UNIVERSITY OF GOTHENBURG
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From Challenges to Success: Navigating AI Adoption in Multinational Settings

A Qualitative Multiple Case Study on the AI Adoption Process within MNEs

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ABSTRACT

While the strategic relevance of artificial intelligence (AI) is widely acknowledged, limited insight exists into how adoption is coordinated across organizational layers in multinational enterprises (MNEs). Although technology adoption is a well-established field, few frameworks account for AI's disruptive nature and the complexity of MNE structures. This study addresses this gap by exploring how MNEs adopt AI, focusing on key phases, challenges, and strategic considerations. A qualitative multiple-case study design was applied, drawing on 18 semi-structured interviews with AI experts, managers, and specialists across eleven MNEs. The analysis was guided by a conceptual framework combining AI readiness, adoption phases, and relational and institutional perspectives.

Findings show that AI adoption is best understood as a cyclical process, comprising Initiation, Adoption Decision, and Adoption, shaped by organizational maturity, and internal and external dynamics. Trust, leadership, governance, and cross-functional collaboration emerge as key enablers, while cultural caution presents hidden barriers. The study illustrates how AI readiness builds over time, influencing the speed and scope of future adoption. Overall, successful AI adoption depends not only on strategy and resources but also on the ability to navigate institutional conditions and organizational tensions, offering insights into managing AI as a dynamic organizational capability.

Keywords: MNE, Artificial Intelligence, AI Adoption Process, Organizational AI Readiness, AI Maturity, Strategy Alignment, HQ-Subsidiary Relationship, Responsible AI.

TABLE OF CONTENTS

1. INTRODUCTION TO ARTIFICIAL INTELLIGENCE

The origins of artificial intelligence (AI) trace back to the 1950s, when Alan Turing, widely regarded as the father of computer science, posed the question, "Can machines think?" in his seminal paper *Computing Machinery and Intelligence*. This inquiry laid the foundation for AI as a field and spurred decades of research, establishing the conceptual groundwork for today's systems (Stryker & Kavlakoglu, 2024).

The concept of AI is defined in various ways depending on the context in which it is discussed. As AI is increasingly integrated into both academic research and organizational practice, it becomes essential to distinguish between the definitions offered by different types of sources. This is key for analytical clarity, particularly when studying how AI is implemented in complex organizational environments like multinational settings.

Sources	Category	Definitions of AI
Russell & Norvig (2016: viii)	Academic	"...agents that receive percepts from the environment and perform actions."
Kaplan & Haenlein (2019: 17)	Academic	"...a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation."
Stryker & Kavlakoglu (2024)	Academic	"...technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy."
OECD (2022: 4)	Intergovernmental	"...a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments."
Capgemini (2024: 35)	Consulting	"...a technology designed to function independently, plan, reflect, pursue higher-level goals, and execute complex workflows with minimal or limited direct human oversight."
McKinsey (2024a: 1)	Consulting	"...a machine's ability to perform some cognitive functions we usually associate with human minds."

Table 1. Definitions of AI.

While the definitions in table 1 vary in wording and emphasis, clear distinctions emerge between the perspectives. Academic sources tend to frame AI as a system based on computational models that imitate cognitive abilities, such as perception, learning, and decision-making, often within agent-based frameworks (Russell & Norvig, 2016: viii; Kaplan & Haenlein, 2019: 17; Stryker & Kavlakoglu, 2024). Consulting firms focus on autonomy and organizational outcomes, emphasizing AI's potential to drive business value and efficiency (Capgemini, 2024: 35; McKinsey, 2024a: 1). The intergovernmental definition from the OECD (2022: 4) is more neutral, centring on goal orientation and environmental interaction without specifying internal processes. In this thesis, academic definitions are prioritized analytically due to their conceptual depth, methodological grounding, and theoretical relevance. Non-academic perspectives remain useful by illustrating how AI is framed and applied in practice. For the purpose of this thesis, AI is defined as a machine-based system that simulates cognitive functions, including learning, reasoning, and decision-making, to support and enhance organizational processes in multinational enterprises (MNEs).

Building on this definition, the following section distinguishes between two main types of AI, traditional and generative, that shape current technological and organizational practices. Traditional AI refers to narrow, rule-based systems that operate through predefined instructions and structured data. Rather than learning or adapting, these systems follow set rules to perform tasks efficiently and accurately. This makes traditional AI particularly useful for repetitive functions where speed and precision are key, such as in search engines, recommendation tools, and voice assistants (Marr, 2023).

Generative AI, which emerged in the 2020s, represents a major leap in AI capabilities. Unlike traditional systems that follow fixed rules, generative AI can create new outputs based on patterns in data. Using large training datasets, these models generate original content such as text, code, visuals, audio, and simulations. Tools like OpenAI's ChatGPT, along with models from DeepMind and Meta, are examples of how generative AI is expanding the scope of AI applications across industries (McKinsey, 2024b: 3, Stryker & Kavlakoglu, 2024). This shift marks a new era of creativity and automation, setting generative AI apart through its ability to generate rather than just process information.

The combined use of traditional and generative AI can yield greater value than either approach used in isolation. Traditional AI is well-suited to processing structured inputs and identifying patterns, while generative AI adds the ability to create new, customized content based on those patterns. When used together, these tools can enable advanced applications, such as tailoring product recommendations using behavioral data or automating customer interactions with human-like fluency. This hybrid approach is increasingly used to streamline operations and enhance user experiences across industries (Marr, 2023).

In response to the accelerating development and widespread adoption of AI technologies, the European Union (EU) has enacted the AI Act, the world's first comprehensive legal framework for regulating AI, covering all member states. The regulation establishes a risk-based approach to AI governance, requiring organizations to assess and mitigate potential harms related to transparency, safety, and ethical usage. The EU AI Act officially came into force on August 1, 2024, and will be fully implemented after a two-year transition period, setting new legal standards for AI deployment in the European market (European Commission, 2025).

1.1 Technology Adoption within MNEs

A multinational enterprise (MNE) is a company that operates across multiple countries, producing goods or providing services (Eurostat, n.d.). MNEs vary in structure based on their global scale, strategic priorities, and market conditions (Raziq et al., 2023: 909). Often organized as networks of semi-autonomous subsidiaries, they balance local adaptation with corporate control (Rosenzweig & Singh, 1991; Birkinshaw, 1997). Subsidiaries combine firm-specific advantages (FSA) with country-specific advantages (CSA) to manage activities and resources effectively, contributing to the MNE's global competitiveness (Meyer et al., 2020: 540).

As technology rapidly evolves, effective adoption processes are crucial to avoid obsolescence and sustain competitiveness. The term *Adoption* refers to the decision to utilize an innovation such as a product, service, or technology (Frambach & Schillewaert, 2002: 163). It can be conceptualized into two dimensions: *implementation* and *internalization*. Implementation refers to the visible actions required for adoption, while internalization occurs when employees see value in the practice and commit to using it. Together, these dimensions determine the depth of adoption, as positive attitudes facilitate both the initial adoption and its long-term resilience. Consequently, successful adoption extends beyond technical deployment and depends on organizational readiness and active employee engagement.

Yet even when organizations are internally prepared, adoption efforts can be challenged by tensions between strategic intent at the corporate level and operational realities within business units (Schmidt et al., 2023: 37). These misalignments can result in inconsistent implementation across different subsidiaries, reducing overall efficiency. Kostova and Roth (2002: 217) emphasize that both institutional and relational contexts shape how subsidiaries respond to parent company initiatives. These dynamics influence perceptions of authority, support, and belonging, ultimately influencing the adoption process within MNEs.

In addition to contextual dynamics, managerial roles at different organizational levels further affect the adoption success. Key enablers include user-friendly tools, time-saving benefits, and strong digital literacy (Schmidt et al., 2023: 36). Equally important are strategies that address security and financial risks while aligning digital initiatives with the organization's overall goals (Xicang et al., 2024: 11-12). These organizational factors become especially important as firms adopt more advanced technologies like AI.

The rapid advancement of AI has made its adoption increasingly critical for MNEs. A global survey of executives from large firms found that 80 percent had increased their investment in generative AI from the previous year, while 20 percent maintained levels (Capgemini, 2024: 4). Global AI-related investments are projected to reach $200 billion in 2025 (Statista, 2024). This growth reflects AI's expanding role across key business functions, from sales and IT to logistics and finance. However, many organizations still struggle to scale AI initiatives effectively, underscoring the need for structured processes, alignment with strategy, and internal capability development.

1.2 Problem Discussion

Despite the growing strategic importance of AI and increasing investments across industries, limited research has explored how AI adoption unfolds within MNEs, from experimentation to full-scale internalization. While technology adoption is a well-established research area, existing models are often shaped by earlier innovations that followed linear implementation paths, aimed to improve existing processes. In contrast, AI adoption is not merely a technical upgrade; it represents a profound organizational shift that affects decision-making, governance, workflows, and employee roles (Jöhnk et al., 2020: 11; Frambach & Schillewaert, 2002: 163). AI systems are data-driven, adaptive, and continuously evolving, demanding iterative learning, cross-functional coordination, and alignment with strategic goals (Capgemini, 2024: 4-5). This makes adoption not only more complex, but also more uncertain, especially in MNEs, where global strategies must be aligned with diverse local conditions without compromising coherence.

The complexity is further compounded by the central role of data in AI adoption. Unlike traditional technologies, AI depends on structured, accessible, and representative data to deliver reliable outputs and improve performance over time (McKinsey, 2024b: 2-3). Many organizations, however, lack the necessary data infrastructure to meet these demands. In MNEs, this challenge is amplified by decentralized operations, legacy systems, and varying regulatory environments. These structural differences across subsidiaries often lead to fragmented data practices that undermine scalability and reliability of AI models. Without unified standards and integration mechanisms, AI systems struggle to deliver meaningful insights or support organizational decision-making (Capgemini, 2024: 32).

In addition to data limitations, many firms experience significant knowledge gaps about how AI can be integrated into business operations. Although executives increasingly recognize AI's strategic potential, employees often lack the capabilities to use these tools effectively (PwC, 2025: 5; Xicang et al., 2024: 11-12). This issue is particularly essential in MNEs, where digital readiness varies across subsidiaries, creating barriers to consistent implementation and internalization (Schmidt et al., 2023: 41; Kostova & Roth, 2002: 217). Despite reported efficiency gains and profitability improvements, only a third of firms have taken concrete steps to align workforce skills with AI integration (PwC, 2025: 2-5). Without a shared understanding of AI's purpose, capabilities, and value, employees are less likely to engage with these tools or contribute to their refinement, undermining both strategic alignment and long-term impact.

Even when data and capabilities are in place, trust emerges as a decisive factor. Employees may resist AI due to concerns about job security, lack of transparency in algorithmic decisions, or fears of bias and inaccuracy (Lussana, 2024). Business leaders, in turn, hesitate to scale AI solutions due to ethical risks, legal uncertainty, and limited auditability or explainability of models (PwC, 2025: 19). Within MNEs, trust-related challenges are magnified by cultural and regulatory differences, as well as the dual influence of corporate HQ and local subsidiaries. Institutional and relational variations affect how subsidiaries interpret and implement corporate initiatives (Kostova & Roth, 2002: 218-220). Without mutual trust, AI adoption risks being resisted, only partially implemented, or misaligned with strategic intent.

While the literature acknowledges AI's growing strategic relevance, research remains fragmented, often emphasizing technical implementation rather than strategic, procedural, and managerial aspects, and tends to focus on specific industries, such as the energy sector (Corrales-Garay et al., 2024; Schmidt et al., 2023). There is limited insight into how adoption is coordinated across organizational layers in MNEs, despite the heightened need for structured strategies in complex, multi-market environments (PwC, 2025: 2, 24). As industry boundaries blur and competitive AI capabilities expand, understanding how MNEs manage the transition from experimentation to full-scale adoption becomes increasingly important. This includes addressing how corporate AI strategies are translated into locally actionable initiatives, and how firms navigate tensions between global standardization and local responsiveness.

In short, AI adoption in MNEs is not yet what it ought to be: a coordinated, scalable, and strategically integrated process. The absence of comprehensive frameworks leaves firms without clear guidance on how to manage adoption across different phases and organizational layers. To address this gap, this study explores how AI adoption unfolds in practice within MNEs, with particular attention to the key phases, challenges, and strategic choices involved in moving from initial exploration to long-term integration.

1.3 Purpose & Research Questions

The purpose of this study is to explore how MNEs adopt AI by identifying the key steps from initial exploration to long-term usage, as well as the associated challenges, and strategic considerations. In doing so, the research contributes to academic understanding of the adoption process while offering practical insights to help organizations navigate its complexity. To address this purpose, the following research question is investigated:

How does an AI adoption process unfold in MNEs?

1.4 Delimitations

This study focuses on MNEs that are actively engaging with AI technologies and includes firms from a range of industries. This cross-sectoral approach aligns with the horizontal scope of emerging AI regulation, such as the EU's AI Act, and allows for a broader understanding of adoption patterns across diverse organizational contexts. However, this variation may limit the depth of industry-specific insights, as sectoral factors like regulatory pressures or digital maturity are not the primary focus.

Similarly, by concentrating on firms already involved in AI, the study does not capture the experiences of those at earlier stages of consideration or opting out entirely. These delimitations are consistent with the study's purpose to explore how the adoption process unfolds once engagement with AI has begun.

1.5 Disposition

This thesis follows a structured approach, beginning with an introduction that outlines the background, problem discussion, and research objectives, with a focus on AI adoption in MNEs. The theoretical frameworks explore AI adoption process, organizational readiness, leading to a conceptual model. The methodology section details the research design, data collection, and analysis approach. Empirical findings from the interviews are then presented, followed by an analysis that links these insights to existing frameworks. Finally, the conclusion summarizes key insights, managerial implications, addresses limitations, and suggests future research directions (see Figure 1).

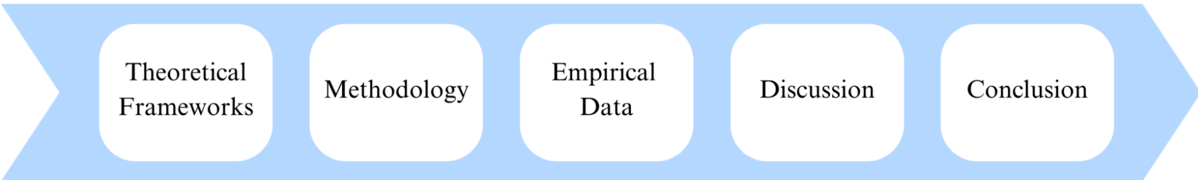


Figure 1. Visualization of thesis disposition.

2. THEORETICAL FRAMEWORKS

2.1 AI Adoption Process

The process of technology adoption in MNEs unfolds through distinct phases and is shaped by both internal managerial decisions and external pressures. Large traditional companies face growing demands to integrate new technologies to maintain competitiveness, comply with regulatory changes, and adapt to industry shifts. The pace and effectiveness of adoption vary across organizations, with some firms emerging as early adopters and others lagging behind (Schmidt et al., 2023: 36, 38).

AI Adoption Process and *Organizational AI Readiness* are two key components for effectively leveraging AI in businesses (Jöhnk et al., 2020: 5). The former relates to the *Initiation*, *Adoption Decision*, and *Implementation* of AI solutions within the adoption process. The latter constitutes factors affecting the organization's readiness to adopt AI. These two elements are interdependent and mutually reinforcing (Jöhnk et al., 2020: 16-17). Below follows an illustration (see Figure 2) of the integration of AI adoption and organizational AI readiness.

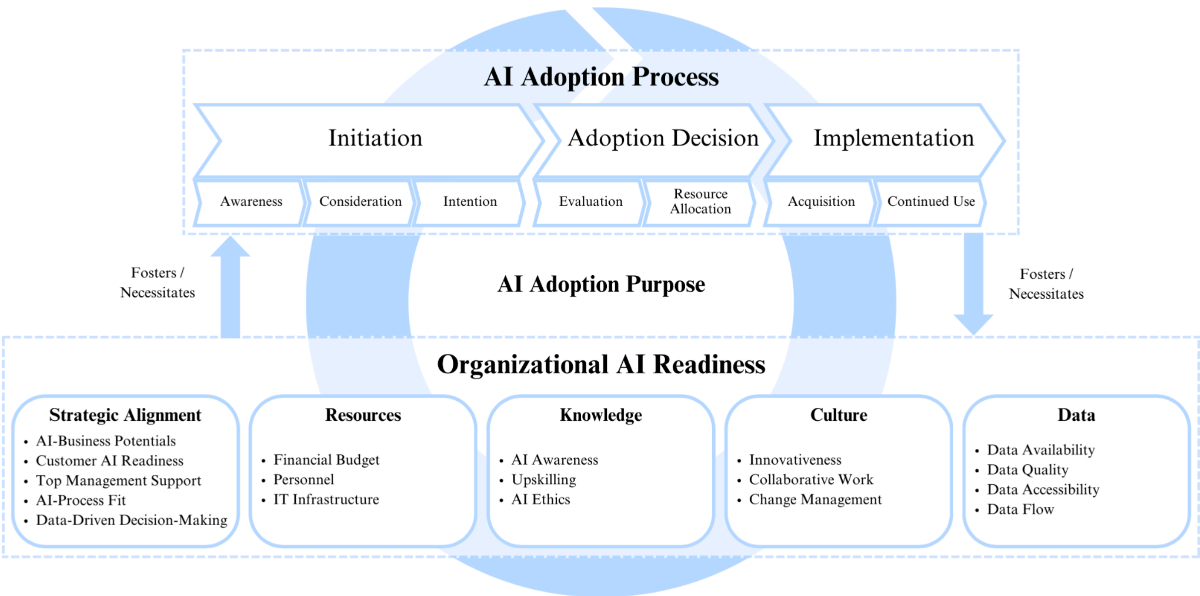


Figure 2. Visualization of AI adoption process based on Jöhnk et al. (2020: 17).

At the core of the model is the *AI Adoption Purpose*, which must align with the business model, guide the adoption process, define the necessary AI readiness factors, and determine how value is generated from AI solutions. Hence, to maximize AI's value potential, organizations must clearly articulate their adoption purpose, ensuring a strategic and well-integrated AI adoption (Jöhnk et al., 2020: 14). Technological, organizational, and environmental factors, adhering to the established TOE-framework originally introduced by Tornatzky et al. (1990), constitute a foundation on which the model rests (Jöhnk et al., 2020: 15).

The following sections examine the three phases: *Initiation*, *Adoption Decision*, and *Implementation*, along with the complementary readiness factors in Jöhnk et al.'s (2020) model. Each phase is further developed and adapted to reflect the complexities of AI adoption within MNEs, incorporating a multinational perspective. Schmidt et al. (2023) contribute to this understanding by analyzing the relationship between HQ and subsidiaries in the context of AI adoption across various organizational functions. The authors identify several key factors that align with Jöhnk et al.'s (2020) framework and significantly influence the pace of technology adoption: constructive tensions, open innovation, and knowledge standardization. Each factor will be further discussed in relation to the phase of the adoption process where its influence is most evident. Kostova and Roth (2002) expand on the second and third phase by emphasizing the relational and institutional context, distinguishing between implementation and internalization, and thereby adding depth to the understanding of long-term integration within the adoption process.

2.1.1 AI Adoption

Initiation-Phase

In the first phase, organizations identify needs, recognize relevant application scenarios, develop an attitude toward the innovations' potential, and formulate a proposal for adoption. Innovation adoption can be understood as a process of organizational change that directly influences both the social and technical systems of a company (Gopalakrishnan & Damanpour, 1997: 17). The initiation phase consists of three sub-phases: *Awareness*, *Consideration* and *Intention*. In the first sub-phase, the firm becomes aware of the innovation and recognizes potential AI applications and use cases. Consideration of different applications and use cases follows in the next sub-phase. Lastly, the firm enters the ending of the initiation phase by coming to the decision to adopt AI (Jöhnk et al., 2020: 7, 10; Pumplun et al., 2019: 5). The overall aim is to identify potential innovation opportunities to improve organizational performance by either solving a problem within the organization or to identify new business opportunities (Jöhnk et al., 2020: 10).

To adapt this model to the context of multinational organizations, Schmidt et al. (2023) introduce an MNE-specific perspective that highlights the relational dynamics between HQ and subsidiaries during the initiation phase, particularly in relation to the formation of intention. Their findings emphasize how internal organizational dynamics shape the adoption path in globally distributed firms. As mentioned, one of the key factors identified by Schmidt et al. (2023: 41) that influences the adoption process is constructive tensions, which plays a particularly important role during this early phase. Constructive tensions arise when strategic priorities at the HQ level do not fully align with the perspectives of subsidiary managers when considering the intention to adopt AI. These tensions can be a source of conflict, but when managed effectively, they drive innovation by fostering debate and collaboration. Constructive tensions encourage subsidiaries to critically evaluate new technologies rather than passively implement top-down decisions. The authors found that early adopters within MNEs were more likely to engage in open discussions with HQ, leading to more effective decision-making and faster adoption processes. By contrast, subsidiaries that avoided confrontation often experienced delays due to misaligned expectations (Schmidt et al., 2023: 41).

Adoption Decision-Phase

The second phase in Jöhnk et al.'s (2020: 8) model is the adoption decision, which includes the sub-phases of *Evaluation* and *Resource Allocation*. These sub-phases collectively lead to a verdict on whether and how to proceed with the adoption plan. As described by Hameed et al. (2012: 361), the evaluation stage involves a formal assessment of the proposal to adopt the innovation, resulting in its approval or rejection. This decision is primarily based on the perceived potential of the innovation to improve organizational performance. The evaluation process typically considers a combination of technical, financial, and strategic factors.

Resource allocation refers to the process of identifying and assigning the necessary resources required for implementation (Hameed et al., 2012: 361). One key resource is the financial budget, which supports investments in areas such as data, infrastructure, and organizational knowledge essential for AI adoption. Human capital is another critical resource, as the adoption of AI depends heavily on internal expertise and experience. Additionally, a thorough IT infrastructure is vital, given that AI technologies rely on access to large volumes of secure, high-quality data (Jöhnk et al., 2020: 12).

While Jöhnk et al. (2020) emphasize the importance of resource allocation, additional considerations arise in the MNE context. Schmidt et al. (2023: 42) expand this view by highlighting open innovation, where MNEs involve external actors to support AI adoption across organizational units. Rather than relying solely on internal R&D, companies benefit from partnerships with OEMs, research institutions, and industry networks, gaining access to cutting-edge insights that enhance adoption. Early adopters actively engaged external stakeholders to refine technologies and adapt them to specific operational needs, improving speed while reducing the risks of untested innovations (Schmidt et al., 2023: 41-42). This collaborative approach also allows firms to integrate best practices from diverse industries and respond to evolving market demands. Moreover, open innovation fosters a culture of continuous learning, encouraging employees to experiment with new solutions. By leveraging external relationships and maintaining strategic flexibility, MNEs enhance their capacity for sustained technological advancement (Schmidt et al., 2023: 41).

In addition to external collaboration, both internal relationships and external institutional environments shape adoption decisions within MNEs. Kostova and Roth (2002) highlight the importance of the relational context, where trust, dependence, and identification influence how subsidiaries respond to parent company initiatives. Trust reflects confidence in HQ's integrity and fairness, dependence implies reliance on HQ for resources and support, implying subordination and control, and identification captures the extent to which subsidiaries see themselves as part of the broader organization. High trust can facilitate practice transfer and reduce coordination costs between HQ and subsidiaries (Kostova & Roth, 2002: 219). At the same time, the institutional context, comprising regulatory (laws and rules), normative (social values), and cognitive (shared beliefs and frameworks) pillars, shape whether and how subsidiaries adopt HQ-led practices (Kostova & Roth, 2002: 217). These contextual factors may lead to varying adoption levels across subsidiaries. Recent studies on AI further underscores the role of institutional contexts and relational dynamics in shaping adoption approaches (Rudko et al., 2025: 274-275).

Implementation-Phase

Lastly, the organization reaches the implementation in Jöhnk et al.'s (2020) framework. If the proposal is accepted, acquisition of the innovation, trials, and continued adoption follows. A rejected proposal may be resumed in a later stage after reassessment (Jöhnk et al., 2020: 7). The goal of implementation is organizational acceptance and use of the innovation, which results in the two sub-phases of *Acquisition* and *Continued use*. Acquisition refers to the stage where the innovation is obtained, introduced, and technically integrated into the organization's infrastructure and workflows. Continued use follows as the innovation becomes embedded in regular operations, accepted by the organization and adapted over time (Hameed et al., 2012: 361).

While Jöhnk et al. (2020) describe the implementation phase in terms of acquiring and using the innovation, Kostova and Roth (2002) add depth to this phase by introducing a relational and institutional perspective tailored to the MNE context. They distinguish between implementation, the tangible activities and formal behaviors involved in introducing a practice, and internalization, when employees within the receiving unit perceive the new practice as meaningful and demonstrate a willingness to engage with and support its continued use. This conceptual separation closely aligns with Jöhnk et al.'s (2020) sub-phases of acquisition and continued use, highlighting the difference between technical integration and long-term organizational adoption within the implementation phase.

As in the adoption decision phase, both relational and institutional contexts influence the extent of implementation in the AI adoption process. Kostova and Roth (2002: 227-228) found that stronger trust and identification with the parent company promote higher implementation levels at the subsidiary, as they reduce uncertainty and encourage mimetic or normative adoption over coercive compliance. Conversely, subsidiaries with high dependence on HQ reported lower implementation levels, likely due to reduced autonomy. The authors argue that interdependence allows for greater local adaptation, while one-sided dependence limits flexibility. On the institutional side, implementation was positively influenced by a favorable cognitive institutional profile where subsidiaries in environments with greater knowledge and practice of quality management demonstrated higher adoption levels. In contrast, regulatory and normative profiles had no significant impact (Kostova & Roth, 2002: 227).

With regard to internalization, Kostova and Roth (2002: 228) found that institutional pressures in the host country significantly influence the extent to which practices are internalized. Regulatory pressures negatively affected internalization by fostering perceptions of coercion, whereas cognitive and normative pressures had a positive influence. Internalization is more likely when societal norms and knowledge align with the practice, leading employees to view it as legitimate and effective. As with implementation, higher trust and lower dependence were associated with greater internalization.

Schmidt et al. (2023: 41) found that knowledge standardization is another mechanism that supports internalization and continuous use in the context of MNEs. It helps ensure that new technologies are integrated consistently across an MNE's operations and multiple subsidiaries. Structured documentation and codification allow subsidiaries to fully leverage technological advancements, preventing inefficiencies and inconsistent implementation. The authors highlighted that early adopters prioritized knowledge codification by developing internal handbooks, training programs, and best practice guidelines to facilitate widespread adoption. When employees in different locations share a common understanding of a new technology's functionality and benefits, they can more effectively implement and optimize it. Furthermore, structured documentation allows organizations to refine and improve technological processes over time, ensuring long-term sustainability (Schmidt et al., 2023: 41)

However, knowledge should not be standardized too early in the adoption process. Instead, knowledge standardization should be implemented at the appropriate stage of the adoption process. In early-adopting subsidiaries, corporate managers were involved in knowledge standardization during later stages of an adoption process, allowing for a reassessment of the business case and alignment with commercialization goals. Standardizing knowledge too soon can limit flexibility and slow down adoption. Waiting until the later phases of adoption facilitates faster overall implementation and improves long-term technological integration (Schmidt et al., 2023: 41-42).

2.1.2 Organizational AI Readiness

Organizational AI readiness refers to an organization's ability to implement AI-related technologies and adapt to associated changes (Alsheibani et al., 2018: 2). Assessment of the AI readiness before adoption decision refers to proactively evaluating readiness and identifying areas needing improvement for AI adoption. It is based on the five categories; *Strategic Alignment*, *Resources*, *Knowledge*, *Culture* and *Data*, and includes 18 factors divided between the categories (Jöhnk et al., 2020: 10).

Holmström (2022: 335) offers a complementary lens to Jöhnk et al.'s (2020: 10-14) AI readiness categories by presenting four transformation dimensions: technologies, activities, boundaries, and goals, to assess an organization's AI readiness. His framework reinforces the importance of aligning technological capabilities, organizational processes, and strategic objectives in preparation for AI adoption. Uren and Edwards (2023: 1) contribute another perspective by emphasizing the need to consider people, processes, and data alongside technology. They suggest that readiness in these areas is essential for long-term AI success and for bridging the gap between business and technical functions within organizations. Together, the framework by Jöhnk et al. (2020) and complementary frameworks by Holmström (2022), Uren and Edwards (2023) support a multidimensional understanding of readiness that spans both technical and organizational transformation necessary for successful AI adoption. The factors and their related categories are presented below.

Strategic Alignment

This category refers to the "Business Potential" of AI solutions and their alignment with organizational goals. It requires an understanding of the potential applications and use cases of AI to solve current problems, and to discover new solutions and business opportunities following AI adoption. "Customer AI Readiness," the degree of customer knowledge and acceptance, is also critical, as the complexity and opacity of AI often reduce perceived usefulness. "Support from Top Management" is another key factor, reflecting leadership's willingness to drive AI initiatives from the top while endorsing bottom-up innovation. "AI-Process Fit" is another factor, referring to the compatibility between the AI strategy and internal processes, facilitated by structured, standardized practices that enhance AI readiness. A strong fit improves integration across the organization. Finally, "Data-Driven Decision-Making" (DDDM), the use of analytics to guide decisions, improves performance and serves as a foundation for future AI-enabled processes, strengthening overall readiness (Jöhnk et al., 2020: 10-12).

Holmström (2022: 333) further emphasizes the importance of integrating organizational goals and activities within the broader process of digital transformation, highlighting how strategic alignment supports successful AI initiatives. Similarly, through their people, process, technology framework, Uren and Edwards (2023: 7-8), stress the critical role of leadership commitment and process alignment in driving AI adoption. Both frameworks emphasize that without compatibility between strategy, technology, and human factors, organizations risk fragmentation and limited value realization from their AI initiatives.

Resources

The first factor related to organizational resources includes the "Financial Budget," referring to the funding allocated to AI adoption, which is typically cost- and time-intensive due to company-specific data and operational needs. Costs also include investments in expertise and efforts to reduce uncertainty around AI's capabilities and value. "Personnel," including business analysts and AI specialists, play a central role. Analysts provide domain knowledge and help translate business needs, while specialists bring technical expertise to develop AI solutions using custom or pre-built models. Analysts often act as intermediaries between business units and technical teams, ensuring alignment between business goals and technological capabilities. Finally, "IT-Infrastructure" must support AI integration through scalable computing, data storage, and networking capabilities for data access, processing, and model training (Jöhnk et al., 2020: 12).

The importance of resources is reinforced in Holmström's (2022: 335) discussion, which highlights the central role of the technology dimension. He emphasizes that organizations need sufficient technical capacity and infrastructure to support AI implementation. In addition, he underlines the importance of human and organizational capabilities to enable effective AI adoption and drive digital transformation. In addition, the technology and people dimensions in Uren and Edward's (2023: 9-10) framework emphasize the necessity of combining thorough technical resources with skilled personnel.

Knowledge

"AI Awareness," a key component of the knowledge category, refers to the workforce's understanding of AI, including its ability to perceive, predict, and generate outputs. Knowledge about AI enables employees to recognize the usefulness of the technology and how the quality of input affects the quality of output. Through "Upskilling," companies develop multidisciplinary skill sets necessary for AI implementation by providing employees with knowledge related to AI. Examples include know-how within statistics, data analytics, data management, and data engineering, along with domain expertise. As a result of the limited AI-knowledge within the labor market, organizations need to invest in the capability development of their workforce. Additionally, "AI Ethics" relates to the prevention of unethical results, as a consequence of biased learning or data. Companies need to create strategies and guidelines to maintain ethical use of AI and mitigate liability risks (Jöhnk et al., 2020: 12-13).

Additionally, Holmström (2022: 335) emphasizes the importance of continuous learning and capability-building as key elements of organizational adaptation in digital transformation. He points out that organizations with limited AI knowledge or experience face strong pressures to learn-by-doing. Developing knowledge across technologies, activities, boundaries, and goals is essential for assessing AI readiness and effectively managing the challenges of AI integration. In a similar way, Uren and Edwards (2023: 6-9) highlight the critical role of the people dimension. They stress the need to strengthen workforce knowledge, promote upskilling, and address capability gaps to achieve organizational readiness for AI.

Culture

An important AI readiness factor within the culture category is an organization's "Innovativeness," which reflects the degree and speed at which employees adapt to change. Successful AI adoption requires transformation across multiple areas, often at a rapid pace. To fully harness AI's potential, companies must foster a culture that encourages experimentation, risk-taking, and strong problem-solving skills as essential aspects of innovative behavior. Large organizations often rely on the status quo, making it especially important to foster a culture of innovation. "Collaborative Work" constitutes the degree of collaboration between domain experts, AI specialists, and IT departments. This is essential in order to avoid isolated work and discover valuable new applications of AI solutions. Moreover, "Change Management" supports employees in the organizational shift, reducing the misinterpretation of job loss due to AI adoption. Instead the possibilities emerging from AI, such as the replacement of repetitive tasks and processes, need to be communicated to the people in the organization to increase acceptance (Jöhnk et al., 2020: 13).

Furthermore, Uren and Edwards (2023: 6-7) highlight the importance of involving stakeholders across levels and engaging end users early in the process to successfully integrate AI into organizational routines. They also note that during the transition from research to operational implementation, change management supports addressing emerging organizational challenges and facilitates acceptance of new technologies. Moreover, they stress that early-stage collaboration between developers and business stakeholders fosters a culture of learning and experimentation, which is essential for organizations seeking to adapt to and benefit from AI integration.

Data

The final category of AI readiness concerns data-related factors. "Data Availability" refers to the quantity and type of data required to train AI models. Structured data (e.g., relational tables) supports standardized applications, while unstructured data (e.g., video, audio, images) is more compatible with advanced AI applications like object recognition. "Data Quality," including dimensions such as completeness and accuracy, is essential for generating reliable outputs. To improve data readiness, organizations must invest in data preparation, processing, and quality assurance. Additionally, "Data Accessibility" ensures that relevant data is easily retrievable by authorized personnel. Centralizing data into unified systems, rather than dispersing it across silos, is one way to enhance access and usability. Lastly, a well-structured "Data Flow" is essential for seamless transfer of data across systems, facilitating both the implementation and maintenance of AI solutions. This is particularly important as data processing continues beyond the initial training phase. Effective data flow is characterized by high-quality extraction, transformation, and loading processes, along with established data pipelines and automated, continuous data streams (Jöhnk et al., 2020: 13-14).

2.2 Conceptual Model of AI Adoption in MNEs

To analyze how AI adoption unfolds in MNEs, a conceptual model has been developed that synthesizes three key theoretical perspectives: Jöhnk et al. (2020), Schmidt et al. (2023), and Kostova and Roth (2002). The foundation of the model is based on Jöhnk et al.'s (2020) framework, which consists of three interlinked components. *AI Adoption Process* refers to how organizations progress through the phases of Initiation, Adoption Decision, and Implementation. *Organizational AI Readiness* captures the internal conditions that support this process, including strategic alignment, resources, knowledge, culture, and data infrastructure. These two components are mutually reinforcing: a strong readiness enables smoother adoption, while adoption activities can also build internal capabilities. At the core of the model lies the *AI Adoption Purpose*, which must align with the business model, guide the adoption process, define which readiness factors are critical, and determine how value is ultimately created from AI solutions. This process-oriented structure emphasizes the need for strategic alignment, and the integration of both technical and organizational capabilities across all phases.

To adapt this model to the specific context of MNEs, we incorporate insights from Schmidt et al. (2023), who emphasize the complexity introduced by global operations, multiple organizational layers, and varying degrees of autonomy between HQ and subsidiaries. Their research identifies cross-cutting factors, divided into themes of constructive tensions, open innovation, and knowledge standardization, that influence the AI adoption process at different stages and across hierarchical levels. These insights highlight the importance of intra-organizational dynamics, external partnerships, and codified knowledge in shaping how AI technologies are introduced and embedded within MNEs. In our conceptual model, these factors are positioned alongside the adoption process phases to capture both vertical relationships between HQ and subsidiaries, and horizontal interactions across functions.

While Jöhnk et al. (2020) describe the implementation phase in terms of acquiring and using the innovation, Kostova and Roth (2002) add further explanatory depth by introducing relational and institutional perspectives that is particularly relevant in the MNE context. In terms of adoption, the authors distinguish between *Implementation*, referring to the formal introduction of new practices, and *Internalization*, which occurs when these practices are accepted, perceived as legitimate, and meaningfully integrated by organizational members. This conceptual separation closely aligns with Jöhnk et al.'s (2020) last sub-phases of acquisition and continued use, where acquisition focuses on the technical and structural aspects of implementing AI, and continued use reflects its sustained application and value generation. By integrating these two frameworks, the model recognizes that successful AI implementation in MNEs requires more than just technological deployment. It also involves fostering trust, ensuring employee engagement, and creating a shared understanding of the purpose and value of AI, particularly important in multinational settings where cultural and institutional differences shape how subsidiaries interpret and respond to HQ-driven initiatives.

Taken together, our conceptual model offers a processual and relational understanding of AI adoption in MNEs. By integrating perspectives on structural phases, global dynamics, and organizational acceptance, it illustrates how readiness factors, adoption purpose, internal dynamics, and managerial implications interact to shape the success of AI initiatives. Figure 3 below visualizes the model and serves as the analytical lens for our empirical exploration.

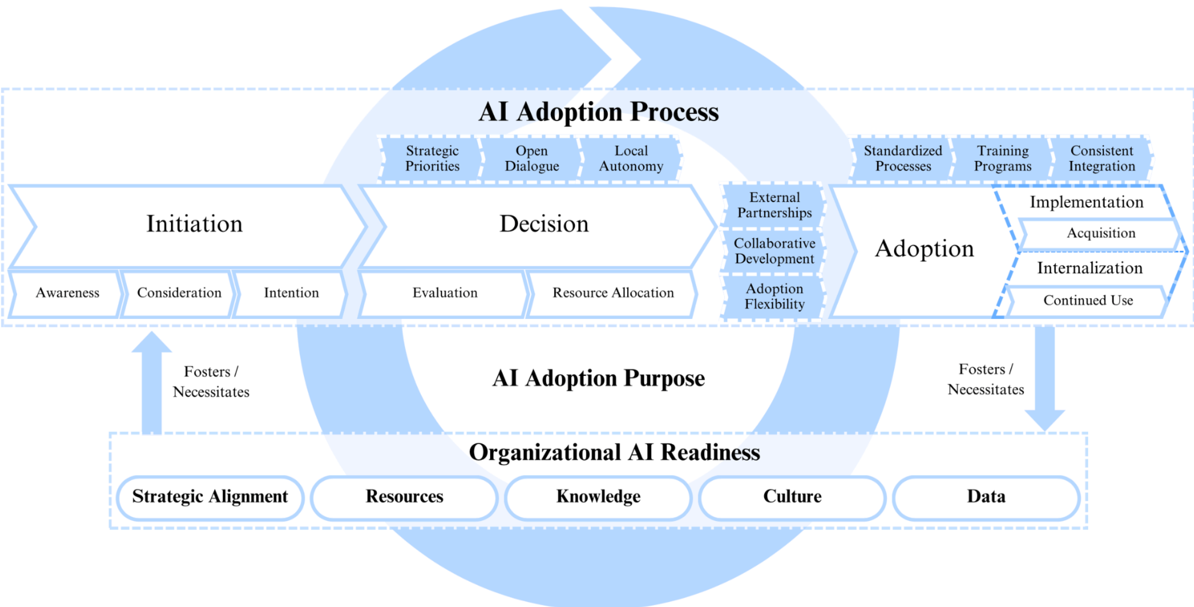


Figure 3. Visualization of the conceptual framework of this study.

3. METHODOLOGY

3.1 Research Strategy

Given the research objective to explore the process of AI adoption within MNEs, a qualitative method was chosen to capture the in-depth reflections from the interviewees and their companies' specific context. Additionally, an abductive approach was employed to integrate both deductive and inductive reasoning, allowing for a combination of theory-driven and data-driven analysis. This approach helped overcome the limitations of purely deductive methods, which rely on strict theory testing and offer limited flexibility to uncover unexpected insights, as well as purely inductive methods, which may lack sufficient structure or data to support robust theory development (Bell et al., 2022: 25).

The chosen research strategy is particularly appropriate for International Business (IB) research, which involves firms operating across varied institutional, cultural, and organizational contexts. The qualitative and abductive approach allowed for the exploration of the complex dynamics that characterize AI adoption within MNEs. By focusing on context-specific insights, this design aligns with Nielsen et al.'s (2020: 11) view that IB research inherently involves contextualizing business, allowing for a nuanced understanding of how MNEs approach and manage AI adoption in practice.

3.2 Research Process

Given the abductive approach, the research process followed an iterative movement between theory and empirical data (see Figure 4). It began with an initial literature review on AI and technology adoption to gain a preliminary understanding of the two fields and find gaps for further research. This was followed by a first round of interviews with AI experts and managers, which provided preliminary insights into how AI adoption unfolds in practice. Emerging themes from the initial analysis of the empirical data guided a targeted literature review on relevant theoretical frameworks related to AI adoption. To further deepen the understanding, follow-up interviews were conducted with individuals in diverse organizational roles. Finally, the analysis and theoretical framework were refined in light of the empirical findings, ensuring that the results were both theoretically informed and empirically grounded.

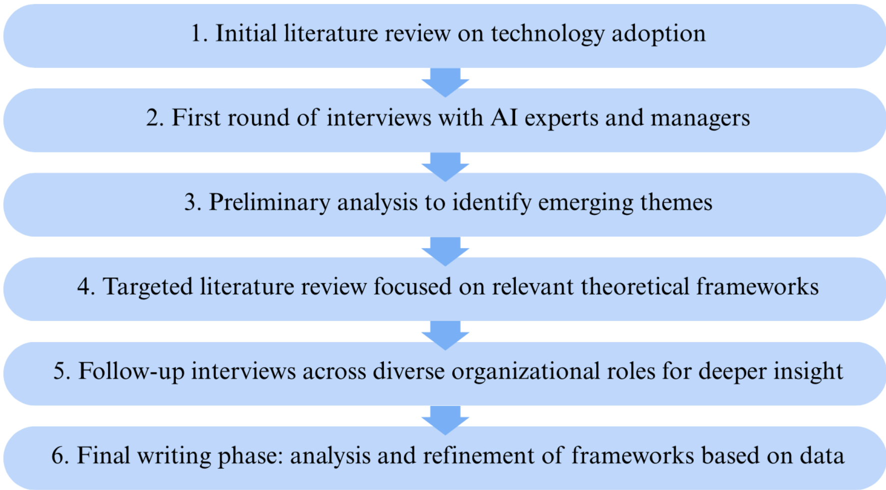


Figure 4. Visualization of the research process.

3.3 Multiple Case Study

Given the exploratory nature of this study, a multiple case study design was chosen to provide contextual insights into AI adoption within MNEs. Case studies are widely used in IB research, particularly for emerging or underexplored topics, and are well-suited for addressing "how" and "why" questions (Ghauri, 2004: 109-110). This approach enabled a deeper understanding of AI adoption by incorporating perspectives from individuals across different companies and roles. Although most respondents requested anonymity due to company-sensitive information, their insights were still valuable in examining the contextual nuances of AI adoption among three respondent categories: *AI Experts* (A), *Managers* (M), and *Specialists* (S). The multiple-case approach not only enriches the contextual depth but also facilitates comparisons across different settings, aligning with Ghauri's (2004: 115) argument that multiple case studies enhance the exploration of diverse dimensions of a phenomenon. Furthermore, by emphasizing real-world contextualization, this approach strengthens theoretical reflections in IB research (Welch et al., 2022: 7), providing empirically grounded insights into AI adoption as it unfolds.

3.3.1 Case Selection

The primary criterion for case selection was that the companies included in the study met the prerequisites to be classified as a MNE in accordance with Eurostat's (n.d.) definition, which states that an MNE operates in more than one country by providing services or goods. Additionally, the case companies needed to have adopted AI to some level within their organization. To identify suitable cases, two sampling processes were conducted. Firstly, companies present on AI Sweden's (2025) list of organizations within the AI Sweden community were contacted, with the requirement of the company being classified as a MNE. Secondly, LinkedIn was used to reach out to individuals with AI-related experience or connections to relevant professionals who could facilitate further recruitment.

As a result, both purposive sampling and snowball sampling was employed to select cases. Companies were strategically chosen based on their relevance to the study's objective to gain insights into AI adoption within MNEs, aligning with the principles of purposive sampling (Bell et al., 2022: 388). Moreover, initial respondents were asked to recommend other potential participants relevant to our study, following the snowball sampling approach (Bell et al., 2022: 394). This method allowed for the identification of further relevant cases, enhancing the study's depth and scope. In addition to the case companies within the study, respondents with AI expertise classified as *AI Experts* provide the study with further insights and knowledge within AI adoption and are represented by AI Company 1-3 in table 2 below.

Overview of Cases	
AI Company 1. Industry: IT & AI Services Builds advanced AI tools and solutions for IT & AI service clients.	AI Maturity Level: High
AI Company 2. Industry: Managerial Consultancy Educates managers on AI strategies and implementation.	AI Maturity Level: High
AI Company 3. Industry: AI Model Development Custom AI models focused on personalizing business processes with behavioral data.	AI Maturity Level: High
Case Company 4. Industry: Automotive Combines traditional and generative AI in self-driving trucks, route planning, and coding.	AI Maturity Level: Medium

Case Company 5. Industry: Automotive Uses traditional and generative AI to improve vehicle safety and driver assistance.	AI Maturity Level: Medium
Case Company 6. Industry: Consultancy Advisory on AI adoption strategies, internal development, and integration.	AI Maturity Level: Medium
Case Company 7. Industry: Consultancy Advisory on AI strategies and value creation for clients.	AI Maturity Level: High
Case Company 8. Industry: Information Technology (IT) Supports clients' AI projects with tailored IT solutions; internal decisions made at HQ.	AI Maturity Level: Medium
Case Company 9. Industry: Chemical Manufacturing Uses AI for R&D, coding support, asset monitoring, and internal LLMs.	AI Maturity Level: Medium
Case Company 10. Industry: Finance Transformation AI-driven financial insights and process optimization.	AI Maturity Level: Medium
Case Company 11. Industry: Audit Limited AI applications in audit processes.	AI Maturity Level: Low

Table 2. Overview of cases.

3.3.2 Categorizing AI Maturity Levels

To support the comparative analysis in the empirical chapter, each case has been assigned an *AI Maturity Level* based on a three-tiered scale: *High*, *Medium*, or *Low* (see table 3 below). These levels were developed to reflect the degree to which AI is integrated into the organization's operations and strategy. The categorizations were based on qualitative indicators such as whether AI is considered core to the business, the extent of internal development (e.g., custom models), how widely AI is implemented across departments, and the level of strategic alignment. The classifications were derived from interview data, including respondents' descriptions of current AI usage, internal structures, and perceived challenges or enablers, as well as company specific secondary data. While the assessment is interpretive in nature, it provides a structured lens for comparing companies with varying levels of AI adoption.

AI Maturity Level	Criteria
High	AI is core to operations or products; custom models; implemented across multiple units; clear strategy.
Medium	AI is used strategically or in selected areas; some organizational support or experimentation.
Low	AI use is ad hoc, experimental, or limited to personal productivity tools; low organizational support.

Table 3. AI maturity level: 3-tier criteria.

3.4 Data Collection

3.4.1 Primary Data Collection

Semi-structured interviews served as the primary data for the study. Within the selected case companies, people at differing levels within the organizations were interviewed in order to gain more breadth in the picture of how the AI adoption process unfolded within the organization, following the advice from Bell et al., 2022: 449) to use qualitative interviews to gain insights not limited to a specific group.

To ensure clarity, the primary data has been categorized into three respondent types: *AI Experts* (A), *Managers* (M), and *Specialists* (S). Managers are individuals in leadership positions who oversee or make decisions about AI adoption within their companies. Specialists are those affected by the implementation of AI in their daily work. When managers and specialists came from the same company, they were assigned the same number in the empirical data (e.g., M10, S10). To distinguish between multiple managers from the same company, different lowercase letters were added after the company number (e.g., M6a, M6b). This structure enabled a comparative view of the company's AI adoption process from different organizational perspectives. Independent AI experts offered an external viewpoint, contributing objective insights and enabled critical reflection on how MNEs, and the individuals within them, approach AI adoption.

3.4.2 Selection of Respondents

Respondents were chosen using purposive sampling, with the aim of gathering the insights needed to address the research question (Bell et al., 2022: 388). Selection was based on specific criteria, including managerial or specialist experience with AI adoption within their organization, or possessing specialist knowledge in AI as an expert. Established contacts were then used to gather additional respondents following the snowball sampling method in the same manner as for the case selection process, ensuring suitable respondents for the purpose of study. Although snowball sampling is a form of convenience sampling, a method based on accessibility (Bell et al., 2022: 394), it was a necessary approach to reach a more representative sample of the target population, specifically individuals with first-hand experience of AI adoption processes. An overview of all respondents and their respective classification, role, industry and date of the interview is presented in table 4 below.

Respondent	Role	Industry	Date
AI Expert A1	AI Engineer	IT & AI Services	Jan 31 2025
AI Expert A2	AI Strategist & Workshop Facilitator	Managerial Consultancy	Mar 6 2025
AI Expert A3	PhD in AI	AI Model Development	May 5 2025
Manager M4	AI Adoption Manager	Automotive	Mar 19 2025
Manager M5	Head of Technology & Collaboration	Automotive	Mar 27 2025
Manager M6a	Senior Advisor	Consultancy	Apr 2 2025
Manager M6b	Senior Lead & Management	Consultancy	Apr 7 2025
Manager M7	Managing Director	Consultancy	Apr 4 2025
Specialist S7a	Strategy Consultant - AI & Humans	Consultancy	Apr 11 2025
Specialist S7b	Consultant - AI Value	Consultancy	Apr 15 2025

Specialist S7c	Consultant - Responsible AI	Consultancy	Apr 23 2025
Manager M8	Country Manager Sweden	IT	Apr 9 2025
Manager M9	Data Portfolio Leader	Chemical Manufacturing	Apr 22 2025
Specialist S9a	Data & Digital Associate	Chemical Manufacturing	Apr 22 2025
Specialist S9b	Technical Support Specialist	Chemical Manufacturing	May 5 2025
Manager M10	Senior Lead & Management	Finance Transformation	Apr 25 2025
Specialist S10	Analyst	Finance Transformation	Apr 25 2025
Specialist S11	Associate	Audit	Apr 29 2025

Table 4. Overview of respondents, arranged by type and company.

3.4.3 Interview Guide

This study employed a semi-structured interview approach, utilizing interview guides to ensure systematic data collection while allowing for adaptability. This format allowed for consistency across interviews while enabling follow-up questions and adaptations based on each respondent's input (Daniels & Cannice, 2004: 192). The interview guides helped maintain focus on key themes, while also allowing for spontaneous exploration of relevant topics as they emerged, an approach well-suited for gathering in-depth insights in qualitative business research (Bell et al., 2022: 427). The format encouraged a conversational tone, allowing for clarification, reordering of questions, and deeper exploration when appropriate (Bell et al., 2022: 439).

The interview guides were developed based on the principles outlined by Bell et al. (2022: 430-431), ensuring that the questions were relevant, clearly formulated, and designed to effectively address the research question. A central consideration was: "What do we need to know to answer the research question?" This ensured comprehensive coverage of key topics without leading respondents. Two distinct guides were created, grounded in the same conceptual framework (see Appendix A & B). One guide was tailored for the respondent type AI Experts (A), focusing on their industry-wide experiences and involvement in multiple AI adoption processes. The other guide was developed for company representatives, including Managers (M) and Specialists (S), to capture perspectives on AI adoption within their specific organizational contexts. Both guides followed a thematic structure covering the AI adoption process from initial discussions through evaluation, decision-making, implementation, and internalization.

3.4.4 Conducting Interviews

As outlined in section 3.4.2, respondents were selected based on specific criteria aligned with the research question, using purposive and snowball sampling. The first interview, conducted in-person at the AI expert's office, allowed for rich interaction through non-verbal communication signals, such as facial expressions and body language (Bell et al., 2022: 436). Subsequent interviews were arranged through LinkedIn or direct email, with candidates receiving detailed information about the study's purpose and data-handling procedures to ensure informed and voluntary participation. All selected respondents agreed to take part in the study.

The interviews lasted between 30 and 60 minutes each and were conducted via digital platforms, such as Microsoft Teams or Google Meet, given the participants' geographical location. Respondents voluntarily kept their cameras on, enabling researchers to observe facial expressions and other non-verbal signals, which enhanced the depth of insights obtained and closely mirrored the benefits of in-person interactions (Bell et al., 2022: 452-453).

To maintain data consistency and minimize bias, both researchers attended each interview. One researcher led the discussion, while the other ensured comprehensive topic coverage by asking follow-up questions or seeking clarifications when necessary. This collaborative approach improved data reliability and streamlined the interview process. All participants consented to recording, which was facilitated by the built-in features of the digital platforms. Recording and transcribing the interviews not only preserved the content for thorough analysis but also compensated for memory limitations and enabled active researcher engagement during discussions (Bell et al., 2022: 436).

3.4.5 Secondary Data Collection

Publicly available information from the case companies related to AI were used to complement and strengthen the data obtained from the qualitative interviews. These materials provided additional insights into the firms' strategic positioning, AI capabilities, implementation practices, and AI maturity. Examples of such materials included press releases and corporate news, marketing and product information, and corporate website content.

3.5 Literature Review

During the research process, a literature review was conducted to investigate the research field and find gaps within the existing research. This enabled us to understand what is known, what theories and concepts that are relevant, and to identify research opportunities, as recommended by Bell et al. (2022: 93). Although studies on both AI implementation and technology adoption exist, studies on how the AI adoption process unfolds within MNEs could not be found. Hence, this study aims to fill this research gap by combining the fields of technology adoption and AI implementation (see Figure 5).

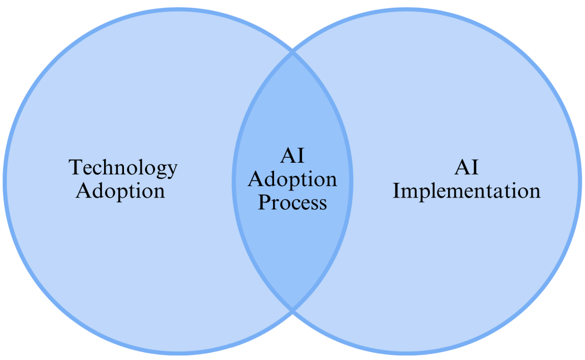


Figure 5. Visualization of the two research areas in consolidation.

Peer reviewed articles have constituted the base for the literature review, in addition to information and data published by major players in the industry, such as Capgemini and McKinsey, as well as by public organizations such as OECD and Eurostat. The combination of academic articles and practical insights from the industry contributed to differing perspectives and a richness in the data, providing a broad and objective presentation of the existing literature.

The literature review was conducted using databases such as Scopus, Web of Science, and Supersearch from the Gothenburg University Library's webpage, ensuring a high-quality framework based on published literature within academic journals (Bell et al., 2022: 100). Further relevant literature was obtained by inspecting references in the collected literature. Journals used for this study are covering topics within relevant fields such as: *Journal of International Business Studies, Research Technology Management, Journal of Management, Strategic Management Journal, Journal of Business Research, Business & Information Systems Engineering, Academy of Management Journal and Sage.*

To identify relevant literature, key search terms closely aligned with the research topic were used within these databases. As the review progressed, additional keywords found in the initially retrieved articles were incorporated to refine and expand the search, ensuring comprehensive coverage of the topic. The used keywords are presented in table 5 below.

Keywords	
Digital Innovation	Process Framework
Artificial Intelligence	Open Innovation
Traditional AI	Business Model Innovation
Generative AI	Digital Transformation
AI Readiness	Technology Adoption
AI Adoption Process	Organization Design

Table 5. Used keywords.

3.6 Analysis Process

The analysis of the collected data followed the Gioia Methodology (Magnani & Gioia, 2023: 2-5), structured into three key stages to systematically derive analytical generalizations from the empirical material. First, first-order codes were generated based on informant-centered data, capturing key concepts directly from the responses. These codes were then grouped into second-order themes and aggregate dimensions, incorporating theoretical perspectives to structure the findings. Second, an iterative process between theory and data was applied, allowing for continuous refinement and deeper theoretical alignment. During the coding process, both researchers were involved and agreed on the interpretations and codes, reducing the bias of having only one researcher analyzing the data. After 18 interviews, no new codes were identified, hence empirical saturation was deemed reached and no new data was collected (Bell et al., 2022: 391). Lastly, the findings are presented using second-order themes, supported by first-order quotes from informants to maintain a clear link between raw data and theoretical interpretation, following the iterative characteristics of the Gioia Methodology to a more abductive research process.

An example of how the methodology was applied is illustrated in Figure 6 below, which presents the coding process for the *Intention* sub-phase within the *Initiation* phase. Drawing directly from respondent quotes and first-order concepts, two second-order themes "Rethinking Technology Projects" and "Leadership & Organizational Structure," were identified. These were subsequently aggregated under the broader conceptual dimension of *Intention* in the theoretical model. The empirical findings are structured with sub-headings according to these coded sub-themes within each phase of the AI adoption process. Other coding examples are available in Appendix C.

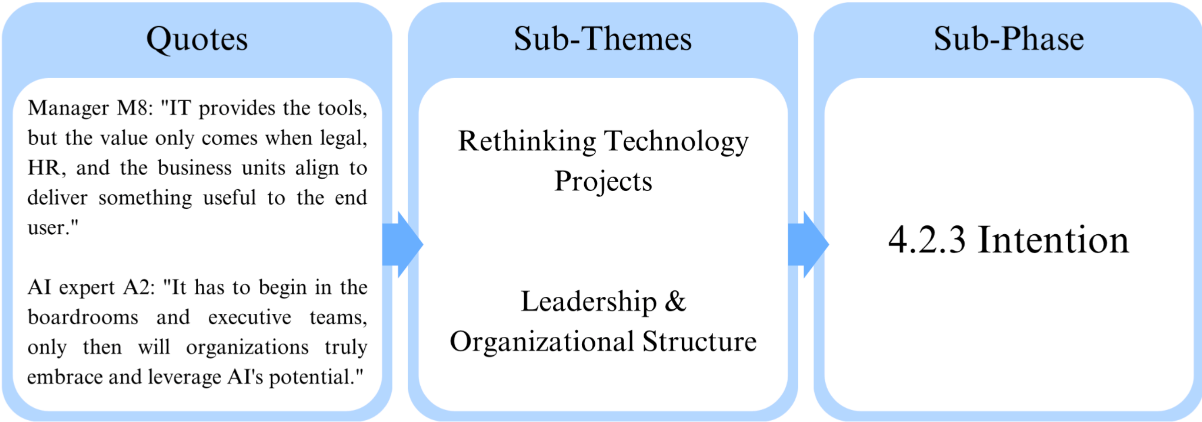


Figure 6. Visualization of an example of the coding process.

3.7 Quality Criteria

The quality of this qualitative study was assessed using the concept of trustworthiness, as proposed by Guba and Lincoln (1994: 106). Trustworthiness comprises four key dimensions: credibility, transferability, dependability, and confirmability, which provide a structured framework suited to the interpretative nature of qualitative research. These criteria acknowledge the complexity of social contexts and the existence of multiple realities, offering a structured way to assess the trustworthiness of this qualitative study. Credibility was enhanced through the use of multiple cases, enabling triangulation (Bell et al., 2022: 369-370). This provided diverse perspectives on the AI adoption process, helped reduce bias, and strengthened the overall quality of the findings.

3.7.1 Credibility

Credibility in qualitative research refers to the extent to which findings accurately reflect participants' perspectives and experiences. Since multiple interpretations of social reality can exist, the plausibility of a researcher's account determines its acceptability. To enhance credibility, established methodological practices were followed, including respondent validation (Bell et al, 2022: 367-368), where key takeaways were shared with participants to confirm the accuracy of interpretations and reduce bias. Triangulation (Ghauri: 2004: 116) further strengthened the study's credibility by enabling comparisons across multiple data sources through the use of several cases, providing a more comprehensive understanding of the phenomenon. The inclusion of secondary data (Merriam, 1998: 122) supported this process by allowing for cross-checking of information, increasing the confidence in the findings, particularly in relation to each case's AI maturity. In line with unit triangulation (Marschan-Piekkari et al., 2004: 254), perspectives were gathered from AI experts, managers, and specialists to ensure a broader and more nuanced understanding of the phenomenon. Additionally, to mitigate the risk of incomplete or withheld information due to confidentiality concerns, participants were guaranteed anonymity. This encouraged openness and increased the likelihood of accessing valuable insights that may not have been shared otherwise.

3.7.2 Transferability

Transferability refers to the extent to which research findings can be applied to other contexts, recognizing that qualitative studies often focus on specific social settings or groups. Since qualitative research emphasizes depth over breadth, its findings are inherently context-dependent (Bell et al. 2022: 369). Lincoln and Guba (1985: 316) argue that the applicability of results to different settings is an empirical question rather than an inherent characteristic of the study. To facilitate transferability, thick descriptions are provided, meaning detailed accounts of the research setting and participants, which allow others to assess the relevance of the findings to their own contexts, as recommended by Lincoln and Guba (1985: 316) and Bell et al. (2022: 369). In IB research, external validity is enhanced by ensuring that the study's context and methodological choices are clearly described while maintaining confidentiality (Andersen & Skaates, 2004: 475). Detailed descriptions of the respondents' professional contexts and industries have been provided, while ensuring their anonymity. By offering insights into the backgrounds of AI experts, managers, and specialists, the study enables future researchers and practitioners to assess the relevance of the findings across different organizational and industry contexts. Furthermore, this research aims to contribute to theory-informed insights on how the AI adoption process unfolds within MNEs by connecting findings to existing concepts and frameworks. This approach aligns with Yin's (2014: 38-39) logic of analytical generalization, allowing results to inform broader understanding beyond the specific cases studied.

3.7.3 Dependability

Dependability in qualitative research ensures that the study's findings are consistent and could be replicated under similar conditions. To achieve this, comprehensive documentation of all research phases has been maintained, making the process transparent and accessible for review in accordance with the recommendations by Bell et al. (2022: 371). Detailed records, including documentation of participant selection, interview transcripts, recordings, and analysis procedures, adheres to the "auditing" approach advocated by Lincoln and Guba (1985: 316). Feedback from other master's students and supervisors was incorporated to refine methodological choices, ensuring a more thorough research design. To enhance consistency, an iterative approach to data analysis was employed, where coding categories were reviewed and refined multiple times, with underlying coding decisions systematically documented. Together, these measures contribute to a structured and well-documented research process, reinforcing the study's dependability.

3.7.4 Confirmability

Confirmability in qualitative research ensures that findings are derived from the data rather than influenced by the researcher's biases or prior assumptions. While complete objectivity is unattainable, transparency in data collection, analysis, and interpretation helps demonstrate that the research has been conducted in good faith (Bell et al., 2022: 371). An auditing approach (Lincoln & Guba, 1985: 316) as previously mentioned, further strengthened the confirmability of the study, by allowing external reviewers to evaluate the research process and determine whether it honored requirements of non-bias.

Several measures were taken to further enhance confirmability, such as standardization in data collection and careful phrasing of questions which helped minimize researchers' influence on participants. Additionally, anonymity was ensured to encourage honest responses and reduce social desirability bias. Participants were asked open-ended questions about their company's AI adoption process, with careful wording to avoid leading their responses, and follow-up questions were used solely for clarification. The same set of questions was asked to all participants, preventing inconsistencies, and information from earlier interviews was not used to shape later discussions. These steps contributed to a transparent and consistent research process, strengthening the confirmability of the findings.

3.8 Ethical Considerations

Ethical considerations are fundamental for conducting responsible research and ensuring the credibility of the study. At the start of each interview, participants were informed about the purpose of the research, how their responses would be used, and were assured of anonymity and confidentiality for both themselves and the companies they represent. This process ensured adherence to the principles of informed consent (Bell et al., 2022: 114-117) and ethical information dissemination (Swedish Research Council, 2024: 77). Given the study's aim to investigate how MNEs adopt AI, it was essential to capture the experiences and perspectives of individuals involved in these processes. Emphasizing anonymity enabled respondents to speak freely and fostered a sense of security, encouraging honest and open reflections without fear of repercussions or judgment. In addition, participants were asked for explicit consent to record and transcribe the interviews, in line with the recommendations by Bell et al. (2022: 436) to fulfill ethical research qualifications.

3.9 Criticism on Methodological Approach

While the methodological approach was appropriate for the study's purpose, it also introduces several limitations that should be acknowledged when interpreting the findings. First, the use of convenience sampling, while practical within the constraints of time and access, raises concerns about sample representativeness and potential bias. Although participants were selected based on their experience with AI adoption, the non-random nature of the sample limits the analytical generalizability of the findings and may skew insights toward more proactive or positively engaged organizations (Bell et al., 2022: 200; Yin, 2014: 38-39).

Second, the cross-industry focus, while intended to reflect the horizontal applicability of emerging AI regulations, may have limited sector-specific insights. Industry-specific drivers, such as regulatory pressures, digital maturity, and competitive dynamics, could have offered deeper explanatory power but were not explored systematically. The resulting analysis emphasizes general patterns at the expense of contextual depth, which may limit the applicability of findings for stakeholders seeking sector-tailored strategies.

Third, the abductive research approach, though suitable for exploring emerging and complex phenomena, relies heavily on researcher interpretation. This introduces the risk of confirmation bias or selective emphasis, especially when navigating between empirical material and theoretical constructs. The researchers' own backgrounds, assumptions, and ontological perspectives inevitably influenced how meaning was constructed from the data (Bell et al., 2022: 25-27). While reflexivity was maintained throughout the research process, complete neutrality is neither achievable nor claimed.

Finally, the study focused exclusively on MNEs already engaging with AI technologies, thereby excluding organizations at earlier stages of awareness or deliberation. This choice may have constrained the understanding of barriers to adoption or reasons for non-engagement, which are critical for building a more comprehensive picture of AI adoption in international business contexts.

4. EMPIRICAL DATA

4.1 Background

For this study, 18 respondents have been interviewed and categorized into three groups: *AI Experts*, *Managers*, and *Specialists*. Respondents from the same company are given the same number, followed by a small letter if they are representing the same classification group. An overview of the respondent and cases is presented in table 6 below.

Overview of Cases		
Respondent	**Role**	**Personal AI Usage**
AI Company 1. Industry: IT & AI Services Builds advanced AI tools and solutions for IT & AI service clients.		AI Maturity Level: High
AI Expert A1	AI Engineer	Develops and integrates AI models for customer interactions, process automation, and decision-making.
AI Company 2. Industry: Managerial Consultancy Educates managers on AI strategies and implementation.		AI Maturity Level: High
AI Expert A2	AI Strategist & Workshop Facilitator	Conducts workshops about AI in decision support and business strategy.
AI Company 3. Industry: AI Model Development Custom AI models focused on personalizing business processes with behavioral data.		AI Maturity Level: High
AI Expert A3	PhD in AI	Builds and trains AI models for business insights, behavioral predictions, and decision-making.
Case Company 4. Industry: Automotive Combines traditional and generative AI in self-driving trucks, route planning, and coding.		AI Maturity Level: Medium
Manager M4	AI Adoption Manager	Leads AI adoption aligning tech with business strategy and operations.
Case Company 5. Industry: Automotive Uses traditional and generative AI to improve vehicle safety and driver assistance.		AI Maturity Level: Medium
Manager M5	Head of Technology & Collaboration	Oversees AI development for product improvement and process innovation.
Case Company 6. Industry: Consultancy Advisory on AI adoption strategies, internal development, and integration.		AI Maturity Level: Medium
Manager M6a	Senior Advisor	Advises on AI strategy, focusing on business integration and adoption.
Manager M6b	Senior Lead & Management	Leads AI-driven initiatives, focusing on implementation and resource allocation.

Case Company 7. Industry: Consultancy AI Maturity Level: High Advisory on AI strategies and value creation for clients.		
Manager M7	Managing Director	Manages AI transformation projects externally and oversees AI adoption across business functions internally.
Specialist S7a	Strategy Consultant - AI & Humans	Advises on AI-human interaction and transformation.
Specialist S7b	Consultant - AI Value	Focuses on evaluating AI's value proposition and business impact.
Specialist S7c	Consultant - Responsible AI	Guides AI projects to ensure alignment with ethical and responsible AI practices.
Case Company 8. Industry: Information Technology (IT) AI Maturity Level: Medium Supports clients' AI projects with tailored IT solutions; internal decisions made at HQ.		
Manager M8	Country Manager Sweden	Informs on AI services offered to clients as external partner.
Case Company 9. Industry: Chemical Manufacturing AI Maturity Level: Medium Uses AI for R&D, coding support, asset monitoring, and internal LLMs.		
Manager M9	Data Portfolio Leader	Uses private LLMs and CoPilot for R&D, asset monitoring, and data projects.
Specialist S9a	Data & Digital Associate	Uses CoPilot for meeting summaries, article search, and formulation development support.
Specialist S9b	Technical Support Specialist	Uses AI occasionally in client support for coating applications on boats.
Case Company 10. Industry: Finance Transformation AI Maturity Level: Medium AI-driven financial insights and process optimization.		
Manager M10	Senior Lead & Management	Leads transformations within finance operations and strategy with assistance from internal LLM.
Specialist S10	Analyst	Supports transformations through data analysis and financial forecasting.
Case Company 11. Industry: Audit AI Maturity Level: Low Limited AI applications in audit processes.		
Specialist S11	Associate	Minimal exposure to AI tools, mainly focusing on traditional audit tasks.

Table 6. Overview of respondents.

AI Experts (A) are individuals with advanced, hands-on experience in AI and deep technical expertise. One respondent has a background in AI engineering, another has been involved in AI implementation and contributed to strategic decision-making at the board level, and a third works with the development and training of proprietary AI systems based on behavioral data, aimed at delivering personalized business solutions.

Managers (M) hold leadership positions, such as AI Adoption Manager, Head of Technology and Collaboration, and Senior Lead and Management. What connects this group is their responsibility for setting strategic direction, overseeing implementation, and aligning AI initiatives with broader organizational goals. Their roles span across industries and typically involve coordinating between technical teams and executive management to ensure that AI adoption supports business needs and long-term objectives.

Specialists (S) are professionals who contribute to AI-related work outside formal management roles. Their expertise includes areas such as strategy consulting, technical support, product development, and auditing. This group offers operational insights into how AI is applied within different business functions, providing a grounded perspective on the practical use and impact of AI across departments.

The participating organizations operate in a variety of industries, including automotive, chemical manufacturing, IT, finance, audit, and consultancy. Several respondents come from consultancy firms and made a clear distinction between experiences drawn from client projects and those based on their internal organizational practices. This separation helped clarify how AI adoption unfolds within their own companies, as well as how it is shaped by broader trends and needs in client organizations. While some companies are still in the exploratory phase of adopting generative AI, others have integrated it into internal workflows, product development, and established governance frameworks to ensure responsible implementation.

Across these organizations, AI is used to improve efficiency, automate routine tasks, and support day-to-day operations. Tools such as AI assistants are widely used for generating meeting summaries, preparing presentations, translating and localizing content, and conducting data-driven analyses. Some companies have taken further steps by developing proprietary Natural Language Processing (NLP)-based systems and secure internal knowledge platforms, reflecting a more advanced stage of AI maturity. These tools enable employees to access and share information across departments, reduce dependence on public solutions, and promote a culture of continuous learning and collaboration. The following section presents the empirical material, structured around the three phases defined by the conceptual model outlined in section 2.2. The Gioia methodology was used to categorize and analyze the data within these phases, beginning with the first phase of AI adoption.

4.2 Initiation

4.2.1 Awareness – Recognizing AI's Potential

Generative AI as a Catalyst

Generative AI played a central role in raising organizational awareness and engagement with AI. While it has existed for decades, mainly in data-driven domains, advances in computing power and the release of tools like ChatGPT shifted the landscape dramatically. These developments made AI more tangible, accessible, and useful beyond technical teams, prompting a surge in experimentation and interest across diverse functions.

Respondents emphasized that this turning point increased both individual experimentation and broader strategic interest. In some cases, employees proactively adopted AI in their daily tasks, while others created entirely new roles dedicated to AI. Executive-level attention also grew in response to external developments and competitor moves, triggering internal discussions around positioning and long-term strategy. One manager reflected this shift, highlighting the complexity that comes with leading AI efforts in times of rapid technological and societal change:

> It's really like a thrill mixed with fear for me. [...] I'm passionate about developing exciting AI applications for companies, people, and society. I truly believe we're taking humanity to the next

> level with AI [...] At the same time, I do feel a sense of concern, especially given today's geopolitical uncertainties and the potential for misuse in areas like military technology. It's easy to imagine how things could go wrong quickly. So, there's definitely a duality to it.
>
> – Manager M7

Limited Knowledge within MNEs

Although interest in AI has grown rapidly, respondents consistently emphasized that many international organizations lack the foundational understanding necessary for effective implementation. A key concern raised by AI experts was that decision-makers often misunderstand what AI can and cannot do. One expert explained that AI systems "identify statistical patterns rather than understand tasks in a human-like manner" (A3), and warned that misconceptions could result in poor decisions if AI is integrated without a realistic understanding of its capabilities. These gaps delay progress and make it difficult to assess risk or unlock AI's full potential.

Consultants and specialists added that organizations tend to frame AI challenges as primarily technical, overlooking the organizational transformation required for success. One consultant noted that "80% of your challenges with adopting AI are about how you change an organization, so it's 20% technology and 80% change management" (S7c). According to several specialists, this disconnect often results in reactive responses and fragmented initiatives.

The knowledge gap was also visible at the employee level. Some specialists described how awareness often emerged informally through workshops or peer recommendations, but many remained unsure about how or when to use AI appropriately, particularly in client-related work. In some cases, tools were rolled out without clear communication or training, resulting in confusion and mistrust. One specialist recalled her confusion when "an AI assistant appeared on my screen unannounced, initially mistaking it for spam or a potential cybersecurity threat" (S9b). These examples highlight that without knowledge, clear guidance, and communication, even well-intended rollouts can undermine employee trust and limit engagement.

4.2.2 Consideration – Exploring Applications

Risks of Inaction

Respondents commonly emphasized that failing to engage with AI entails significant strategic and financial risks. Rather than driving investments based on structured strategies, "many companies are caught by a fear-of-missing-out and just pumping money into it" (S7a). This reactive approach, while widespread, can result in poorly considered investments with limited long-term value. Others viewed early investments, even if imperfect, as necessary learning steps. One expert estimated that "Sweden loses up to 160 billion SEK annually in productivity due to inadequate AI adoption" (A2), reinforcing the urgency. Beyond individual firms' learning curves, broader market shifts are expected. A manager anticipated a rise in mergers and acquisitions, as more efficient firms absorb those lagging in AI adoption: "Those companies that haven't leveraged AI to improve, streamline, or raise the quality of their operations [...] are going to suddenly become cheap acquisition targets to others wanting their brand or customer base" (M6b).

Overconfidence in AI Maturity

A disconnect between perceived and actual AI use emerged across cases. One AI expert illustrated this gap, stating, "74% of Swedish executives claim they are doing fairly well with AI, [...] but in practice, only 19% of the workforce uses generative AI weekly, compared to 54% in the European average, and 61% globally" (A2). This overestimation of AI maturity may contribute to underinvestment in structural transformation and delay necessary changes. Respondents linked this complacency to Sweden's reputation as a digital frontrunner, with firms referencing tech giants like Klarna and Spotify as signs of national progress, despite limited AI integration within their own organizations.

Cultural Caution

Cultural and regional attitudes were seen to shape how organizations approach AI, particularly in Sweden, where respondents described a more cautious and responsible stance compared to countries like the U.S. and China. One manager estimated that "only 25% of Nordic employees view AI as an opportunity" (M7), while most remain skeptical. It was further emphasized that this value-based mindset affects both the speed and focus of AI adoption:

> In China, it's for the interest of the country. In the US, it's made for the interest of the company to just excel, and in the EU, we're more concerned about the individual and the individual's rights. – Specialist S7a

These broader cultural attitudes toward AI are also reflected within organizations, where perspectives vary by role, experience, and workplace culture. One manager noted that while some employees in their medium-mature firm are eager to experiment, others view AI as a passing trend. Several respondents observed hesitancy in disclosing AI use due to fears of judgment. As one AI expert explained: "fear of being seen as a cheater, fear of being perceived as incompetent, and fear of deviating from workplace norms" (A2). Others noted that concerns about AI replacing jobs can become an excuse for disengagement, though as one respondent clarified, "We're just not even seeing 5-10% being taken over at the moment" (S7a). This stigma makes it difficult for organizations to accurately assess their AI use and slows down collective progress.

Confidence in AI increases when tools are well-understood and supported by leadership. In several cases, employees were more open to using AI when guided and shown practical benefits. At one medium-maturity firm, a junior specialist expressed cautious curiosity, always verifying outputs, reflecting a culture that encouraged exploration but remained risk-aware. Meanwhile, a manager at the same firm adopted AI quickly for defined tasks, demonstrating how perceived reliability and autonomy influence uptake. These contrasts suggest that specialists often seek approval, while managers tend to adopt AI with greater independence and confidence.

4.2.3 Intention – Defining Purpose & Direction

Rethinking Technology Projects

Respondents stressed that AI adoption differs significantly from traditional IT projects. While digital infrastructure remains important, several emphasized that AI must be rooted in business needs to create value. Treating it solely as an IT initiative is a common pitfall among MNEs. Without broader organizational rethinking, such efforts risk failure. Instead, successful adoption was described as an "end-to-end reinvention" of operations with cross-functional coordination. As one manager put it: "IT provides the tools, but the value only comes when legal, HR, and the business units align to deliver something useful to the end user" (M8).

Unlike structured systems designed for workflow optimization, generative AI was frequently described as more experimental, less deterministic, and requires ongoing adaptation. This was particularly evident in knowledge-intensive environments, where ambiguity and context play a larger role. One expert described building competitive models as "art more than science" (A3), highlighting the need for dynamic, collaborative approaches. These characteristics demand that organizations move away from rigid delivery models toward more iterative, cross-functional ways of working. While traditional systems are usually mandatory, generative AI tools are often optional in daily workflows. Their adoption depends on individual initiative and workplace culture, which can slow transformation unless actively supported and encouraged.

Learning by Doing

Several respondents noted that AI adoption often begins informally, through bottom-up learning rather than formal strategies. The accessibility of generative AI tools encourages individual experimentation, gradually raising organizational awareness. One manager explained: "It starts out as employees just getting started and using it, and then Legal or someone else realizes that 'Oh, something is happening here that needs to be monitored'" (M5). Managers supported early efforts by creating secure environments, such as internal versions of ChatGPT, and advised starting small, e.g., within a region or division, while covering an entire value chain. These low-risk pilot spaces built trust and visibility, enabling firms to observe usage before formalizing direction.

Despite the value of internal exploration, several respondents stressed the importance of building internal capability alongside it. One medium-maturity firm developed a "sandbox" where employees and clients could safely explore both opportunities and risks. Others stressed the value of combining internal engagement with external support. As one specialist warned: "There's a lot of value in getting consultancies on quickly, but not to [...] just lean back and let the consultancies do all of the implementation" (S7a). While central units may initiate AI efforts, learning often takes hold in business units through hands-on experimentation. In contrast, a top-down rollout of a chatbot in a low-maturity firm reduced local input and limited engagement. Hence, AI initiatives that evolve through grounded, practice-based experiences often foster stronger trust, clearer insights, and more sustainable usage.

From Ideas to Use Cases

As experimentation generated insights, organizations faced the challenge of moving from individual insights to structured use cases. Several respondents noted a contrast between technology-push approaches driven by central AI or IT teams at HQ, who explored AI broadly, and problem-driven approaches from business units, which focused on addressing specific operational needs. When these perspectives aligned, use cases became more relevant and actionable as intention and application aligned. One manager from a medium AI-mature firm noted that while exploratory work is important, value emerges when experimentation is tied to real business problems, supported by cross-functional dialogue between technical and operational roles.

Managers further emphasized that identifying relevant AI use cases depends on their fit within the organizational context. Encouraging informal experimentation helped surface practical applications, but these needed to be anchored in core processes to create value and justify further investment. Often successful early wins came from smaller functional teams, such as HR or finance, where pain points were clear and outcomes measurable. Structured methods like workshops and design sprints supported this process by enabling organizations to evaluate, prioritize, and scale the most promising ideas. The respondents agreed that these small but meaningful successes, whether individual or team-based, build momentum in an organization's journey when they are simple, effective, and visibly impactful.

> You identify a few areas in marketing, a few use cases in procurement, R&D, supply chain, finance, HR, and then, if you're the one leading AI, you know which ones could be the quick wins and which ones could have a high impact but not so much a quick win. – Specialist S7b

Leadership & Organizational Structure

While grassroots experimentation can ignite interest, respondents repeatedly highlighted leadership as the critical enabler for moving from intention to action. It was emphasized that without board-level attention and executive ownership, even the most capable teams struggle to scale initiatives. One expert noted that meaningful AI integration "has to begin in the boardrooms and executive teams, only then will organizations truly embrace and leverage AI's potential" (A2). However, leadership interest alone was not considered sufficient. Several respondents stressed that formal prioritization and resource allocation were equally necessary to turn vision into impact. As one manager put it: "the workforce is often more upskilled in AI than the leadership, yet it is the latter making strategic decisions, creating a fairly new, complex, and sometimes limiting dynamic" (M7).

Aligning AI adoption across international organizational levels adds complexity, particularly when global strategies must be adapted to local contexts. Respondents described tensions arising when centralized leadership and AI strategies conflicted with the need for local relevance and adaptation. One expert emphasized the need for "open discussions between HQ and subsidiaries" (A2), warning that top-down initiatives without local involvement risk being perceived as externally imposed. A specialist from a low AI-mature company illustrated this through a project where a global chatbot rollout failed to engage local users due to lack of early participation, highlighting the importance of involving operational voices from the start.

Strategic Intent & Adoption Readiness

To guide intentional thinking before adoption, some organizations developed structured models. A manager (M7) described his consultant company's use of a "Defend – Extend – Disrupt" framework to structure AI initiatives internally across three horizons. "Defend" includes efforts to protect existing core operations through automation and efficiency, "Extend" involves using AI to enhance customer-facing functions, and "Disrupt" aims at transformative innovations that could redefine the business model. While this model serves both internal and client-facing strategy, most AI initiatives still fall within the "Defend" horizon, where few firms are prepared to redesign their business models and commit to disruptive change. As one consultant observed, "It's a new coworker, essentially, that you need to get familiar with" (S7a), yet most companies do not approach it this way, instead using it to support tasks without reimagining broader systems. This cautious approach was especially evident in subsidiaries, where AI's potential to improve efficiency was recognized, but limited knowledge and lack of AI support hindered local engagement despite broader HQ strategies. Hence, it was described as a gap between strategic intention at HQ and operational readiness in subsidiaries.

Beyond strategic intent, several respondents emphasized the importance of thinking in terms of adoption levels. A manager (M6b) outlined a three-tier model reflecting increasing organizational readiness. The first level involves enhancing individual day-to-day productivity by employees using tools like Copilot to automate routine tasks and learn through hands-on experimentation. This level offers a low-risk way to build familiarity relevant to their roles. The second level involves redesigning workflows to enhance team collaboration and outcomes, such as implementing AI for real-time supplier risk management, shifting from reactive manual processes to AI-assisted, proactive ones. This stage marks a shift from tool usage to process transformation. The third level, rare but growing, involves embedding AI into long-term strategic decisions at the top of the organization, reflecting on a higher organizational readiness. One example of third level adoption involved a private equity firm automating 80 percent of routine tasks thanks to a long-term roadmap tailored to capabilities, use cases, and stakeholders. As one consultant put it, this type of implementation must be "anchored in where the organization is today, but aimed at what it wants to achieve across 1, 2, 5, or even 10 years" (S7b).

4.2.4 Summary of Initiation

	Sub-Phase	Key Insights	Variations Across Respondents & Cases
Initiation	Awareness	Generative AI triggered widespread interest beyond tech teams. Awareness emerged organically, often via peer use & public tools. Lack of foundational knowledge led to fragmented & mistrustful adoption.	AI awareness was often informal & varied across functions. Employee reactions ranged from enthusiasm to confusion & mistrust. Specialists emphasized AI misconceptions; experts warned of unrealistic expectations.
	Consideration	Fear of inaction drives AI engagement, often without clear strategy. AI maturity is often overestimated, leading to underpreparedness. Stigma & skepticism limit open discussion & learning.	Managers in mid/high-maturity firms viewed early adoption as necessary despite risks. Nordic firms showed more cultural caution; U.S./China firms cited as more aggressive. Managers acted with more autonomy, while specialists showed caution.
	Intention	AI requires rethinking of traditional tech projects - Cross-functional input is vital. Informal experimentation enables bottom-up learning & insights. Translating ideas into use cases builds momentum when linked to operations.	Medium maturity firms promoted bottom-up experimentation in safe sandboxes. Centralized rollouts often lacked local adaptation & ownership. Lower maturity firms struggled with leadership knowledge gaps & inconsistent strategic alignment.

Table 7. Summary of initiation.

4.3 Adoption Decision

4.3.1 Evaluation – Assessing Use Cases

Evaluating Usefulness

In large MNEs, several respondents noted that the evaluation of AI applications often depends on practical constraints and organizational structures. A manager at a medium AI-mature firm explained that while business units might explore innovative uses of AI, they are typically limited by top-down platform decisions and licensing agreements. The selection of AI platforms is often centralized to align with existing infrastructure and strategy, leaving business units to optimize use rather than choose tools themselves. She clarified that this division illustrates how HQ and subsidiaries may approach AI differently based on authority, resources, and strategic alignment.

From a managerial perspective, evaluating AI tools involves determining whether they generate enough operational value to justify continued use and investment. One example concerned AI-generated transcripts, which were initially tested for internal communication but later adopted more widely after proving useful in content accessibility and knowledge sharing. Another medium AI-mature firm involved an AI tool used in recruitment, which had to be adjusted because it "often flags candidates who don't even have the formal qualifications" (M5). Rather than isolating AI to specific use cases, value emerges when solutions are tested in real contexts. However, respondents agreed that success is rarely immediate. Usefulness must be assessed dynamically and in alignment with business goals to justify further investment.

Measuring Value

Across roles, respondents described the challenges of measuring AI's impact and true potential, often due to leadership misconceptions and uncertainty around return on investment (ROI). A specialist at a medium AI-mature firm noted that without strong data quality, it is difficult to demonstrate value, making further investment unlikely: "We intentionally wait with AI, because it won't succeed without proof of value" (S9a). This hesitation was reinforced by a manager who noted that the benefits of data and digital investments often appear with a time lag, which complicates early valuation. She stressed that such initiatives are too often seen as cost centers rather than strategic assets, especially when disconnected from core business priorities. Other managers similarly mentioned that traditional ROI metrics often miss the benefits of AI, particularly when gains are qualitative or long-term. A consultant manager shared that although generative AI spread quickly due to ease of use, efforts are now focused on tracking its effect through KPIs, especially related to efficiency and quality: "It's not completely easy, but we try to be able to follow up, and ROI is of course always interesting" (M6a).

Respondents emphasized that generative AI demands rethinking workflows and how value is assessed. A consultant from a high AI-maturity firm explained that tools like Copilot can generate 70-80 percent of a solution quickly, but the remaining complexity is often underestimated. Traditional KPIs may overlook benefits like improved output quality, better decisions, or time savings. Thereby, ROI is often hard to quantify, especially when benefits are long-term or diffuse: "A key reason why many AI projects never scale beyond the pilot phase is insufficient ROI, not because the return is negative, but because it falls short of what was initially envisioned" (S7a). This uncertainty can deprioritize promising initiatives. He stressed the need for a shift in mindset, from short-term automation to long-term productivity and support: "It's a new coworker, essentially, that you need to get familiar with" (S7a). These insights point to the need for more flexible, qualitative ways to evaluate AI impact.

Securing the "Right" Data

Across industries, respondents agreed that poor data quality is a major barrier to AI success. One manager noted, "If bad data goes in, bad results come out" (M6b), highlighting how flawed input reduces effectiveness and can amplify errors when AI models attempt to generalize. In high-risk environments like autonomous driving, evaluation must go beyond functional performance to include safety, verifiability, and consequences of failure. "When you drive a car, the tolerance for making mistakes is much less, and that means you've to test much more [...] and have much more data to know that you're good enough" (M5). A R&D manager also highlighted the gap between ideal conditions in training environments and the messy reality of operational data. In practice, AI had to work with inconsistent formats, such as yes/no, pass/fail, or numeric, generated by 250 chemists, making model training challenging. These inconsistencies became even more complex across geographies, further complicating data sharing and analysis within international firms.

Securing high-quality data is not only a technical but also a legal and strategic challenge. Regulatory differences between countries add complexity to cross-border AI initiatives. One manager described how private cloud environments help reduce risk by creating secure infrastructures, but sectors like defense or finance require even stricter safeguards. Another noted that while MNEs benefit from diverse data sources, uncertainties around restricted data access and varying national laws can delay or block international AI initiatives. This reinforces that successful AI evaluation requires alignment between data governance, compliance, and strategic direction across jurisdictions.

4.3.2 Resource Allocation – Building the Foundation for AI

Strategic Alignment

A recurring theme across interviews was the need to align AI initiatives with broader business strategy. When treated as siloed IT projects, AI risks being seen as experimental rather than value-generating. Strategic anchoring was viewed as essential to move beyond isolated innovation labs and integrate AI into core operations. Several respondents noted that companies often fail to reassess strategic priorities, even as AI reshapes competition and commodifies knowledge. As one consultant reflected, "What made a company successful in the past may no longer be what drives success in the future" (M6b). Without strategic integration, AI adoption tends to remain fragmented and lack long-term impact.

Managers emphasized embedding AI into annual planning to ensure momentum and cross-functional coherence. Leadership support and defined outcomes were seen as key to translating interest into execution. Still, many firms struggle to scale from pilots to impact due to weak strategic foundations. One consultant warned that pursuing too many disconnected AI projects spreads resources thin and limits effectiveness. Instead, he recommended focusing on a few strategically important initiatives with sufficient delivery capacity. In complex MNEs, this prioritization was emphasized as even more important, especially when translating ambition into execution across geographically and functionally diverse organizations.

Structural misalignment was also cited as a barrier to scaling AI. A consultant warned: "Not to have a centre of excellence that is anchored in the right place in the organization, that's one of the top challenges we see across the globe" (S7a). Without integration into the organizational ecosystem, AI remains peripheral. A manager added: "You've to work on the data, the technical infrastructure, and all the systems. [...] It's a huge machine" (M4). Simply layering AI onto existing routines often limits its value. As one consultant explained, "The use cases that make it into production create fairly little value [...] because it's not AI in your core business processes" (S7c).

In MNEs, balancing global direction with local autonomy adds complexity. Respondents emphasized that corporate AI strategies must be flexible enough for local units to adapt implementation to specific needs. A dual-stage approach was described: global strategy sets direction, while business units tailor use cases to local priorities. One medium AI-mature firm aligned its central digital strategy with local R&D by developing capabilities across three dimensions: platform, process, and people. This involved providing shared tools, embedding AI in workflows, and training employees to use the systems effectively and responsibly. The approach illustrates how coherence and contextual flexibility can be combined to support strategic alignment across a multinational structure.

Re-Organization

Respondents across roles and companies described how AI adoption is prompting structural changes to enable cross-functional collaboration and break down silos. Rather than fitting AI into rigid frameworks, firms are rethinking how work is organized to support data sharing and end-to-end processes. A manager from a medium-maturity firm noted that real value comes when AI operates across departments, not within isolated units. Consultants and managers emphasized that scaling AI requires evolving organizational design across units and geographies. From one multinational's perspective, the role of AI was not just technological but structural:

> The current reorganization is probably more driven by AI than it's for other efficiency reasons, the traditional reason for reorganization. So it's more intended for us to have a structure that makes it easier to work with AI. – Manager M5

To support this, many firms established governance structures such as steering groups or AI coordinators. Specialists from high-maturity companies noted that generative AI enables greater autonomy, reducing the need for hierarchical escalation. "Tasks that previously required escalation can now be handled more independently" (S7a). Consultants observed a shift toward flatter, more flexible structures better suited to AI's fast pace and wide impact. Still, structural change must be backed by new operating models. Informal collaboration needs systematic coordination and clear processes. "How you're organized needs to change quite radically" (S7c), one consultant argued. Centers of excellence were cited as key enablers for minimizing individual dependency, improving transparency, and facilitating learning across teams. At one medium-mature firm, input from business units was funneled to a central innovation team to align local initiatives with broader strategic goals and reduce duplication. Ultimately, successful reorganization requires leadership to connect global operations through shared systems and strategic coordination.

Investment Shifts

Reallocating financial resources is another central concern in AI adoption. Respondents consistently described how AI changes investment priorities, particularly in terms of infrastructure. A manager from a medium mature firm explained that "to develop AI, you shift costs from programmers […] to using large data centers" (M5). He pointed out that the most resource-consuming aspect is often not the development of algorithms but the labor-intensive work of preparing and training data. Consultants confirmed this shift in cost structure from both internal and client perspectives. While many organizations still accept higher costs due to AI's perceived strategic value, financial investments are expected to grow as firms move beyond pilot projects and expand their use of AI. Although early efforts may appear cost-neutral, sustained implementation requires long-term funding and clearer prioritization. Several respondents emphasized that successful investment strategies go beyond infrastructure and include parallel efforts in capability development and change management.

> Everyone talks about foundational IT, but that applies to all tech investments. Few focus on investing in talent and change management afterward. [...] The most successful weren't the first to adopt Gen AI, but the first to skill up their people. […] They invested early, then paused to reinforce their foundation. – Specialist S7a

The issue of central versus local funding was an underlying theme. While not always directly stated, several respondents described tensions between HQ and subsidiaries regarding resource allocation. Centralized investments, such as in foundational models or shared platforms, may not always align with the localized needs of business units. A manager highlighted that these competing priorities must be carefully managed to avoid friction and risks of non-use, especially in multinational contexts where strategic goals and market conditions can differ widely.

Capability Building

> It's about being able to translate the technology into how it creates value in your own business. Then you need to have a willingness and ability to change [...] as well as technical competence to build or develop these services. – Manager M6b

Once companies define AI's strategic value, they must identify the capabilities needed to realize it. Respondents emphasized that success requires more than technical talent, it also demands the ability to integrate AI into core operations, customer needs, and transformation efforts. One consultant noted that many firms, both in Europe and globally, lack the skills or operating models to act on their AI ambitions. Rather than build everything internally, companies were advised to leverage industry frameworks and partnerships. Consultants from high-maturity firms noted that completing thousands of AI projects had helped them guide clients past common pitfalls. However, some experts voiced concern over inconsistent advisory quality, as the pace of AI evolution outstrips expertise. "It's as hard to give AI-advice, as it's for other areas right now. Just look at where the stock market started this morning and where it is now" (M6b). This underscores the need for adaptability in both internal efforts and external guidance.

An AI expert warned that traditional IT profiles are often mistakenly applied to generative AI projects, leading to delays and poor decisions: "Just because someone understands traditional AI doesn't mean they understand generative AI. Listening to the wrong experts only increases confusion and reinforces misconceptions" (A2). Hence, mismatched talent and unclear understanding of AI's potential frequently slow down implementation.

Approaches to capability-building varied across organizations, combining both centralized and grassroots strategies. A specialist emphasized the need for a coordinated, global training model to avoid fragmented learning across units. In some firms, mandatory initiatives aimed to raise digital literacy at scale, such as one where "all our 800,000 employees need to go through AI training" (M7). Others relied on internal communication and role-based upskilling to inspire AI use and address varying levels of AI interest and resistance to change among employees. One manager explained that instead of hiring new staff, their strategy was to empower existing employees to integrate AI into their workflows. As he put it, real momentum lies in targeting the right employees:

> You can almost skip the top 20% [...] and the bottom 20% as they are not interested. [...] So focus on the 60% in the middle. That's where you have the greatest leverage to build capability, spread knowledge, and really develop the organization as a whole.
>
> – Manager M6b

Other respondents emphasized the need for structured learning environments. At a medium AI-mature firm, a manager described a central team focused on digitizing R&D and promoting knowledge sharing of AI related reflections via an internal platform connecting dispersed departments. However, engagement remained low. A specialist from the same company attributed this to unclear communication and the lack of mandatory training, with few AI-courses being offered despite having the infrastructure in place. To move forward, several respondents stressed that capability-building must go beyond technical skills to include cultural confidence and a shared vision. As one expert noted, aligning human capital with AI requires internal buy-in, ongoing learning, and integration into broader change efforts.

4.3.3 Summary of Adoption Decision

	Sub-Phase	Key Insights	Variations Across Respondents & Cases
Adoption Decision	Evaluation	Evaluation depends on real-world usefulness, not isolated pilots. ROI is hard to quantify; qualitative benefits are often overlooked. Data quality & access are key.	Specialists focus on operational gains; managers on business value. Shifted mindset of high-maturity firms; from short-term savings, to long-term value creation. Managers highlight risks of poor data; others stress internal access hurdles.
	Resource Allocation	Strategic alignment prioritized over financial investment. Organizational shifts often needed to enable AI adoption. Human capital is seen as a key enabler.	HQ drive strategic investments; subsidiaries follow with less autonomy. Experts & specialists highlighted skill gaps. Higher maturity firms have mandated training; lower maturity firms lack dedicated support.

Table 8. Summary of adoption decision.

4.4 Adoption

4.4.1 Implementation – Integrating AI into the Organization

Collaborative Implementation

A key challenge in AI implementation is the slow transition from planning to execution, which risks making solutions obsolete due to the rapid pace of AI development. This can erode internal trust and sponsorship, ultimately stalling progress. To counteract this, both managers and AI experts emphasized the importance of collaboration, though with different emphases. Managers pointed to internal, cross-functional cooperation as essential for overcoming resistance, especially when departments such as legal or compliance act in isolation. In contrast, multidisciplinary teams foster shared responsibility, enabling quicker progress by identifying and addressing obstacles collectively:

> If it just represents your function or your responsibility, it's always super easy to say no. [...] But if you're part of a cross-functional team, your task is to enable these things for the company, you're responsible for identifying the obstacles, but also for finding solutions. – Manager M6b

AI experts emphasized broader collaboration beyond organizational boundaries, warning that executive-level misunderstanding of AI, particularly around generative tools, can hinder successful adoption. To drive internal progress, "leaders need to go back to school" (A2). As a result, strategic partnerships with research institutions, OEMs, and industry peers were seen as essential for accessing external expertise, developing adaptable solutions, and improving executive fluency.

Balancing Governance

Across all respondent groups, the need for clear and effective AI governance was widely emphasized. However, several managers from medium AI-mature firms observed that the pace of AI experimentation often outpaces policy development. This creates uneven awareness of risk and inconsistent practices across teams. One manager noted, "Some are cautious, some are almost too careless" (M5), adding that the organization was not using AI to its full potential due to limited internal education and cautious governance. These reflections underscore the importance of internal guardrails that both enable responsible exploration and mitigate risk. Another manager similarly pointed out that such policies serve a dual purpose: offering structure for hesitant users while curbing overconfidence among early adopters. As one described,

> We've the real cowboys, the ones who shoot wild and don't hesitate for a second when sending in any kind of data. For them, those guidelines are necessary to at least help them make fewer mistakes. They'll keep making mistakes anyway, but if we can manage it a bit, that's already very helpful. – Manager M4

The form and intent of governance varied across case companies. Some firms emphasized flexible, principle-based frameworks to encourage experimentation, while others focused on compliance and ethical safeguards. A few respondents advocated for a risk-based approach that evaluates AI systems by their intended use and potential consequences, rather than attempting deterministic documentation. "Documenting AI models is inherently challenging because they don't produce consistent outputs in response to identical inputs, which makes clear and predictable documentation nearly impossible," one manager (M6b) explained, noting that rigid expectations can be counterproductive. Another pointed out that overly legalistic language often makes internal policies difficult to interpret and use in practice:

> These are often formulated by the wrong people. [...] They're rarely educators; instead, they're almost lawyers. And you know how difficult it's to get a clear answer from a lawyer. It's impossible. It always depends. – Manager M4

From the specialists' perspective, governance clarity was essential for building trust and ensuring consistent use. In one low-maturity case, strict internal rules had led to the shutdown of a chatbot, due to lack of traceable outputs, pushing employees to rely on internal experts or unregulated tools. Similarly, at a high-maturity firm, unclear guidelines and low initial trust restricted internal AI use. Drawing on her client work, one consultant emphasized the need to tailor governance to organizational contexts, whether global or local. While autonomy is crucial at the business unit level as the units often understand their contexts best and are held accountable for their outcomes, some level of structure is equally important: "you want to give them some freedom, but still maintain structure" (S7b). As another specialist put it, "A lot of what we do is about finding that balance, at what level should you place your processes, and how much autonomy should the business have?" (S7c). This balance between flexibility and control was seen as key to scaling AI use responsibly, particularly in complex multinational settings.

Geographical Variation

Geographical context and cultural norms significantly influence how organizations approach AI-related risks, especially concerning ethics, compliance, and regulatory alignment. Respondents from all groups acknowledged the complexities of operating across jurisdictions, but their views differed in terms of how to address them and what role regulation should play.

Managers from medium-maturity firms were particularly focused on regional constraints. One case company blocked tools hosted in countries with weaker data protections: "We've built barriers into our IT system. [...] If we go ahead and use a Chinese-hosted one, IT gets in touch almost immediately" (M5). A consultant manager added that many European firms, especially those earlier in their AI journeys, avoid tools from North America due to legal uncertainty and the lack of frameworks like the EU AI Act or GDPR. While this caution may limit short-term innovation, it was seen as building long-term trust in both data practices and technology. For this reason, the consultant welcomed the EU AI Act for providing structural clarity and viewed it as an enabler: "Regardless of the specific content, the Act is valuable because it gives businesses a concrete framework to relate to and operate within" (M6b).

> In China, it's for the interest of the country. In the US, it's made for the interest of the company to just excel, and in the EU, we're more concerned about the individual and the individual's rights. – Specialist S7a

With this quote, the strategy consultant from a high AI-mature firm, illustrated how ethical priorities and regulatory frameworks reflect broader societal values. He emphasized that MNEs must carefully navigate these variations when deploying AI globally. From the consultant's perspective, cultural context is not just a constraint but a key driver of how AI systems should be designed and governed. In regions prioritizing individual rights, such as the EU, transparent and accountable decision-making becomes essential to securing public trust. While such frameworks can slow deployment in the short term, several specialists underscored the need for multinational firms to adapt AI governance not only to legal frameworks but also to the societal values embedded in each market.

4.4.2 Internalization – Securing Long-Term Adoption

Continued Use

Respondents across all groups emphasized that continued use of AI relies on embedding tools into everyday workflows, fostering supportive organizational cultures, and maintaining leadership commitment. One specialist described how their high mature firm had successfully integrated AI by weaving it into routine tasks rather than treating it as a standalone initiative. Generative AI was applied to a variety of activities, such as creating PowerPoint presentations, responding to internal queries, conducting financial variance analysis, and assisting with talent reviews. This seamless integration made AI feel like a natural extension of daily work, reducing time spent on repetitive tasks and enhancing overall efficiency.

Managers also supported this view, highlighting structured approaches to implementation across teams, functions, and geographies. For example, one manager explained that their consultancy organization began with small-scale use cases before expanding to other departments and markets. Initially, the focus was on supporting individual tasks, but as experience grew, AI was implemented in more business-critical areas. While early interest often came from individual employees, broader internalization was driven by top-down leadership, with the CEO and senior managers steering the scaling process. Similarly, another manager emphasized that in their high mature consulting firm, AI adoption is not seen as a finite project but as an ongoing journey. AI tools now support a broad range of internal tasks, such as help-desk operations and forecasting, and have been introduced into client-facing activities by co-presenting with digital colleagues. This continuous learning approach encourages employees to stay current with evolving tools and practices.

However, as one consultant manager noted, many organizations still struggle with this final stage of internalization. While pilot projects may be successful in the initial phases, scaling them across the organization remains a key barrier. He explained that many companies "have hit a wall" when it comes to embedding pilots into daily operations. The remaining effort, often the last 10 to 20 percent, can be the most difficult, especially in the absence of coordination or sustained support. Without completing this final step, companies risk failing to fully roll out AI more broadly and to realize the full value of their AI initiatives.

Trust & Responsible AI

Trust was consistently highlighted as essential for successful AI internalization. One AI expert explained that while their organization had embedded AI across many functions, adoption depends on recognizing the technology's probabilistic nature. Since outputs are not always predictable, transparency, ethical alignment, and human oversight are critical, especially when AI mimics human judgment. A consultant emphasized that "responsible AI is really everything from governance and processes to the technologies that enable it" (S7c). This includes mechanisms to monitor public-facing tools like chatbots, ensuring organizations can respond quickly to misuse. These efforts help build the confidence required to scale AI across business areas while safeguarding against risk.

Responsible AI also provides a foundation for regulatory compliance and strategic alignment for further roll-out across MNE. A specialist at a high maturity firm acknowledged that responsibility must be embedded into governance structures, technical systems, and day-to-day practices to reach higher maturity. Respondents saw frameworks like the EU AI Act as enablers rather than constraints, particularly because they offer clarity on sector-wide obligations. "AI is becoming a more regulated technology […] The EU's regulation is not limited to one sector, it applies across industries based on the risk level," explained a consultant (S7c). By aligning technical implementation with legal standards, companies can navigate sector-specific risks and increase the stability needed for broader AI deployment. This is particularly important for high-stake domains like education, employment, and healthcare, where inconsistent AI use could undermine public trust and hinder adoption.

Internally, trust also shaped employee acceptance of AI tools. Respondents stressed that perceived fairness is essential when AI is introduced in sensitive areas like performance evaluation. "As an employee, I want to be sure that when we've our annual performance reviews, a human makes the final decision, not just an AI model ranking everyone" (S7c). Responsible AI practices, such as human-in-the-loop decision-making and clear communication, were seen as key to ensuring cultural acceptance. Respondents further noted that shared governance frameworks help reduce fragmentation and accelerate scaling. "Standardized processes make it easier to ensure compliance, but also streamline AI development […] In the long run, this will help companies move faster from development to production," a consultant from a high AI mature firm concluded (S7s). Thus, responsible AI is both a framework and a tool: it offers clear guidance through governance, ensures accountability, and supports scale by building trust and enabling alignment across global operations.

Cultural Foundations

Among specialists, culture was seen as central to embedding AI in daily work, with cross-functional and cross-border collaboration often hindered by human factors. One specialist explained that while such collaboration is common, differences in time zones, work styles, and learning approaches can slow momentum. These barriers, she noted, are "people-related," making interpersonal dynamics crucial to success (S9a). Another described her company's AI internalization as still "informal and personal" (S10), calling for stronger alignment between cultural encouragement and formal structures like role-specific guidelines and success stories. Without such frameworks, she argued, cultural efforts alone are unlikely to drive lasting change.

From a managerial perspective, continued AI use was more linked to normalizing the technology as a practical tool that eases daily work. One manager stressed that AI should not be imposed top-down but embraced for its ability to help with heavy workloads: "People have so much to do, so they consider it as something that makes things easier" (M5). An AI expert who educates managers added that fear of exclusion or judgment can discourage engagement if AI is not openly discussed. Both emphasized the importance of leadership in modeling use, encouraging dialogue, and fostering a learning-oriented environment where experimentation is supported and AI becomes part of everyday culture.

Continuous Adaptation

The importance of ongoing learning and adaptation was emphasized by both managers and AI experts. One manager highlighted that while their medium-mature organization works with a three-year strategic plan that includes AI, the rapid pace of both technological change and operational applications requires constant revision and flexibility. He reflected upon a broader understanding that AI adoption is not static or a one-time effort but an ongoing process of adjustment. Another manager pointed out how this continuous evolution may also reshape both the workforce and workflows. As AI tools and agents become increasingly integrated, their presence may eventually surpass that of human employees. He explained that while their high-mature organization continues to grow, future expansion may rely more on digital agents than on hiring people:

> We're 800,000 people now. [...] We're growing by maybe around 100,000 people per year. I'm not entirely sure we'll ever be more than a million, because at some point [...] I think there'll be fewer human employees and more digital AI asset-agents. – Manager M7

4.4.3 Summary of Adoption

	Sub-Phase	Key Insights	Variations Across Respondents & Cases
Adoption	Implementation	Cross-functional & external collaboration accelerates implementation & creates shared responsibility. Governance must balance risk mitigation with flexibility to support experimentation. AI governance is most effective when tailored to context & clearly communicated.	Medium-maturity firms struggle with slow policy development & inconsistent governance. Higher mature firms emphasize principle-based governance; lower mature firms often impose strict rules. Approaches to regulation vary by region; EU firms are more cautious & favor structured compliance.
	Internalization	AI must be embedded in daily workflows with leadership support to sustain use. Trust & responsible AI are prerequisites for large-scale internalization. Normalizing AI use depends on leadership & open dialogue. Ongoing learning is essential as tools & roles evolve.	High mature firms scale AI across units with responsible AI; others stall after pilots due to limited structure. Specialists stress human oversight; consultants emphasize standardized governance for scale. Managers link internalization to strategic updates & changing workforce needs.

Table 9. Summary of adoption.

4.5 Summary of Empirical Data

The findings from this chapter illustrate that AI adoption in MNEs is not a straightforward or uniform process. Rather, it is shaped by a complex interplay between strategic intent and operational realities, influenced by both organizational roles and industry-specific dynamics. While AI experts and managers often emphasized strategic alignment and top-down frameworks, specialists highlighted the importance of practical experience, trust, and localized adaptation. Across all phases, a pattern emerged where successful cases relied on cross-functional collaboration, open communication, and a clear link between AI initiatives and business value. One manager (M7) encapsulated these factors in what he called the "magic formula” for successful AI adoption:

1. Always lead with value; business-driven instead of technology/IT-driven.
2. Have control over your data in a secure, controlled way, because if you've really poor data, your AI algorithms will still be pretty bad too.
3. If you have employees or managers who don't trust the technology, you'll never be able to realize its potential.
4. Recognize the importance of continuously evolving. Dare to create a culture and courageous leaders who are willing to try new things.
5. Adopt a responsible perspective on AI.

5. DISCUSSION

5.1 Initiation

5.1.1 Awareness

Generative AI Reshapes Awareness

The empirical findings largely confirm the importance of organizational awareness, use case identification, and the development of innovation attitudes in the initiation phase, as highlighted by Jöhnk et al. (2020). According to Jöhnk et al. (2020: 10), organizations must first recognize AI's potential and form an attitude toward it before deciding on adoption, which was evident in respondents' descriptions. The emergence of generative AI, in particular, heightened overall awareness and perceived value, accelerating engagement.

The cases also reveal a lack of AI knowledge at both individual and organizational levels, with inadequate communication and technology introduction. As emphasized by Jöhnk et al. (2020: 12-13), Holmström (2022: 335), and Uren and Edwards (2023: 6-9), organizational knowledge and awareness are key readiness factors for successful adoption. The observed knowledge gaps and related insecurity reinforce the importance of addressing these dimensions early. Furthermore, the fragmented communication and cautious experimentation described by specialists highlight weaknesses in cultural readiness, particularly regarding change management and collaboration (Jöhnk et al., 2020: 13; Uren & Edwards, 2023: 6-7), underscoring that multiple dimensions influence awareness.

Maturity Shapes Engagement

The cases showed clear variation in the time spent in the awareness phase, depending on the firm's AI maturity. High-maturity firms, particularly specialized AI companies and consultancies, did not remain long in this phase, as they already possessed a strong understanding of AI. Instead, they concentrated their efforts on later phases where real value could be created, while also focusing on educating clients and correcting misconceptions. In contrast, medium-maturity firms, such as those in automotive, chemical manufacturing, and finance, showed a more fragmented picture. Some managers explored AI proactively and created specific AI-roles, but operational practices remained inconsistent, with specialists reporting lack of knowledge, unclear communication, and low confidence in tools. These gaps may reflect unresolved tensions between organizational levels. According to Schmidt et al. (2023: 41), such tensions can be managed through dialogue between HQ and subsidiaries. When managed effectively, the authors note, these tensions can become constructive, accelerating adoption, and improving decision quality.

5.1.2 Consideration

Strategic Urgency & Misjudged Readiness

The empirical findings largely confirm existing frameworks on organizational readiness and AI adoption (Jöhnk et al., 2020; Pumplun et al., 2019). Most firms demonstrated awareness of AI's potential and recognized the strategic risks of inaction, aligning with the theoretical emphasis on structured consideration, readiness evaluation, and capability building. Readiness dimensions such as strategic alignment, resources, knowledge, culture, and data were evident, particularly among high-maturity firms that approached AI adoption with long-term vision. However, this structured approach was not mirrored in less AI-mature firms. Contrary to theory, these organizations often rushed into AI initiatives under competitive pressure rather than strategic alignment. Emotional and reactive triggers, such as fear of falling behind, frequently drove decisions, suggesting that readiness is not always a prerequisite for progression. This extends existing models by highlighting how urgency and competition can short-circuit formal evaluation processes.

A key insight is the tendency among firms to overestimate their AI maturity, confirming Jöhnk et al.'s (2020: 12-13) and Uren and Edwards' (2023: 6-9) caution about overconfidence and the need for realistic readiness assessments to avoid poor investment decisions. Beyond this, the empirical material revealed internal misalignments that go beyond the HQ-subsidiary tensions noted by Schmidt et al. (2023: 41). Divides were observed across departments, roles, and organizational levels, shaping how

AI adoption was approached. AI experts highlighted the gap between perceived maturity and actual readiness, stressing the risks of premature scaling. Managers, from a top-down optimistic perspective, focused on strategic urgency and external pressure, while specialists emphasized lack of leadership, operational hurdles, and cultural hesitation. This variation underscores the need for better internal alignment and suggests that existing frameworks could be strengthened by incorporating intra-organizational dynamics, beyond HQ-subsidiary relationships. Recognizing and managing these constructive tensions may be critical to ensuring that strategic intent translates into coordinated and feasible adoption efforts.

Cultural Norms & Institutional Pressures

Cultural and normative dynamics, central to frameworks by Kostova and Roth (2002) and Jöhnk et al. (2020), were clearly reflected in the findings. Several respondents described Europe's more cautious stance on AI compared to faster adoption in China and the U.S. A particularly salient inductive insight was the role of workplace stigma. Employees often cited data security concerns to justify avoiding AI, while others hesitated to admit using generative tools out of fear of being seen as cheating or incompetent. These behaviors reveal deeper psychological and normative barriers that emerge early in the process, affirming the relevance of Kostova and Roth's (2002) institutional pillars even before formal adoption.

Normative and cognitive pillars, such as industry expectations, professional standards, and shared beliefs about AI, were shown to influence how readiness was interpreted and how adoption decisions were framed. These influences were embedded not only in national cultures but also in organizational routines. While existing theory emphasizes cultural readiness (Jöhnk et al., 2020; Uren & Edwards, 2023), our findings add nuance by highlighting how social dynamics and individual fears create hidden barriers. Change management must therefore move beyond organizational structures and actively address psychological and social concerns, calling for theoretical frameworks to integrate institutional influences earlier in the adoption process to better capture how readiness is socially and culturally constructed.

5.2.3 Intention

Iterative Learning over Top-Down Plans

While theory often emphasizes top-down transformation, the empirical findings reveal that bottom-up, iterative learning frequently plays a central role. Many organizations engage with AI informally at first, with employees integrating tools into daily work before formal strategies are in place, a dynamic that is less emphasized in the existing literature. The empirical findings further demonstrate that AI adoption differs fundamentally from traditional IT projects. While theoretical models often draw on IT transformation literature (Jöhnk et al., 2020; Schmidt et al., 2023; Hameed et al., 2012) that assumes structured, top-down implementation, AI initiatives are typically more experimental and characterized by iterative learning. This distinction suggests that frameworks focusing on linear, technology-driven change may be insufficient to fully capture the flexible, exploratory, and cross-functional nature of AI adoption observed in practice.

As emphasized by Jöhnk et al. (2020), Uren and Edwards (2023), and Schmidt et al. (2023), as well as confirmed by the empirical findings, intentional, strategic approaches are critical in the initiation phase, along with the need for cross-functional integration and strong leadership engagement. Comparing the respondent groups, a difference between perspectives is noticeable. Experts and managers emphasize strategy and top-down management as well as the importance of using framework to guide different levels of adoption, such as the individual-, process-, and strategic level concerning the core business. Specialists highlight bottom-up experimentation and the importance of being provided the necessary tools to increase practical experience of AI usage. Employees are aware of possibilities with AI and that it could improve their individual work, but the support from the top is not always perceived to be enough, with gaps between strategic intentions at the HQ and the readiness within subsidiaries.

Bridging Strategic Intent & Operational Practice

Organizational learning also emerges as essential among the respondents, contributing to the development of know-how and the identification of potential AI use cases. The use of interactive learning and "sandbox" environments, where employees are provided with safe spaces for competence-building and experimentation, further reinforces the theoretical emphasis on upskilling. Providing the tools, resources, and opportunities for such learning is a core responsibility of leadership, underscoring theory's importance of top management support and commitment (Jöhnk et al., 2020: 10-12; Uren & Edwards, 2023: 7-8). Without this foundation, the transition from intention to concrete action is unlikely to succeed.

At the same time, the empirical data also supports Kostova and Roth's (2002: 219) view of the complex HQ-subsidiary relationship, revealing an imbalance where operational staff were often more upskilled in AI than their managers, yet it was still central management that decided whether an initiative should proceed to the adoption phase. This uneven power dynamic can be addressed through open dialogue and collaboration, aligning with Schmidt et al.'s (2023: 41) concept of constructive tensions in early adoption phases.

AI Maturity & Multi-Level Readiness

Multi-level dynamics in AI adoption are further revealed from the empirical data, expanding the current theory. Jöhnk et al. (2020) and Uren and Edwards (2023) emphasize phase-based organizational readiness and AI adoption following a distinct process. The empirical findings, however, suggest that adoption unfolds simultaneously across multiple levels, such as individual, process and strategic levels, exemplified by the "Defend-Extend-Disrupt" framework described by a manager at a high AI maturity company (M7). The company categorized adoption efforts based on operational impact and ambition. These insights indicate that companies with more advanced AI maturity are not only more intentional in their strategies but also more nuanced in aligning AI adoption with different organizational levels and purposes.

Our findings suggest that the degree of AI maturity significantly influences how organizations navigate the early stages of AI adoption, namely, Awareness, Consideration, and Intention. High-maturity firms, such as the consultancy in case 7, benefit from prior experience and established capabilities that allow them to move more quickly through these phases. They demonstrate structured approaches from the outset, using roadmaps, clear frameworks, and internal expertise to align strategic vision with local implementation. These practices reflect the principles of strategic alignment between HQ and subsidiaries, knowledge development, and resource preparation outlined by Jöhnk et al. (2020), enabling high-maturity firms to concentrate their efforts on the later stages of adoption.

By contrast, firms with lower or medium AI maturity face greater challenges in these early phases. Low-maturity firms, such as the audit company in case 11, rely on individual-driven initiatives and struggle to move beyond initial awareness. These organizations lack clear communication, internal expertise, and leadership engagement, leading to fragmented adoption efforts and minimal scaling potential, leaving employees uncertain about AI's role. Medium-maturity firms, including those in the automotive, chemical manufacturing, finance, and general consultancy sectors, show more varied patterns. Although they often recognize AI's strategic relevance, their efforts are marked by partial alignment, "fear-of-missing-out," reactive experimentation, inconsistent leadership involvement, and sometimes an overreliance on external consultants. These findings align with Schmidt et al.'s (2023) observations on internal tensions between organizational levels and role misalignment, which can hinder coherent adoption. Ultimately, our data indicate that organizations with higher AI maturity carry forward learning from previous adoption cycles, giving them a head start in subsequent ones and allowing for a faster, more structured transition into the Adoption Decision phase.

5.2. Adoption Decision

5.2.1 Evaluation

The Complexity of Evaluating AI Solutions

The empirical findings confirm that evaluation is a critical step in AI adoption, aligning with Jöhnk et al. (2020: 8), who emphasize the need to align AI capabilities with strategic priorities and measurable value. However, the empirical data reveals that evaluation in MNEs is far more complex than the theoretical framework suggests. It is shaped by contextual factors and organizational constraints, including access to quality data, technological dependencies, and difficulties in assessing the value of AI applications. Several respondents pointed out how legal restrictions and geographic differences influence data access, further complicating the evaluation process.

Additionally, limited autonomy in evaluating or selecting AI platforms, especially when decisions are centralized at HQ, can restrict local flexibility. These findings highlight how relational and institutional dynamics (Kostova & Roth, 2002: 2017-219; Rudko et al., 2025: 274-275) influence the evaluation phase in MNEs. While key performance indicators (KPIs) and return on investment (ROI) remain central metrics, respondents emphasized the difficulty in capturing qualitative benefits, such as improved information access, faster decision-making, or enhanced employee support. These challenges were noted regardless of AI maturity level, suggesting that even experienced firms struggle to measure the intangible value AI can create. This persistent mismatch between expected and perceived value often leads to stalled or deprioritized initiatives, reinforcing the need for more nuanced evaluation tools that reflect the realities of AI solutions to ensure successful adoption.

Experience Shape Evaluation Effectiveness

Although all case companies identified evaluation as a core challenge, their approaches varied. Firms with higher AI maturity and experience employed more structured models and leveraged prior knowledge to evaluate the strategic fit and potential of AI tools. In contrast, less experienced firms faced greater difficulty articulating how to assess and demonstrate value. These differences point to the influence of AI readiness, as outlined by Jöhnk et al. (2020: 10), and suggest a strong link between organizational maturity and the ability to progress through the adoption process.

Differences across respondent groups once again reflect role-specific perspectives and priorities in the evaluation phase. Managers focused on strategic alignment and long-term business value of AI investments, adopting a top-down perspective. AI experts emphasized the importance of experimentation and prototyping to test feasibility and performance in real-world contexts. Meanwhile, specialists highlighted operational barriers such as low data quality, insufficient support, and vague KPIs. They also noted a disconnect between leadership expectations and operational realities, underscoring the need to align strategic intent with practical execution.

5.2.2 Resource Allocation

Strategic Alignment & Organizational Transformation

Across the empirical cases, strategic alignment consistently emerged as a foundational enabler of effective resource allocation during AI adoption. This supports theoretical insights from Jöhnk et al. (2020: 10-12) and Uren and Edwards (2023: 7-8), which emphasize the need to integrate AI into broader business strategies. Respondents from medium- and high-maturity firms warned that AI efforts lose value when disconnected from core objectives and underscored the importance of embedding it into strategic and annual planning processes to ensure continuity and long-term value creation. A consultant also highlighted the pitfalls of launching pilot projects without a coherent strategy, reinforcing Holmström's (2022: 333) emphasis on strategic coherence and cross-functional collaboration.

A specialist from a high-maturity firm emphasized the importance of end-to-end thinking, integrating AI across entire business processes to create long-term value. She highlighted that sustained competitive advantage relies on an organization's ability to realign its strategic foundation in response to technological change, while maintaining flexibility for local adaptation within global AI strategies. While MNE literature (e.g., Kostova & Roth, 2002; Schmidt et al., 2023) acknowledges the importance of aligning people, goals, and activities across borders, the transformational potential of AI remains underexplored. Existing theory, often rooted in IT transformation, tends to assume incremental change and overlooks AI's disruptive potential. These frameworks fail to fully capture how AI drives organizational restructuring, shifting roles, workflows, and decision-making, and necessitates long-term strategic repositioning.

Beyond alignment, respondents also emphasized the need to redesign organizational structures to support AI transformation. Specialists, representing a high AI maturity firm, described how AI can drive operational autonomy, potentially making certain roles or management layers redundant. This trend points toward flatter, more agile structures. However, transformation also requires top-down leadership, centralized coordination, and structured knowledge-sharing systems, according to respondents. These dynamics reflect the complex balancing act MNEs face in navigating both relational (trust, dependence, identification) and institutional (regulatory, normative, cognitive) contexts (Kostova & Roth, 2002: 217-219). The findings suggest that structural decisions must be tailored to these contextual pressures, calling for theoretical models that better capture AI's role as a transformative force in multinational settings.

Coordinating AI Capabilities

Human capital emerged as the most critical resource in AI adoption. Respondents across all roles emphasized that success hinges not only on technical skills but on the willingness and ability to translate AI into business value. This aligns with Jöhnk et al.'s (2020: 10-14) view that AI readiness includes cultural, strategic, and knowledge dimensions, and is reinforced by Holmström (2022: 335) and Uren and Edwards (2023: 9-10). Cross-functional competence and a culture open to change were identified as central components of this readiness to learn and adapt continuously.

The value of external partnerships, especially in firms with low maturity, was also emphasized. While internal capability building remains essential, several respondents described how external consultants can help overcome common pitfalls and accelerate early progress where foundational readiness is lacking. This supports Schmidt et al.'s (2023) call for open innovation and aligns with Uren and Edwards' (2023: 6-7) advocacy for early cross-level collaboration to facilitate learning and experimentation. However, reliance on consultancies also introduces trade-offs. Multiple case firms exhibited dependency on external actors, risking underinvestment in internal capability development critical to long-term AI readiness and organizational learning. This balance between outsourcing and internal growth highlights an underexplored area in current theory.

Misconceptions around IT, traditional AI, and generative AI formed another barrier to effective adoption. Respondents from all respondent groups pointed out that these misunderstandings and knowledge gaps often lead to poor decision-making, delays, and inefficient resource use. These findings reinforce Jöhnk et al.'s (2020: 16-17) argument that AI readiness and adoption are mutually reinforcing: a higher degree of readiness supports effective adoption, while experience with adoption efforts further enhances readiness over time. Human capital development must therefore go beyond technical upskilling to include systems that support cross-functional learning, experimentation, and organizational confidence.

For MNEs, a globally coordinated approach to capability-building is especially important. Fragmented knowledge across units and geographies risks weakening the firm's overall AI competence. Respondents from high-maturity firms highlighted centrally coordinated mandatory training and shared platforms to build common AI literacy. Yet engagement remained uneven among respondents. In medium-maturity cases, respondents described employee resistance driven by unclear communication and lack of support, indicating that learning efforts must be accompanied by strong leadership messaging and visible role modeling from management. These challenges are magnified by the dual institutional and relational complexity of MNEs. Internal pressures, such as fragmented organizational capabilities, intersect with external ones, like diverse regulatory standards and national norms. Although Kostova and Roth (2002) and Schmidt et al. (2023) recognize these layers, the data highlight a practical gap, few models offer concrete guidance on how MNEs can manage global-local tensions during AI transformation. This signals a need for new frameworks that integrate strategic alignment, relational dynamics, and institutional context in AI-driven change.

The Silent Role of Investment

Interestingly, financial resources were rarely discussed by respondents apart from reallocating resources. This could imply that investment is viewed as an underlying requirement, implicit in all strategic projects, and not uniquely critical for AI. Alternatively, as firms progress beyond pilots into scaling, financial planning may gain importance. The lack of explicit discussion suggests an area for future empirical investigation, particularly regarding how investment decisions shape long-term AI outcomes.

5.3 Adoption

5.3.1 Implementation

Balancing Speed & Readiness

The empirical findings largely support theoretical suggestions for the implementation phase of AI adoption. A key theme was the need to balance speed and readiness, moving too slowly risks obsolescence, while rushing can undermine successful adoption due to insufficient preparation. Respondents across cases emphasized the importance of cross-functional collaboration, knowledge sharing, and documentation, aligning with prior research. For example, Schmidt et al. (2023) highlight the value of constructive tensions, knowledge standardization, and open innovation, while Uren and Edwards (2023) stress collaboration across functions. Notably, participants underscored the importance of delaying knowledge standardization until later phases. This supports Schmidt et al.'s (2023) argument that early standardization may hinder experimentation, which is crucial for developing AI capabilities. Instead, standardizing knowledge in later stages can facilitate long-term integration and more sustainable AI adoption.

However, several respondents identified misconceptions and limited knowledge among leaders as key barriers to successful adoption. One AI expert noted that many leaders would benefit from returning to a learning mindset, suggesting they need to "go back to school" to build the competence required for informed decision-making. This knowledge gap, combined with existing power dynamics, both between business units like HQ and subsidiaries (Kostova & Roth, 2002) and across hierarchical levels within subsidiaries, can hinder effective implementation. When leadership lacks sufficient insight yet retains decision-making authority, misalignment often follows. These challenges highlight the need for stronger collaboration across organizational levels to fully leverage the AI competence already present within different parts of the organization.

Power in Policy

Moreover, policies were frequently mentioned by respondents, which stressed their supporting, regulating, and trust building effects concerning AI within organizations. Literature (Jöhnk et al., 2020; Schmidt et al., 2023) stress the need for guidelines to ensure ethical use and risk minimization. This was confirmed in the data, where policies were expressed to be used with this purpose. However, the encouraging and supporting role of policies to increase trust and confidence in AI tools has not been reflected in the literature in the same manner as in the empirical data. This illustrates an important finding of the relevance and importance of AI policies and guidelines to support AI adoption within organizations. AI policies act not only as risk management tools but also as enablers of safe and scalable adoption by providing both structure and education.

Nevertheless, implementing well functioning policies is not straightforward. Businesses need to balance the level of openness and governance to promote usage and experimentation, while considering unethical and riskful usage of AI tools. In relation to the MNE perspective, this complexity is magnified, due to geographical discrepancies and differences in governance and ethical regulations (e.g. EU AI Act and GDPR) which raise the need for context specific adaptations, and hence, less centralized and standardized AI initiatives across MNEs. Theoretical frameworks by Kostova and Roth (2002) and Schmidt et al. (2023) support the need to align with local regulatory and cultural contexts but offer limited guidance on how to develop specific policies.

Furthermore, discussions on how the difficulties in documenting generative AI tools affects AI implementation are needed. This proves an interesting and well-needed research area for future studies on AI adoption, especially concerning the effects of policy, guidelines, and documentation on MNEs. As of now, we assume that it negatively affects AI implementation by minimizing trust and confidence in AI, making it appear more complex and risky to tackle AI adoption, potentially slowing down implementation on a global scale.

Geographical Complexities faced by MNEs

Even though the different regulations, such as the EU AI act, may increase the complexity of AI adoption, it was welcomed by respondents across groups as it provides structure and clarity. This can be compared to the internal policies and guidelines within organizations, where the AI act promotes responsible usage in a similar way, and might minimize the complexities for MNEs operating in Europe due to more uniform regulations and frameworks. This reflects a broader view that well-defined rules can support responsible innovation by removing ambiguity and helping organizations make informed decisions.

While prior literature, particularly Kostova and Roth (2002), highlights the role of HQ-subsidiary dynamics in shaping implementation processes, this perspective was not consistently highlighted across the cases. Instead, the data pointed to regulatory and institutional divergence between regions and business units, with less emphasis on ownership-based power dynamics. Although some of the studied firms included subsidiaries in the traditional sense (i.e., partly or wholly owned separate legal entities), the majority of interviews involved business units operating within the same legal entity. Nonetheless, Kostova and Roth's (2002) framework remains useful for interpreting the balance between central control and local autonomy. The limited visibility of HQ involvement in later stages of AI adoption may indicate a decentralization of operational decision-making, with HQ primarily influencing early phases, such as strategic framing and resource allocation. This may also relate to the power dependence dynamic described by Kostova and Roth (2002: 219), where HQ rely on local expertise and initiative. Given the varied ownership structures across MNEs, further research is needed to examine how these dynamics unfold in organizations with more clearly delineated HQ-subsidiary relationships.

Ground-Level Realities & Strategic Intent

Reflections from the respondents concerning the implementation phase of AI adoption indicate that high- and medium-maturity firms generally show greater awareness of what is needed for successful implementation. While some apply "lessons learned" from earlier phases, others experiment with approaches they believe are suitable. These firms consistently recognize the need for action, highlighting collaboration, knowledge sharing, and internal policies as foundational elements for advancing implementation, regardless of industry. Managers and AI experts frequently emphasize the importance of balancing flexibility with governance and display a growing awareness of the risks associated with AI deployment going wrong. Specialists, on the other hand, provide valuable ground-level insights into how policies and guidelines function, or fail, in everyday work. Their accounts reveal that policy design and communication are often unclear or disconnected from operational realities. This highlights the importance of open dialogue between organizational levels, as emphasized by Schmidt et al. (2023: 41), where managers must engage with employees' perspectives to design effective governance structures. In contrast, the low-maturity firm showed minimal engagement with the implementation phase, reflecting an earlier stage of the adoption process where structured implementation efforts and policy development are largely absent.

These findings illustrate that the implementation phase serves as a critical bridge between planning and sustained use. It is here that the practical consequences of earlier strategic and organizational decisions become visible. High- and medium-maturity firms show how accumulated readiness, such as leadership support, cultural alignment, and policy infrastructure, translates into more coordinated and scalable AI practices. Conversely, low maturity cases reveal how gaps in these areas stall progress. Thus, implementation not only reflects organizational preparedness but also exposes where further investment and advancement is needed to ensure continuity into the internalization phase.

5.3.2 Internalization

Culture, Leadership, & the Human Factor

The empirical data highlights that people are at the core of the internalization phase. Building and maintaining trust, ensuring transparent and ethical use, and embedding AI into everyday workflows are seen as essential steps in making AI a natural part of work life and encouraging widespread use. Organizational culture emerges as a critical enabler, shaping how individuals perceive AI, attitudes toward its use, and the extent to which support, innovation, and continuous learning are viewed as shared values across the organization. This, in turn, supports the interdependence of these AI readiness factors and AI adoption highlighted by Jöhnk et al. (2020), illustrating how they affect the adoption process throughout the different phases, from initiation towards internalization.

According to respondents, top management plays a central role in cultivating this culture and guiding internalization efforts in the right direction. These findings reinforce the theoretical perspectives of Kostova and Roth (2002) and Jöhnk et al. (2020), who emphasize the importance of cultural factors, both internal and external, in shaping adoption practices. For MNEs, this includes not only the corporate culture but also the broader institutional cultures in which the organization is embedded. The complexity of working cross-border and adapting to different working styles further illustrates this point. Moreover, Schmidt et al. (2023) underlines the significance of managerial actions and roles within different organizational levels in enabling successful technology adoption, an insight strongly supported by the empirical accounts in this study. The findings further point to the essence of successful policies and guidelines to promote an AI encouraging culture within MNEs, due to its effects on trust, empowerment, and reassurance of responsible AI usage. The human oversight of AI, as discussed by several respondents, is a prime example of a valuable function to ensure trust throughout the organization, promoting continued use.

Internalization as an Ongoing Process

The concept of internalization as an ongoing process requiring continuous adaptation, emphasized by multiple respondents, aligns with Kostova and Roth's (2002) view that successful internalization depends on how individuals perceive the value of a practice, engage with it, and support its ongoing use. This perspective directly applies to AI adoption, where similar dynamics are observed, sustained usage is driven not just by implementation, but by whether people see AI as valuable and relevant in their daily work.

The difficulty of scaling AI initiatives is further evident in the empirical data, with a lack of coordination and support frequently cited as key barriers. These challenges align with the AI readiness factors outlined by Jöhnk et al. (2020), suggesting that insufficient organizational support hinders the internalization of AI. Our findings indicate that companies with higher AI maturity levels tend to possess stronger foundational knowledge and readiness, which in turn facilitates greater usage and supports internalization, as well as the other adoption phases. Moreover, the use of shared frameworks, cross-functional collaboration, and standardized processes was highlighted as critical enablers of efficiency, allowing projects to advance more effectively toward internalization. Since respondents from diverse roles and industries consistently described the internalization phase in similar terms, it confirms that this stage of AI adoption unfolds uniformly across the studied sectors. This consistency highlights an important practical insight into how MNEs integrate AI regardless of industry or role differences.

Taken together, the findings reinforce that AI adoption is not a linear path but a multi-phase journey shaped by evolving levels of readiness and maturity. From early awareness and consideration to implementation and internalization, progress depends on the dynamic interplay between leadership, organizational culture, structural alignment, and knowledge capabilities. High-maturity firms appear better equipped to advance through the early phases more efficiently, drawing on established experience and strategic readiness. However, sustaining this advantage requires continuous adaptation, as the AI landscape evolves rapidly. The analysis of the internalization phase makes clear that foundational readiness factors such as, cultural, structural, human, and strategic, remain critical throughout the process. Their interconnectedness illustrates the iterative nature of AI adoption, where each phase builds on the last and success relies on aligning resources, fostering a supportive environment, and maintaining strategic direction across the organization.

5.4 Revised Conceptual Model

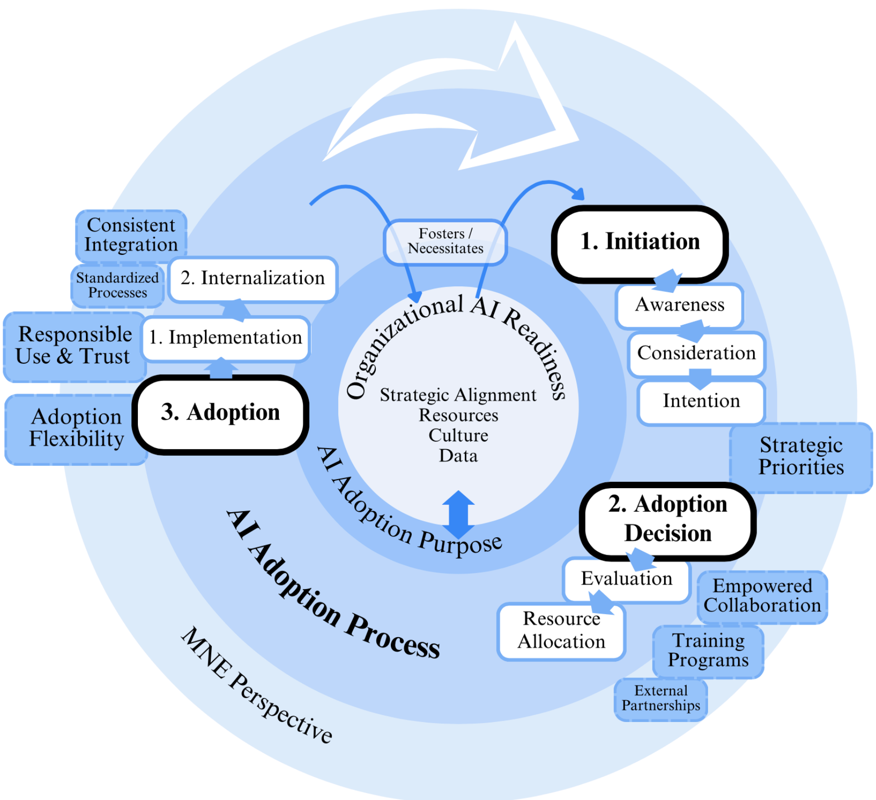


Figure 7. Visualization of revised conceptual model.

The revised conceptual model maintains the structure of *Initiation*, *Adoption Decision*, and *Adoption*, but reconceptualizes the process as cyclical rather than linear (see Figure 7). Empirical findings show that AI adoption unfolds iteratively, where experience from one cycle influences the next. This is illustrated through a circular model, with a growing arrow connecting cycles to indicate how new capabilities and organizational conditions emerge over time. Thereby, *Organizational AI Readiness* factors are treated as fluid and recurring, with varying relevance across phases. For instance, firms with more experience can move more swiftly through early phases, reinforcing the cyclical character. The category "Knowledge" has been removed and included in "Resources," based on the prominence of human capital in the empirical data. Financial aspects are still included within resources, reflecting their less prominent role. The readiness factors are now ordered by empirical significance: (1) *Strategic Alignment*, (2) *Resources*, (3) *Culture*, and (4) *Data*. A double-sided arrow has also been added between *Readiness Factors* and *Adoption Purpose* to illustrate how increased readiness may lead to a reframing of strategic intent, reinforcing the learning-oriented nature of AI adoption over time.

In the MNE-specific layer of the model, several factors have been resized or repositioned to reflect their relative importance. Most notably, *Strategic Priorities* have been extended to cover both *Initiation* and *Adoption Decision*, acting as a bridge between intention and action. "Collaborative Development," "Open Dialogue," and "Local Autonomy" have been grouped as *Empowered Collaboration* and moved earlier in the process to reflect their role in fostering engagement and local involvement. *Training Programs* have also been shifted to the second phase, emphasizing the need for early managerial and operational learning. *Adoption Flexibility* remains central in the final phase, enlarged to reflect its significance in enabling adaptive integration. *Responsible Use & Trust* has been added as a new factor, emphasizing the importance of ethical considerations and trust-building when scaling AI across culturally and institutionally diverse contexts, particularly relevant for multinational environments.

Less prominent factors have been reduced or removed to reflect their limited empirical relevance. "Acquisition" and "Continued Use" were excluded, as these are conceptually embedded within *Implementation* and *Internalization*. *External Partnerships* is depicted with a smaller size, as reliance on external actors decreases with growing internal maturity when experience is gathered from previous adoption cycles. *Standardized Processes* has also been reduced in size, as experienced organizations increasingly rely on adaptive policies and local tailoring rather than rigid procedures. The revised model captures the iterative and context-dependent nature of AI adoption in MNEs, offering a theoretically informed yet empirically grounded lens for understanding how global organizations navigate this evolving process.

6. CONCLUSION

6.1 Research Question

How does an AI adoption process unfold in MNEs?

This study demonstrates that AI adoption within MNEs is best understood as a cyclical process comprising three interrelated phases: *Initiation*, *Adoption Decision*, and *Adoption*. Importantly, each adoption cycle lays the foundation for the next. As MNEs build experience, they increase their AI readiness, reducing the need for prolonged deliberation in future adoption phases. This dynamic reinforces that AI maturity is cumulative, where organizations with higher adoption experiences tend to exhibit stronger strategic alignment, internal development capacity, and integration across units.

In the *Initiation* phase, awareness, often triggered by developments like generative AI, evolves into a concrete intention, shaped by fragmented knowledge, cultural hesitancy, experimentation, and emerging strategic priorities. Here, organizations begin to define the role of AI, whether at the individual, operational, or core business level. This initial phase evolves differently depending on organizational AI maturity. High-maturity firms demonstrate clearer strategic intent, leveraging prior experience, and cross-level alignment to move swiftly toward adoption. In contrast, lower-maturity firms rely on individual efforts, revealing weak leadership engagement and limited organizational support. These findings underscore the importance of addressing institutional dynamics, psychological barriers, and intra-organizational tensions early in the adoption process to build a solid foundation for AI integration.

In the *Adoption Decision* phase, firms identify and evaluate use cases, align them with business goals, and allocate resources strategically. Despite differences in AI maturity, firms consistently struggle to assess the value of AI due to poor data quality, IT infrastructure, and the intangible nature of qualitative benefits. This complexity reveals a gap in existing evaluation tools, which often fail to reflect the practical realities of AI. In this phase, clear top management sponsorship and commitment from business leaders were seen as essential to ensure AI adoption becomes business-driven rather than externally pushed. Human capital emerges as the most critical enabler, with success depending on leadership support, cross-functional collaboration, and upskilling to translate AI capabilities into concrete business outcomes.

The *Adoption* phase marks the transition from planning to practice, where successful AI implementation depends on balancing speed with organizational readiness. For MNEs, this phase is shaped by geographical and regulatory complexity, requiring localized adaptations rather than centralized control. For internalization, the key enablers, trust, responsible governance, cross-functional collaboration, and clear policies, play a critical role in both scaling AI and securing long-term success. Trust between HQ and subsidiaries fosters open communication, local adaptation, and reduces resistance to AI-driven change. Responsible governance, reflected in transparent decision-making, ethical oversight, and clearly defined accountability, supports organizational confidence in scaling AI initiatives and ensures alignment with strategic goals. Without these foundations, AI risks remaining confined to siloed teams or experimental use. When these enablers are in place, AI becomes more integrated into global workflows and embedded in day-to-day operations across the enterprise.

The adoption process is further shaped by geographical differences in culture, regulation, and data governance. Firms in Europe and the Nordics often take a more cautious, compliance-driven approach, influenced by cultural norms and regulations, such as the EU AI Act and GDPR. In contrast, regions like the U.S. and China tend to pursue AI adoption more boldly, with greater risk tolerance and a stronger focus on experimentation. These divergent approaches influence not only the pace at which organizations move through the adoption phases but also how AI is perceived and integrated internally. Cross-border implementation is further complicated by data transfer restrictions and varying privacy regulations within MNEs.

6.2 Theoretical & Practical Contributions

This study contributes to the technology adoption literature by demonstrating that AI cannot be approached as a conventional IT initiative. Unlike traditional tools with clearly defined implementation paths, AI adoption evolves through ongoing interaction between people, processes, and organizational structures. Existing theories, often rooted in incremental IT change, fail to capture AI's disruptive impact on roles, workflows, and strategic decision-making. This highlights the need for updated frameworks that reflect AI's transformative nature and the strategic repositioning it demands in MNEs. The study extends current models by proposing a cyclical view of AI adoption, where each iteration builds future readiness, adding a temporal and evolutionary dimension. Furthermore, the findings position AI adoption as an inherently socio-technical process, shaped by individual motivation, trust, cultural norms, and organizational fears. In this context, the interplay between human agency and technological advancement emerges as a defining characteristic, underscoring the need for frameworks centered on organizational dynamics.

For practitioners, regardless of industry, this study provides actionable guidance on how to navigate the complexity of AI adoption in multinational settings. It outlines the importance of combining top-down strategic alignment with bottom-up experimentation to enable continuous learning environments, and emphasizes the role of leadership in shaping AI culture. Companies should invest in trust-building, responsible AI governance, and cross-functional coordination, especially as they move from pilot projects to scaled solutions. MNEs are further encouraged to view AI not as a single project, but as a strategic capability requiring long-term commitment and reinvention. An AI maturity-based perspective, like the one presented in this study, could help organizations reflect on their current phase and identify tailored steps to move forward.

6.3 Limitations & Future Research

A limitation of this study is the concentration of case companies with medium AI maturity levels, most of which were based in Northern Europe. The limited representation of high-maturity firms, likely due to many organizations still being in the early stages of adoption, may have constrained our ability to capture more advanced practices. Additionally, while Kostova and Roth's (2002) framework on relational and institutional contexts informed our theoretical foundation, its empirical relevance was less pronounced. This may stem from the geographic concentration of cases within similar institutional environments, reducing observable variation in trust, power dependence, and regulatory divergence. Although our data reflect some cross-national differences, such as in data privacy and compliance, a more geographically diverse sample, particularly beyond Northern Europe, may be needed to fully explore the relational dynamics highlighted by Kostova and Roth (2002). Future research could benefit from comparative studies across regions with different ownership structures to assess in greater detail how institutional and relational contexts shape AI implementation and internalization.

Given the rapid pace of AI development and the early stage of adoption in many organizations, several directions for future research emerge. This study found no major differences in the AI adoption process across industries, only minor variations in maturity levels and experience. These differences affected how much time and focus organizations placed on each phase, suggesting that current adoption dynamics are shaped more by organizational readiness than by industry-specific factors. Future studies could examine whether sectoral differences become more pronounced as generative AI use becomes more widespread and maturity increases. There is also a need to revisit existing frameworks, including the one proposed here, to assess their relevance over time and across organizational contexts. As AI evolves, more adaptive models may be required to reflect feedback loops, non-linear progressions, and shifting readiness conditions.

Future research should also examine how the scale and scope of AI initiatives shape adoption, particularly regarding resource allocation and stakeholder involvement. Differentiating between explorative and exploitative use cases may clarify strategic variations across phases. While this study included both traditional and generative AI, most case companies focused on generative tools, likely due to current trends. However, no major differences were observed in the adoption process. Longitudinal studies could further explore how internal capabilities evolve and how prior experiences influence future implementation.

Additionally, more attention should be given to the role of internal AI policies in multinational contexts, specifically, how to balance global consistency with local adaptation. The growing complexity of managing and documenting generative AI underscores the need for thorough governance frameworks that can address emerging risks and support responsible implementation.

REFERENCES

AI Sweden. (2025). *Organizations*. https://my.ai.se/organizations [2025-03-23]

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial intelligence adoption: AI-readiness at firm-level. *PACIS 2018 Proceedings*, *37*. https://aisel.aisnet.org/pacis2018/37/

Andersen, P. H., & Skaates, A. M. (2004). Ensuring Validity in Qualitative International Business Research. In R. Marschan-Piekkari and C. Welch (Eds.), *Handbook of Qualitative Research Methods for International Business* (464-484). Cheltenham: Edward Elgar Publishing. https://doi.org/10.4337/9781781954331.00045

Bell, E., Harley, B., & Bryman, A. (2022). *Business Research Methods* (6th ed.). Oxford: Oxford University Press.

Birkinshaw, J. (1997). Entrepreneurship in multinational corporations: The characteristics of subsidiary initiatives. *Strategic Management Journal*, *18*(3), 207-229. https://doi.org/10.1002/(SICI)1097-0266(199703)18:3<207::AID-SMJ864>3.0.CO;2-Q

Capgemini. (2024). *Harnessing the value of generative AI 2nd edition: Top use cases across sectors*. https://www.capgemini.com/wp-content/uploads/2024/11/Generative-AI-in-Organizations-Refresh_25112024.pdf

Corrales-Garay, D., Rodriguez-Sanchez, J.-L., & Montero-Navarro, A. (2024). Co-Creating Value With Artificial Intelligence: A Bibliometric Approach to the Use of AI in Open Innovation Ecosystems. *IEEE Access*, 12, 56860-56871. https://doi.org/10.1109/ACCESS.2024.3391054

European Commission. (2025). *AI Act*. https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai [2025-03-28]

Eurostat, (n.d.). *Glossary: Multinational enterprise (MNE)*. European Union. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Multinational_enterprise_(MNE) [2025-02-11].

Frambach, R. T., & Schillewaert, N. (2002). Organizational innovation adoption: a multi-level framework of determinants and opportunities for future research. *Journal of Business Research, 55(2)*, 163-176. https://doi.org/10.1016/S0148-2963(00)00152-1

Ghauri, P. N. (2004). Designing and conducting case studies in international business research. In R. Marschan-Piekkari & C. Welch (Eds.), *Handbook of Qualitative Research Methods for International Business* (109-124). Cheltenham: Edward Elgar Publishing. https://doi.org/10.4337/9781781954331.00019

Gopalakrishnan, S., & Damanpour, F. (1997). A review of innovation research in economics, sociology and technology management. *Omega (Oxford)*, *25*(1), 15-28. https://doi.org/10.1016/S0305-0483(96)00043-6

Guba, E. G., & Lincoln, Y. S. (1994). Competing Paradigms in Qualitative Research. In N. K. Denzin and Y. S. Lincoln (Eds.), *Handbook of Qualitative Research* (105-117). Thousand Oaks, CA: Sage.

Hameed, M. A., Counsell, S., & Swift, S. (2012). A conceptual model for the process of IT innovation adoption in organizations. *Journal of Engineering and Technology Management*, *29*(3), 358-390. https://doi.org/10.1016/j.jengtecman.2012.03.007

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons, 65*(3), 329-339. https://doi.org/10.1016/j.bushor.2021.03.006

Jöhnk, J., Weißert, M., & Wyrtki, K. (2020). Ready or Not, AI Comes - An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, *63*(1), 5-20. https://doi.org/10.1007/s12599-020-00676-7

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15-25. https://doi.org/10.1016/j.bushor.2018.08.004

Kostova, T., & Roth, K. (2002). Adoption of an organizational practice by subsidiaries of multinational corporations: Institutional and relational effects. *Academy of Management Journal, 45(1)*, 215-233. https://doi.org/10.5465/3069293

Lincoln, Y. S., & Guba, E. (1985). *Naturalistic Inquiry*. Beverly Hills, CA: Sage.

Magnani, G., & Gioia, D. (2023). Using the Gioia Methodology in international business and entrepreneurship research. *International Business Review*, *32*(2), 102097. https://doi.org/10.1016/j.ibusrev.2022.102097

Marr, B. (2023, 24 July). *The Difference Between Generative AI And Traditional AI: An Easy Explanation For Anyone.* Forbes. https://www.forbes.com/sites/bernardmarr/2023/07/24/the-difference-between-generative-ai-and-traditional-ai-an-easy-explanation-for-anyone/ [2025-02-04]

Marschan-Piekkari, R., Welch, C., Penttinen, H., & Tahvanainen, M. (2004). Interviewing in the multinational corporation: Challenges of the organisational context. In R. Marschan-Piekkari & C. Welch (Eds.), *Handbook of Qualitative Research Methods for International Business* (244-264). Cheltenham: Edward Elgar Publishing. https://doi.org/10.4337/9781781954331.00028

McKinsey. (2024a, April 3). *What is AI (artificial intelligence)?* https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-ai#/ [2025-02-11]

McKinsey. (2024b, April 2). *What is generative AI?* https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-generative-ai#/ [2025-01-28]

Merriam, S. B. (1998). *Qualitative Research and Case Study Applications in Education*. San Francisco: Jossey-Bass Publishers.

Meyer, K. E., Li, C., & Schotter, A. P. J. (2020). Managing the MNE subsidiary: Advancing a multi-level and dynamic research agenda. *Journal of International Business Studies*, *51*(4), 538-576. https://doi.org/10.1057/s41267-020-00318-w

Nielsen, B.B., Eden, L., & Verbeke, A. (2020). *Research Methods in International Business*. Springer International Publishing. https://doi.org/10.1007/978-3-030-22113-3

OECD Trade Policy Papers. (2022). *Artificial Intelligence and international trade: Some preliminary implications*. OECD Publishing, no. 260. https://doi.org/10.1787/13212d3e-en [2025-02-11]

Pumplun, L., Tauchert C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence - exploring organizational readiness factors. *ECIS 2019 Proceedings*. https://aisel.aisnet.org/ecis2019_rp/106/

PwC. (2025, January 20). *Reinvention on the edge of tomorrow*. PwC's 28th Annual Global CEO Survey. https://www.pwc.com/gx/en/ceo-survey/2025/28th-ceo-survey.pdf [2025-02-04]

Raziq, M. M., Benito, G. R. G., & Kang, Y. (2023). Multinational Enterprise Organizational Structures and Subsidiary Role and Capability Development: The Moderating Role of Establishment Mode. *Group & Organization Management*, *48*(3), 908-952. https://doi.org/10.1177/10596011211060952

Rudko, I., Bashirpour Bonab, A., Fedele, M., & Formisano, A. V. (2025). New institutional theory and AI: toward rethinking of artificial intelligence in organizations. *Journal of Management History*, *31*(2), 261-284. https://doi.org/10.1108/JMH-09-2023-0097

Russell, S., & Norvig, P. (2016). Artificial Intelligence: A Modern Approach (Global edition.). Pearson Education, Limited.

Schmidt, A., Mom, T. J. M., & Volberda, H. W. (2023). Factors Influencing Technology Adoption in a Traditional Multinational Energy Company. *Research Technology Management*, *66*(5), 36-43. https://doi.org/10.1080/08956308.2023.2235535

Statista. (2024). *Global vs. the United States investments in artificial intelligence (AI) forecast for 2025*. https://www.statista.com/statistics/1456578/ai-investment-comparison/ [2025-05-11]

Stryker, C., & Kavlakoglu, E. (2024, August 9). *What is artificial intelligence (AI)?*. IBM. https://www.ibm.com/think/topics/artificial-intelligence [2025-01-28]

Swedish Research Council. (2024). God forskningssed 2024 [Good research practice 2024]. https://www.vr.se/analys/rapporter/vara-rapporter/2024-10-02-god-forskningssed-2024.html

Tornatzky L.G., Fleischer M., & Chakrabarti A.K. (1990). *The processes of technological innovation*. Lexington: Lexington Books.

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, *68*, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588

Welch, C., Paavilainen-Mäntymäki, E., Piekkari, R., & Plakoyiannaki, E. (2022). Reconciling theory and context: How the case study can set a new agenda for international business research. *Journal of International Business Studies*, *53*(1), 4-26. https://doi.org/10.1057/s41267-021-00484-5

Xicang, Z., Bilal, M., Jiying, W., Sohu, J. M., Akhtar, S., & Itzaz Ul Hassan, M. (2024). Unraveling the Factors Influencing Digital Transformation and Technology Adoption in High-Tech Firms: The Moderating Role of Digital Literacy. *SAGE Open*, *14*(4). https://doi.org/10.1177/21582440241300189

Yin, R. K. (2009). *Case Study Research: Design and Methods* (4th ed.). SAGE.

APPENDIX

A. Interview Guide – AI Experts

Interview Guide - AI Experts

1. **Introduction**
   Can you briefly describe your role and background in AI?
   How are you involved in AI adoption across organizations or industries?

2. **Interest in AI**
   What typically drives AI discussions at the executive level?
   Are these driven more by internal needs, trends, or competitive pressure?
   How have leadership views on AI changed over time?

3. **Consideration & Decision-making**
   What usually drives the decision to adopt AI in MNEs?
   How do companies assess if an AI solution fits their operations?
   Do organizations often adapt their strategy to support AI?
   What types of resources are typically required?

4. **Execution & Implementation**
   What are common approaches to implementing AI?
   How do different departments collaborate during the process?
   What role do external partners usually play?
   How is AI scaled across large organizations?

5. **Evaluation & Lessons Learned**
   What major changes does AI bring to organizations?
   What common challenges have you observed?
   How does AI adoption differ from other change processes?
   What advice would you give to companies aiming for successful AI adoption?

B. Interview Guide – Company Representatives

Interview Guide - Company Representatives

1. **Introduction**
   Can you briefly describe the company, your role, and current use of AI?

2. **Interest in AI**
   How and when did AI-related discussions begin internally?
   Were these driven by internal needs, market trends, or other factors?

3. **Consideration & Decision-making**
   What drove the decision to adopt AI?
   How did you assess whether the AI solution was suitable for your operations?
   Did AI align with your existing strategy, or did you need to adapt it?
   What resources were required?

4. **Execution & Implementation**
   What did the implementation process look like?
   What role did different internal departments and external partners play?
   How were experiences documented and shared within the organization?
   Has AI been implemented across multiple parts of the organization or only in a specific area?

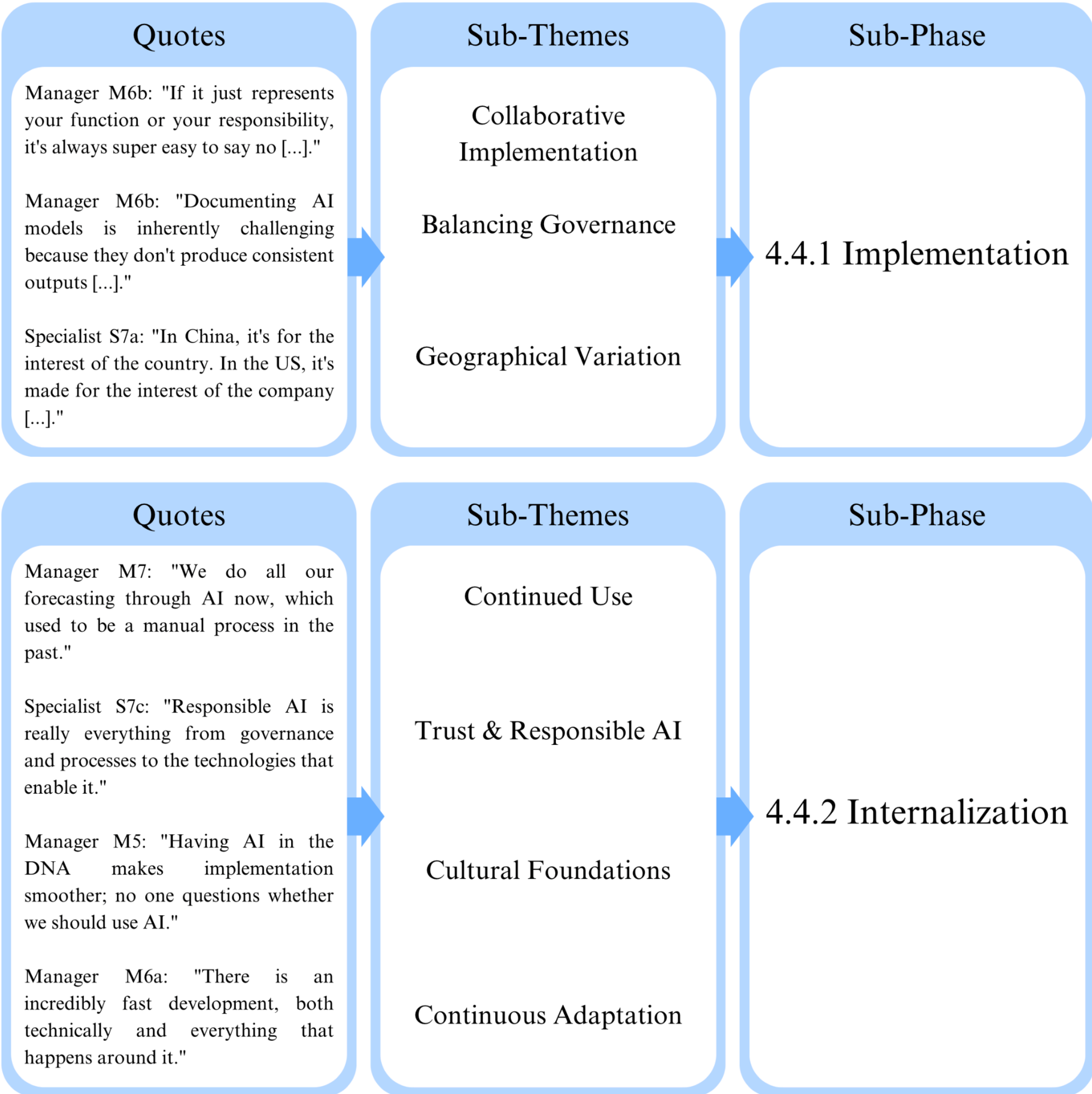
5. **Evaluation & Lessons Learned**
   How has AI changed the organization?
   What challenges have you encountered?
   How did this change process differ from others you have experienced?
   What advice would you give to other companies considering AI?

C. Analysis Coding Process – Examples

Quotes	Sub-Themes	Sub-Phase
Manager M6a: "I saw that this as something that will really change everything [...] and I believe that is what the company realized too." Specialist S9b: "An AI assistant appeared on my screen unannounced, initially mistaking it for spam or a potential cybersecurity threat."	Generative AI as a Catalyst Limited Knowledge within MNEs	4.2.1 Awareness
Specialist S7a: "Many companies are caught by a fear-of-missing-out and just pumping money into it." AI expert A2: "74% of Swedish executives claim they are doing fairly well with AI, [...] but in practice, only 19% of the workforce uses generative AI weekly [...]." Manager M7: "We have a much more nervous approach to this technology [...] in Sweden, only about 25% see AI more as an opportunity than a risk."	Risks of Inaction Overconfidence in AI Maturity Cultural Caution	4.2.2 Consideration
Manager M8: "IT provides the tools, but the value only comes when legal, HR, and the business units align to deliver something useful [...]." Manager M5: "It starts out as employees just getting started and using it [...]." Manager M4: "They need to try i themselves and get their own experience of how it works." AI expert A2: "It has to begin in the boardrooms and executive teams, only then will organizations truly embrace and leverage AI's potential." Manager M4: "It's useful to reflect on where each application of AI fits."	Rethinking Technology Projects Learning by Doing From Ideas to Use Cases Leadership & Organizational Structure Strategic Intent & Adoption Readiness	4.2.3 Intention

Quotes	Sub-Themes	Sub-Phase
Manager M5: "It often flags candidates who don't even have the formal qualifications." Specialist S9a: "We intentionally wait with AI, because it won't succeed without proof of value." Manager M6b: "If bad data goes in, bad results come out."	Evaluating Usefulness Measuring Value Securing the "Right" Data	4.3.1 Evaluation

Quotes	Sub-Themes	Sub-Phase
Manager M6b: "What made a company successful in the past may no longer be what drives success in the future." Manager M5: "The current reorganization is probably more driven by AI than it's for other efficiency reasons [...]." Manager M5: "To develop AI, you shift costs from programmers […] to using large data centers." Manager M7: "All our 800,000 employees need to go through AI training."	Strategic Alignment Re-Organization Investment Shifts Capability Building	4.3.2 Resource Allocation


Quotes
Manager M6b: "If it just represents your function or your responsibility, it's always super easy to say no [...]."
Manager M6b: "Documenting AI models is inherently challenging because they don't produce consistent outputs [...]."
Specialist S7a: "In China, it's for the interest of the country. In the US, it's made for the interest of the company [...]."
Sub-Themes
Collaborative Implementation
Balancing Governance
Geographical Variation
Sub-Phase
4.4.1 Implementation
Quotes
Manager M7: "We do all our forecasting through AI now, which used to be a manual process in the past."
Specialist S7c: "Responsible AI is really everything from governance and processes to the technologies that enable it."
Manager M5: "Having AI in the DNA makes implementation smoother; no one questions whether we should use AI."
Manager M6a: "There is an incredibly fast development, both technically and everything that happens around it."
Sub-Themes
Continued Use
Trust & Responsible AI
Cultural Foundations
Continuous Adaptation
Sub-Phase
4.4.2 Internalization