literature

SMEs are often quick and flexible, which can help them experiment with AI. However, they also face some big challenges:

- **Barriers:** Insufficient investment resources (Gupta & Khan, 2024), lack of skilled people (Adwan, 2024), and old infrastructure (Hunke et al., 2022). Plus, SMEs often say it's hard to find AI vendors and support systems they can afford (Tominc et al., 2024).

- **Drivers:** Making operations more efficient, pressure from competitors, and just trying to survive (Falahat et al., 2020; Rehman et al., 2024; Weber, 2023). In several studies, AI is seen not just as a chance but as something necessary for digital transformation.

- **Solutions Preferred:** Cloud-based tools, SaaS (Software as a Service), and Gen-AI applications (Park & Lee, 2024; Yen et al., 2024). These make it easier to start and allow for quick deployment.

Many SMEs use an artisanal or tactical approach, meaning They adopt cost-effective, pragmatic solutions aimed at rapid outcomes (Grashof & Kopka, 2023; Mantri & Mishra, 2023). This is different from the more strategic and joined-up approaches you usually see in large corporations. Also, SMEs tend to focus more on short-term ROI than on building up innovation capacity for the long run, and they often use trial-and-error because they don't have much capacity for planning and analysis (Yang et al., 2024).

2.4 AI Adoption in Large Enterprises: General Overview from Literature

LCs generally adopt AI as part of a bigger strategic transformation:

- Drivers: Getting a better competitive position, radical innovation, and global optimization (Arranz et al., 2023; Kolagar et al., 2024; Zhang & Peng, 2025). They often go for AI projects with a long-term view.

- Barriers: Integrating AI with their old systems (Mateev, 2024), data governance issues, and being slow to change as an organization (El Hilali et al., 2020; Park &

Lee, 2024). Following regulations and being accountable to stakeholders are other concerns that get bigger with the size of the company.

- Preferred Tools: Custom-built platforms, internal AI teams, and systems that cover the whole enterprise (Rehman et al., 2024; Zhang & Peng, 2025). LCs often have dedicated innovation departments or centers of excellence to lead AI projects.

LCs tend to act as systemic integrators, using AI across their entire business models, while SMEs are more tactical, sort of picking and choosing (Csordás & Füzesi, 2023; Limpeeticharoenchot et al., 2022). Their strategic goals also affect how much risk they're willing to take, how much they invest, and what results they expect from AI.

2.5 Identifying Key Comparative Dimensions from Existing Literature

Based on putting together the themes from 71 studies, these comparative dimensions come out (Y. Liu et al., 2024; Schwaeke et al., 2025):

- Drivers of Adoption: Efficiency, innovation, reducing risk. While both types of firms share these, how they frame these drivers strategically is different depending on their size (Sommer, 2023).
- Barriers: Lack of resources versus complexity of integration. SMEs find it hard to get access, LCs find it hard to integrate (Mateev, 2024).
- Technologies Used: Simpler tools (SMEs) versus custom platforms (LCs). This choice shows not just what they can do but also their strategy (Weber, 2023).
- Observed Benefits: From gains that help them survive to big strategic shifts. What they expect in terms of ROI is shaped by the firm's goals and how they measure success (Tummalapalli et al., 2025).
- Implementation Models: Opportunistic (taking chances as they come) versus strategic. SMEs tend to iterate, LCs make it more formal (Grimaldi et al., 2023).
- Contextual Influences: Sector, where they are located geographically, and regulations (Glebova et al., 2024). How digitally ready a region is and the policy support available can vary a lot (Ricci et al., 2021).

These dimensions will guide the structured comparison I'll develop in Chapter 4. Importantly, they also help in designing AI strategies that are tailored to the company, suggesting that approaches sensitive to company size might work better than one-size-fits-all methods.

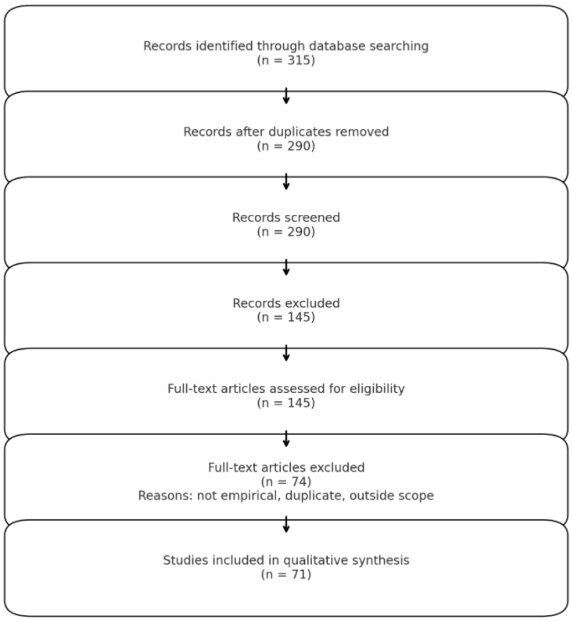
Chapter 3
Methodology

This chapter explains the methodology I used for the systematic literature review (SLR), which is the empirical basis of this thesis. The main goal of this review is to understand how Small and Medium-sized Enterprises (SMEs) and Large Corporations (LCs) are similar and different in how they adopt Artificial Intelligence (AI). By systematically finding, checking, and putting together the relevant literature, this chapter gives a solid base for answering the research questions.

Systematic reviews are known for being transparent, repeatable, and methodologically strong (Page et al., 2021; Tranfield et al., 2003). This method is especially good for this study because the literature on AI in business is quite fragmented and changes fast. The review process I followed uses guidelines from the PRISMA 2020 framework and has strong rules for including studies, a structured way to get data, and methods for checking quality. I reviewed 79 full-text articles, and 71 were included in the final synthesis; 8 were left out based on set criteria.

3.1 Adherence to PRISMA Guidelines

The whole review process followed the PRISMA 2020 guidelines (Page et al., 2021). These guidelines are recognized internationally and help make systematic reviews rigorous and transparent. PRISMA gives a clear framework for reporting how studies are selected, including how they are identified, screened, checked for eligibility, and finally included. A PRISMA flow diagram at the end of this paragraph (Figure 3.1) shows a visual summary of this selection process. It's interesting that several articles I selected for this review are also systematic reviews that say they follow PRISMA, which shows a common standard in methodology.



(Figure 3.1) presents the PRISMA 2020 flow diagram that summarizes the identification, screening, eligibility, and inclusion phases of the systematic literature review process..

3.2 Search Strategy

I designed the search strategy carefully to make sure I covered all the relevant studies. I searched in major multidisciplinary and specific databases like Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ProQuest (Computer Science), and ScienceDirect (Elsevier). To add to the peer-reviewed academic literature, I also did a targeted search for grey literature. This meant looking at sources like the OECD, EU policy documents, reports from consulting firms (like McKinsey, Stanford HAI), and doctoral theses. I used Google Scholar to find more grey literature and some academic papers that were hard to find.

The search terms were based on four main ideas:

- **Artificial Intelligence**: "Artificial Intelligence", "AI", "Machine Learning", "Deep Learning", "Intelligent Systems", "Cognitive Computing"

- **Adoption**: "Adoption", "Implementation", "Uptake", "Integration", "Diffusion", "Deployment"
- **SMEs**: "SME", "Small and Medium-sized Enterprises", "Small Business", "Medium Business", "PMI"
- **Large Enterprises**: "Large Enterprise", "Large Firm", "Corporation", "MNC"

I used Boolean operators (AND, OR) to create complex search strings for each database, fitting their specific syntax. For example, one string was: ("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("Adoption" OR "Implementation") AND (("SME" OR "Small and Medium-sized Enterprises") OR ("Large Enterprise" OR "Large Firm")).

I limited the search to articles published between January 1, 2019, and early 2025. This was to get the most recent information on AI and how it relates to current business situations (Ojeda et al., 2024).

3.3 Inclusion and Exclusion Criteria

The choice of articles was based on strict inclusion and exclusion criteria, following the best practices for systematic reviews (Booth, 2016; Gough et al., 2017). These criteria helped make sure that only studies that directly related to my research objectives were kept.

- **Inclusion Criteria**:
    - Empirical (quantitative, qualitative, or mixed-methods), conceptual, or review articles.
    - Published in peer-reviewed journals, conference proceedings, or good quality grey literature.
    - Studies written in English or Italian.
    - Articles focused on AI adoption in business, including things like ML, NLP, RPA, and Gen-AI.
    - Studies looking at SMEs, LCs, or both, with clear information on firm size.

- **Exclusion Criteria**:
    - Studies that only focused on the technical side of AI algorithms without talking about organizational aspects.
    - Articles that didn't clearly mention firm size or business application.
    - Editorials, book reviews, conference abstracts without the full text, or papers that were retracted.
    - Publications outside the 2019–2025 time frame.

Out of the 79 articles I read in full, 8 were excluded. For instance, (Csordás & Füzesi, 2023; Vahadane & Clarke, 2022) were excluded because they didn't have AI-related content, even though they discussed SMEs. One of them was removed because it was confirmed as retracted. I kept a detailed log of why each article was excluded in the data extraction file.

3.5 Data Extraction

In order to support the thematic synthesis and ensure analytical consistency across the selected studies, each paper was systematically mapped using a structured framework. This mapping included key attributes such as the type of company (SMEs or Large Enterprises), the method and domain of AI application, identified drivers and barriers to adoption, and the strategic and operational outcomes reported.

While the full database developed for this analysis—originally compiled in Excel and supported by a complementary Word file—is not included in this thesis for reasons of conciseness and readability, a **sample excerpt of this structured classification** is provided in **Appendix C**.

This structured classification enabled a clearer comparison of findings across studies, supported the thematic clustering presented in Chapter 4, and provided a transparent foundation for the interpretive discussion developed in Chapter 5.

This supported the structured dataset and helped with the thematic synthesis (Nowell et al., 2017).

3.6 Quality Appraisal / Risk of Bias Assessment

To check the methodological quality and any potential bias, I used three different appraisal frameworks, depending on the type of study:

- **Empirical studies (around 61)**: Appraised using the Mixed Methods Appraisal Tool (MMAT 2018) (Hong et al., 2018). Most studies were methodologically coherent, but some had small sample sizes or were too focused on narrow contexts.
- **Systematic reviews (7)**: Evaluated with the AMSTAR 2 checklist (Shea et al., 2017). Common issues were a lack of protocol registration or not enough reporting on bias.
- **Conceptual and theoretical papers (3)**: Assessed qualitatively for logical structure, theoretical contribution, and coherence (Gough et al., 2017).

I didn't exclude lower-quality studies, but I was careful when interpreting them during the synthesis phase.

The results of this analysis could be viewed Appendix – B.

3.7 Data Synthesis Method

I used a thematic synthesis approach, following (Braun & Clarke, 2006). This involved these iterative steps:

1. Familiarization: I read the extracted data and key notes many times to get a deep understanding.
2. Initial Coding: I assigned codes to relevant data features (e.g., "cost reduction", "legacy systems").
3. Theme Development: I grouped codes into broader categories like "Barriers", "Drivers", "Implementation Models".
4. Reviewing Themes: I refined the themes to make them clear, removed any repetition, and combined similar insights.

5. Defining Themes: I gave final names and definitions to each theme.

6. Producing the Report: I structured the findings around these themes and presented them with supporting evidence in Chapter 4.

Importantly, the coding scheme had a specific column for SME vs. LC distinctions. This allowed for a structured comparison and made sure that the main comparative aspect of my research questions was kept throughout the synthesis.

Chapter 4
Results: Summary of Findings from the Literature

This chapter presents the core findings that emerged from the systematic review of the 71 selected studies. It is structured in two main sections. The first offers a descriptive overview of the reviewed literature, focusing on aspects such as publication trends, geographical distribution, sectoral focus, types of AI technologies examined, company size orientation, and methodological approaches. This preliminary analysis provides context for interpreting the more detailed findings.

The second section develops a thematic synthesis directly aligned with the research questions (RQ1 and RQ2), with a strong comparative lens between small and medium-sized enterprises (SMEs) and large corporations (LCs). Specifically, it explores six key thematic areas: drivers of AI adoption, barriers and enablers, AI technologies and application areas, observed benefits, strategic approaches to implementation, and the influence of contextual factors (sector, geography, policy). In each section, findings for SMEs and LCs are discussed separately before presenting a direct comparison.

References to individual articles are integrated throughout the chapter to ensure evidence-based synthesis.

4.1 Descriptive Analysis of the Selected Studies (N=71)

The 71 studies selected through the systematic literature review offer a broad and detailed overview of how artificial intelligence (AI) adoption is currently being researched across different firm sizes and contexts. This descriptive analysis outlines the main characteristics of the reviewed literature and sets the stage for the subsequent thematic synthesis.

Publication Trends

The vast majority of the selected studies were published from 2021 onwards, highlighting the increasing relevance of AI in the post-pandemic digital economy (Sipos et al., 2024; Tominc et al., 2024). Several papers already accepted for 2024 and 2025 publication further emphasize the momentum of AI as a transformative business force (Cho et al., 2025; Duan et al., 2025; Tummalapalli et al., 2025). The rise of Generative AI (GenAI), especially after 2023, has significantly influenced the research agenda, particularly in relation to SMEs (Farmanesh et al., 2025; Ridho, 2023).

Geographical Focus.

Europe and Asia account for the largest share of studies. Notable European contributors include Italy (Proietti & Magnani, 2025; Ricci et al., 2021), Germany (Muto et al., 2024), the UK (Tawil et al., 2024), Spain (Ferreira et al., 2023), and France (Grimaldi et al., 2023). In Asia, studies focus primarily on China (Li et al., 2024), South Korea (Park & Lee, 2024), Malaysia (Limpeeticharoenchot et al., 2022), and Indonesia (Siregar et al., 2024). Some studies analyze North America (Godbless Ocran et al., 2024), Latin America (Castillo-Vergara et al., 2025), and Australia (Sullivan & Fosso Wamba, 2024), though these regions are underrepresented. Africa appears only marginally, pointing to an area of opportunity for future research (Bar-Gill et al., 2024).

Sectoral Focus.

A wide range of industry sectors is represented. Manufacturing is the most frequently studied, often in the context of Industry 4.0 and predictive maintenance (Arranz et al., 2023; Mateev, 2023; Zheng et al., 2025). Other sectors include professional services and consulting (Kolagar et al., 2024; Yang et al., 2024), retail and e-commerce (Grashof & Kopka, 2023; Mantri & Mishra, 2023), healthcare (Hunke et al., 2022; Muto et al., 2024), construction (Bermeo-Giraldo et al., 2022), and finance/insurance (El Hilali et al., 2020; Wang & Zhang, 2025). Several studies adopt a multi-sectoral or cross-industry perspective (Glebova et al., 2024; Ojeda et al., 2024), especially when discussing strategic or technological frameworks.

Types of AI Technologies Discussed.

Machine Learning (ML) and Big Data Analytics (BDA) appear most frequently, followed by Natural Language Processing (NLP) and Robotic Process Automation (RPA) (Ardito et al., 2024; Bhatia & Diaz-Elsayed, 2023; Ciampi et al., 2021). Generative AI is increasingly prominent, particularly in studies focused on SMEs and marketing automation (Cho et al., 2025; Godbless Ocran et al., 2024; Yang et al., 2024). Several studies also explore the integration of AI with IoT, blockchain, and cloud computing (Farmanesh et al., 2025; Weber, 2023), often in relation to SMEs that benefit from scalable SaaS-based solutions.

Company Size Focus.

Approximately half of the selected articles focus exclusively on SMEs (e.g., (Adwan, 2024; Huang et al., 2023; Rehman et al., 2024)), while fewer are dedicated solely to large corporations (Ferreira et al., 2023; Mateev, 2024). Only a limited number of studies offer a direct and structured comparison between SMEs and LCs (Rehman et al., 2024; Sullivan & Fosso Wamba, 2024; Tummalapalli et al., 2025), further confirming the identified research gap. In many cases, studies that include both company types treat them as part of a heterogeneous sample without systematic differentiation (Limpeeticharoenchot et al., 2022; Maroufkhani et al., 2023).

Research Methodologies.

Methodologically, the corpus includes a balanced mix of quantitative (e.g., surveys, SEM) and qualitative (e.g., case studies, interviews) approaches (Maroufkhani et al., 2020; Trinh, 2024; Zhang & Peng, 2025). Mixed-method studies are also represented, often in applied settings or exploratory contexts (Schwaeke et al., 2025). A smaller number of articles are conceptual or propose analytical frameworks for AI adoption (Bettoni et al., 2021; von Garrel & Jahn, 2023), while others are systematic literature reviews themselves (e.g., (S. Liu & Cheng, 2025; Schwaeke et al., 2025)), contributing to theoretical consolidation.

4.2 Thematic Synthesis: Comparative Analysis of AI Adoption

This section presents a thematic synthesis of the findings, structured around the two main research questions (RQ1 and RQ2). Drawing on the 71 selected studies, the analysis identifies six core themes that reflect both the shared and divergent experiences of SMEs and large corporations (LCs) in their approach to artificial intelligence (AI) adoption.

These themes are:

1. Drivers of AI adoption

2. Barriers and enabling conditions
3. AI technologies and application areas
4. Observed benefits and outcomes
5. Strategic implementation models
6. Influence of contextual factors (sector, geography, and policy)

For each theme, the results are structured in three parts: (1) insights specific to SMEs, (2) insights specific to LCs, and (3) a comparative synthesis. The analysis is based on both structured data (e.g., Excel synthesis tables) and qualitative notes (e.g., case-level findings, quotes, and author interpretations), allowing a triangulation of findings across multiple methodological perspectives (Nowell et al., 2017; Schwaeke et al., 2025).

A strong comparative focus is maintained throughout, as suggested by several prior works that emphasize the importance of company size as a determinant of technological adoption capacity, strategic intent, and resource allocation (Kolková & Ključnikov, 2022; Lemos et al., 2022; Zhang & Peng, 2025). The synthesis also draws attention to recurring patterns across firm types, sector-specific nuances, and the evolving role of technologies such as Generative AI and cloud-based solutions in shaping the AI maturity path for firms of different sizes (Cho et al., 2025; Farmanesh et al., 2025).

4.2.1 Theme 1: Drivers of AI Adoption

The motivations compelling organizations to adopt artificial intelligence (AI) vary in strategic scope and operational focus depending on firm size. Although certain drivers—such as efficiency, data use, and competitiveness—are common to both SMEs and large corporations (LCs), the intensity, urgency, and expected outcomes differ substantially.

Drivers for Small and Medium-sized Enterprises (SMEs)

For SMEs, the primary driver of AI adoption is the need to improve internal efficiency, reduce costs, and optimize resource usage (Ardito et al., 2024; Limpeeticharoenchot et al., 2022). AI is commonly seen as a tool to automate repetitive tasks, streamline workflows, and compensate for human resource shortages (Falahat et al., 2020; Siregar et al., 2024).

Customer-facing applications are also a frequent motivator. SMEs increasingly use AI to enhance personalization, improve service quality, and engage clients through low-cost tools like chatbots and basic analytics platforms (Godbless Ocran et al., 2024; Ridho, 2023). Generative AI is emerging as a viable enabler of content creation, marketing automation, and communication tasks (Cho et al., 2025; Farmanesh et al., 2025).

Innovation also plays a role, though usually in an incremental and operational sense—e.g., improving existing services or launching small-scale experiments—rather than large-scale transformation (Bettoni et al., 2021; Mantri & Mishra, 2023). Many SMEs pursue AI with a clear need for short-term return on investment (ROI), which limits the complexity and scale of the solutions they adopt (Schwaeke et al., 2025; Tawil et al., 2024).

Drivers for Large Corporations (LCs)

In contrast, LCs often adopt AI to achieve broader strategic objectives, including competitive advantage, global scalability, and long-term innovation (Li et al., 2024; Zhang & Peng, 2025). AI is used to drive enterprise-wide digital transformation and support the reinvention of core business models (Duan et al., 2025; Ferreira et al., 2023).

One of the most cited motivations among LCs is the ability to process and analyze large volumes of data to guide strategic decision-making at scale (Mateev, 2024; Tummalapalli et al., 2025). LCs leverage advanced analytics, predictive modeling, and internal R&D to deploy AI in complex, high-impact areas such as supply chain optimization, risk management, and product innovation (Kolagar et al., 2024; Soni et al., 2019).

Unlike SMEs, LCs are more likely to have the time and financial stability to tolerate delayed ROI. Their AI investments are often embedded in long-term roadmaps, with formal KPIs and enterprise-level integration plans (Grashof & Kopka, 2023; Maroufkhani et al., 2020).

Comparative Analysis

Both SMEs and LCs recognize AI as a tool for improving efficiency, making better decisions, and remaining competitive. However, SMEs adopt AI as a tactical enabler, often triggered by external pressures such as digitization or limited human capacity (Weber, 2023; Zairis & Zairis, 2022). They pursue practical, affordable tools with clear outcomes. Conversely, LCs adopt AI as a strategic asset, often as part of top-down digital transformation agendas aimed at long-term growth, market dominance, or radical innovation (El Hilali et al., 2020; Yang et al., 2024).

Some studies suggest that SMEs often use AI techniques to invent or refine processes (the so-called "invention of methods of inventing" – IMI), while LCs focus on deploying AI as a general-purpose technology (GPT) across integrated platforms (Grashof & Kopka, 2023; Sullivan & Fosso Wamba, 2024). The distinction lies not only in the "why" of AI adoption but also in how firms conceptualize AI's role within their organizational goals.

Table 4.2.1: Comparative Summary of AI Adoption Drivers: SMEs vs. Large Companies

Driver	**SMEs**	**Large Companies**
Operational Efficiency	**Very High** – Priority driver due to limited resources (Ardito et al., 2024; Siregar et al., 2024)	**High** – Integrated into larger optimization programs (Zhang & Peng, 2025)
Cost Reduction	**Very High** – Often tied to survival and ROI (Falahat et al., 2020; Ridho, 2023)	**Medium-High** – Cost reduction within broader strategic goals (Mateev, 2024)
Competitiveness / Survival	**High** – Particularly in fast-changing markets (Limpeeticharoenchot et al., 2022)	**Medium** – Framed more as market leadership than survival (Ferreira et al., 2023)
Improved Customer Engagement	**High** – AI used in marketing, chatbots, personalization (Godbless Ocran et al., 2024)	**High** – Especially in multichannel strategies (Tummalapalli et al., 2025)
Innovation (Product / Service / Process)	**Medium** – Usually incremental or experimental (Mantri & Mishra, 2023)	**Very High** – Focus on radical and systemic

Driver	SMEs	Large Companies
		innovation (Duan et al., 2025)
Strategic Advantage / Market Leadership	**Low–Medium** – Focused on niche positioning (Yang et al., 2024)	**Very High** – AI as core to market leadership (Li et al., 2024; Zhang & Peng, 2025)
Solving Complex Problems / Decision-Making	**Medium** – Often limited by data availability (Bettoni et al., 2021)	**Very High** – Enabled by advanced analytics and data infrastructure (Mateev, 2024)
Scalability of Operations	**Low** – Focus is on improving current processes (Farmanesh et al., 2025)	**Very High** – Key strategic goal across global operations (Kolagar et al., 2024)

This table directly addresses a fundamental aspect of the research question by providing a clear, evidence-backed comparison of AI adoption drivers. It effectively illustrates that while certain motivations, such as the pursuit of efficiency, are shared, their relative importance and strategic interpretation vary considerably according to firm size.

4.2.2 Theme 2: Barriers to AI Adoption

The path to AI adoption is fraught with obstacles, the nature and severity of which often differ depending on company size, although certain challenges are universally experienced across organizational types (Grimaldi et al., 2023; Zairis & Zairis, 2022).

Barriers for SMEs

SMEs typically encounter a constellation of interconnected challenges that can create a vicious cycle, difficult to break without external support or strategic intervention (Schwaeke et al., 2025; Tawil et al., 2024).

- **Resource Constraints.**

  This is the most ubiquitously cited and impactful barrier. It includes the lack of financial capital to invest in technologies and skills (Ardito et al., 2024), a shortage of qualified personnel with AI expertise (Adwan, 2024), and outdated or inadequate technological infrastructure (Bettoni et al., 2021; Farmanesh et al., 2025). For example, (Proietti & Magnani, 2025) explicitly link "limited resources" to both "inadequate infrastructures" and a persistent lack of digital capabilities in Italian SMEs.

- **Data-Related Challenges.**

  Many SMEs lack access to large volumes of high-quality data. They also report difficulties in data collection, cleaning, and integration, as well as limited capabilities in data governance and analytics (Weber, 2023; Zhang & Peng, 2025). These limitations reduce the effectiveness of AI tools and often prevent firms from initiating even basic automation.

- **Lack of Knowledge and Skills.**

  Beyond the absence of AI specialists, general managerial and operational staff often lack digital literacy or awareness of AI's strategic potential (Mantri & Mishra, 2023; Ridho, 2023). This results in a poor alignment between business needs and technology choices.

- **Organizational and Cultural Factors.**

  Resistance to change, fear of job loss, and insufficient top management support are common. SMEs may lack structured internal change management processes, which compounds reluctance to adopt new technologies (Godbless Ocran et al., 2024; Maroufkhani et al., 2023).

- **External and Institutional Barriers.**

  SMEs often report difficulties in interpreting AI-related regulations, lack of affordable external vendors, and limited public support schemes (Cho et al., 2025; Ricci et al., 2021). This "ecosystem gap" is particularly severe in non-metropolitan areas or less digitally developed regions.

Barriers for Large Corporations (LCs)

LCs, despite possessing greater financial and technical resources, face a different set of challenges, mainly stemming from their organizational scale and structural complexity (Kolagar et al., 2024; Mateev, 2024)

- **Integration Complexity.**

  Integrating new AI solutions into deeply embedded, often fragmented legacy IT systems is among the most commonly cited challenges (El Hilali et al., 2020; Li et al., 2024). This issue is exacerbated by the presence of internal data silos and inconsistent system architectures across departments.

- **Organizational Inertia and Change Management.**

  Large firms often struggle to adapt quickly due to rigid hierarchies, formalized processes, and departmental resistance (Ferreira et al., 2023). These factors can slow decision-making and obstruct the implementation of cross-functional AI initiatives.

- **Large-Scale Data Governance and Ethics.**

  While LCs have abundant data, ensuring its ethical use, compliance with privacy laws (e.g., GDPR), and managing algorithmic bias across millions of records represents a major governance challenge (Bhatia & Diaz-Elsayed, 2023; Duan et al., 2025).

- **Acquisition and Retention of AI Talent.**

  Despite offering higher salaries, LCs face intense global competition for top-tier AI experts. Moreover, upskilling large internal teams remains a costly and time-consuming process (Huang et al., 2023; Soni et al., 2019).

- **Strategic Alignment and ROI Justification.**

  AI investments in large organizations often require multi-million-dollar budgets. Justifying these projects—especially those not tied to short-term KPIs—can be difficult, particularly in risk-averse corporate environments (Schwaeke et al., 2025).

Comparative Analysis

- **Similarities:**
  Both SMEs and LCs struggle with talent shortages, data-related limitations, and the ethical implications of AI (Adwan, 2024; Glebova et al., 2024). Creating a culture of innovation and change remains critical for both.

- **Differences:**
  SMEs are fundamentally constrained by financial, human, and infrastructural limitations. This often leads to a loop of underinvestment and weak capacity development (Tawil et al., 2024)t. LCs, on the other hand, face challenges linked to scale and system complexity: legacy integration, organizational inertia, and multi-layered governance.

Interestingly, SMEs tend to be more agile and willing to experiment—but lack the means. LCs have the resources, but often lack speed and internal alignment (Rehman et al., 2024; Weber, 2023). As a result, SMEs may abandon or delay AI initiatives due to cost, while LCs may stall due to structural resistance or overly cautious ROI logic.

Table 4.2.2: Comparative Summary of AI Adoption Barriers: SMEs vs. Large Enterprises

Barrier Category	**SMEs**	**Large Corporations**
Financial Resources	Very High – Major constraint to adoption (Ardito et al., 2024; Proietti & Magnani, 2025)	Low–Medium – Budget exists but must be strategically justified (Mateev, 2024)
Talent and Skills Shortage	Very High – Lack of internal expertise, can't compete for top AI professionals (Adwan, 2024)	High – Global competition for top-tier talent (Huang et al., 2023; Soni et al., 2019)
IT Infrastructure	High – Often outdated or missing entirely (Bettoni et al., 2021)	Medium – Complexity and fragmentation of legacy systems (Li et al., 2024)

Barrier Category	SMEs	Large Corporations
Data Access, Quality & Governance	High – Lack of structured data systems (Weber, 2023; Zhang & Peng, 2025)	Medium–High – Data silos and standardization issues at scale (Grimaldi et al., 2023)
Organizational Culture / Resistance	Medium–High – Driven by fear and lack of vision (Godbless Ocran et al., 2024)	High – Bureaucratic inertia and internal silos (Ferreira et al., 2023)
AI Integration Complexity	Medium – Mostly basic setup issues (Farmanesh et al., 2025)	Very High – Legacy complexity and interoperability challenges (El Hilali et al., 2020)
Ethical/Legal/Regulatory Barriers	Medium – Often lack resources for compliance (Ricci et al., 2021)	High – Must ensure explainability, ethics, and compliance at scale (Duan et al., 2025)
Strategic Alignment / ROI Justification	Medium – Driven by clear ROI needs (Schwaeke et al., 2025)	High – Justification of exploratory projects can be difficult (Zhang & Peng, 2025)

This table is crucial for understanding the distinct challenges faced by different firm sizes. It clearly delineates unique versus shared obstacles, which is instrumental for devising targeted mitigation strategies and effective policy interventions. The interconnected nature of these barriers—such as financial limitations leading to skill shortages in SMEs, or legacy systems complicating integration in LCs—is also made evident.

4.2.3 Theme 3: AI Technologies and Application Areas

The types of AI technologies adopted and the specific business areas where they are applied differ notably between SMEs and LCs, reflecting their varying capabilities, strategic priorities, and available resources. There is often a mismatch between the advanced AI solutions offered by vendors, which may be implicitly designed with LC resources in mind (Cho et al., 2025), and the specific, resource-constrained needs of many SMEs (Bettoni et al., 2021). However, the rise of cloud AI (Ridho, 2023) and more accessible Gen-AI tools (Farmanesh et al., 2025) is beginning to address this gap, lowering adoption barriers and enabling smaller firms to experiment with intelligent systems once exclusive to large players.

AI Technologies and Applications in SMEs

- **Predominant AI Types:** SMEs typically opt for AI solutions that are simpler to implement, more readily accessible, and often cloud-based or standard off-the-shelf software. Common technologies include Big Data Analytics (often using simpler tools like Excel or Power BI initially, then progressing to more advanced tools if resources allow) (Limpeeticharoenchot et al., 2022), basic forms of Machine Learning for sales prediction and segmentation (Mantri & Mishra, 2023), chatbots for customer service (Godbless Ocran et al., 2024), and, increasingly, Generative AI for specific tasks such as content creation, basic coding, or automating particular job functions (Farmanesh et al., 2025; Proietti & Magnani, 2025). Cloud solutions are particularly important, as they lower the barrier to entry and reduce the need for internal infrastructure (Ridho, 2023).

These technological choices are driven by SMEs' tactical and operational logic. Their focus is on technologies that offer measurable and fast ROI, align with resource constraints, and address clearly identified business needs (Schwaeke et al., 2025). The Technology–Organization–Environment (TOE) framework helps explain these patterns, as SMEs are constrained both technologically and organizationally, and often rely on environmental enablers like external consultants or government programs.

- **Application Areas:**
  AI applications in SMEs are frequently concentrated in areas that offer direct improvements in operational efficiency or customer interaction. Key areas include:
  - **Customer Service:** Automation of responses and support via chatbots and voice bots (Godbless Ocran et al., 2024).
  - **Marketing:** Personalization of campaigns, sentiment analysis of customer feedback, and SEO optimization (Yang et al., 2024).
  - **Operational Efficiency:** Automation of back-office processes, inventory management, and manufacturing activities (Rehman et al., 2024).
  - **Human Resources (HR):** Streamlining recruitment processes (e.g., CV parsing), onboarding, and AI-supported training platforms (Siregar et al., 2024).

In SMEs, these applications often emerge from a trial-and-error logic, where AI tools are tested for functional fit and quickly scaled only if they show tangible value.

AI Technologies and Applications in Large Companies (LCs)

- **Predominant AI Types:**

  LCs are more likely to invest in and deploy complex, often bespoke or highly customized AI solutions that require substantial investment and specialized expertise. These include advanced Machine Learning and Deep Learning models (Zhang & Peng, 2025), large-scale predictive and prescriptive analytics systems (Mateev, 2024), advanced robotics and automation in manufacturing and logistics (Arranz et al., 2023), and integrated AI platforms that operate across the entire enterprise (Ferreira et al., 2023). These technologies are often internally developed or co-designed with strategic partners and embedded within broader digital transformation strategies.

The resource availability and structural capacity of LCs allow them to treat AI as a general-purpose technology (GPT), embedding it across multiple levels of the organization and linking it to innovation and long-term competitiveness (Grashof &

Kopka, 2023). Strategic foresight and scale economies make high-investment AI feasible, even when returns are uncertain or delayed (Duan et al., 2025).

- **Application Areas:**

  AI applications in LCs are typically more strategic and wide-ranging, targeting core business functions and long-term objectives. Common areas include:

  - **Research & Development (R&D):** Accelerating innovation cycles, drug discovery, and new product development (Tummalapalli et al., 2025).
  - **Strategic Decision Support:** Utilizing AI-driven insights for high-level corporate strategy and complex problem-solving (Duan et al., 2025).
  - **Supply Chain Optimization:** Enhancing logistics, demand forecasting, and inventory management on a large scale (Li et al., 2024).
  - **Predictive Maintenance:** Applied in critical sectors such as manufacturing, energy, and transportation to reduce downtime and costs (El Hilali et al., 2020).
  - **Advanced Risk Management:** Especially in finance, insurance, and cybersecurity, AI is used for fraud detection, credit scoring, and compliance monitoring (Wang & Zhang, 2025).
  - **Core Process Transformation and Automation:** Re-engineering and automating end-to-end business processes (e.g., procurement, finance, operations) (Kolagar et al., 2024).
  - **Business Model Innovation:** Creating new revenue streams or fundamentally altering how the company operates and delivers value (Zairis & Zairis, 2022).

These applications reflect the LCs' strategic intent to derive value not only from operational gains but also from systemic transformation and market leadership.

Comparative Analysis

- **Similarities:**

  Both SMEs and LCs utilize AI for process automation and data analysis to improve performance and decision-making. Customer service and marketing represent common starting points across firm sizes (Weber, 2023; Yang et al., 2024). Additionally, both increasingly explore the use of Generative AI, although the scale and sophistication differ.

- **Differences:**
  The primary distinctions lie in the scale, complexity, and strategic framing of AI applications. SMEs focus on specific, functional improvements with an expectation of relatively quick ROI, and rely on affordable, ready-made solutions (Mantri & Mishra, 2023). LCs, possessing greater resources and internal capabilities, embark on AI initiatives aimed at strategic transformation, new business models, or solving complex R&D challenges (Ferreira et al., 2023; Zhang & Peng, 2025).

One study suggests that SMEs are more focused on AI **techniques**—methods to enable innovation in constrained environments—while LCs concentrate on AI **applications** as part of enterprise-wide architectures (Grashof & Kopka, 2023). The advent of Generative AI, however, may contribute to reducing this gap by giving SMEs access to tools that previously required significant resources (Farmanesh et al., 2025; Tawil et al., 2024).

Table 4.2.3 – Predominant AI Technologies and Application Areas: SMEs vs. Large Enterprises

Aspect	**SMEs**	**Large Enterprises**
Predominant AI Types	Cloud/SaaS tools, Basic ML, Chatbots, BDA, GenAI for content creation (Farmanesh et al., 2025; Ridho, 2023)	Advanced ML/DL, Custom enterprise platforms, Robotics, Predictive Analytics (Ferreira et al., 2023; Zhang & Peng, 2025)
Technological Complexity	Generally low to medium complexity, plug-and-play or off-the-shelf tools	Medium to high complexity, highly customized or fully integrated systems
Source of Solutions	Predominantly external providers; off-the-shelf or cloud-based services	Mixed: in-house development, strategic vendor alliances, dedicated AI teams

Aspect	SMEs	Large Enterprises
Primary Application Areas	Customer service (chatbots), marketing personalization, back-office automation, recruitment (Godbless Ocran et al., 2024; Siregar et al., 2024)	R&D, strategic decision-making, supply chain optimization, predictive maintenance, compliance (Grashof & Kopka, 2023; Wang & Zhang, 2025)
Strategic Focus of Applications	Functional improvements, quick ROI, niche operational problems	Strategic transformation, long-term innovation, business model reinvention

This table effectively details the “what” and “how” of AI utilization across firm sizes, underscoring the differences in technological sophistication, solution sourcing, and strategic objectives. These insights reinforce the idea that AI adoption is not merely about technology availability but about organizational readiness and strategic intent, which differ substantially between SMEs and LCs.

4.2.4 Theme 4: Observed Benefits and Outcomes of AI Adoption

The adoption of AI is ultimately driven by the expectation of tangible value. This section explores the observed and reported benefits of AI adoption across SMEs and large corporations (LCs), highlighting both shared outcomes and key differences in scope, strategic relevance, and impact intensity.

Benefits in Small and Medium-sized Enterprises (SMEs)

For SMEs, the observed benefits of AI adoption are primarily practical and operational. Most reported outcomes revolve around improved efficiency, lower costs, and incremental innovation.

Operational and Financial Gains:

A major benefit observed in SMEs is enhanced operational efficiency—achieved through automation of repetitive tasks, improved resource allocation, and streamlined workflows (Bettoni et al., 2021; Rehman et al., 2024). For instance, productivity gains of over 6%

were documented in specialized Chinese SMEs using AI-driven process optimization (Li et al., 2024). These improvements often translate into measurable cost savings (Godbless Ocran et al., 2024; Mantri & Mishra, 2023).

Improved Decision-Making:

Even with basic analytics tools, SMEs report improvements in decision speed and quality. AI-based dashboards, forecasting tools, and predictive models are used to support tactical and financial decisions (Ridho, 2023; Tawil et al., 2024).

Revenue Growth and Financial Performance:

Some SMEs experience a direct impact on sales and profitability. Studies in European contexts show revenue increases when AI is adopted in marketing and e-commerce (Cho et al., 2025; Trinh, 2024). For example, eBay vendors using analytics tools reported a 3.6% increase in revenue (Bar-Gill et al., 2024).

Customer-Focused Benefits:

AI also enhances customer engagement and satisfaction. Chatbots, personalized communications, and faster response times improve the overall service experience (Siregar et al., 2024; Yang et al., 2024).

Incremental Innovation and Competitive Positioning:

AI supports product/service updates and internal innovation, albeit typically in incremental forms (Proietti & Magnani, 2025). The capacity to differentiate via customer experience or process efficiency is a frequent strategic outcome (Zairis & Zairis, 2022).

Emerging Sustainability Impact:

In a growing number of cases, AI supports SMEs' environmental and social sustainability goals—for instance, by reducing energy waste or improving supply chain traceability (Farmanesh et al., 2025; Lemos et al., 2022). However, these outcomes are usually secondary and not the main drivers of adoption.

Benefits in Large Corporations (LCs)

LCs benefit from AI in a more comprehensive and strategic way. Due to their greater scale and investment capabilities, they can deploy AI to generate long-term returns, drive business model innovation, and secure market leadership.

Strategic ROI and Market Advantage:

AI is used not only to reduce costs but to create competitive differentiation and long-term shareholder value (Zhang & Peng, 2025). In sectors like finance, logistics, and manufacturing, LCs report multimillion-dollar savings and enhanced EBITDA margins (Ferreira et al., 2023).

Disruption and Innovation:

Many LCs use AI to fuel radical innovation, particularly in R&D-intensive industries. Applications such as generative design, drug discovery, and autonomous product development are reshaping entire value chains (Grashof & Kopka, 2023; Tummalapalli et al., 2025).

Enterprise-Wide Efficiency:

The scale of automation is broader: from predictive maintenance to AI-assisted procurement, AI enables deep transformation of complex systems (Duan et al., 2025). The gains are not limited to one department but span multiple business units.

Advanced Decision-Making and Risk Management:

Through integration with Big Data platforms, LCs enhance forecasting, real-time decision-making, and strategic scenario analysis (Mateev, 2024). In highly regulated sectors, AI also supports risk identification and compliance efforts (Wang & Zhang, 2025).

Customer Experience and Hyper-Personalization:

LCs use AI for advanced segmentation, real-time personalization, and customer journey orchestration across digital channels, contributing to stronger brand loyalty and increased CLV (Li et al., 2024; Yang et al., 2024)

Sustainability at Scale:

LCs embed AI into their Environmental, Social, and Governance (ESG) strategies. AI-driven energy optimization, emissions tracking, and ethical sourcing systems are increasingly common in multinational enterprises (Ferreira et al., 2023; Kolagar et al., 2024).

Comparative Analysis

Shared Benefits:

Both SMEs and LCs benefit from improved efficiency, decision-making support, and enhanced customer satisfaction. They also recognize AI's role in boosting competitiveness and enabling innovation. However, the scale, scope, and strategic framing of these benefits differ greatly.

Key Differences:

- **Strategic Depth and Impact:**

  For SMEs, AI typically leads to tangible, short-term gains, often essential for survival or modest growth. For LCs, AI underpins long-term strategic transformation, enabling disruption and market dominance.

- **Nature of Innovation:**

  SMEs focus on incremental improvements—optimizing what they already do. LCs use AI for radical innovation, including launching new lines of business (Tawil et al., 2024).

- **ROI Horizon and Expectations:**

  SMEs require rapid ROI due to limited financial flexibility, whereas LCs can wait longer for AI payoffs, especially when linked to enterprise-level investments (Zairis & Zairis, 2022).

- **Sustainability Role:**

  While both firm types increasingly link AI to sustainability, LCs embed it into formal ESG strategies, while SMEs benefit indirectly, primarily through resource efficiency (Farmanesh et al., 2025).

Table 4.2.3 – Comparative Summary of AI-Driven Benefits in SMEs and Large Enterprises

Benefit Category	SMEs	Large Enterprises
Operational Efficiency Improvement	Very High – AI is used for automating tasks, streamlining workflows (e.g., (Ardito et al., 2024; Mantri & Mishra, 2023; Proietti & Magnani, 2025; Zhang & Peng, 2025; Zheng et al., 2025))	Very High – Enterprise-level process reengineering and automation (e.g., (Ferreira et al., 2023; Li et al., 2024; Ojeda et al., 2024; Soni et al., 2019; Sullivan & Fosso Wamba, 2024))
Cost Reduction	Very High – Reduction in operating costs via automation, better resource use (e.g.,(Ardito et al., 2024; Muto et al., 2024; von Garrel & Jahn, 2023; Willetts & Atkins, 2023; Yen et al., 2024))	High – Strategic savings across global operations (e.g., (Godbless Ocran et al., 2024; Kulkov et al., 2024; Mateev, 2024))
Enhanced Decision-Making	High – Simpler analytics help improve decisions quickly (e.g., (Godbless Ocran et al., 2024; Maroufkhani et al., 2020; Trinh, 2024; von Garrel & Jahn, 2023; Zheng et al., 2025))	Very High – AI enables complex decision-making at strategic level (e.g., Art. (Grimaldi et al., 2023; Li et al., 2024; Ojeda et al., 2024; Soni et al., 2019))
Revenue Growth / Financial Performance	Medium–High – Some SMEs see revenue increase from AI use in marketing/IoT (e.g., (Ardito et al., 2024; Bar-Gill et al., 2024))	High – AI supports new business models and value creation (e.g., Art. (Huang et al., 2023; Li et al., 2024; Sullivan & Fosso Wamba, 2024))

Benefit Category	SMEs	Large Enterprises
Customer Satisfaction & Engagement	High – Chatbots and personalization improve service quality (e.g., Art(Rehman et al., 2024; Ridho, 2023; Willetts & Atkins, 2023))	High – Hyper-personalization and multichannel service improve customer lifetime value (e.g., Art. (Sullivan & Fosso Wamba, 2024; Yang et al., 2024))
Innovation Capacity	Medium – Often incremental innovation tied to existing offerings (e.g., (Ardito et al., 2024; Proietti & Magnani, 2025; Zhang & Peng, 2025))	High – Focus on radical and disruptive innovation (e.g., Art. (Godbless Ocran et al., 2024; Grashof & Kopka, 2023; Soni et al., 2019))
Competitive Advantage	Medium – Mainly in niche positioning or differentiation (e.g., Art. (Arranz et al., 2023; Lemos et al., 2022; Limpeeticharoenchot et al., 2022))	High – Often sectoral or global leadership (e.g., (Kulkov et al., 2024; Perifanis & Kitsios, 2023; Sullivan & Fosso Wamba, 2024))
Sustainability (Environmental / Social)	Emerging – Often indirect via efficiency gains (e.g., (El Hilali et al., 2020; Lemos et al., 2022; Muto et al., 2024))	Growing – AI is embedded in formal ESG strategies (e.g., Art. (Bernovskis et al., 2024; Ferreira et al., 2023; Kolagar et al., 2024))

4.2.5 Theme 5: Strategic Approaches and Implementation Models

AI adoption is not only about technologies or outcomes—it is equally about the strategic approach and implementation pathway that firms choose. This section analyzes how SMEs and large corporations (LCs) design and execute their AI strategies, highlighting fundamental differences in planning, resource use, governance, and maturity logic.

Strategic Approaches in Small and Medium-sized Enterprises (SMEs)

SMEs typically adopt AI in a more pragmatic, flexible, and incremental manner. Due to limited resources, their strategic orientation is often reactive or opportunity-driven rather than guided by a formal top-down roadmap (Proietti & Magnani, 2025; Trinh, 2024).

- Iterative and Agile Implementation:

  SMEs usually start with small pilot projects or proof-of-concept (PoC) initiatives focused on solving specific problems (Ridho, 2023; Zheng et al., 2025). The approach is phased, with each step contingent on the ROI of the previous one.

- Focus on Quick Wins:

  Due to cash flow sensitivity, most SMEs prioritize fast, measurable benefits from AI tools—such as improved marketing performance or automated customer service (Tawil et al., 2024). Strategic transformation is rare; the emphasis is on tactical functionality.

- Reliance on External Expertise:

  SMEs often lack in-house AI capabilities and depend on consultants, cloud vendors, or academic partnerships for development and deployment (Farmanesh et al., 2025; Ricci et al., 2021). SaaS and low-code solutions are preferred.

- Cloud-based and Off-the-shelf Solutions:

  SMEs show a strong preference for plug-and-play tools that require minimal infrastructure and offer fast onboarding (Limpeeticharoenchot et al., 2022).

- Bottom-up and Opportunistic Adoption:

  Many adoption cases are driven by individual managers or digital-savvy employees rather than central planning. This results in decentralized and ad hoc initiatives (Trinh, 2024).

- Customized Maturity Pathways:

AI maturity in SMEs does not follow a linear enterprise model. Recent studies propose alternative maturity models tailored to SMEs, which allow for stabilization at intermediate stages (Bettoni et al., 2021; Willetts & Atkins, 2023).

Strategic Approaches in Large Corporations (LCs)

In contrast, LCs adopt AI through structured, long-term strategies integrated into broader digital transformation programs (Duan et al., 2025; Ferreira et al., 2023). Their approaches are more formal, centralized, and resource-intensive.

- Formal Top-Down Strategies:

  AI initiatives in LCs are usually part of corporate-level plans, led by executives and governed through structured digital roadmaps and KPIs (Zhang & Peng, 2025).

- Enterprise-Scale Implementation:

  Rather than focusing on isolated applications, LCs aim for organization-wide integration, often through centralized platforms and governance policies (Kolagar et al., 2024).

- Internal Capability Development:

  LCs invest in AI Centers of Excellence, in-house data science teams, proprietary platforms, and upskilling programs. This creates strategic assets and long-term independence from vendors (Mateev, 2024).

- Change Management Programs:

  Due to scale and inertia, LCs adopt formal change management frameworks to address resistance and coordinate cross-functional transformation (Ferreira et al., 2023; Grashof & Kopka, 2023).

- Strategic Partnerships and Acquisitions:

  Collaborations with AI providers, research centers, or the acquisition of startups are common routes to accelerate capability building and gain access to frontier knowledge (Li et al., 2024; Soni et al., 2019).

- Focus on Robustness and Scalability:

  Solutions are selected based on their scalability, security, and compliance features, as they must support large volumes of users, data, and processes.

Comparative Analysis

- **Similarities:**
  - Both firm types may experiment with pilots or PoCs.
  - Both rely (at different levels) on external partners for technology or knowledge.
  - Both benefit from flexible implementation frameworks tailored to their size.
- **Key Differences:**
  - **Strategic Formality:**

    SMEs often follow ad hoc or bottom-up approaches, guided by operational needs. LCs typically deploy top-down, systematic strategies with formal governance (Perifanis & Kitsios, 2023).
  - **Implementation Scope and Pace:**

    SMEs adopt incrementally and scale cautiously. LCs plan transformative rollouts, often slower but broader (Xin et al., 2024; Yang et al., 2024).
  - **Resource Allocation:**

    SMEs rely heavily on external tools and services. LCs build internal capabilities, investing in infrastructure and people (Kolagar et al., 2024; Li et al., 2024).
  - **Risk Appetite:**

    SMEs are risk-averse, needing predictable ROI. LCs can absorb more risk for long-term strategic gain (Grashof & Kopka, 2023).
  - **AI Maturity Pathways:**

AI maturity is non-linear. SMEs may stabilize at “satisficing” levels of integration, whereas LCs target full AI integration (Limpeeticharoenchot et al., 2022; Willetts & Atkins, 2023).

Table 4.2.5 – Strategic Approaches and Implementation Models: SMEs vs. Large Enterprises

Aspect	**SMEs**	**Large Enterprises**
Strategic Planning	Informal, opportunistic, bottom-up (Proietti & Magnani, 2025; Trinh, 2024)	Formal, top-down, vision-aligned (Ferreira et al., 2023; Yang et al., 2024)
Implementation Approach	Iterative, agile, PoC-based, quick wins (von Garrel & Jahn, 2023; Zheng et al., 2025)	Systematic, planned, enterprise-wide (Xin et al., 2024; Yang et al., 2024)
Resource Strategy	External tools/services, SaaS, limited internal investment (Farmanesh et al., 2025; Ricci et al., 2021)	Internal development, AI CoEs, talent hiring (Li et al., 2024; Soni et al., 2019)
Risk Profile	Lower – focused on predictable ROI (Ridho, 2023; Yang et al., 2024)	Higher – willing to take risks for strategic gain (Grashof & Kopka, 2023; Perifanis & Kitsios, 2023)
Governance and Change	Limited change management, informal adoption structures	Formal change management, enterprise integration programs
Capability Building	Opportunistic, relies on external partners	Long-term internal capacity building and standardization
AI Maturity Trajectory	Adaptive, non-linear, satisficing (Bettoni et al., 2021; Willetts & Atkins, 2023)	Progressive, enterprise-scale maturity targets (Limpeeticharoenchot et al., 2022; Xin et al., 2024)

4.2.6 Theme 6: Influence of Contextual Factors (Sector, Geography, Policy)

AI adoption is not driven solely by internal organizational characteristics. External contextual factors—such as industry dynamics, geographical setting, and the regulatory/policy environment—play a substantial role in shaping how and to what extent firms engage with AI. This section explores how such contextual elements affect SMEs and large corporations (LCs) differently.

Contextual Influences on SMEs

- **Industry-Specific Pressures and Opportunities:**

  SMEs in technology-intensive or highly competitive industries (e.g., manufacturing, retail, professional services) face stronger incentives to adopt AI to increase efficiency or sustain market presence (Mantri & Mishra, 2023; Tawil et al., 2024). In contrast, SMEs in traditional sectors or low-tech environments often lag behind unless niche-specific use cases are clearly defined (Tawil et al., 2024).

- **Dependence on Local Ecosystems:**

  SMEs are strongly influenced by their immediate **regional ecosystems**. Proximity to universities, innovation hubs, accelerators, or AI vendors greatly facilitates access to knowledge, partnerships, and infrastructure (Proietti & Magnani, 2025; Ricci et al., 2021).

- **Digital Infrastructure Disparities:**

  Limited broadband coverage, insufficient cloud access, or fragmented IT service networks in certain regions act as bottlenecks to AI uptake (Proietti & Magnani, 2025; Zhang & Peng, 2025). The digital divide is particularly pronounced in rural and less industrialized areas.

- **Supportive Public Policies:**

  SMEs often rely on **regional or national government programs** for funding, training, and consultancy support. Well-designed incentives, like grants or tax credits, can significantly accelerate adoption (Cho et al., 2025; Tawil et al., 2024).

Conversely, absence of targeted support often leaves SMEs excluded from the AI transition.

- **Regulatory Complexity:**

  SMEs report difficulties in navigating complex and ambiguous regulations related to AI ethics, data protection (e.g., GDPR), and cybersecurity (Muto et al., 2024; Wang & Zhang, 2025). Their lack of internal legal or compliance functions makes them vulnerable to regulatory overload.

Contextual Influences on Large Corporations (LCs)

- **Sectoral Imperatives and Competitive Landscape:**

  LCs operating in rapidly evolving industries—such as finance, automotive, pharmaceuticals, or telecommunications—are more likely to adopt AI for strategic advantage and differentiation (Li et al., 2024; Ojeda et al., 2024). Highly regulated sectors also shape the form and pace of adoption due to strict compliance needs (Wang & Zhang, 2025)

- **Global Ecosystem Integration:**

  Multinational corporations benefit from access to **global innovation ecosystems**, including elite research institutions, international R&D hubs, and AI startup clusters (Soni et al., 2019). This access enables more diverse sourcing and experimentation.

- **Influence on Policy and Standard Setting:**

  LCs not only comply with regulations—they often **shape them**. Through industry coalitions, lobbying, and involvement in standards development, they influence the direction of AI-related policies (Duan et al., 2025; Yang et al., 2024).

- **Cross-Jurisdictional Compliance Challenges:**

  Operating across multiple regions, LCs must manage a **complex regulatory mosaic**—including GDPR (EU), CCPA (US), and local AI laws. While they often have legal resources to handle this, the burden remains significant (Ferreira et al., 2023; Godbless Ocran et al., 2024).

- **Infrastructure Readiness and Strategic Location:**

  LCs strategically locate AI units in regions offering strong digital infrastructure, talent pools, and innovation incentives. Their scale allows **selective investment** in high-potential environments.

Comparative Analysis

- **Similarities:**
  - Both SMEs and LCs are strongly shaped by **industry dynamics**, where pressure to innovate or comply is sector-dependent.
  - **Infrastructure readiness** is a foundational requirement for any meaningful AI adoption.
  - Well-designed **public policies** and access to supportive ecosystems act as enablers in both contexts.
- **Key Differences:**
  - Ecosystem Dependency:

    SMEs are highly dependent on local support networks and public funding. LCs can build their own ecosystems or tap into global ones, reducing reliance on specific geographies ((Ricci et al., 2021) vs. (Soni et al., 2019)).
  - Regulatory Navigation Capacity:

    SMEs often experience regulation as a barrier, while LCs, despite the burden, have the capacity to absorb and influence policy frameworks (Wang & Zhang, 2025; Yang et al., 2024).
  - Policy Reach and Focus:

    SME adoption is strongly influenced by local and national initiatives, whereas LCs respond to global policy trends and participate in international governance frameworks ((Cho et al., 2025)vs. (Li et al., 2024)).

- Strategic Orientation:

  LCs can take a proactive stance, shaping standards and lobbying for AI policies. SMEs remain mostly reactive, adapting to the existing regulatory and ecosystem landscape (Zairis & Zairis, 2022).

Table 5.6 – Contextual Factors Influencing AI Adoption in SMEs and Large Enterprises

Contextual Factor	**SMEs**	**Large Enterprises**
Industry Pressure	High in tech/competitive sectors, low in traditional industries (Tawil et al., 2024)	Very high in innovation-driven sectors (e.g., pharma, fintech) (Li et al., 2024; Ojeda et al., 2024)
Ecosystem Dependency	Strong reliance on local networks, universities, and public support (Ricci et al., 2021)	Access to and influence on global ecosystems and elite partnerships (Soni et al., 2019)
Digital Infrastructure	Regional gaps significantly limit adoption (Proietti & Magnani, 2025; Zhang & Peng, 2025)	Can invest in or relocate to high-infrastructure regions
Public Policy and Incentives	Crucial enabler – adoption often tied to funding or policy-driven programs (Cho et al., 2025; Tawil et al., 2024)	Less dependent but benefits from stable, innovation-oriented frameworks
Regulatory Burden	High – lack of internal legal capacity to manage AI/data law complexity (Muto et al., 2024; Wang & Zhang, 2025)	High but manageable – dedicated teams handle cross-border compliance (Godbless Ocran et al., 2024; Yang et al., 2024)
Policy Influence	Minimal – SMEs are mostly recipients of regulation and support	High – LCs participate in shaping policy, standards, and regulatory direction (Duan et al., 2025)

4.3 Summary of Findings and Transition to the Discussion

This chapter presented the main empirical findings of the systematic literature review, based on 71 selected studies. Through a thematic and comparative lens, it explored how SMEs and large enterprises are adopting AI across six key dimensions: drivers, barriers, technologies and applications, benefits, strategic approaches, and contextual factors.

A central insight emerging from the analysis is the pervasive influence of resource asymmetry. SMEs are defined by financial, human, and infrastructural constraints that shape their AI adoption as a pragmatic, incremental, and externally supported process, with a strong focus on efficiency and short-term ROI. Conversely, large corporations leverage their substantial internal resources to implement strategic, often transformative AI initiatives, aimed at innovation, competitive leadership, and long-term scalability. However, LCs also face significant challenges related to organizational inertia, complexity, and cross-functional integration.

Regarding drivers, while both firm types seek operational improvement and competitiveness, SMEs are mostly driven by immediate survival and functional needs, whereas LCs pursue broader strategic goals, such as business model reinvention and enterprise-wide transformation.

On the barriers side, SMEs are often locked in a "vicious circle" of low resources, which reinforces technical and knowledge gaps. LCs, instead, struggle with complex system integration, data governance at scale, and internal resistance due to size and structure.

In terms of AI technologies and applications, SMEs favor low-cost, standard, cloud-based tools (e.g., chatbots, basic ML, emerging GenAI) applied to marketing, customer service, and operational automation. LCs deploy advanced, customized systems (e.g., deep learning, enterprise AI platforms) across strategic functions such as R&D, supply chain, and corporate decision-making.

The benefits observed reflect these dynamics: SMEs tend to realize tangible, short-term operational and financial improvements, while LCs benefit from strategic, enterprise-wide gains—including radical innovation and long-term competitive positioning.

As for strategic approaches, SMEs typically follow bottom-up, opportunity-driven models supported by external providers. LCs adopt formal, top-down strategies embedded in digital transformation agendas, with internal AI teams, CoEs, and cross-functional planning.

Finally, contextual factors such as sector, geography, infrastructure, and policy significantly influence adoption. SMEs depend more heavily on local ecosystems, public incentives, and accessible infrastructures, while LCs operate within global policy frameworks, shape regulatory standards, and access high-tier innovation networks.

These findings provide a solid empirical foundation for the upcoming Chapter 5 – Discussion, which will interpret the results through the theoretical frameworks introduced in Chapter 2: Technology–Organization–Environment (TOE), Resource-Based View (RBV), Dynamic Capabilities, and Diffusion of Innovation. The discussion will examine the underlying reasons behind the observed patterns, analyze the interaction of internal and external factors, and reflect on the broader implications for research, managerial practice, and policy design.

Particular attention will be paid to emerging paradoxes—such as the resource–agility trade-off in SMEs and the resource–inertia tension in LCs—which offer valuable insights into differentiated AI adoption pathways. These conceptual patterns will serve as the core structure of the theoretical interpretation in the next chapter.

Chapter 5
Discussion

5.1 Introduction to the Discussion and Analytical Frameworks

This chapter builds on the findings presented in Chapter 4, with the goal of going beyond simple description and trying to understand *why* the patterns we observed make sense. After reviewing how AI is being adopted by both Small and Medium-sized Enterprises (SMEs) and Large Corporations (LCs), this chapter now focuses on interpreting those results through a set of well-established theoretical lenses. The aim is to make sense of the drivers, barriers, technologies, benefits, strategies, and contextual factors we found—while keeping the comparison between SMEs and LCs central throughout.

As explained in Chapter 1, this thesis aims to answer two main research questions:

- **RQ1:** What are the main drivers that lead SMEs and LCs to adopt artificial intelligence (AI) technologies?
- **RQ2:** What are the key similarities and differences between SMEs and LCs when it comes to the factors that support or hinder AI implementation?

To help interpret the findings and give proper answers to these questions, I decided to use a combination of four theoretical frameworks introduced in Chapter 2:

- **Technology–Organization–Environment (TOE):** which looks at how adoption is shaped by technological features, internal organization, and external pressures.
- **Resource-Based View (RBV):** which highlights how a firm's unique resources and capabilities can provide long-term advantages.
- **Dynamic Capabilities (DC):** which focuses on how firms adapt and reconfigure what they have when the environment changes.
- **Diffusion of Innovation (DOI):** which explains how innovations spread over time, and what influences that process.

These models aren't being used to test any hypotheses, but more as tools to help interpret what emerged from the literature. AI adoption is complex and multi-layered—it's about more than just the technology itself. It involves organizational priorities, available resources, strategic intentions, and external conditions. No single theory can fully capture all of that, especially when comparing two very different types of companies like SMEs and LCs. But together, these frameworks help paint a fuller picture.

To keep things structured, each main theme from Chapter 4 will be interpreted using the frameworks that best fit:

- **Drivers** of AI adoption → mostly through TOE and RBV
- **Barriers and enablers** → through TOE and DC
- **Technologies and how they're used** → through DOI and DC
- **Strategic approaches** → through RBV and DC
- **Contextual factors** → mainly through the environment part of TOE

Using these frameworks together allows for a more balanced and layered reading of the results. For example, we can look at how the availability of resources (RBV) affects how complex technologies (TOE) are actually adopted in practice (DOI), or how dynamic capabilities help companies navigate difficult environments.

In short, this chapter shows how combining these theories helps explain the different paths that SMEs and LCs follow when it comes to adopting AI. It adds depth to the analysis and helps connect what we found in the literature to broader ideas in business and innovation research.

5.2 Drivers of AI Adoption through TOE and RBV (RQ1)

The analysis of the main drivers that motivate SMEs and large corporations (LCs) to adopt Artificial Intelligence (AI), as outlined in Section 4.2.1, can be effectively interpreted using a combination of the **Technology–Organization–Environment (TOE)** framework and the **Resource-Based View (RBV)**. These two perspectives help explain how technological features, internal resources, organizational characteristics, and external pressures influence firms' motivations in different ways depending on their size.

Technological Drivers (TOE and DOI)

Technological factors, central to the TOE model and often expanded upon by the **Diffusion of Innovation (DOI)** theory, play a key role in shaping adoption. Elements such as **relative advantage**, **compatibility** with existing systems and values, and **complexity** of the technology influence how both SMEs and LCs perceive and approach AI adoption.

In SMEs, technological drivers tend to be **highly pragmatic**. These firms are primarily looking for AI solutions that offer **clear and immediate operational benefits**, are easy to implement, and work well with their existing systems. This explains the strong preference for **cloud-based tools**, **standard software**, and increasingly, **Generative AI applications** that support content creation, automation, or basic analytics. These tools are perceived as offering a **high ROI and low complexity**, making them well-suited to resource-constrained environments ((Cho et al., 2025; Farmanesh et al., 2025; Ridho, 2023); Sections 4.2.1 and 4.2.3).

LCs, on the other hand, are often motivated to adopt AI technologies that may be **more complex** and harder to integrate with legacy systems—but are nonetheless seen as offering **long-term strategic value**. Their ability to invest in advanced tools and manage integration challenges allows them to adopt AI not only to improve operations, but also to support **radical innovation** and long-term **market leadership** (Sections 4.2.1 and 4.2.3).

Organizational Drivers (RBV and TOE)

The **Resource-Based View (RBV)**, closely related to the "Organization" dimension of TOE, highlights how internal resources and competencies shape firms’ adoption behavior.

In LCs, the presence of **dedicated AI teams**, large datasets, formalized knowledge systems, and strong financial capabilities make it possible to **treat AI as a strategic asset**. These firms tend to view AI as a way to enhance existing capabilities or create new ones, contributing to sustained competitive advantage and innovation (Table 4.2.1).

In contrast, SMEs are often driven by a **resource-compensatory logic**: they adopt AI to **make up for what they lack**, not necessarily to pursue long-term transformation. However, this doesn't mean their approach is passive. Many SMEs adopt AI tactically, leveraging it to **optimize niche capabilities**, reduce manual workloads, or improve customer service without significantly increasing staff or complexity. Their internal knowledge may be less formal, but the agility and adaptive mindset of management often play a critical role in enabling adoption.

Environmental Drivers (TOE)

The "Environment" dimension of TOE emphasizes the role of **competitive pressure** and **external support mechanisms**.

Both SMEs and LCs are influenced by competitive dynamics, but in different ways. For SMEs, competition often threatens **short-term survival** or market position within a specific niche. Adopting AI becomes a way to remain relevant in a fast-moving digital landscape. For LCs, environmental drivers are more about **maintaining market dominance**, anticipating competitors' moves, or **reshaping sectors** through AI-enabled innovation.

External support—such as public funding, tax credits, training programs, partnerships with universities or research centers, and specialized AI vendors—is particularly critical for SMEs. Their limited resources mean that **policy design and local ecosystems** can significantly influence whether and how they adopt AI (Cho et al., 2025; Ricci et al., 2021; Tawil et al., 2024); Section 4.2.6). LCs benefit from such support too, but are less dependent on it, and often act as shapers of their external environments rather than just beneficiaries.

Comparative Interpretation

Taken together, the TOE and RBV frameworks reveal that **the motivations for AI adoption are shaped by both what firms have (resources) and what they face (technological and environmental conditions).**

- For **SMEs**, the adoption is often **reactive**, resource-constrained, and driven by **efficiency goals**, **cost control**, and short-term ROI. AI is approached as a **tactical**

enabler that helps the firm stay competitive without overstretching its limited assets.

- For **LCs**, the motivation tends to be more **proactive and strategic**. AI is seen as an **investment in transformation**, used to support innovation, strategic positioning, and long-term advantage. It is treated as a **strategic asset**, not just a tool.

It's also important to see drivers as **dynamic**, not static. A small firm may initially adopt AI for basic process automation (low-complexity tools with quick ROI). But a successful implementation can build internal knowledge and capacity, becoming a **new resource** in RBV terms. This may lead to a shift in perception and ambition: the firm may begin to pursue more advanced use cases, influenced by evolving competitive pressures or opportunities in the external environment (TOE). Over time, what begins as a reactive tactic may evolve into a more strategic, proactive posture.

Understanding AI drivers as part of a **co-evolving system**—where internal capabilities and external conditions constantly interact—is essential for managers, policymakers, and scholars alike. It also highlights the need for flexible, adaptive policy tools and firm-level strategies that account for where a company is starting from, and where it is trying to go.

5.3 Barriers and Enablers: A Resource and Capabilities Perspective

The analysis of barriers and enablers to AI adoption, discussed in Section 4.2.2, benefits from an interpretation that integrates the **Resource-Based View (RBV)** and the **Technology–Organization–Environment (TOE)** framework with the **Dynamic Capabilities (DC)** perspective. This combined approach helps to explain not only *what* obstacles firms face, but also *why* some firms are better at overcoming them than others.

Barriers through TOE and RBV

For SMEs, the most pervasive barriers are clearly linked to **resource scarcity**—limited financial capital, a lack of skilled personnel, and inadequate technological infrastructure (Section 4.2.2; Table 4.2.2). These constraints can be understood as both **a lack of strategic assets (RBV)** and as weaknesses in the **"Organization" component of the**

TOE model. These conditions often trap SMEs in a **“vicious cycle”** of underinvestment and weak capability development, where the lack of resources limits their ability to build the very capacities needed to adopt AI effectively.

Organizational culture and structure also play an ambivalent role. In SMEs, **resistance to change**—from employees or even management—combined with a lack of strategic vision regarding AI, can significantly hinder adoption. In LCs, although resource availability is generally not a problem, **complex internal hierarchies**, **rigid routines**, and the presence of deeply embedded **legacy systems** can lead to **organizational inertia**, making it difficult to integrate new AI solutions or adapt core processes (Ferreira et al., 2023; Godbless Ocran et al., 2024; Xin et al., 2024).

Introducing the Dynamic Capabilities Perspective

The **Dynamic Capabilities** framework adds a powerful interpretive layer by explaining how firms navigate these barriers. DCs refer to a firm’s ability to **sense** opportunities and threats, **seize** them by mobilizing resources, and **reconfigure** internal processes and routines to sustain competitiveness in changing environments.

- **Sensing:** Large firms often have formalized R&D departments and market intelligence systems to scan for AI opportunities. In contrast, SMEs may rely on the intuition of the owner-manager or informal networks to identify smaller-scale, more immediate applications (Ricci et al., 2021; Sipos et al., 2024).
- **Seizing:** While LCs can allocate large budgets and dedicated teams to develop or acquire AI capabilities, SMEs are more likely to **adopt agile, low-cost approaches**, leveraging SaaS tools or external collaborations (Section 4.2.5).
- **Reconfiguring:** SMEs tend to be structurally leaner and potentially faster at making adjustments, but their efforts are often limited by their small resource base. LCs, on the other hand, may have the means to reconfigure at scale—but their structural complexity and sunk costs in legacy systems make such changes slow and difficult.

Explaining the Resource Trap in SMEs and Inertia in LCs

- **The “Resource Trap” in SMEs:** Resource scarcity (RBV) not only blocks direct investment in AI but also **limits the development of dynamic capabilities**. For example, without funding, SMEs may be unable to invest in market scanning activities (sensing), act on promising tools (seizing), or adjust internal processes (reconfiguring). This constraint reinforces itself: the absence of DCs perpetuates the lack of resources, because firms cannot generate the benefits that would otherwise unlock further investment. As shown in Section 4.2.2, SMEs often remain trapped in a **cycle of underinvestment and limited growth**.
- **The “Inertia Paradox” in LCs:** In large firms, resource abundance may paradoxically lead to **reduced flexibility**. Established routines, previous investments in legacy systems, and hierarchical decision-making structures (TOE) can hinder DCs—especially the ability to reconfigure. As a result, **even well-resourced firms may fail to adapt quickly**, despite having the tools and people to do so (Section 4.2.2).

Comparative Interpretation

The interaction between a firm's **resource base (RBV)** and its **dynamic capabilities (DC)** is therefore essential. It's not just about having resources, but about being able to **deploy, adapt, and renew** them effectively in response to technological change.

- For **SMEs**, a weak resource base limits the development of DCs, creating a self-reinforcing trap that makes strategic adoption difficult.
- For **LCs**, a strong resource base can coexist with weak dynamic capabilities—especially in terms of reconfiguring processes—resulting in slow adaptation and missed opportunities.

Thus, **enablers of AI adoption must go beyond resource provision**. For SMEs, access to external support and ecosystem partnerships can ease their resource burden—but they also need **support in developing adaptive capabilities**. For LCs, the challenge lies in **unlocking agility and reducing internal rigidity**, so that their resources can be put to more effective use.

Policy interventions and managerial strategies should therefore aim to foster **tailored dynamic capabilities**:

- For SMEs: agile experimentation, low-cost innovation, and learning-oriented cultures.
- For LCs: inter-functional integration, change management systems, and process renewal frameworks.

Ultimately, what determines whether a firm can overcome barriers to AI adoption is not what it owns—but what it can **sense, seize, and reconfigure**.

5.4 Technologies and Application Patterns: Adoption Logic and Innovation Types

The analysis of AI technologies and their application areas (Section 4.2.3) can be deepened through the lens of **Diffusion of Innovation (DOI)** theory (Rogers), alongside concepts related to **incremental versus radical innovation**, **General Purpose Technologies (GPTs)**, and **absorptive capacity**. This combination allows for a more nuanced interpretation of how firms adopt AI and what types of innovation outcomes result from these adoption choices.

DOI and the Logic of AI Adoption

According to DOI theory, five perceived attributes influence the adoption of an innovation: **relative advantage**, **compatibility**, **complexity**, **trialability**, and **observability**.

SMEs tend to favor AI technologies that are:

- **Easy to test on a small scale (trialability)**
- **Low in perceived complexity**
- **Highly compatible** with existing processes
- And that show **quick, observable benefits**

This explains their preference for SaaS tools, ready-to-use chatbots, intuitive analytics platforms, and more recently, Generative AI applications for content creation and automation tasks (Section 4.2.3; Articles (Cho et al., 2025; Farmanesh et al., 2025; Godbless Ocran et al., 2024; Proietti & Magnani, 2025; Ridho, 2023)). These choices are typical of **early adopters** or the **early majority** in the DOI model: firms that are pragmatic, cautious, and risk-averse.

Large Corporations (LCs), while still considering the above attributes, are more likely to adopt **complex and customized AI systems**, such as enterprise-level ML platforms or integrated AI infrastructures for R&D and supply chain transformation (Godbless Ocran et al., 2024; Li et al., 2024; Soni et al., 2019). These technologies often involve **longer learning curves** and **delayed returns**, but the perceived **strategic relative advantage** justifies the investment. Such firms may represent **innovators** or **technology leaders** in Rogers' terms, often pushing the diffusion frontier.

Incremental vs. Radical Innovation

The adoption of AI leads to different innovation outcomes depending on the firm's size, objectives, and context.

SMEs, driven by operational efficiency and short-term ROI, tend to focus on **incremental innovation**—improving existing products, services, or processes. For example, using AI to personalize marketing campaigns or automate customer service does not radically change what the firm offers, but makes it more effective (Sections 4.2.1 and 4.2.4). According to (Grashof & Kopka, 2023), SMEs often use AI techniques to engage in what they call the *"invention of methods of inventing"* (IMI), suggesting process-level improvements that may eventually enable broader innovation.

LCs, with broader resources and strategic horizons, are more likely to pursue **radical innovation**. This includes the creation of entirely new business models, product categories, or market entries driven by AI-enabled transformation (Sections 4.2.1 and 4.2.4). LCs benefit more from **AI applications**—not just techniques—by leveraging the **general-purpose nature of AI** to orchestrate change across complex systems and business functions.

AI as a General Purpose Technology and the Role of Absorptive Capacity

AI is increasingly recognized as a **General Purpose Technology (GPT)**—a technology with wide-ranging impact potential across industries. However, the extent to which a firm can benefit from a GPT depends on its **absorptive capacity**—its ability to recognize, assimilate, and apply new external knowledge for commercial purposes.

LCs typically have higher absorptive capacity due to:

- Specialized R&D units
- Diverse knowledge bases
- Investment in exploration and experimentation

This enables them to exploit AI as a GPT in a **systemic and strategic** way, turning it into a catalyst for large-scale innovation (Grashof & Kopka, 2023).

SMEs, by contrast, may possess **tacit or informal absorptive capacity**, embedded in agile teams or entrepreneurial managers. Their focus is more often on **applying AI to specific, bounded problems** rather than orchestrating full-system transformation (Schwaeke et al., 2025; Trinh, 2024). However, the growing availability of **user-friendly, low-barrier GenAI tools** is helping to lower the absorptive capacity threshold for certain tasks, offering new innovation opportunities even for resource-constrained firms (Cho et al., 2025; Proietti & Magnani, 2025).

Integrated Interpretation: Resources, Capabilities, and Innovation Scope

The type of innovation pursued—incremental or radical—is not just a matter of strategic choice; it is deeply influenced by the firm's **resource structure (RBV)**, its **dynamic capabilities**, and its **perception of the technology's attributes (DOI)**.

- **SMEs**, with limited resources (RBV), tend to adopt AI tools that are easy to implement and test (DOI), leading to incremental innovations focused on optimization. Their **organizational agility** (DC) supports this approach, even in the absence of formal infrastructure.
- **LCs**, with more abundant resources, can invest in AI systems with long-term, strategic benefits, even if they are less immediately observable (DOI). Their challenge lies in the **reconfiguration of complex systems** (DC), needed to fully exploit the potential of AI.

Importantly, the nature of GPTs like AI implies high potential across the board—but realizing that potential depends on each firm's absorptive capacity, which is itself both a **resource and a capability**. Therefore, promoting radical AI-led innovation in SMEs requires not just giving them access to tools, but also **supporting their development of strategic vision and absorptive capacity**. For LCs, the challenge is to unlock enough **organizational flexibility** to transform potential into results.

5.5 Benefits and Strategic Impact: Short-Term Value vs Long-Term Advantage

The interpretation of the benefits derived from AI adoption (Section 4.2.4) reveals a clear distinction between **short-term operational gains**, often prioritized by SMEs, and **long-term sustainable competitive advantage (SCA)**, typically pursued by large corporations (LCs). This dichotomy reflects differences in external pressures, resource availability, and strategic ambitions.

Functional vs Transformational Benefits

The results presented in Section 4.2.4 differentiate between **functional** and **transformational** benefits.

SMEs tend to focus on the former: automation of repetitive tasks, operational cost reduction, process efficiency improvements, and better resource utilization are the most frequently observed outcomes. These benefits are tangible, measurable, and directly contribute to short-term operational and financial performance. In this view, AI is mainly used to "do things better."

LCs, while not neglecting functional gains, are more often oriented toward **transformational benefits**. These include the creation of new business models, disintermediation of existing markets, development of radically innovative products or services, and the reconfiguration of entire value chains. In this context, AI becomes a catalyst to "do new things" or to "do old things in entirely new ways."

Short-Term ROI vs Sustainable Competitive Advantage (SCA)

This distinction also applies to the **investment time horizon**.

Due to limited resources (RBV) and the need to quickly validate returns (TOE – Organizational), **SMEs** tend to favor AI projects that promise a **short-term ROI**. The ability to demonstrate quick improvements in cash flow or cost reduction is crucial to justify further investment and ensure continuity. Studies such as Ardito et al. (2024) and Bar-Gill et al. (2024) report short-term revenue gains in SMEs adopting AI, confirming the importance of immediate, visible returns.

LCs, benefiting from greater financial flexibility and dedicated resources (RBV), can afford to invest in AI initiatives with **longer ROI horizons**, aiming to build **sustainable competitive advantage (SCA)**. This aligns with the RBV, which holds that SCA derives from the development and exploitation of resources and capabilities that are valuable, rare, inimitable, and non-substitutable (VRIN)—characteristics that can be embedded in AI-enabled systems and knowledge.

The Role of AI in Strategic Innovation

AI adoption is closely tied to **strategic innovation**, although the dynamics differ by firm size.

For **LCs**, AI often plays a **central role in innovation strategy**, enabling new value propositions, market exploration, or even the redefinition of industry rules (DC – seizing and reconfiguring). Here, AI is not just a tool, but a **driver of strategic transformation**.

In **SMEs**, AI's role in strategic innovation may be **more emergent than planned**. Initially adopted to solve operational problems, AI can gradually reshape strategic thinking as internal capabilities grow and new opportunities arise. This reflects the dynamic nature of adoption drivers discussed in Section 5.2: operational success can uncover previously unseen strategic potential. Section 4.2.4 (Table 4.5) shows that LCs tend to focus more heavily on radical innovation ("High"), while SMEs show a "Medium" orientation, usually through incremental improvements.

While the short-term ROI focus of SMEs is logical given their constraints, it may unintentionally limit their ability to achieve broader strategic transformation through AI—unless they **strategically reinvest early gains** into capability development. Functional benefits and rapid ROI, though essential for survival and justifying further experimentation (aligned with DOI's trialability and observability), should ideally serve as **a launchpad for long-term value creation**.

If the focus remains solely on incremental gains without parallel efforts to develop **absorptive capacity** or a strategic vision for AI (DC – sensing and seizing), SMEs risk missing AI's broader transformative potential.

LCs, on the other hand, are explicitly positioned to pursue SCA with AI. However, they risk falling into **"innovation theater"**—launching high-profile projects without truly embedding AI into their strategy and core capabilities. Therefore:

- **SMEs** must balance the need for short-term gains with a **longer-term perspective** on how AI can reshape their business. A step-by-step approach, where early wins finance capability building for deeper transformation, may be ideal.
- **LCs** must ensure that AI is not just explored at the periphery but becomes **deeply integrated** into their strategic core to realize its full potential.

5.6 Strategic Models and Implementation Logics

The strategies and implementation models for AI adoption differ significantly between SMEs and large corporations (LCs), reflecting distinct organizational capabilities, resource structures, cultures, and strategic goals, as discussed in Section 4.2.5. These differences can be further interpreted through the lenses of the **TOE** framework and **Dynamic Capabilities (DC)**.

Bottom-Up vs Top-Down Approaches (TOE & DC)

SMEs often adopt **bottom-up or opportunistic approaches** to AI (Section 4.2.5, implementation table). Initiatives frequently arise from specific departmental needs, the intuition of owner-managers, or the initiative of tech-savvy employees. This is enabled by their organizational flexibility (TOE – Organization), their responsiveness to accessible technologies (TOE – Environment), and their localized sensing and seizing capabilities (DC) (Proietti & Magnani, 2025; Trinh, 2024; Zheng et al., 2025).

In contrast, **LCs** typically implement **top-down strategies** that are more structured and systematic. These are often aligned with company-wide visions, formalized in digital transformation roadmaps, and supported by significant investments and dedicated teams or Centers of Excellence. This approach reflects their more complex and formalized organizational structure (TOE – Organization) and their efforts to reconfigure large-scale capabilities (DC) (Carayannis et al., 2025; Perifanis & Kitsios, 2023; Xin et al., 2024).

Organizational Context, Maturity, and Change Management

The **organizational context**—including corporate culture, leadership style, existing competences, and risk appetite (TOE and RBV elements)—strongly shapes implementation logic. An innovation-friendly culture and supportive leadership are critical in both cases, though they manifest differently.

AI maturity level also influences the strategic model. Less mature firms tend to focus on foundational capacity-building and experimentation, whereas more mature firms pursue **systemic integration and enterprise-wide transformation** (Bettoni et al., 2021; Limpeeticharoenchot et al., 2022; Willetts & Atkins, 2023).

Change management is another critical factor. LCs require formal change management programs to overcome inertia, align departments, and foster adoption across large workforces. SMEs, on the other hand, often rely on more informal processes, direct leadership involvement, and adaptable teams to manage change effectively (Section 4.2.5).

Slowness vs Agility: A Tension Between Resources and Speed

A fundamental tension emerges:

- **LCs** possess abundant resources (RBV) but may be **slow in decision-making and implementation** due to complexity, bureaucracy, and legacy systems (TOE – Organization). This can limit their agility in seizing emerging AI opportunities (DC).
- **SMEs** lack resources (RBV) but are often **highly agile**, with fast decision cycles and short implementation times (TOE – Organization, DC). This enables rapid prototyping and experimentation (DOI – trialability), but limited resources can prevent scaling successful initiatives.

As noted in Section 4.2.2:

“SMEs are often more agile and open to experimentation but lack the means. LCs have the resources but often lack speed and internal alignment.”

Contingency and Hybrid Strategies

The "optimal" strategic model for AI adoption is highly contingent on firm size and context. A rigid top-down approach may fail in an agile SME with limited resources, while a purely bottom-up approach in a LC may lead to fragmented, non-scalable efforts disconnected from broader strategy.

Success depends on aligning the adoption strategy with a firm’s **existing capabilities (RBV, DC)** and **operational context (TOE)**. Misalignment—for example, a LC attempting to act overly agile without restructuring deep organizational layers, or an SME imposing a top-down plan without adequate support—often leads to implementation failure.

Firms may benefit from **hybrid or adaptive strategies**:

- **LCs** can create internal “startup units” or “agility pockets” to experiment with AI more flexibly.
- **SMEs** can seek external guidance to develop more structured plans without losing their operational agility.

Ultimately, AI adoption strategy should **match the firm's structural and cultural DNA**, allowing innovation to scale sustainably while preserving the capacity for experimentation and responsiveness.

5.7 Contextual Influences and Policy Implications

AI adoption does not occur in isolation; it is strongly shaped by external contextual factors, as outlined in Section 4.2.6. The **TOE framework**, with its emphasis on the **environmental dimension**, offers a useful lens for interpreting how these factors influence adoption differently for SMEs and large corporations (LCs).

Sector, Geography, and Regulation (TOE – Environment)

Sectoral dynamics play a significant role. Industries characterized by high technological intensity, strong competitive pressure, or data-rich operations—such as advanced manufacturing, financial services, e-commerce, or healthcare—tend to exhibit **higher AI adoption rates** and more sophisticated use cases compared to more traditional or low-digitization sectors. Industry-specific requirements (e.g., compliance in pharma, personalization in retail) often shape the type of AI adopted and investment priorities.

Geographic factors are equally important. The availability of robust digital infrastructure (e.g., broadband, cloud), proximity to innovation hubs (e.g., universities, research centers, tech clusters), and access to qualified talent or collaborative ecosystems varies significantly across regions. These differences strongly influence a firm's—especially an SME's—ability to access, experiment with, and scale AI solutions (Sections 4.1 and 4.2.6).

Regulation—including frameworks such as GDPR or the emerging EU AI Act—also plays a dual role. On the one hand, regulation can act as a **barrier**, imposing compliance costs (especially burdensome for SMEs without dedicated legal departments) and creating uncertainty. On the other hand, well-designed regulation can be an **enabler** by fostering trust, standardizing practices, and stimulating ethical and responsible AI development. Notably, in some contexts (e.g., China), clear AI regulations have been shown to **moderate and enhance** the positive impact of AI adoption, particularly among SMEs (Wang & Zhang, 2025).

Innovation Ecosystems and Industrial Policy: Different Levers for SMEs and LCs

Innovation ecosystems and industrial policy are essential levers, though their impact differs by firm type.

LCs can often access—and in some cases shape—**global innovation ecosystems**, collaborating with leading research institutions or acquiring startups in various regions. As such, their dependence on any single local ecosystem is lower (Section 4.2.6).

SMEs, by contrast, are much more dependent on **local and regional ecosystems**. Proximity to sources of knowledge, funding, and collaboration is critical to overcoming their resource constraints. For SMEs, industrial policies typically focus on:

- Direct financial incentives (e.g., grants, tax credits)

- Training programs
- Technology transfer
- Facilitation of collaboration (e.g., competence centers, university-industry partnerships)
  (Sections 1.4 and 4.2.6; (Ardito et al., 2024; Cho et al., 2025; Lemos et al., 2022; Proietti & Magnani, 2025; Ricci et al., 2021; Tawil et al., 2024; von Garrel & Jahn, 2023; Yen et al., 2024)

For **LCs**, policies may emphasize:

- Large-scale R&D incentives
- Development of AI standards
- Support for frontier innovation in competitive environments

How Context Shapes Capabilities, Risks, and Opportunities

In summary, the external **environment (TOE)** interacts dynamically with internal characteristics (RBV, DC), shaping how firms **perceive risks and opportunities** related to AI—and influencing the types of capabilities they develop.

A favorable context—strong digital infrastructure, supportive public policy, vibrant ecosystems—can significantly lower the perceived risks of AI adoption for SMEs and unlock opportunities that would otherwise be out of reach.

For LCs, clear and stable regulatory frameworks and global access to talent can facilitate **large-scale, strategic AI investments**.

There is also a **co-evolutionary relationship** between firms and their context. While businesses adapt to their environment, **LCs—and sometimes SME collectives—can also influence that environment**, through lobbying, investment in local talent, or the promotion of industry standards.

This dynamic implies that **AI policy should go beyond direct firm-level support** and also focus on **ecosystem-building**—creating environments where firms can not only thrive but also **contribute to the governance and evolution of AI**. Effective policy must be **adaptive, ecosystem-focused, and differentiated**, recognizing the distinct roles and capacities of SMEs and LCs in shaping—and being shaped by—the AI landscape.

5.8 Theoretical Synthesis and Emerging Patterns

The analysis conducted in the previous sections, interpreted through the theoretical lenses of **TOE**, **RBV**, **Dynamic Capabilities (DC)**, and **Diffusion of Innovation (DOI)**, leads to a more integrated understanding of the distinct pathways through which SMEs and LCs approach AI adoption. This section summarizes the main theoretical insights and presents two key emergent patterns—framed as paradoxes—that characterize the adoption dynamics in the two firm types. It concludes with the conceptual proposal of a visual model.

Summary of Theoretical Contributions

Each framework provided a unique but complementary perspective on the phenomenon:

- **TOE** helped explain how **technological**, **organizational**, and **environmental** contexts shape AI adoption decisions and strategies. Differences between SMEs and LCs were clearly reflected across these dimensions: SMEs face resource constraints and respond to environmental opportunities with agility, while LCs navigate structural complexity, but often benefit from institutional influence and better infrastructure.
- **RBV** clarified how a firm's **resource endowment**—financial, human, technological, and informational—conditions its ability to invest in AI and derive competitive advantage. LCs leverage abundant and diversified resources to pursue strategic and long-term initiatives, while SMEs strive to maximize the impact of limited resources in targeted, pragmatic ways.
- **Dynamic Capabilities** revealed how firms adapt (or fail to adapt) to technological change. The ability to **sense** opportunities, **seize** them through action, and **reconfigure** internal processes proved crucial. SMEs are often agile but constrained; LCs are capable but potentially slow-moving.

- **DOI** helped interpret adoption timing and technological preferences, based on perceived characteristics such as **relative advantage**, **compatibility**, **complexity**, **trialability**, and **observability**. These perceptions vary significantly across firm sizes and industries, influencing the pace and depth of adoption.

Two Key Patterns: The AI Adoption Paradoxes

From the interplay of these frameworks, two recurring patterns emerge—framed as **paradoxes**—that capture core tensions faced by SMEs and LCs:

1. Resource–Agility Paradox (SMEs)

SMEs often possess **high organizational agility**: lean structures, fast decision-making, and flexibility that support experimentation and rapid learning. This agility—interpreted as a dynamic capability—should theoretically enable quick AI adoption, especially for **niche applications** or in response to local opportunities (DOI – trialability).

However, this potential is often **neutralized by chronic resource scarcity** (RBV): limited funds, lack of skilled staff, outdated IT infrastructure, and data limitations. This creates a **tension**—they can identify opportunities and even initiate pilots, but struggle to scale, sustain, or integrate AI effectively. As a result, **agility prompts action**, but **resource constraints limit follow-through**.

2. Resource–Inertia Paradox (LCs)

LCs have abundant resources (RBV): capital, talent, data, infrastructure, and strategic partners. These should support large-scale, transformative AI initiatives. However, their very size, complex organizational structures, legacy systems, and rigid routines (TOE – Organization) create inertia that undermines dynamic capabilities—especially the ability to reconfigure.

This leads to a second paradox: despite heavy investments, LCs may experience slower-than-expected adoption cycles, with AI projects failing to scale or produce meaningful strategic change. Initiatives can become siloed or disconnected from core operations—AI adoption becomes superficial rather than systemic.

These paradoxes are not deterministic traps but critical tensions that successful firms must actively manage. Addressing them is essential to effective AI adoption:

- SMEs can mitigate the resource–agility paradox by leveraging external ecosystems (e.g., partnerships, public support), adopting cloud-based scalable solutions, and focusing on high-impact niche use cases.
- LCs can tackle the resource–inertia paradox by creating internal agile units (e.g., "corporate garages"), fostering a culture of experimentation, investing in effective change management, and using modular implementation approaches that enable iterative learning.

These tensions define the strategic challenges of AI adoption. Managerial and policy focus should be on developing targeted strategies to directly address them.

Proposed Visual Summary Model

To consolidate the theoretical discussion, a **visual conceptual model** (Figure 5.1) is proposed. This model would include:

- **Two central adoption paths** (for SMEs and LCs), showing their core characteristics (e.g., SMEs: Resource Scarcity, High Agility; LCs: Resource Abundance, High Complexity/Inertia).
- The **TOE Contextual Layers** (Technology, Organization, Environment) influencing both firm types at the onset.
- **Internal Mediators**, derived from RBV and DC (e.g., available resources, sensing/seizing/reconfiguring capabilities).
- The **Adoption Process**, shaped by DOI attributes (e.g., perceived relative advantage, complexity).
- **Adoption Outputs**, linked to Chapter 4 themes (e.g., specific drivers, barriers, strategies, and observed benefits).
- **Illustration of the Two Paradoxes**, showing how they emerge from the interaction of contextual, resource, and capability factors.
- **Feedback Loops**, highlighting how adoption outcomes influence future resource availability and capability development, thus feeding into subsequent adoption cycles.

This figure would visually synthesize the arguments of Chapter 5, clarifying the interplay between theoretical frameworks and empirical findings, and presenting a clear view of the differentiated adoption trajectories and critical tensions faced by SMEs and LCs.

Chapter 6
Conclusions

This final chapter synthesizes the key findings of the research, explicitly answers the research questions, outlines the theoretical contributions and managerial and policy implications, recognizes the limitations of the study, and suggests directions for future research. The goal is to provide a concise yet comprehensive overview of the work and its significance within the broader context of AI adoption studies.

6.1 Summary of Key Findings

Through a systematic literature review of 71 academic studies, this thesis explored how Small and Medium-sized Enterprises (SMEs) and Large Corporations (LCs) approach the adoption of Artificial Intelligence (AI). The findings show that while both firm types recognize the transformative potential of AI, their motivations, resource investments, chosen technologies, and implementation models differ significantly.

Direct answers to RQ1 and RQ2:

RQ1: What are the main drivers that lead SMEs and LCs to adopt AI technologies?

- For SMEs, the key drivers include operational efficiency, cost reduction, enhanced customer engagement, and competitive pressure—typically with a tactical focus and need for quick return on investment (ROI). AI is perceived as a means to optimize existing processes and compensate for resource limitations.
- For LCs, the drivers are more strategic: achieving sustainable competitive advantage, market leadership, radical innovation, the ability to analyze large volumes of data, and enterprise-wide transformation.

RQ2: What are the key similarities and differences between SMEs and LCs in terms of enabling factors and challenges during AI implementation?

- Similarities: Both face challenges such as AI talent shortages, data quality and governance issues (though at different scales), and growing ethical concerns. A clear strategic vision and supportive leadership are common enablers.

- Differences: SMEs are mainly hindered by resource constraints (financial, human, infrastructural) and limited AI-specific awareness or expertise. Enablers include accessible and low-cost technologies (e.g., cloud, SaaS) and support from external ecosystems (e.g., consultants, public programs). LCs, on the other hand, face challenges related to legacy system integration, organizational inertia, large-scale change management, and data governance. Their key enablers include strong internal capabilities (dedicated teams, R&D) and robust governance frameworks.

Thematic insights:

- Drivers: Tactical and operational for SMEs; strategic and transformative for LCs.
- Barriers and Enablers: Resource scarcity for SMEs; complexity and inertia for LCs.
- Technologies and Applications: SMEs use standard, cloud-based tools focused on specific functions (e.g., marketing, customer service); LCs employ customized enterprise platforms and strategic applications (e.g., R&D, supply chain).
- Benefits: SMEs seek operational and financial improvements in the short term; LCs aim for strategic gains, radical innovation, and long-term competitive positioning.
- Strategic Models: SMEs often adopt bottom-up, agile, and opportunistic approaches; LCs use top-down, structured strategies integrated into digital transformation plans.
- Contextual Factors: SMEs depend more on local ecosystems and public incentives; LCs operate globally and influence industry standards.

A general pattern emerges: firm size is a mediating variable that shapes not only what AI is adopted, but also how and why. This leads to qualitatively distinct adoption trajectories rather than a shared maturity pathway. As such, one-size-fits-all approaches to understanding or promoting AI adoption are likely to be ineffective unless they account for size-specific dynamics.

6.2 Theoretical Contributions

This systematic literature review offers several contributions to the academic understanding of Artificial Intelligence (AI) adoption in business settings.

First, the primary contribution lies in delivering a structured and comparative synthesis of AI adoption across firm sizes—specifically, between Small and Medium-sized Enterprises (SMEs) and Large Corporations (LCs). As discussed in Chapter 1.2, most existing studies tend to focus on either SMEs or LCs in isolation or treat firm size merely as a control variable. This thesis addresses that gap by placing firm size at the center of the analysis, integrating fragmented findings into a cohesive narrative.

Second, the study demonstrates the value of a multi-theoretical framework in explaining the complex and heterogeneous nature of AI adoption. By applying the Technology-Organization-Environment (TOE) framework, the Resource-Based View (RBV), the Dynamic Capabilities (DC) perspective, and the Diffusion of Innovation (DOI) theory in combination, the research was able to derive deeper and more nuanced insights than any single theory would allow. While RBV clarifies resource-based differences, TOE highlights contextual influences, DC explains how firms adapt over time, and DOI accounts for technological characteristics and adoption patterns. This integration enabled not just the description of firm-level differences but also an interpretation of their underlying causes.

A more specific theoretical contribution is the identification and conceptual framing of two key paradoxes: the *resource–agility paradox* (typical of SMEs) and the *resource–inertia paradox* (typical of LCs). These constructs help articulate the structural tensions that shape firms' AI adoption paths and offer a basis for further theoretical exploration.

Finally, by applying well-established theories to the emergent and rapidly evolving phenomenon of AI adoption, this thesis both confirms their ongoing relevance and reveals areas where extensions or refinements may be needed. The ethical complexity of AI, its "black-box" nature, and its reliance on large volumes of data pose challenges that these theories did not originally address. As discussed in Chapter 5, the results largely align with existing theoretical predictions based on firm size, but they also suggest that AI-specific dynamics—such as rapid technological change or governance concerns—could prompt further theoretical development. Future research may adapt these frameworks for the digital age or propose new mid-range theories specifically tailored to AI adoption.

6.3 Managerial and Policy Implications

The findings of this research offer a number of practical takeaways for managers working in both Small and Medium-sized Enterprises (SMEs) and Large Corporations (LCs), as well as for policymakers involved in shaping AI-related strategies.

Implications for Small and Medium-sized Enterprises (SMEs)

- Strategic Focus

  SMEs should concentrate on clearly defined domains where AI implementation yields tangible value, especially considering their limited budgets and internal resources. Rather than trying to follow the complex systems used by larger firms, it's more effective to concentrate on tools and solutions that are simple, useful, and aligned with their business needs.

- Choose Accessible Solutions

  Cloud-based tools, SaaS platforms, and user-friendly generative AI applications are a good fit for SMEs. They don't require big upfront investments and can deliver quick results, which is important when resources are tight.

- Skills and Partnerships

  Since hiring AI experts can be difficult, SMEs should invest in upskilling their current teams. At the same time, it's smart to rely on external partners—like consultants, tech vendors, universities, or innovation hubs—to bring in expertise they don't have internally.

- Start Small, Then Scale

  A gradual, test-and-learn approach often works best. Starting with small pilot projects helps reduce risk, show value early, and build internal confidence. This enables progress despite limited financial resources.

- Use What's Available

Public support programs, local innovation networks, and financial incentives are there to help. SMEs should take the time to explore and make use of these opportunities to strengthen their capabilities.

Implications for Large Corporations (LCs)

- Learn from SME Agility

  Big companies have more resources, but that doesn't always translate to flexibility. LCs can benefit from introducing agile structures—like cross-functional teams or dedicated innovation units—to experiment more freely and respond faster to change.

- Tackle Internal Barriers

  Legacy systems, rigid hierarchies, and long decision chains can slow down progress. That's why LCs need solid change management and clear communication across teams if they want AI adoption to work beyond isolated departments.

- Keep It Aligned

  AI initiatives should always connect back to the company's broader goals. Otherwise, they risk becoming trendy side projects that don't really create impact.

- Act Early on Governance

  Ethical and regulatory issues matter more the bigger the company gets. LCs should make sure they put the right data governance and responsible AI practices in place from the start—especially given the scale and visibility of their operations.

Implications for Policymakers

- One-Size-Doesn't-Fit-All

  SMEs and LCs have different needs. SMEs benefit more from accessible training, direct funding, and hands-on support. LCs, instead, might benefit more from support for advanced R&D or testing environments like regulatory sandboxes.

- Build Stronger Ecosystems

  Local and national innovation ecosystems can make a big difference—especially when they connect companies with universities, public institutions, and each other. These networks help share knowledge and spread good practices.

- Make Sure Standards Are Clear

  Having clear rules and shared standards for AI use—especially around safety, ethics, and interoperability—helps build trust and encourages adoption across the board.

- Invest in Digital Infrastructure

  Reliable broadband, cloud access, and computing power shouldn't be a luxury. Investments in infrastructure are key to making sure all firms, not just the big ones, can work with AI.

- Promote Responsible AI

  Policymakers have a role in making sure innovation doesn't come at the cost of fairness, privacy, or job quality. Regulations should protect people without blocking progress—striking the right balance is key.

In the end, adopting AI isn't just about having the right tools. It's also about leadership, company culture, and knowing how to manage change. SMEs can do a lot with limited means if they stay focused and move quickly. LCs, even with their resources, can fall behind if they don't manage complexity or lack a clear direction.

That's why training leaders—not just on the tech itself, but on how to think strategically, lead change, and build adaptive organizations—is going to be essential. Both SMEs and LCs need those skills if they want to make AI adoption work in practice.

6.4 Limitations of the Study

As with any research, this study has some limitations that should be acknowledged to properly understand the scope of its findings and conclusions.

Limitations of the Systematic Literature Review (SLR)

First of all, this thesis is based entirely on secondary data—academic articles and a selection of grey literature. That means the analysis depends on what's already been published. If those original studies had gaps or biases, they might have influenced this review as well.

There's also a risk of **publication bias**, where studies showing strong or positive results are more likely to get published than those with neutral or inconclusive findings. That could skew the picture of how AI adoption really plays out across different firms.

Although I tried to include relevant grey literature, as described in Chapter 3.2, it's possible that some useful insights from recent industry reports or non-indexed studies were left out simply because they weren't accessible or didn't meet inclusion criteria.

Finally, even though I followed a structured review method (PRISMA) and applied a clear coding framework, interpreting qualitative findings from dozens of different studies always involves some degree of subjectivity.

Methodological, Temporal, and Geographic Limitations

- **Methodological**: A literature review like this one offers a broad and comparative view but can't provide the kind of depth and context that would be possible through primary research, such as interviews or in-depth case studies. The methodological diversity of the reviewed papers also made it hard to synthesize some findings in a consistent way.
- **Temporal**: AI is moving fast. This review includes studies published up until early 2025. Since then, new technologies, practices, or challenges may have emerged—especially in the field of generative AI—which are not fully captured here.
- **Geographic**: Even though the review aimed for wide coverage, most of the studies came from Europe and Asia. Research from regions like Latin America or Africa was more limited, which could affect the generalizability of certain conclusions.

These limitations don't invalidate the study, but they do help define its boundaries. In fact, they also highlight areas where future research can go deeper—by gathering fresh data, exploring underrepresented contexts, or updating the analysis as the AI landscape continues to evolve.

6.5 Future Research Directions

Based on what emerged from this literature review—and considering its limitations—there are several promising directions for future research on AI adoption in companies, especially when comparing SMEs and large corporations.

Topics That Deserve More Attention

- **The Impact of Generative AI (GenAI)**

  With GenAI becoming more accessible, it's worth exploring how it's changing adoption patterns—particularly for SMEs. Does it really help them become more competitive? What are the new risks and ethical issues that come with it?

- **AI and Sustainability (ESG)**

  Future studies could look more closely at how AI helps (or complicates) the pursuit of environmental, social, and governance goals. For example, how can it improve energy efficiency or supply chain transparency? And are there unintended consequences to watch out for?

- **Cross-Country and Cross-Cultural Studies**

  AI adoption doesn't happen the same way everywhere. Comparing different countries and regions—especially those underrepresented in current research like Latin America or Africa—could help us understand how culture, regulation, and local context shape adoption.

- **Longitudinal Research**

  Most of the literature focuses on initial adoption. What's missing is a better understanding of how things evolve over time—how companies move from pilot projects to full integration, how benefits are sustained, or how barriers change.

- **AI and Value Chain Transformation**

AI doesn't just affect internal processes—it can reshape entire value chains. Future research could explore how AI changes the way firms collaborate, compete, or position themselves within their industry ecosystem.

Ideas for Future Research Methods

- **In-Depth Case Studies**

  Qualitative case studies—especially from specific industries or lesser-studied regions—can offer valuable, detailed insights into how AI is really adopted in practice.

- **Mixed Methods**

  Combining large-scale surveys with interviews or document analysis would allow researchers to get both the big picture and the nuanced motivations and experiences behind AI adoption.

- **Cross-Industry Surveys**

  Broad surveys across multiple sectors could help identify general patterns and spot sector-specific challenges or opportunities that might otherwise go unnoticed.

- **Action Research and Design Science**

  Collaborating directly with companies to design, implement, and test AI adoption frameworks or assessment tools can help bridge the gap between theory and practice—especially for SMEs looking for guidance.

Open Questions and Gaps to Explore

- How can SMEs break out of the "resource–agility paradox" and turn their flexibility into long-term competitive advantage?
- What specific leadership skills and organizational mechanisms help large firms overcome inertia and achieve real, large-scale AI transformation?
- Is GenAI truly "democratizing" AI access, or is it creating new types of inequality? What are the second-order effects on competition between SMEs and LCs?

- What policies are most effective in supporting responsible and inclusive AI adoption—ones that benefit both small and large firms without deepening existing gaps?
- How do ethical practices and AI governance actually differ between SMEs and LCs, and how can both be supported in managing these issues effectively?

In short, future research shouldn't just focus on how AI is adopted—it should increasingly look at what adoption leads to. What are the long-term economic, social, and ethical impacts? And how do these vary depending on the size of the company and the context in which it operates?

So far, much of the literature has focused on the early stages of adoption: drivers, barriers, and initial implementation patterns. But as AI becomes more deeply embedded in business processes, new questions are emerging. For example: How is AI reshaping jobs, business models, and market structures?

For SMEs, the impact might be more local—affecting employment, regional economies, or competitiveness in niche markets. For LCs, the stakes are often global—market concentration, supply chain restructuring, or large-scale workforce transformation.

Future research should be ready to capture all of this, keeping a critical eye on both outcomes and inequalities. And throughout, the comparison between SMEs and LCs remains essential to understanding not just *how* AI is being adopted, but *why it matters*—and for whom.

Final Considerations

To conclude, this thesis provided a structured and comparative view of how SMEs and large corporations are approaching AI adoption. By combining different theoretical lenses and analyzing 71 academic sources, it highlighted the main differences, challenges, and strategic directions that characterize AI implementation across firm sizes.

The findings not only help clarify why adoption patterns vary, but also underline that AI is not just a technological shift—it is a strategic and organizational one. For both SMEs and LCs, success in AI adoption will depend on how well they align tools, people, and vision.

Hopefully, this work can offer useful insights not only for researchers and managers, but also for policymakers seeking to design more effective, inclusive, and context-aware AI strategies.

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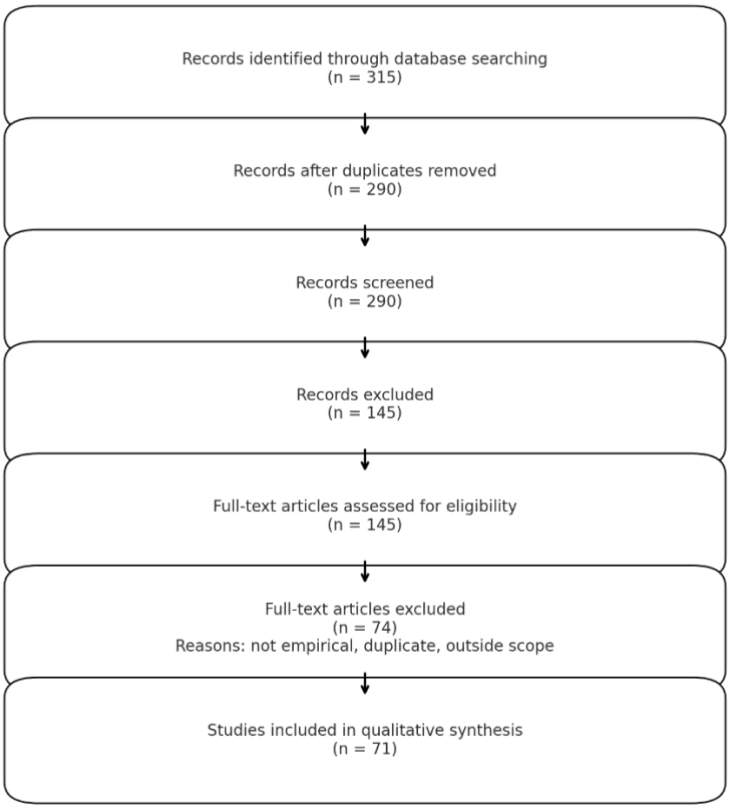
Appendix – A

PRISMA flow diagram:

Appendix A shows the PRISMA 2020 flow diagram used in the systematic selection of articles (see Chapter 3.2). This diagram summarizes the identification, screening, eligibility, and inclusion phases of the literature review process, in line with PRISMA guidelines.



Appendix – B

AMSTAR 2 and MMAT criteria:

List of criteria for AMSTAR 2:

1. Is the review question clear and does it include PICO?
2. Is there a protocol recorded before the review begins?
3. Have the inclusion criteria been justified?
4. Is the search strategy inclusive?
5. Has the selection of studies been duplicated?
6. Has data extraction been duplicated?
7. Were the reasons for exclusion reported?
8. Was the risk assessment of bias adequate?
9. Are statistical methods appropriate (if applicable)?
10. Has the presence of conflict of interest been assessed?

Ref	C#1	C#2	C#3	C#4	C#5	C#6	C#7	C#8	C#9	C#10
(Ridho, 2023)	H	H	M	H	H	L	M	H	L	H
(Perifanis & Kitsios, 2023)	H	M	H	M	H	H	M	L	L	H
(Ciampi et al., 2021)	L	H	M	M	M	M	H	H	M	M
(Gupta & Khan, 2024)	M	M	M	H	M	M	M	M	H	M
(Bernovskis et al., 2024)	L	M	L	M	M	M	M	M	M	H
(Schwaeke et al., 2025)	M	H	M	H	H	L	H	H	H	L

(L=low, M=medium, H=high)

List of criteria MMAT:

1. Clearly formulated research question
2. Appropriate study design for the question
3. Appropriate data collection techniques
4. Well-described and well-founded data analysis
5. Consistent interpretation of results

Reference	**C#1**	**C#2**	**C#3**	**C#4**	**C#5**
(Zheng et al., 2025)	M	H	H	M	H
(Cho et al., 2025)	H	L	L	H	H
(Vahadane & Clarke, 2022)	H	H	H	M	L
(Limpeeticharoenchot et al., 2022)	M	M	H	H	H
(Ojeda et al., 2024)	H	H	H	H	H
(Godbless Ocran et al., 2024)	L	H	H	H	H
(Csordás & Füzesi, 2023)	H	M	H	L	L
(Sipos et al., 2024)	H	H	L	H	M
(Trinh, 2024)	M	M	H	H	M
(Ardito et al., 2024)	H	M	H	M	H
(Yang et al., 2024)	H	H	H	M	H
(Sullivan & Fosso Wamba, 2024)	L	M	H	M	L
(Lemos et al., 2022)	H	M	H	H	H
(Farmanesh et al., 2025)	M	H	M	H	L
(Grashof & Kopka, 2023)	H	H	M	M	H

(Li et al., 2024)	L	M	M	M	H
(Zhang & Peng, 2025)	H	M	L	H	M
(Muto et al., 2024)	L	L	H	M	M
(Glebova et al., 2024)	H	M	H	H	H
(Weber, 2023)	H	H	H	M	H
(Regona et al., 2022)	H	H	L	M	H
(Maroufkhani et al., 2020)	M	M	H	M	H
(Adwan, 2024)	L	H	H	H	L
(Chen et al., 2021)	L	L	H	M	H
(Hunke et al., 2022)	M	M	L	H	H
(Kolková & Ključnikov, 2022)	M	M	M	M	H
(von Garrel & Jahn, 2023)	H	L	H	H	M
(Maroufkhani et al., 2023)	M	H	H	M	H
(Castillo-Vergara et al., 2025)	H	H	M	H	H
(Zairis & Zairis, 2022)	L	M	H	M	M
(Lăzăroiu et al., 2024)	M	M	H	H	H
(Arranz et al., 2023)	H	M	H	M	M
(Rehman et al., 2024)	H	H	H	M	H
(Agarwal et al., 2025)	H	M	L	H	H
(Mantri & Mishra, 2023)	L	H	M	H	M
(Carayannis et al., 2025)	H	M	H	L	M
(Park & Lee, 2024)	M	M	L	H	H
(Tummalapalli et al., 2025)	H	H	H	M	M

(Bianchi & Stoian, 2024)	H	H	M	M	H
(Ricci et al., 2021)	H	M	H	M	L
(Bhatia & Diaz-Elsayed, 2023)	M	H	H	H	H
(Bermeo-Giraldo et al., 2022)	H	H	M	M	H
(Sharma et al., 2024)	H	M	H	M	M
(Wang & Zhang, 2025)	H	H	L	M	H
(Bar-Gill et al., 2024)	H	H	M	M	M
(Mateev, 2024)	M	H	H	H	H
(Siregar et al., 2024)	H	H	H	L	H
(Ferreira et al., 2023)	M	H	M	H	H
(Kolagar et al., 2024)	L	H	H	H	M
(Farida & Nuryakin, 2021)	H	H	H	M	H
(Willetts & Atkins, 2023)	M	H	H	H	H
(Mateev, 2023)	M	H	H	M	L
(El Hilali et al., 2020)	M	M	H	L	H
(Grimaldi et al., 2023)	H	M	H	L	M
(Falahat et al., 2020)	H	H	M	H	M
(Kulkov et al., 2024)	H	H	H	H	H
(Tominc et al., 2024)	M	H	H	M	H
(Sommer, 2023)	H	H	M	H	H
(S. Liu & Cheng, 2025)	M	H	H	H	H
(Xin et al., 2024)	M	M	H	M	M
(Duan et al., 2025)	H	H	M	H	M

(Y. Liu et al., 2024)	M	M	H	H	M
(Tawil et al., 2024)	L	L	H	H	H
(Godbless Ocran et al., 2024)	H	H	M	H	H
(Proietti & Magnani, 2025)	M	H	M	H	H
(Soni et al., 2019)	L	M	M	M	H

(L=low, M=medium, H=high)

Appendix – C

This table presents a representative sample of how academic papers were systematically classified for the literature review. For each selected study, key dimensions were extracted, including:

- **Reference** (formatted as in-text references, i.e., Author, Year),
- **Type of company** studied (SMEs or Large Enterprises),
- **Method of AI application**,
- **Mentioned adoption barriers**,
- **Reported benefits of adoption**,
- and **Observed differences** between SMEs and large firms.

The aim of this excerpt is to illustrate the structured mapping approach used to synthesize insights across the selected literature.

Reference	Type of Company	Method of AI Application	Mentioned Adoption Barriers	Benefits of Adoption	Differences (SMEs vs. LCs)
(Ardito et al., 2024)	SMEs	Data analytics & automation	Limited resources, skills gap	Operational efficiency, cost reduction	More agile use of AI tools by SMEs
(Godbless Ocran et al., 2024)	Both	AI in decision support	Complexity in scaling	Better decisions, efficiency	LCs integrate AI into strategic planning more extensively
(Grashof & Kopka, 2023)	Both	Process innovation with AI	Legacy systems (LCs), funding (SMEs)	Innovation capacity	SMEs apply AI tactically, LCs strategically
(Li et al., 2024)	Large	R&D integration, ML systems	Organizational complexity	Competitive advantage	LCs use AI for radical innovation
(Ferreira et al., 2023)	Large	Enterprise AI transformation	Inertia, data governance	Efficiency, ESG compliance	Focus on enterprise-wide integration

(Proietti & Magnani, 2025)	SMEs	Marketing automation	Skill shortage, infra gaps	Customer engagement	SMEs adopt small-scale tools faster
(Zhang & Peng, 2025)	SMEs	AI for internal ops	Tech infrastructure	Process automation	Limited access to advanced AI platforms
(Muto et al., 2024)	SMEs	Data-driven decision-making	Regulatory burden	Faster response time	Higher policy dependency in SMEs
(Ojeda et al., 2024)	Large	AI in supply chain	Integration complexity	Efficiency, flexibility	LCs implement large-scale AI systems
(Sullivan & Fosso Wamba, 2024)	Large	Customer analytics, AI personalization	Data governance	Customer satisfaction	LCs invest in deep personalization