



Vaasan yliopisto
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AI adoption capabilities and the role of data architecture in AI transformation

School of Management
Master's thesis in Strategic
Business Development

Vaasa 2026

UNIVERSITY OF VAASA**School of Management**

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Title of the Thesis: AI adoption capabilities and the role of data architecture in AI transformation
Degree: Master of Science in Economics and Business Administration
Programme: Strategic Business Development
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Year: 2026 **Pages:** 82

ABSTRACT:

As AI revolutionizes the world in private and corporate world, organizations try to find ways to navigate the adoption of AI tools and systems while integrating them into existing systems and organizational culture. Adopting AI in an organization is seen as necessary to keep up with the competition and get ahead. Employees are expected to embrace new tools and improve their professional skills. Most importantly organizations want to adopt the new technologies successfully while avoiding common pitfalls and wasting resources. The significant investment in AI in recent years is based on the assumption that it will transform the world, thereby escalating the need to manage this transition successfully. To answer this emerged need, this study explains the most critical elements needed in AI adoption and ultimately AI transformation.

This study is based on a framework developed from a comprehensive literature review on the critical elements in AI adoption. The study was conducted as a qualitative single case-study of an industrial incumbent listed MNC. The data was gathered through interviews of seven people related to the AI adoption process to ensure valuable insights. The study also utilized the Gioia methodology to structure data.

The findings show that the most important factors in AI adoption are aligning the strategy, available and accessible data, compatible technology, robust security, and modern data architecture. The strategy needs to allocate resources and capabilities effectively to enable success. The main findings of the study were the importance of adequate resources, innovative and collaborative organizational culture, and data governance. Inadequate resources coupled with resistance adopting new technologies will significantly hinder the transformation. Moreover, bureaucratic and sluggish data governance will decelerate access to data which is the fuel of AI. The findings also suggest that centralized data governance will decrease the value of data making it more generic and less actionable.

The findings suggest that the case company should cultivate a culture of innovativeness and collaboration among employees and managers. Furthermore, adequate resources, particularly recruiting experts with experience in AI adoption, are imperative. The findings also suggest that a modern approach to data architecture such as data mesh should be adopted to prevent further data governance challenges. Finally, the findings indicate that the democratization characteristics of general-purpose technologies have some differences to more advanced tools.

KEYWORDS: AI, AI transformation, digital transformation, data architecture, AI transformation capabilities, organizational culture, business development

Vaasan Yliopisto**Johtamisen yksikkö**

Tekijä:	Simo Kallioinen	
Tutkielman nimi:	AI adoption capabilities and the role of data architecture in AI transformation	
Tutkinto:	Master of Science in Economics and Business Administration	
Oppiaine:	Strategic Business Development	
Työn ohjaaja:	Tuire Hautala-Kankaanpää	
Valmistumisvuosi:	2026	Sivut: 82

Tiivistelmä:

Tekoälyn mullistaessa maailmaa niin yksityisellä kuin yrityssectorillakin organisaatiot pyrkivät löytämään tapoja hallita tekoälytyökalujen ja -järjestelmien käyttöönottoa sekä integroida niitä olemassa oleviin järjestelmiin ja organisaatiokulttuuriin. Tekoälyn käyttöönottoa organisaatioissa pidetään välttämättömänä kilpailussa mukana pysymiseksi ja kilpailuedun saavuttamiseksi. Työntekijöiden odotetaan omaksuvan uusia työkaluja ja kehittävän ammatillista osaamistaan. Ennen kaikkea organisaatiot haluavat ottaa uudet teknologiat käyttöön onnistuneesti välttämällä yleiset sudenkuopat ja resurssien hukkaamisen. Viime vuosien merkittävät investoinnit tekoälyyn perustuvat oletukseen, että se tulee muuttamaan maailmaa, mikä korostaa entisestään tarpeita hallita tämä siirtymä onnistuneesti. Tähän esiin nousseeseen tarpeeseen vastatakseen tämä tutkimus tunnistaa tekoälyn käyttöönoton ja lopulta tekoälytransformaation kanalta kriittisimmät elementit.

Tämä tutkimus perustuu viitekehukseen, joka kehitettiin kattavan kirjallisuuskatsauksen pohjalta tekoälyn käyttöönoton kriittisistä tekijöistä. Tutkimus toteutettiin laadullisena yhden tapauksen tapaustutkimuksena teollisesta, pörssilistatusta monikansallisesta yrityksestä. Aineisto kerättiin haastatteleamalla seitsemää tekoälyn käyttöönottoon liittyvää henkilöä arvokkaiden näkemysten varmistamiseksi. Lisäksi tutkimuksessa hyödynnettiin Gioia-metodologiaa aineiston jäsentämiseen.

Tulokset osoittavat, että tekoälyn käyttöönoton tärkeimpiä tekijöitä ovat strategian linjaus, saatavilla oleva ja helposti hyödynnettävä data, yhteensopiva teknologia, vahva tietoturva sekä moderni data-arkkitehtuuri. Strategian tulee kohdentaa resursseja ja kyvykkyyksiä tehokkaasti. Tutkimuksen keskeisiä löydöksiä olivat riittävien resurssien, innovatiivisen ja yhteistyöhön perustuvan organisaatiokulttuurin sekä datanhallinnan merkitys. Riittämättömät resurssit yhdistettynä vastustukseen uusien teknologioiden käyttöönottoa kohtaan hidastavat merkittävästi transformatiota. Lisäksi byrokraattinen ja hidas datanhallinta vaikeuttaa pääsyä dataan, joka toimii tekoälyn polttoaineena. Tulokset viittaavat myös siihen, että keskitetty datanhallinta voi vähentää datan arvoa tekemällä siitä yleisluontoisempaa ja vähemmän hyödynnettävää.

Tulosten perusteella kohdeyrityksen tulisi edistää innovatiivisuuteen ja yhteistyöhön perustuvaa kulttuuria työntekijöiden ja johdon keskuudessa. Lisäksi riittävät resurssit, erityisesti tekoälyn käyttöönotosta kokemusta omaavien asiantuntijoiden rekrytointi, ovat välttämättömiä. Tulokset viittaavat myös siihen, että moderni lähestymistapa data-arkkitehtuuriin, kuten data mesh, tulisi ottaa käyttöön uusien datanhallinnan haasteiden ehkäisemiseksi. Lopuksi havainnot osoittavat, että yleiskäyttöisten teknologioiden demokratisoitumiseen liittyvissä ominaisuuksissa on eroja verrattuna kehittyneempiin työkaluihin.

KEYWORDS: AI, AI transformation, digital transformation, data architecture, AI transformation capabilities, organizational culture, business development

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1 Introduction

In recent years artificial intelligence (AI) and especially generative artificial intelligence (GenAI) have achieved widespread popularity. Companies are investing billions in AI development and utilization (Challapally et al., 2025). In Finland 38% of all companies and 68% of companies employing over 100 people used AI in 2025 (Statistics Finland, 2025). The most common use case was analyzing written text followed by image, video, audio, text, and code generation. Globally, up to 78% of companies utilize AI for at least one purpose and 71% are utilizing GenAI based on a McKinsey international survey conducted in 2024 (Singla et al., 2025).

However, as Challapally et al. (2025) found, organizations are in the middle of a “GenAI divide”. According to them, adoption of individual-level productivity tools like Microsoft Copilot is high at over 80% of companies. Yet only 5% have succeeded in achieving measurable financial impact or genuine transformation. Furthermore, Acemoglu (2025) estimates that the increase in total factor productivity (TFP) over 10 years is no more than 0.53%. He argues that productivity gains by AI will stall once the easy tasks are executed with AI. On the other hand, Brynjolfsson et al. (2021) found that often the productivity effects of new transformative technologies are initially underestimated. AI transformation still being a new phenomenon could experience this underestimation. Moreover, Davenport & Srinivasan (2026) found that 90% of companies achieved either a great deal of value or moderate value from their AI investments.

According to Challapally et al. (2025) the biggest obstacle is not the technology itself but a learning gap. Investments into AI in corporations are not successful because the acquired tools do not integrate into existing processes, learn from feedback, or adapt to organizations unique structures. Indeed, many established industrial companies have found it difficult to fully leverage the benefits of AI due to challenges posed by process dependency, legacy systems, as well as culture and mindsets, which limit them from exploiting the full potential of AI solutions (Ritala et al., 2024). Additionally, Furr & Shipilov (2025) believe that many leaders are currently making the same mistakes with AI

adoption as with digital transformation (DT). According to them, leaders at that time did not allocate resources and development targets with careful consideration, resulting in under-resourced and poorly focused projects that failed to yield the expected benefits. Finally, it is clear that leveraging AI in many cases depends on data, particularly internal data can be leveraged to exploit its' potential (Weber et al., 2024). Indeed, Kaplan & Haenlein (2019) define AI as system's capability to understand data accurately, learn from it, and to leverage that knowledge to successfully accomplish tasks. Thus, the learning gap mentioned by Challapally et al. (2025) could also defined as a memory gap since AI systems do learn from past data and inputs but may forget them outside of that session. Gregory et al. (2021) continue that the value of AI is based on the existence of big data. According to them big data is characterized by four characteristics: the immense volume of data, the velocity of its processing, the variety of its sources, and the veracity required to ensure it represents reality. The value of data thus means that the company's ability to produce high quality data, manage it, and process it is critical for the success of their AI transformation (Rana et al., 2022; Ritala et al., 2024).

Ritala et al. (2024) are among the first to have studied the AI transition, viewing it within a larger framework as a continuum of, yet a distinct phenomenon from, digital transformation. Furthermore, they emphasize that industrial companies must develop AI capabilities that are organization-driven rather than solely technical. Yan et al. (2026) add that since AI cannot replicate uniquely human learning capabilities, organizations still need to invest in their workforce's capabilities which are crucial in navigating drastic transformations. Moreover, Khan et al. (2025) continue that the adoption of GenAI is directly linked to a company's innovation capability and performance in the manufacturing industry. Finally, Ruokonen & Ritala (2023) describe companies in traditional sectors such as machinery that aim for gradual AI implementation as asset augmenters. Additionally, they found that these asset augmenters often struggle with implementing AI systems due to legacy systems with limited compatibility, data silos, outdated working practices, and concerns over AI adoption.

Success requires placing AI within the company's unique historical and operational context and processes. The objective of this thesis is to examine how the case company can bridge the GenAI Divide described by Challapally et al. (2025) with academic and empirical research. The thesis identifies current obstacles like organizational culture, data dependency, and technological readiness including integration of legacy systems to AI using theoretical frameworks by Ritala et al. (2024) and Jöhnk et al. (2021).

The scientific significance of this master's thesis is also directly connected to the need identified in the article by Ritala et al. (2024, pp. 17): "A fuller empirical understanding of how different kinds of industrial incumbent firms heavy with legacy assets (i.e., "asset augmenters"; Ruokonen and Ritala, 2023) deal with the inevitability of AI transformation would be of great value".

The case company represents the "asset augmenter" mentioned by Ruokonen & Ritala (2023) and is therefore particularly suitable as the subject of this research. This topic is crucial to ensure that companies do not fall behind in development and achieve the desired results from their investments.

Thus, the purpose of this thesis is to tap into this research opportunity by answering the following research question.

How does an incumbent industrial firm orchestrate AI transformation through strategic alignment of AI adoption capabilities and data architecture?

The thesis contributes to literature in three ways. Firstly, it will give insights into an incumbents firm's AI transformation in a traditional industry which has been scarcely researched so far as noted by Ritala et al. (2024). Second, it underscores the importance of recruiting experts not only as developers but also as drivers of change. Finally, the study complements the existing literature on data and data architecture. Particularly,

adding to the literature on the importance of data governance and modern approaches to data architecture such as data mesh.

This thesis is structured as follows. Firstly, the introduction explains the study's purpose, theoretical motivation for the study, and the research question. In the second section, the literature related to AI, AI transformation, and data architecture are analyzed in depth. The second section also includes a theoretical framework for the study. In the third section the methodology of the study is introduced, and the following section analyses the findings from the data collection. Finally, the fifth section synthesizes the main findings of the thesis including theoretical and empirical contributions as well as limitations of the thesis and avenues for future research.

2 Theoretical background

2.1 Artificial intelligence

In recent years it has been quite unavoidable to not hear conversation about AI or interact with it yourself. Companies related to developing AI services and products or hardware like graphics cards have seen their stocks rise to all-time highs. The best example of this may be Nvidia, which experienced their stock skyrocket 173% just in 2024 alone (*Nasdaq.com*). Although all the potential of AI has yet to be utilized or even discovered, companies and governments are investing in it heavily. One estimate states that U.S. companies spent around \$37 in 2025 for GenAI alone (Davenport & Srinivasan, 2026). It is clear that AI has seen a drastic increase in interest by companies and governments but also in research (Sardanelli et al., 2023). Dwivedi et al. (2021) argue that AI has the same transformative potential as industrial revolution had by augmenting and replacing human tasks in a wide range of applications. Mirroring this enthusiasm, businesses are committing substantial financial resources toward AI integration.

The origins of AI can be traced to 1950s when Alan Turing published his paper “Computing Machinery and Intelligence” where he described how to create intelligent machines and how to test their intelligence (Hoffman et al., 2022; Nguyen et al., 2022). More recently, Kaplan & Haenlein (2019) define AI as system’s capability to understand data accurately, learn from it, and to leverage that knowledge to successfully accomplish tasks. Most research agrees with this definition of AI (Dwivedi et al., 2021; Fui-Hoon Nah et al., 2023). The definition of AI has certainly changed from the 1950s as new technologies have emerged. The contemporary view of AI has gotten more complex in recent years as new innovations on where and how AI could be used. Consequently, Nguyen et al. (2022) explain that one cannot easily define AI as the term encompasses multiple underlying technologies that have changed over the years. In recent years the discussion about AI has been mainly focused on GenAI (Fui-Hoon Nah et al., 2023). Finally, machine learning (ML) is an important part of AI. Hoffman et al. (2022) define ML as computer techniques that use large data sets to generate deductions using algorithms and probabilities.

Feuerriegel et al. (2024) argue that GenAI encompasses a variety of computational methods designed to synthesize novel and contextually coherent content including text, images, and audio by identifying and replicating patterns derived from extensive training datasets. Moreover, they define GenAI as a system that embodies a generative modeling approach implemented using a machine learning architecture, such as a deep neural network, enabling the creation of fresh data samples derived from learnt patterns. Finally, a GenAI system includes complete infrastructure, comprising the model, data processing, and user interface component. According to Fui-Hoon Nah et al. (2023) GenAI has various applications in different industries such business, education, healthcare, and content creation. For example, businesses can leverage it in marketing, operations, finance, and multiple other functions.

Furthermore, a key concept that is related to AI and especially GenAI is a large language model (LLM) (Feuerriegel et al., 2024). According to Feuerriegel et al. (2024) it refers to neural networks for modeling and generating text data that commonly embodies three characteristics. First, a large scale sequential neural network architecture, typically transformers employing an attention mechanism. Second the network is pre-trained with self-supervision to learn natural language. Third, the pre-training is completed on massive datasets such as Wikipedia and eventually they can be fine-tuned using specific datasets and unique tasks. Recently LLM's like GPT-5 have been trained using billions of parameters. (Feuerriegel et al., 2024; Vaswani et al., 2017; Zhao et al., 2025).

GenAI, however, has challenges as well. Fui-Hoon Nah et al. (2023) lists five major categories where GenAI has challenges in: ethics, technology, regulations and policies, economy, and human-centered AI collaboration. The main ethical concerns regarding AI include harmful content, bias, over-reliance, misuse, privacy, and security. Technology challenges refer to the limitations of GenAI which include data quality, hallucinations, and explainability. Regulation and policy challenges stem from copyright and governance questions. GenAI may also cause labor market issues when jobs can be replaced with AI

leading to a disruption of industries. Economic issues also include income inequality and monopolies. Finally, human-centered AI collaboration refers to raising concern that AI will replace humans instead of collaborating with them.

In manufacturing companies in recent years AI has accelerated their digital transformations as it can streamline operational processes and facilitate decision-making in addition to automation (Yu et al., 2024). Moreover, enabling AI in manufacturing systems the company can effectively adapt to dynamic market conditions and achieve more efficient production (Yu et al., 2024). According to Davenport & Ronanki (2018) there are three types of AI: process automation, cognitive insight, and cognitive engagement. Process automation refers to automating digital and physical tasks, cognitive insight refers to machine learning and data analytics like sales predictions and personalized advertisements, and finally cognitive engagement refers to natural language processing and machine learning like chatbots. The most common AI type is process automation then cognitive insights, and finally cognitive engagement.

Below in Table 1 there are 10 different AI techniques and multiple application areas defined in the literature review of AI by Sarker (2022).

Table 1. A summary of AI tasks and methods in several popular real-world applications areas (Sarker, 2022).

AI techniques	Application areas
Machine learning	Healthcare Cybersecurity Smartcity Recommendation systems
Neural network and deep learnig	Healthcare Cybersecurity Smart cities Smart Agriculture Business and Finance Virtual Assistant Visual Recognition
Data mining, knowledge discovery and advanced analytics	Education Business Cybersecurity Diagnostic analytics Prescriptive analytics
Rule-based modeling and decision-making	Intelligent systems Healthcare Recommendation system Smart systems
Fuzzy logic-based approach	Healthcare Agriculture Cybersecurity Business
Knowledge representation, Uncertainty reasoning and Expert system modeling	Smart systems cloud computing cybersecurity Mobile expert system
Case-based reasoning	Healthcare Smart cities Smart Industry Recommendation Systems
Text mining and natural language processing	Sentiment analysis Business Cybersecurity Healthcare
Visual analytics, computer vision and pattern recognition	Healthcare Computer vision Visual Analytics
Hybrid approach, searching and optimization	Mobile application Recommendation systems Sentiment analysis Business Cybersecurity

2.2 AI transformation

Ritala et al. (2024) view that a new phenomenon created by digital transformation and AI is AI transformation. Thus, AI transformation is a continuum of digital transformation sharing many similarities while developing new distinct characteristics. However, they note that AI transformation is a new phenomenon and not thoroughly investigated as of

now. Although, they view AI transformation as a separate phenomenon to digital transformation it is likely a continuation of digital transformation and would be considered a more developed form of digital transformation. Especially, considering that digital transformation is most commonly defined by Vial (2019, pp. 118) as: "A process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies". The transformative force of AI, however, cannot be ignored and thus AI specific measures are needed. Under this definition AI transformation most definitely can be categorized under digital transformation even though it is in some ways different as Ritala et al. (2024) explain. They also remind that what companies have done in their digital transformations remain applicable in the case of AI transformation. AI transformation is, however, the new frontier for companies to build progress on.

As with digital transformation, in AI transformation the fear of losing jobs is still prevalent (Favoretto et al., 2022; Ritala et al., 2024). However, with the increased tasks AI may perform over previous digital tools there is a difference between DT and AI in how the job may change. Budhwar et al. (2023) suggest that with the rise of GenAI, even high-skilled positions may change due to GenAI's ability to create content and mimic human thought processing. Now more than ever before AI can replace professions that are easily automated. Still, adopting AI is labor intensive and often a long process which will happen gradually rather than in fast displacement events (Challapally et al., 2025). The fear of losing jobs or the scope of the work greatly changing will likely create barriers which can be overcome with the right organizational culture and leadership. Implementing a chat bot can be quite straightforward but replacing an engineer with an AI solution is still uncommon and unfavored. This is corroborated by Challapally et al. (2025), who found that only 10% of people would assign complex projects such as multi-week work or client management to AI. Thus, organizations must focus on implementing AI in specific processes to truly enhance productivity. Furthermore, Uren & Edwards (2023) argue that AI transformation is different from previous phenomena and organizations must determine how much responsibility should be given to AI systems. Recently, Srinivasan

et al. (2026) found that rather than only eliminating jobs, GenAI creates demand in augmentation-prone roles. They suggest that companies reskill and upskill their workforce which is also supported by (Jaiswal et al., 2022).

The challenges noted by Ritala et al. (2024) and Dwivedi et al. (2021) have some similarities to digital transformation but are increasingly AI-centric. Dwivedi et al. (2021) lists seven AI specific challenges: social, economic, data, organizational, technological, political, and ethical. Social challenges have been identified as a potential barrier to AI adoption due to fear of losing jobs, reluctance to work with AI tools, and insufficient knowledge about AI. Economic challenges stem from the need to invest significant resources in AI and changes to working practices. Data challenges such as format and quality and technology challenges such as lack of transparency and data architecture, are particularly important to address in incumbent industrial firms where data is siloed and existing systems integrate poorly (Campbell et al., 2020; Dwivedi et al., 2021; Ruokonen & Ritala, 2023). According to Dwivedi et al. (2021) the lack of strategy in AI adoption could also affect core operations causing organizational challenges. Finally, political and ethical challenges include judicial and regulatory issues along with liability concerns All these challenges need to be addressed when adopting AI in an organization.

2.3 AI adoption

Adopting AI in an organization requires identifying the triggers and barriers. Ritala et al. (2024) divide antecedents of AI adoption into two categories: perceptual triggers and barriers, and functional triggers and barriers of AI utilization. They define perceptual triggers as the perceived importance of data and digital technology in the managerial process or a data-centric mindset. Functional triggers encompass the operational processes executed by technical roles, such as data scientists. Perceptual barriers are factors such as limited managerial and organizational understanding of data and AI, also individual data literacy and fear of losing jobs are considered perpetual barriers. Finally, functional barriers such as existing products or current level of technology can hinder AI adoption.

While AI comes with a multitude of possibilities many companies are facing difficulties in integrating the new tools and changing the organizational culture to embrace new ways of working (Ritala et al., 2024). Implementing AI presents incumbent organizations with complex socio-technical challenges, often resulting in high failure rates similar to the high failure rates that digital transformation had previously (Challapally et al., 2025; Ramesh & Delen, 2021).

According to Siau & Wang (2019) a fundamental barrier is the enigmatic or "black box" nature of AI systems; unlike traditional software, these systems are often non-transparent and autonomous, making it difficult for people to understand the technology or predict outcomes, which complicates project planning and internal communication. The "black box" nature of sophisticated AI often leads to misplaced trust; because the inner workings are opaque, users tend to accept the output as fact, swayed by the impressive capabilities of the technology itself (Weber et al., 2023). von Eschenbach (2021) goes as far to say that the black box nature of AI means that AI itself cannot be trusted but rather people need to evaluate whether the people designing and implementing these systems can be trusted. One solution to solve this trust issue is explainable AI (XAI). XAI is intended to create more explainable models which still facilitate for high performance (Barredo Arrieta et al., 2020). However, XAI still has many challenges which hinder the ability to implement it in scale such as new AI models with billions of parameters, elucidating the main concepts, evaluating XAI methods and explanations, and creating human-understandable explanations (Barredo Arrieta et al., 2020). The enigmatic nature results in decreased trust and therefore could lead to an evolution of AI where it is without guidance or control (Siau & Wang, 2019). This is aggravated by a critical dependency on data, where issues such as fragmented legacy data, poor quality, and the continuous need to update models due to environmental changes create significant management burdens (Weber et al., 2023).

Beyond technical constraints, incumbents face strategic and structural barriers, including the difficulty of estimating AI's business impact, identifying scalable use cases, and

overcoming path dependencies associated with rigid legacy systems and processes (Ritala et al., 2024). Furthermore, an AI transformation requires substantial investment in resources and capabilities, often leading to excessive costs, while encountering cultural resistance from a workforce fearful of job replacement (Weber et al., 2023). Finally, Ritala et al. (2024) suggests that the development of AI capabilities in incumbent industrial firms is deeply embedded in the organizational history and asset base where existing processes are barriers to AI adoption. Thus, the scalability is typically more limited than in other firms.

To successfully leverage AI, organizations must develop a complete set of AI capabilities, defined as the ability to choose, coordinate, and leverage specific AI-based resources (Ghosh, 2025). According to Ghosh (2025) these capabilities are commonly categorized into three sections: first **tangible resources** such as data, technology, and basic infrastructure. Second, **human skills** encompassing both technical expertise and business insight. Third, **intangible resources** such as inter-departmental coordination, organizational change capacity, and risk tendency. In industrial contexts, these capabilities are often implemented as data pipeline capabilities to secure data flow, algorithm development capabilities to create contextualized solutions, and AI democratization capabilities to make AI accessible to the wider workforce (Sjödín et al., 2021). Ghosh (2025) argues that tangible resources particularly data capabilities including the acquisition, quality, and modern data architecture can be a significant competitive advantage for the organization. Other tangible resources such as technology and basic infrastructure are focused on democratization of AI analytics for a wider workforce through employee empowerment and having cloud-based solutions. Furthermore, Ghosh (2025) note that technical experts with AI specific skills including programming and mathematics are essential in AI adoption. The experts should also develop robust business skills by collaborating with business leaders and product engineers. Finally, intangible resources such as change management and risk mitigation can greatly affect AI capability development and data-driven decision making. On the other hand, having a high organizational adaptability including can be driver of AI adoption and thus be a competitive advantage.

2.3.1 Data requirements

Data is the single most important factor enabling AI adoption. Accurate, available, secure, and exploitable data is fundamentally crucial to leverage AI (Ghosh, 2025). According to Mikalef & Gupta (2021) 20% of organizations do not fully comprehend the data requirements to leverage AI and the infrastructure needed to house and move data across the organization. Furthermore, they say that the primary issue for failing AI initiatives was the failure to integrate legacy systems and data which was also corroborated by Challa-pally et al. (2025). Regarding IT infrastructure, organizations need to focus on three capabilities according to Jöhnk et al. (2021): data storage such as data warehouses and lakes, networking which enables to access, process, and move data, and strong computing power to handle workloads created by AI.

The data that organizations collect are commonly categorized into two types internal such as ERP data and external data such as competition analysis (Mikalef & Gupta, 2021). Internal data includes all the data which is created by the organization's internal processes. Previously, internal data was utilized more but recently the amount of external data, data which is not directly linked to the firm's operation, has enabled more opportunities to gain competitive advantage. The amount of data however, comes with challenges in managing it and ultimately leveraging it. Jöhnk et al. (2021) categorize data related requirements for AI adoption as: data availability, quality, accessibility, and flow. **Data availability** refers to relevant amount and type of data. They point out that there is a fundamental difference in utilizing structured data that is stored in relational tables and unstructured data such as images. Furthermore, as Mikalef & Gupta (2021) point out that the availability of big data has been one of the catalysts in AI transformation and it is critical for training AI algorithms. Also Sjödin et al. (2021) note that obtaining and combining internal and external data can be used to train more sophisticated models.

According to Jöhnk et al. (2021) **data quality** is defined by the specific dimensions that determine its suitability for end users. By improving the quality dimensions, the AI

readiness increases (Jöhnk et al., 2021). Mikalef & Gupta (2021) found that a key issue is ensuring that only high-quality data is used to train AI models. Thus, they suggest that organizations should ensure that the data used in training the models or analyzed with AI should be cleansed to avoid errors and bias. Ghosh (2025) found that any organization involved in AI analysis should have efficient data cleansing capability along with data labeling, annotation, and classification capabilities. Consequently, the data inputted into an AI system will directly correlate with the output (Sjödín et al., 2021). Now perhaps the concept of Garbage in, Garbage out (GIGO) is more relevant than ever.

Data accessibility refers to the prompt and easy access to data which is facilitated by access management (Jöhnk et al., 2021). Data accessibility can be improved by utilizing modern data architecture solutions such as data lakes, lakehouses or data mesh, instead of silos (Dolhopolov et al., 2024; Janssen et al., 2024; Jöhnk et al., 2021).

Finally, **data flow** enables the movement of data from its source to its use. Consequently, companies need to consider how they carry out their data infrastructure. Thus, building a robust data foundation is imperative since the requirements for using that data for AI are relatively high (Campbell et al., 2020). Furthermore, many businesses, especially incumbent, experience data silos which means that the data is isolated in one IT system or department leading to challenges in data availability, accessibility, flow (Campbell et al., 2020; Ruokonen & Ritala, 2023). In one case a European bank found that its data-management strategies were hindering their AI transformation which lead it to unify their data architecture and management, ultimately enabling a successful transformation (Fontaine et al., 2019).

Finally, Uren & Edwards, (2023) argue that data drives AI adoption, requiring the seamless alignment of an organization's people, processes, and technology (Figure 1). Furthermore, they found that successful AI adoption requires data to be first understood, available, and managed which is widely agreed upon in literature (Ghosh, 2025; Gregory et al., 2021; Kaplan & Haenlein, 2019).

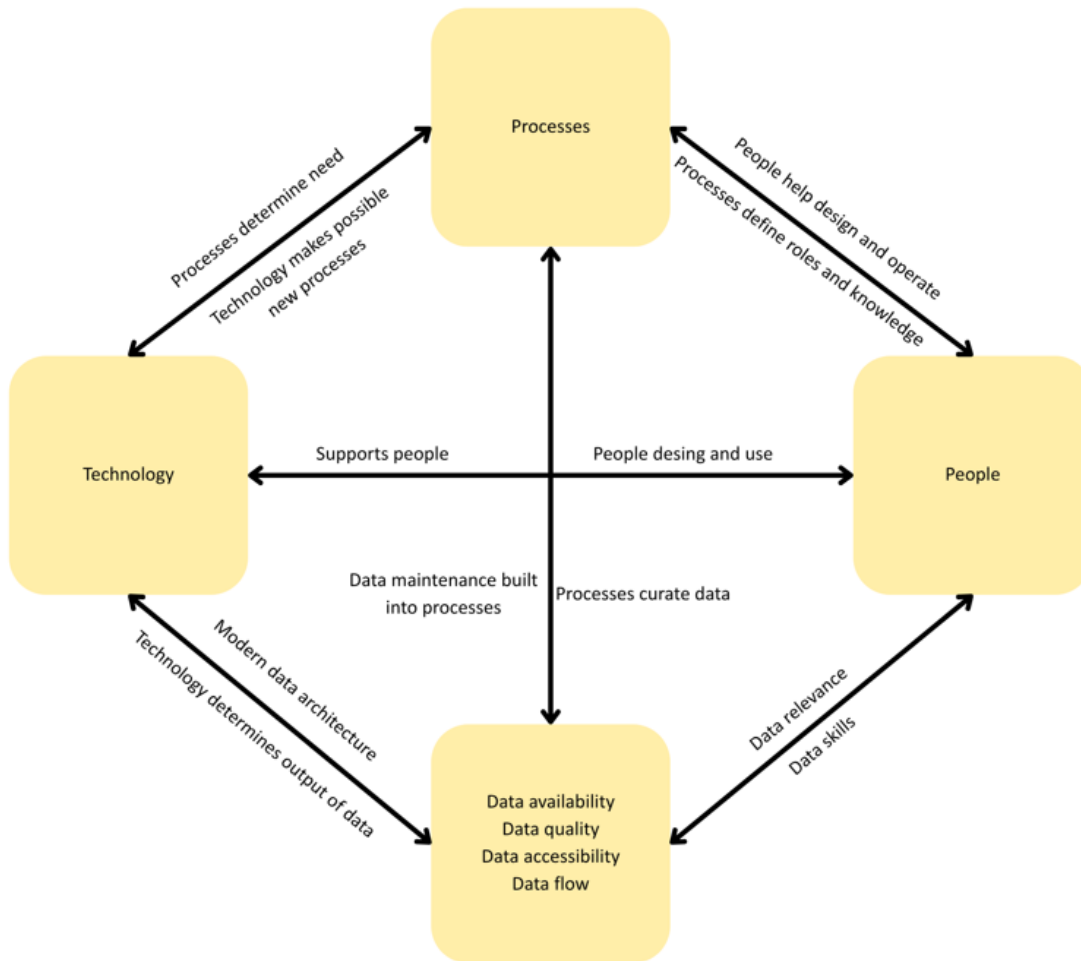


Figure 1. People, Process, Technology and Data adapted from (Uren & Edwards, 2023)

2.3.2 Strategic alignment

Strategic alignment refers to strong top management support including the approving new initiatives and technologies, allocating resources, and change management towards a common vision about the value of the transformation (Solaimani & Swaak, 2023). Jöhnk et al. (2021) divide strategic alignment into five categories: AI business potentials, customer AI readiness, top management support, AI process fit, and data-driven decision-making (DDDM). AI-business potentials describe how effectively an organization can adopt and scale AI technologies. They agree with Challapally et al. (2025) that

companies need to explore novel and purposeful AI use cases. In turn, customer AI readiness refers to knowledge and acceptance of AI from the customer side.

As illustrated in Figure 2 by Jöhnk et al. (2021) there are a number of factors that are needed in AI transformation. Along with data; management, strategic alignment, resources, knowledge, culture, technological capabilities, and leadership are among the factors that influence an AI transformation (Ghosh, 2025; Jöhnk et al., 2021; Ritala et al., 2024).

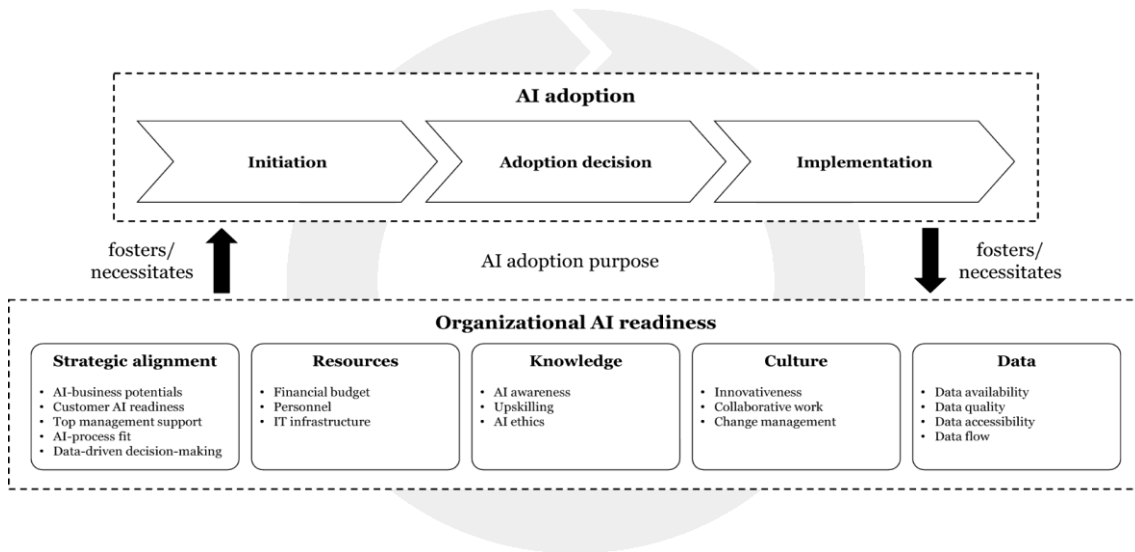


Figure 2. Integrating AI Readiness in the AI Adoption Process (Jöhnk et al., 2021).

Li et al. (2021) note that deploying AI requires top management to communicate objectives and the value of AI. They continue that having a chief information officer is recommended since they can provide technical knowledge and communicate effectively with decision makers to shape the AI adoption process. Moreover, Chong & Chan (2012) confirm that top management support is one of the most important determinants of organization's IT implementation. They also found that top management support is particularly important in the early stages of adoption and decreases as the process develops. Finally, Jöhnk et al. (2021) remind that AI adoption can only succeed with strong top management support by providing an organization wide signal.

AI process fit as defined by (Jöhnk et al., 2021) is the linkage between AI strategy and its processes. The importance of this finding purpose fit AI tools and integrate them into workflows was also highlighted by (Challapally et al., 2025; Chatterjee et al., 2021). Jöhnk et al. (2021) suggest that DDDM which refers to using insights based on data analytics to make decisions leads to performance improvement and increased AI readiness which is key in AI adoption. Peres et al. (2020) notes that DDDM enabled by AI can increase profitability in manufacturing processes while also being more sustainable and efficient. Furthermore, Fosso Wamba et al. (2024) found that AI capabilities impacts the firm performance while a data-driven culture bridges the relationship between AI capabilities and firm performance. Finally, according to Dutt et al. (2026) firms that have been successful in AI transformation by not just improving processes but reinventing how to create value have experienced EBITDA gains up to 25%.

Cultivating a receptive environment for technologies like AI is often hindered by the slow pace of cultural change (Yu et al., 2023). Thus, top management need to foster a creative and innovative organizational culture with dedicated AI champions to experience the transformation collectively across the organization (Yu et al., 2023). Mikalef & Gupta (2021) emphasize that managers must establish organizational structures and cultures that prioritize cross-departmental coordination, mutual understanding, and cooperation specifically regarding the seamless flow of information and data. Finally, Jöhnk et al. (2021) suggest that the three most important factors for AI ready organizational culture are: **Innovativeness** meaning experimentation, risk-taking, and diverse problem solving, **Collaborative work** which describes the degree to which different departments communicate and work together, and **Change management** which includes communication towards employees to reduce resistance to change. Mikalef & Gupta (2021) adds that the culture should also include collective goals and shared resources.

2.3.3 Technology

Technology is also crucial for AI adoption and most literature see it as a separate category from data (Ghosh, 2025; Jöhnk et al., 2021; Uren & Edwards, 2023). Mikalef & Gupta

(2021) note that radically new technologies are needed to store, process, transfer, and secure data. Thus, they call on organizations to invest in storage infrastructure that supports large volumes of data in different formats and is scalable. According to Enholm et al. (2022) three things are needed to successfully deploy AI in an organization: computing power infrastructure, algorithms, and rich data sets. They continue that often these resources are not feasible to have on-site and thus many companies rely on cloud-based solutions provided by other companies. For example, more than 90% of Fortune 500 companies use Microsoft AI (Microsoft, 2026). Moreover, they often complement their services with other providers such as Snowflake which provides services to 766 companies of the Forbes Global 2000 list companies (Snowflake, 2026). The key factor in the technology itself is whether the employees find it easy and intuitive to use (Chatterjee et al., 2021). If the users find the technology difficult to use, they will perceive it as useless and laborious. Furthermore, if existing technologies are compatible with new technologies the users are more likely to adopt them (Chatterjee et al., 2021). Consequently, finding purpose-fit solutions that integrate well, learn, remember, and adapt over time is crucial for a successful AI transformation. However, Enholm et al. (2022) notes that how complexity of an AI systems affects the value creation is still not thoroughly investigated.

2.3.4 People and resources

Mikalef & Gupta (2021) notes that changing the existing technology along with culture are the most important barriers in AI adoption. This is particularly prevalent in incumbent firms (Ritala et al., 2024). Furthermore, Mikalef & Gupta (2021) suggest that a culture that embraces risks and radical actions is a crucial part of culture in AI adoption. Fostering a culture of innovativeness is based on the amount and pace of adaptability that employees possess (Jöhnk et al., 2021). To make the employees perceive a new technology easy and intuitive as recognized by Chatterjee et al. (2021) organizations must have competency to use that technology. Through the emergence of Big Data, data-driven culture has become increasingly important for AI transformation (Uren & Edwards, 2023). Furthermore, success necessitates data to be understood, available, managed

according to (Uren & Edwards, 2023). As stated by Enholm et al. (2022) innovative cultures are characterized by enthusiasm and willingness to experiment with novel ideas such as AI. Therefore, employees who are willing to expand their knowledge and innovate constantly are more likely to support the adoption of AI.

According to Banks et al. (2024) reaping the productivity and efficiency benefits of AI necessitates intentional and functional collaboration between people and technology. Furthermore, they agree with Chatterjee et al. (2021) that the best human-AI collaboration happens when workers understand the systems nature and purpose, and develop skills to use it. Moreover, higher levels of satisfaction with technology lead to increased job satisfaction and productivity. These factors highlight the emphasis on effective communication by top management and finding purpose fit technologies to reduce repetitive tasks and wasted time. Fui-Hoon Nah et al. (2023) point out that human-AI collaboration is key to addressing challenges and seizing opportunities created by GenAI.

To prevent dissatisfaction by workers towards AI systems, it is important not to overpromise the capabilities of technology (Zirar et al., 2023). Success regarding people is not only dependent on organizational culture and perceptions of AI, but also upskilling workers (Jaiswal et al., 2022). Jaiswal et al. (2022) categorize skills into three categories on how important they are to upskill: technological, cognitive, and evergreen. Technological skills are data analysis and digital skills. Data analysis and digital skills according to Jaiswal et al. (2022) enable working with new technologies to enable AI while making data-driven decisions. Moreover, cognitive skills are essential to upkeep competence and critical thinking when AI can complete more repetitive tasks. Critical thinking enables employees to make better data-driven decisions. Additionally, continuous learning is crucial for employees to stay relevant. Finally, evergreen skills refer to an individual's skills that are needed regardless of time such as leadership, interpersonal, and communication. These skills are crucial for the individual's success now and in the future.

Henkel et al. (2020) notes that ideally AI augments rather replace humans resulting in a symbiosis where efficiency and productivity increases. Furthermore, Zirar et al. (2023) delineate this symbiosis as a multidimensional requirement, encompassing technical proficiency, interpersonal competencies for collaborative human engagement, and the conceptual capacity to visualize AI integration within the organizational framework. Finally, companies need to invest in their own people by upskilling and reskilling them proactively through trainings and education (Zirar et al., 2023). Ghosh (2025) suggests that organizations should develop proper training and empowerment programs to democratize AI for all business users in their regular functions.

Beyond the previously discussed factors, successful AI adoption also demands appropriate resources (Chatterjee et al., 2021; Enholm et al., 2022; Jöhnk et al., 2021; Yu et al., 2023). According to Mikalef & Gupta (2021) resources are tradable and non-specific assets of the organization and capabilities are non-tradable abilities unique to the organization that are used to deploy the resources. They continue that an organization's capabilities are dependent and developed based on the availability resources. Therefore, effective utilization of resources is paramount in AI adoption to leverage AI and establish it as a capability. Madan & Ashok (2023) subscribe to this view and point out that organizational capabilities are distinct from resources and add that organizations function as a collection of resources and capabilities that are used in value creation by leveraging their resources. It is the responsibility of top management to allocate the resources appropriately which directly affects the velocity of AI adoption (Yu et al., 2023). Jöhnk et al. (2021) identify three primary resources essential for AI adoption: financial budget, specialized personnel including both business analysts and AI specialists like data scientists, and a robust IT infrastructure capable of providing data storage, networking, and scalable computing power.

2.3.5 Privacy and regulations

The fact that AI has become a part of everyday life and its use will only increase in the near future asks the question whether regulation is needed and how to leverage AI

ethically (Haenlein & Kaplan, 2019; Meskó & Topol, 2023). According to Díaz-Rodríguez et al. (2023) trustworthy AI is based on three core factors: legislation, ethics, and reliability. To achieve these core factors, they list seven requirements: human oversight, technical reliability, transparency, privacy and data governance, fairness, wellbeing, and responsibility. In essence the three core factors working in harmony ensure that AI systems comply with the legislation, adhere to ethical standards, and work reliably without causing unintended harm. Furthermore, the technical requirements establish a framework to ensure that systems are human-centric, safe, and legally compliant through their life cycle. AI developers and AI users are responsible for the system's decisions and monitoring it for errors and bias and proactively removing them (Radanliev et al., 2024). Thus, to achieve trustworthy AI as suggested by Díaz-Rodríguez et al. (2023) and minimize the potential negative impacts of AI adoption, the developers take responsibility of the integrity of the AI systems while managers and leadership take responsibility of ethical and responsible use of AI in the organization (Radanliev et al., 2024; Spisak et al., 2023). Kumar et al. (2025) note that the impact of AI adoption on firm performance is greatly affected by ethical leadership and responsible use of AI. Finally, data privacy and adhering to regulations have direct implications on firm performance (Quach et al., 2022)

Shneiderman (2020) offer their governance structure (Figure 3) to achieving human-centered AI or symbiosis as proposed by Henkel et al., 2020; Zirar et al. (2023). The inner core consists of reliable systems including sound software engineering practices. The second layer is the safety culture through efficient management strategies. Often vulnerabilities to cyber security are the result of user's poor decision making (Rodrigues et al., 2022). Consequently, awareness of cyber security is important in an organization. Advising which systems are safe to use and what kind of information can be shared in which system is crucial. Finally, the outer layer includes the trustworthy certification by external reviews.

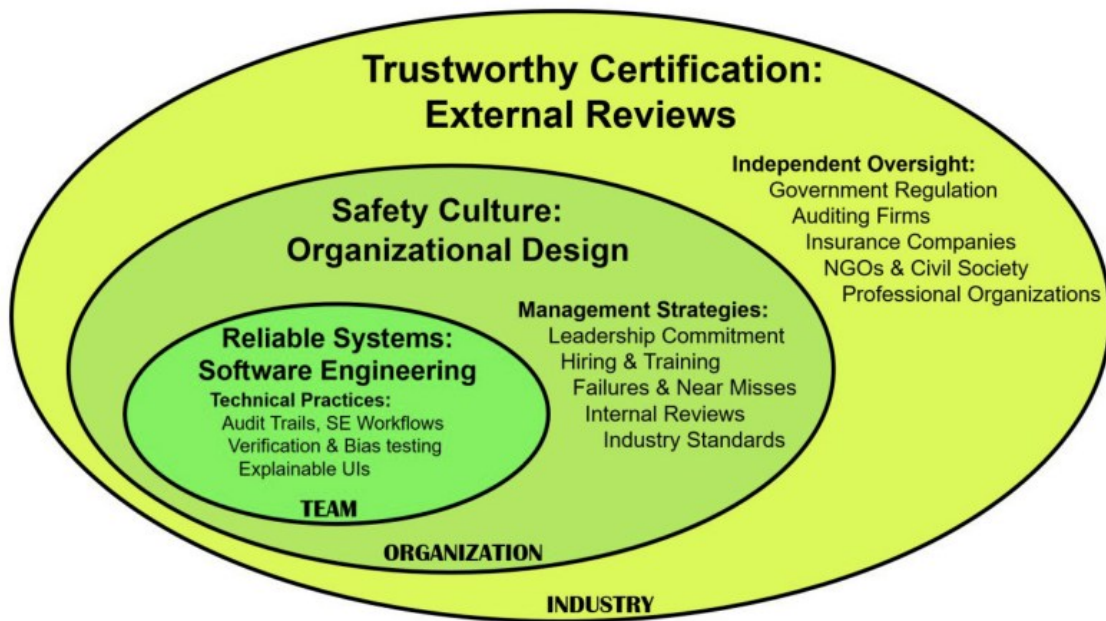


Figure 3. Governance structures for Human-centered AI (Shneiderman, 2020).

Firms also need to be aware of the important challenges that come with privacy and regulation, particularly in EU the General Data Protection Regulation (GDPR) directs how firms manage customer's data (Campbell et al., 2020). Moreover, some AI industry leaders and government policymakers fear that regulation would only limit innovation but examples from other industries have shown that carefully executed regulations may even accelerate innovation (Shneiderman, 2020). There are however differences in regulatory landscapes, for example in the EU lawmakers have distressed the need for regulation and meanwhile in the U.S the government has advocated for voluntary consensus standards within the industry (Shneiderman, 2020). The differing policies internationally exacerbates this issue even further and create challenges for international companies (Aldoseri et al., 2023; Shneiderman, 2020).

Finally, regarding data, firms need to address the security and privacy issues that dealing with large amounts of data comes with, including external and internal data (Aldoseri et al., 2023). To ensure data security firms must choose their external partners carefully, particularly with AI which will need wide access to company data to provide accurate analysis.

2.4 Data architecture

The huge increase in innovative technologies such as AI, IoT, and cloud computing has further escalated the need for robust and adaptable data architectures (Espinoza et al., 2025). These technologies create such a high volume of data in increasingly different formats which challenges the capabilities of conventional systems such as data warehouses which rely on structured data (Espinoza et al., 2025). Thus, selecting a fitting data architecture has become critical to leverage these new technologies. According to IBM (2025) data architecture describes how data is managed as it moves from its raw source to its final business utility. Essentially, data architecture serves as the organizational framework for the entire data lifecycle, governing the ingestion, processing, and distribution of information to ensure a coherent, strategic flow across the organization. There are multiple data architecture frameworks from which TOGAF, and Zachman framework are the most common (Bondar et al., 2017; Databricks, n.d). According to Kaidalova et al. (2018) The Open Group Architecture Framework (TOGAF) is the industry standard in enterprise architecture (EA). Data architecture is one part of TOGAF. Essentially TOGAF is a high-level approach to design with two critical elements: the architecture development method (ADM) and architecture content framework (ACF) (Kotusev, 2018). ADM explains what needs to be done and ACF explains what it should look like once complete. Zachman framework on the other hand uses a matrix of six questions to guide enterprise architecture: what, how, where, who, when, and why (Bondar et al., 2017). Essentially, they complement each other by using Zachman as a checklist and TOGAF as roadmap for execution.

As data has become increasingly important and leveraging AI requires quality data architecture, companies are compelled to evaluate their data housing methods. Currently there are three primary methods for housing data: data warehouses (DWH), data lakes (DL), and data lakehouses (DLH) which all have their strengths and weaknesses based on their usage (Janssen et al., 2024). The storage architectures have evolved over time from data warehouses to the most recent solutions data lakehouses and fabric. As noted by Gieß & Hutterer (2025) significant changes are expected in data management that are

more adaptable and flexible with increased privacy and security to meet the needs of new AI systems.

A data warehouse is a traditional, centralized data housing architecture that stores structured data from various sources mainly for analysis, reporting, and business intelligence (Janssen et al., 2024; Mezzoudj et al., 2025). According to Mezzoudj et al. (2025) It is characterized by four main features: subject orientated, integrated, time-variant, and non-volatile. This means that the data is organized by subject, standardized and combined into the warehouse. The data is also stored over extended periods allowing for trend analysis and once loaded it is not frequently updated ensuring stability and reliability. Mezzoudj et al. (2025) continue that the architecture of a data warehouse typically has a three-tier model: a bottom tier as the database server, a middle tier that reorganizes data into a multidimensional format, and a top tier for SQL analytics and business intelligence tools. It relies heavily on Extract, Transform, and Load (ETL) processes to clean and organize raw data into a specific structure before saving (Janssen et al., 2024; Mezzoudj et al., 2025). This method is known as a “schema-on-write”, meaning the data must be in a specific format when saving to the database (Janssen et al., 2024; Mezzoudj et al., 2025).

Moreover, data warehouse architecture offers extremely fast query performance and is optimized for analyzing structured data (Janssen et al., 2024; Mezzoudj et al., 2025). Data warehouses also offer other technical strengths such as support for ACID (atomicity, consistency, isolation, and durability) transactions, strong security, strict data quality frameworks, and advanced metadata management. However, data warehouse architecture is not without weaknesses. Since data warehouses lack the capability to manage semi-structured or unstructured data, they are not ideal for contemporary workloads such as AI or real-time data streaming. Finally, because storage and processing capacities are often tightly connected, scaling becomes complex and expensive, leading to high initial implementation and ongoing maintenance costs. (Janssen et al., 2024).

Whereas data warehouses offer rigid structure, a data lake is highly flexible and is designed to hold massive amounts of raw data in its native format (Mezzoudj et al., 2025). Data lakes can handle diverse data including structured, semi-structured, and unstructured such as images and text without complex preprocessing and transformation (Mezzoudj et al., 2025). Instead of the ETL process used data warehouse architecture, data lake uses a “schema-on-read” approach (Janssen et al., 2024). This means that raw data is poured into the lake quickly and cost-effectively, and the schema is only applied when a user specifically queries the data for analysis (Janssen et al., 2024). According to Janssen et al. (2024) to maintain order, data lakes store data in four distinct zones: bronze, silver, gold, and governing zones. Raw data is stored in bronze, intermediate meaning cleaned and processed data in silver, trusted and verified data in gold, and the governing zone that handles security measures and metadata. This divided structure makes data lakes exceptionally scalable, agile, and much better suited for modern workloads such as AI and real-time streaming analytics unlike the older warehouse model (Janssen et al., 2024; Mezzoudj et al., 2025).

However, data lakes are not without weaknesses either. According to Janssen et al. (2024) key issue is data governance and metadata management over raw data. Another weakness is security, which is also caused by the varying formats of data (Janssen et al., 2024). Consequently, the lack of metadata management and poor security leads to an increased risk of turning the lake into a data swamp (Mezzoudj et al., 2025). As there is no control over the data format poured into the lake, there is possibility that data is corrupt or never used and still stored (Janssen et al., 2024). Finally, data lake’s performance is inconsistent due to varying formats and ELT processing (Janssen et al., 2024).

Combining the benefits of both data warehouses and data lakes is a recent hybrid approach, the data lakehouse (Schneider et al., 2024). Data lakehouse architecture emerged from the need to address the weaknesses of both data warehouses and lakes particularly the security and governance of data lakes and the need to still store all formats of data (Schneider et al., 2024). The architecture for data lakehouses consists of

five components: data sources, data storage, compute layer, application programming interface (API), and use-cases for data consumption (Schneider et al., 2024). According to Janssen et al. (2024) by integrating the scalable storage layer of a data lake with the governance methods typical of a data warehouse, the lakehouse model addresses the weaknesses of data lakes and warehouses. They continue that a lakehouse allows flexible storage including structured, semi-structured, and unstructured data along with a robust metadata and governance layer that provides the performance and data management capabilities typical to data warehouses (Janssen et al., 2024). This includes support for ACID transactions, schema enforcement, indexing, and data versioning which collectively ensures high quality data and prevents the risk of deteriorating into a data swamp (Schneider et al., 2024, 2024). Finally, by the strengths of both data warehouses and lakes, a lakehouse can simultaneously execute various workloads on the same data without it being moved or transformed into other formats (Janssen et al., 2024; Schneider et al., 2024). The lakehouse architecture provides the structured querying capabilities needed for business intelligence and SQL reporting and advanced, modern applications such as ML and AI (Janssen et al., 2024)

However, lakehouse architecture has some drawbacks as well. According to Janssen et al. (2024), data lakehouse architecture, due to its novel nature, still lacks extensive research and proven implementation use cases. Moreover, they note that performance can also be an issue due to the higher latency caused by the need to log every transaction and the data being distributed into cloud object storage. Additionally, since lakehouse architecture concentrates all data onto a single type of storage system, organizations cannot leverage specialized storage engines which can reduce query performance and analytical features (Schneider et al., 2024). Security also remains an issue and a robust security solution has yet to be found (Janssen et al., 2024). There is also a risk of vendor lock-in due to the narrow competition on the vendor side (Schneider et al., 2024). Finally, similarly to other changes, there is people-related barriers including slow client adoption, reluctance to acquire new skills, and the risk of poor technical expertise. (Janssen et al.,

2024). In Table 2 is a comparison of the three different data housing methods adapted from Janssen et al. (2024).

Finally, the most recent approaches to data architecture are data mesh and fabric which have emerged from the need to remove barriers between operational and analytical teams and address challenges like data silos and regulatory compliance (Dolhopolov et al., 2024; Gieß & Hutterer, 2025; Machado et al., 2022). Goedegebuure et al. (2024) claims that while developments in data analytics enable companies to turn raw data into value, difficulties in integration, management, and governance of data hamper them. They continue that currently centralized data management teams commonly collect, process, and manage data as opposed to domain teams. To tackle this current paradigm, they suggest a novel approach: data mesh. Blohm et al. (2024) define data mesh as socio-technical, decentralized, and distributed concept which has four characteristics: domain ownership, data-as-a-product, self-serve, and federated computational governance. Domain ownership means that data responsibilities are distributed into business units or domains that produce and manage it. Data-as-a-product necessitates that data is treated as self-contained, consumption-ready artifact. Furthermore, self-serve ensures interoperability and connectivity as well as providing necessary tools and interfaces. Finally, federated computational governance balances centralization and decentralization by defining global interoperability standards while allowing distributed teams to maintain self-sovereign governance. Essentially, data mesh is not a technology but an approach to data management.

Data fabric is a data architecture approach which is designed to achieve reusable data integration, semantics, and data pipelines to enable flexible, consistent, and integrated data delivery across the organization (Blohm et al., 2024). Data fabric provides the necessary technical infrastructure to support data mesh approach by creating a symbiotic relationship between the two (Gieß & Hutterer, 2025). Data fabric architecture is divided into five layers according to Gieß & Hutterer (2025): collection, storage, processing, analytics, and application layer. Moreover, according to Blohm et al. (2024), data fabric

relies on metadata and knowledge graphs to show how different data entities relate to one another. To create this metadata, it uses data cataloging which is achieved by classifying and identifying data. Finally, the approach uses machine learning and automated pipelines to ingest, transform, clean, and integrate data. They summarize data fabric as a data architecture approach that uses semantic virtualization layer which allows for automation in data management and connecting individual data sources to break data silos.

However, both data mesh and fabric still lack empirical evidence directly linked to real-world use cases (Gieß & Hutterer, 2025). Although data mesh combined in symbiosis with data fabric as suggested by Blohm et al. (2024) and Gieß & Hutterer (2025) does sound promising but the absence of industry examples make it a risky endeavor. Therefore, ideally organizations that want to leverage data extensively and adopt modern tool such as AI, should adopt a data lake or lakehouse architecture. They allow for all data formats and modern workflows. Data lakehouse architecture is promising but still lacks proven use-cases and empirical research as stated by Janssen et al. (2024) which could cause difficulties in adoption.

As suggested by Challapally et al. (2025) AI systems should be integrated into deeply workflows to enable meaningful AI transformation. However, LLM's still have challenges in understanding relationships in the data leading to poor execution accuracy (Li et al., 2023). For example, Vals AI (2026) found that even the best performing GenAI model at the moment, Claude Opus 4.7 only managed an accuracy of 72.21% across finance and coding tasks. Worryingly, Bernal-Utrera et al. (2026) found that only 7% of ChatGPT-4 responses in clinical questions were reasonably accurate. Moreover, Li et al. (2023) note that human accuracy was 92.96%, proving that responses generated with GenAI still cannot be taken as a single truth and human oversight is imperative.

Li et al. (2023) found 2 critical challenges that LLM's have in analyzing data. First as opposed to academic study, in real world situations data is often messy and databases are massive. Second, the models must be provided with external knowledge and reasoning

to improve performance and understanding of the database. The most common error types in LLM's are wrong schema linking and misunderstanding database content. Wrong schema linking means that the system accurately comprehends the structure of a database but inaccurately associates it with wrong columns and tables. Misunderstanding the database content means that the model forgets the database structure or fabricates non-existent columns, especially with massive databases. To increase the performance of the model and reduce the mentioned challenges, a semantic parsing method should be used (Dou et al., 2023).

A common issue with AI models is hallucinations and incorrect responses caused by the lack of understanding relationships in the database and semantic information (Li et al., 2023; Yang et al., 2025). Yang et al. (2025) suggest a Retrieval-Augmented Generation (RAG) integration technique for enhancing LLM's with structured knowledge. They define RAG as a method which integrates LLM's with a retrieval mechanism. The retrieval mechanism then fetches important information from the documents or knowledge in real-time during the generation process. The RAG approach enables LLM's to generate more accurate answers particularly when the training data is outdated or incomplete. Other than RAG, the system should also involve a semantic layer which is defined by IBM (2026) as a piece of enterprise data architecture which aims to simplify synergy between data storage systems and business users. Furthermore, IBM (2026) explains that the semantic layer standardizes the business terms to both the user and the AI to produce more accurate and consistent answers. Finally, combining data tables with primary keys and foreign key is needed as it is the basis for forming queries (IBM, 2021).

2.5 Theoretical framework

The previous chapters included a literature review on both AI transformation process and the data architecture needed to enable it. Figure 4 summarizes the reviewed literature and represents the theoretical framework on what factors influence AI adoption and how data architecture provides the needed technical infrastructure to enable that process. The AI adoption process and ultimately AI transformation begins with a strategy

that aligns all the resources and capabilities of the organization. The strategy should include the role of top management as the enabler of change. Moreover, the strategy dictates that the organizational culture fosters innovation, collaboration, and change management. Finally, people can either be a catalyst or hindrance in AI adoption, thus organizations must actively recruit experts and upskill the existing workforce. The objective of the strategy is to align the other major components of AI adoption: data, technology, privacy and regulation, and data architecture. Once these components are aligned with the strategy a successful AI adoption and ultimately AI transformation is possible.

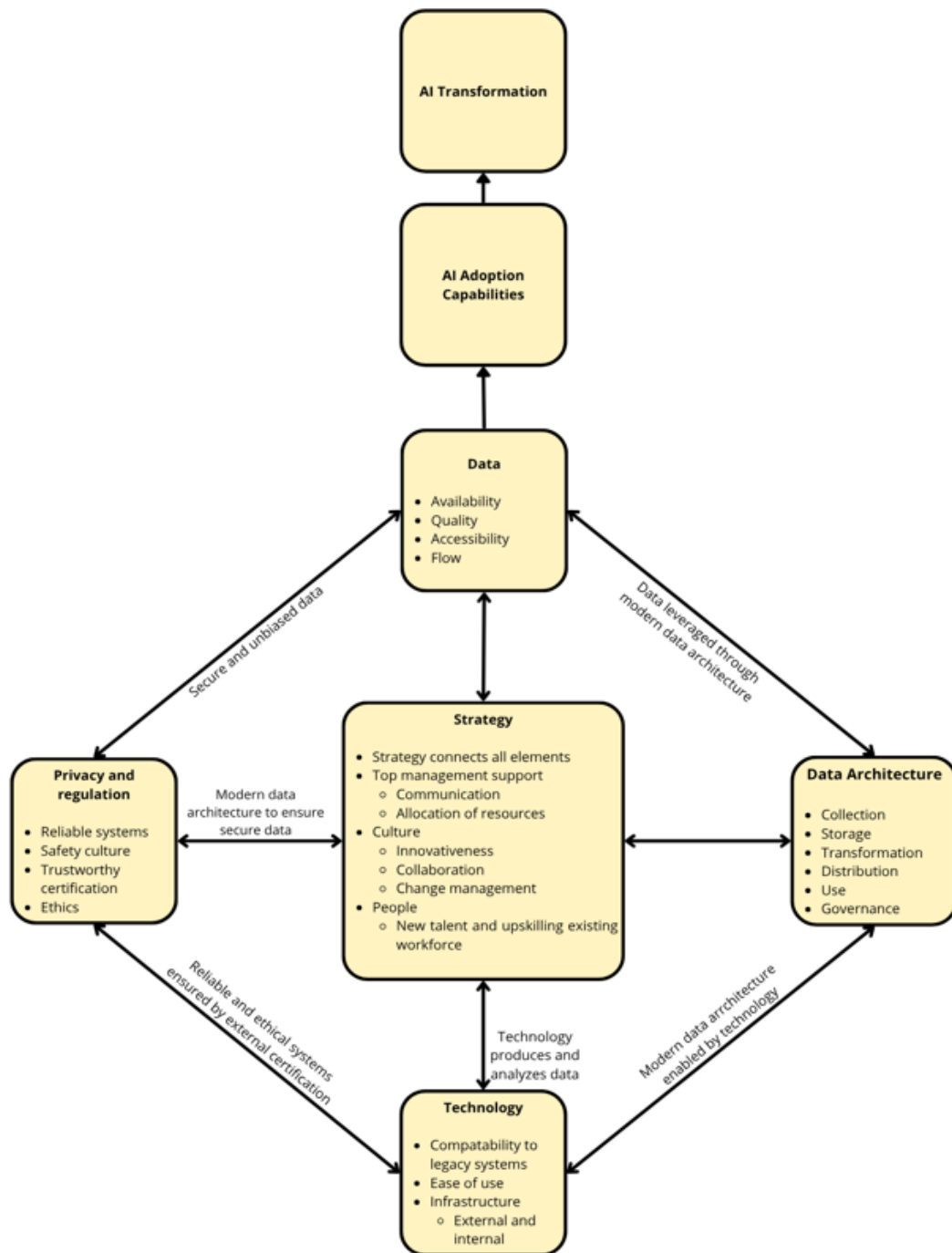


Figure 4. Theoretical framework

3 Methodology

This chapter first discusses the methodology chosen for this thesis in subchapter 3.1 and the case company characteristics in subchapter 3.2. The subchapters aim to provide the reader with an extensive understanding of why the research approach was selected and how it correlates with the case company and the research question presented in the introduction: How does an incumbent industrial firm orchestrate AI transformation through strategic alignment of AI adoption capabilities and data architecture? This chapter will then conclude with a closer look at the data: how it was collected, analyzed, and finally how that data's quality was assessed.

3.1 Research approach

According to Eisenhardt & Graebner, (2007, pp. 26): "Sound empirical research begins with strong grounding in related literature, identifies a research gap, and proposes research questions that address the gap". This thesis has extensively covered available literature, presented a research gap as identified by Ritala et al. (2024) concerning the AI transformation of industrial incumbents, and proposed a research question in the introduction thus covering the elements of robust empirical research. This thesis exploits a qualitative research approach, as it aims to understand the questions "how" or "why" as opposed to "how many" or "how often" of the quantitative research (Pratt, 2009). Eisenhardt et al. (2016) call qualitative research method as inductive method. They argue that the term inductive accentuates the method's emphasis on the emergence of theory from data, rather than the type of data. Moreover, they insist that inductive methodology facilitates research in complex topics and creating novel ideas. This thesis employs a single case study because they are excellent in generating holistic and contextual knowledge and it allows for diversity and complexity (Eriksson & Kovalainen, 2015). The single case study method is also required due to the researcher's access to data through employment and time constraints.

Pratt (2009) argues that qualitative research lacks a standardized template, unlike quantitative research. Thus, he recommends avoiding common pitfalls such as interpretations without showing the data, failure to connect data to theoretical background, and quantifying qualitative data. To navigate these pitfalls, he offers suggestions including representing data that remains true to the people studied, demonstrating how the researcher moved from data to theoretical insights, and contributing to theory. This thesis also utilizes the research onion framework by Saunders et al. (2023) (figure 5) as it gives the thesis and the researcher structure on various layers of the research approach. The research onion represents the process that a researcher goes through from broad philosophical assumptions to specific practical techniques. In the outermost layer is the philosophy which addresses the researcher's world view and belief system. Second, is the approach to theory development, which defines how theory is utilized. Next is the methodology, which explains why a certain method, in this case, qualitative approach was chosen. Inside methodology layer is the strategy. The second innermost layer explains the time horizon. Finally, the core represents the next steps of the thesis including access, ethics, sample selection, data collection, and analysis.

The philosophy this study adapts is the interpretivism as it aims to look at businesses from the perspectives of different groups (Saunders et al., 2023). In this study AI transformation is viewed from the group level down to the divisional level and individual employees. Furthermore, according Saunders et al. (2023) there are three approaches to theory development: deduction, induction, and abduction. As mentioned above this study employs a qualitative research method which Eisenhardt et al. (2016) characterizes as inductive. The inductive approach to theory development allows to generalize from specific to general (Saunders et al., 2023). Data is gathered through interviews and internal documents. Furthermore, this thesis employs a single case study of one division of an MNC operating in automation and electrification. In this thesis a cross-sectional timeline was chosen due to a time constraint.

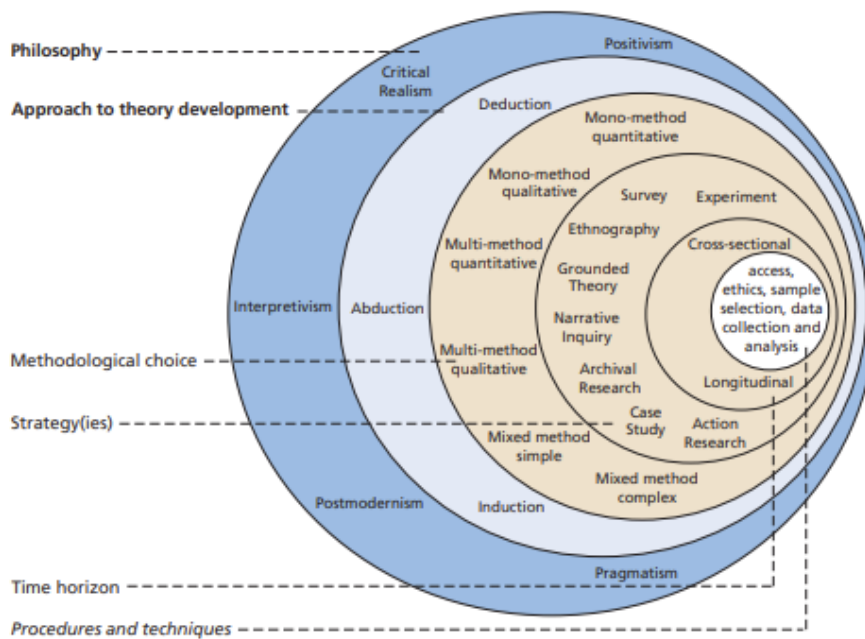


Figure 5. The research onion (Saunders et al., 2023, pp. 130).

3.2 The case company

The case company is a large listed European multinational industrial company mainly operating in the fields of electrification and automation. The company operates in three business areas with multiple divisions. The study focuses on one division, but many characteristics are shared with the larger business area and group company. Due to the competitive nature of the industry and the sensitive data shared during interviews, the case company's identity has been anonymized. All specific confidential information and proprietary processes have been generalized to protect the organization's commercial interests while preserving the integrity of the research findings. Thus, from here on the case company will be referred to as "division X". Division X is driving an AI transformation by fostering a culture of adoption, providing employees with the necessary tools, resources, and comprehensive training. In division X the parent company chooses and provides the systems and tools which the local divisions will then adopt. The local divisions can also choose to independently develop those tools further and innovate more use cases for them. There are several AI tools and systems available such as Microsoft Copilot for personal AI assistant duties. Along with Copilot, division X has their own proprietary

personal AI assistant that understands firm specific information better and utilizes multiple large language models such as Claude and Gemini. Finally, there are clear restrictions on what information can be inserted into which AI system based on the confidentiality classification. The case company in this thesis was analyzed on the local Finland division where the organization has identified bottlenecks on their independent AI system development.

3.3 Data collection

The data collection in this thesis was conducted through semi-structured interviews among staff of various levels, expertise, and functions. As all good qualitative research, this thesis used multiple data sources including semi-structured interviews along with company surveys, PowerPoint presentations, organizational strategy, guidelines and policies related to AI, personal observations, and public reports (Gioia et al., 2013). Moreover, the semi-structured interview method can be used to answer questions: “how” and “why”, essentially aligning with the qualitative research approach (Eriksson & Kovalainen, 2015). According to Eriksson & Kovalainen (2015) the key strength of semi-structured or guided interviews is that the materials are systematic and comprehensive, while still allowing the tone of the interview to remain conversational and informal. They do remind, however, that the researcher must focus on analyzing and comparing the data, although it might be difficult since the interviews might differ from one another to some extent.

Furthermore, Gioia et al. (2013) suggests that in the data collection stage, it might be beneficial to ignore the literature to some degree to avoid confirmation bias. In this thesis the interviewees were selected with theoretical sampling to ensure that they can provide meaningful insights into the research area while also allowing to adjust the sample if new opportunities or insights emerge (Eisenhardt et al., 2016). In this thesis, the interviewees were categorized into two categories based on their expertise: end users and technical specialists. The selected interviewees were deemed to have deep knowledge or important insights on the subject. Particularly the technical specialists were embedded in the AI and data architecture initiative in the company.

The interviews were held on Teams. They were recorded and transcribed regardless of the location of the interview. As mentioned above, two different approaches for the interviews were prepared (Appendices 1 & 2). The interviews took place in March or April 2026 and they were conducted either in English or Finnish. Finally, all participants signed a privacy notice and consent form based on university guidelines.

3.4 Data analysis

The data analysis in this thesis employs the Gioia methodology (Gioia et al., 2013). As mentioned, the thesis employed semi-structured interviews to collect retrospective and real-time accounts by people experiencing the phenomenon of theoretical interest as suggested by (Gioia et al., 2013). Following the methodology, the first-order concepts were identified by analyzing the interview answers and recognizing common themes from informant-centric terms and codes. Then, in second-order analysis, the researcher analyzed whether the concepts from the first-order could help describing and explaining the phenomenon. Here focus was also kept on novel concepts that did not have adequate references in the existing literature or existing concepts that otherwise stood out. Finally, once workable concepts and themes had been identified, the second-order themes were distilled into overarching theoretical dimensions where appropriate.

The concepts and themes were reflected against the theoretical framework to understand how they related to existing theory or if any new concepts could be identified. Interview records were automatically transcribed, and incorrect transcripts were corrected where needed. The interviewees were anonymized but their role in the organization was kept visible.

3.5 The assessment of the quality of data

According to Yin (2018) there are four common tests that address the quality of the data: construct, internal, and external validity, and reliability. Construct validity refers to the

degree to which the study explores the subject and how a method leads to accurate observations (Gibbert et al., 2008). To increase the construct validity, Yin (2018) and Gibbert et al. (2008) suggest two tactics: multiple sources of evidence and a chain of evidence. This study provided the chain of evidence with the Gioia methodology (Figure 6) and used multiple data sources as explained in the data collection subchapter. Internal validity or logical validity refers to the causal relationship between variables and results (Gibbert et al., 2008). To enhance the internal validity of the study, it should employ a clear research framework which was presented previously and pattern matching to compare empirically observed patterns with predicted patterns or patterns from previous studies (Gibbert et al., 2008). The Gioia method along with the established research framework ensured the internal validity of study (Gioia et al., 2013).

The third test, external validity, refers to the generalization beyond the case study. Gibbert et al. (2008) argues that case studies do not allow for statistical generalization but rather analytical generalization. It refers to empirical observations from theory rather than a population. Consequently, case studies can be a starting point for theory development. This study aims to draw conceptual insights from the case company by connecting the findings to theory. Thus, the practical implications of this thesis may not be applied directly to other organizations. Finally, reliability refers to consistency and reliability of producing the case study's findings and the absence of random error (Gibbert et al., 2008; Yin, 2018). Both Gibbert et al. (2008) and Yin (2018) suggest setting up a case study data base to establish a chain of evidence. Essentially, reliability aims for repeatability so that others can perform the same study and arrive at the same conclusion. In this study, the database includes literature, interviews, and transcripts. The data collection subchapter explains in more detail how the data was collected.

4 Findings

The findings of this study will approach AI adoption from two perspectives which are reflected in the research question: strategic alignment of AI adoption capabilities and data architecture. The first perspective, strategic alignment of AI adoption, aims to answer which AI adoption capabilities are utilized and how effective they are perceived. The second perspective examines the intersection of data and data architecture, treating them as a unified factor in AI adoption due to their inherent interdependence.

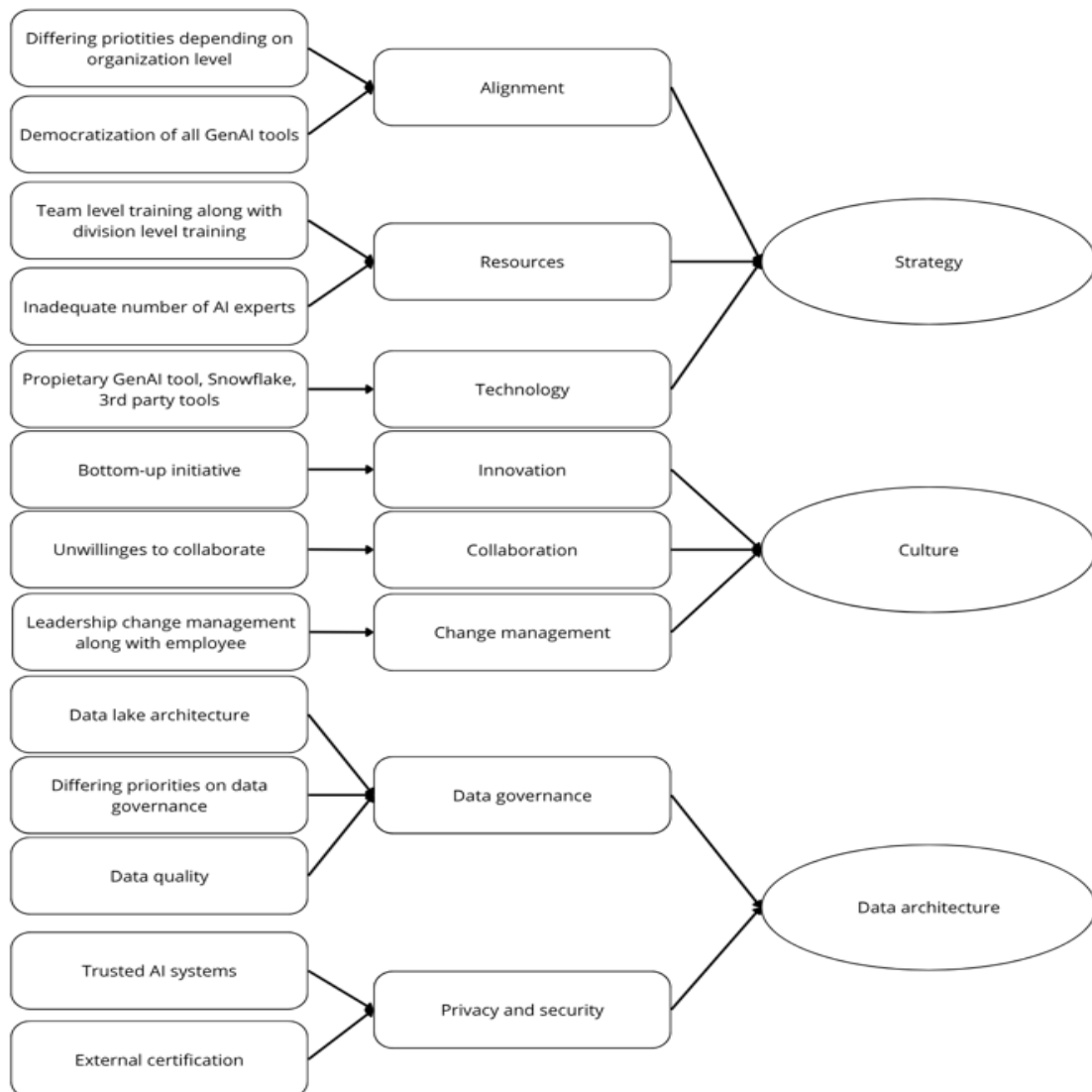


Figure 6. Data structure

4.1 AI adoption

4.1.1 Strategy

The strategy is commonly based on organizational resources and capabilities which are then leveraged to drive the adoption of the strategy. The business area to which division X belongs recognizes AI as one of three strategic priorities and a technology which will shape the future. The strategy in the business area for AI and other digital technologies is to extend the automation further, enable autonomous operations, and productization and growth. There is also an information system (IS) strategy which focuses on IS themes. Division X's strategy does not mention AI as a priority for the year 2026 but does acknowledge it in the strategy for 2030. The strategy integrates AI as a core product feature, leveraging it to accelerate time-to-market while driving operational efficiency and customer satisfaction. The strategy on AI enhanced internal processes in division X, relies on three pillars: communication, awareness, and democratization of general-purpose tools. Communication is frequent and the goal is to spread awareness of available AI tools and how to use them. It is mostly performed through internal messaging such as Teams, email, and SharePoint. Despite the frequent communication and awareness campaigns on AI, the strategy on AI implementation is unclear to employees.

“I would assume—though I don’t know for certain—that we have a strategy to increase the use of these tools. This is based on how things are communicated from the top down: we are informed about the tools and encouraged to both use them and find new ways to apply them. In that sense, yes. I have never actually read such a strategy, but in everyday practical life, it certainly feels like we have one.” Interviewee 3

Communication is perceived to be efficient and frequent. However, many interviewees agree that communication should be brought to immediate manager level instead of general information messaging from higher level.

“If someone sends you an email and a calendar invite from Norway asking you to join, it’s not necessarily the same as your own supervisor saying: ‘Hey, you should go listen to this; you could actually learn something from it’. In a way, you can’t

just blame the divisional level for the lack of training; it needs to be brought down to the immediate supervisors to truly activate and engage the employees." Interviewee 2

"If it's considered important in the company, it should probably be brought more to the team level, and the communication should happen there. We actually have a personal goal related to AI now, so it has been introduced in that sense" Interviewee 5

Top management support and resources are mostly targeted at these awareness campaigns and communication, but interviewees would like more involvement from their immediate management. As mentioned, the strategy relies on the democratization of general-purpose tools. The awareness and training of the available tools are distributed equally regardless of origin (proprietary or commercial). The training on all AI tools has been comprehensive and has advanced from beginner level to more advanced applications where even experienced AI users have found value. The trainings have mostly come either from group level or business area highlighting the centralized approach to general purpose tools. In the engagement survey trainings were found to be great quality and managers encourage people to attend them. Contradictory to them, more advanced tools such as Snowflake, a data analysis and storage platform, have not been widely advertised internally although some business areas and divisions have used it more extensively than division X.

Fear of losing jobs is a common theme when discussing AI and its effects on businesses. At division X however, the fear of losing jobs was not yet relevant according to interviewees. Furthermore, the organization strives rather to upskill their personnel than to actively find ways to decrease headcount. Additionally, the AI transformation process is still focusing on democratization of general-purpose tools to increase efficiency and human-AI collaboration which does not create the circumstances where layoffs are needed.

"Regarding the project manager role, we discussed how clients will likely always insist on a human being rather than a machine. I believe that requirement significantly limits the extent to which my work could be replaced." Interviewee 5

"We aren't at the point where it could replace us yet. It requires more development; agents need to be built, and to truly replace human labor, we would likely need to hire specialists to implement it. While we are skilled, it's a significant undertaking." Interviewee 3

Although layoffs have not been relevant, the AI adoption process has been centrally dependent on a few people and hiring new experts has been sluggish until recently. According to one interviewee, the responsibilities typically assigned to a six-member team were effectively consolidated into a single role. Furthermore, interviewees viewed that the efficiency increase achieved from the Snowflake tool could be up to 50% in some departments. In conclusion, the resources to adopt a purpose-fit tool have been somewhat inadequate and active people have initiated the process alongside their main duties.

"It is justified to state that additional resources are required. Demand is rising steadily, and the overall workload continues to increase" Interviewee 7

The technology infrastructure aligns with the strategy well. Currently AI tools are provided with various providers. Interviewees generally agree that Microsoft Copilot is the most used among people at division X and the proprietary tool specifically developed for division X is used less. Many interviewees found that Copilot is more accessible, familiar, and was available before the proprietary tool which increases the barrier to change. Another factor is awareness; some interviewees had the assumption that the proprietary tool is only for internal intranet searching. However, that is not the case, and it can complete similar tasks to CoPilot. Moreover, division X has won an award recognizing the proprietary tool as a driver of impact.

"I think it's partly because it's perceived as such a new thing. And since it is new, people—myself included—experience this slight resistance to change or a bit of friction. Whenever you start learning new apps or anything else, it always requires that extra bit of effort" Interviewee 5

"I would say I haven't used it much; I think I've only used it three times during this six-month period" Interviewee 6

However, there are people who use only the proprietary tool. The reasoning behind this decision is data security, cost, and the availability of multiple LLM's such as ChatGPT, Claude, Gemini, and DeepSeek.

"I use it simply as a matter of principle because we don't have to pay for it. Since it's free, it should be used as much as possible. You should also choose the most expensive language model available there" Interviewee 2

"If I need to process internal data I use the proprietary tool since you can insert confidential information and choose the language model" Interviewee 7

Apart from the general-purpose tools which are provided company wide. There is also Snowflake for deeper data analytics and AI analytics. However, as mentioned before, it is not widely advertised although available at division level. The limited awareness for it stems from the data access it requires and possibly a perceived lack of importance. Snowflake is a data platform which connects all major enterprise software such as SAP and Salesforce. Thus, there needs to be access control built-in before it could be used by wider workforce to prevent accessing confidential data. However, this is not currently the case, and Snowflake is only utilized by a small number of people within division X.

"Only about 10 to 15 of us probably have access there [Snowflake], and out of those, maybe only four are active" Interviewee 1

Snowflake is a good example of a purpose-fit tool adopted by division X to reduce time spent on data analysis by previous tools. The interviewees agreed that Snowflake has integrated into existing legacy systems well which can be an issue in an incumbent industrial company. Both Snowflake and the discussed general-purpose tools were found to be easy to use, intuitive, and well-integrated into the workflow. However, one department did note that they did not find any added value from Snowflake since their current BI tools can achieve the same results faster. They noted that AI agents could be more valuable and increase productivity.

“It was a bit slow and clunky. We built very efficient Power BI tools for procurement about 4 to 5 years ago, so we are already using that data very effectively. Simply giving a command to an AI system and getting a visual view in return isn't efficient enough for us. It needs to go much further than that.” Interviewee 3

Finally, interviewees agreed that the black box nature of new AI systems is not an issue, and their answers can be trusted when they are provided with specific data. Therefore, distrust or reserved attitudes towards AI were not present and AI is seen more as a performance enhancing tool. Moreover, interviewees felt that most people do not have to understand how AI works but rather understand the underlying data to evaluate if the AI produced analysis is trustworthy.

“I don't view the fact that people don't understand the underlying technology as a major issue in the long run.” Interviewee 3

“I would still say we cannot blindly trust AI, and we still need subject matter experts. That's the thing I always say to people that don't be afraid of AI. That it will take your job. It's not going to take your job. You'll still be there on top of AI and you are still checking whether the data is fine or not? You can make codes using AI, but you don't know whether that code is fine or not if you have no understanding, you cannot just implement the things.” Interviewee 6

4.1.2 Culture

Successful AI adoption necessitates innovativeness, collaboration, and change management, however, particularly collaboration and barriers to execution are currently seen as the top challenges in the organization which hinder the AI adoption process. Another engagement survey respondent argues that innovativeness is not a common organizational culture at division X.

However, demonstrating innovativeness the adoption of Snowflake started from the bottom at division X by active personnel coming outside the organization, trying to leverage data gathered over the years and adopt AI tools to enhance their work. Interviewees did agree that top management support is valuable, but more could be done to drive change,

particularly with more purpose-fit systems. The developers involved in the Snowflake adoption agreed that leadership was person-dependent leading to inconsistent and variable mindset in adopting the system. Moreover, upper management often required proof of concept before developing further.

“Things have been developed for those who happened to get excited about it. Our entire data project is perhaps a bit of a 'bottom-up' model: you have to spend time creating something first to show that these solutions are impressive and functional, and then maybe a manager will make a decision.” Interviewee 1

“It's been a bit of a process to get the organization on board with investing in this. We only really got backing once we had results to show. Right now, the leadership side of things seems too tied to specific individuals. I'd say we still have some work to do on our overall ability to manage development in this area” Interviewee 7

The organizational culture is highlighted by eagerness to adopt new tools and technologies which are noted in the strategy for 2030 and priorities for 2026 and the dedicated IS strategy. However, there is some unwillingness to share data and tools between teams and people leading to data silos, and decreased collaboration and data flow. Furthermore, internal engagement surveys highlight challenges in removing barriers to execution and collaboration. Respondents also expressed skepticism regarding whether corrective actions would actually be implemented indicating some trust issues. Furthermore, one survey respondent expressed that departments work in their own silos unaware of other departments. This was confirmed by interviewees.

“I have also seen that people are trying to conceal their data. My superiors got word and said: ‘no, this is only our data, you shouldn't give it to anyone else.’” Interviewee 6.

Currently, division X does not have dedicated AI champions to drive change, but some personnel have taken this role naturally by spreading awareness and finding new use cases. They have demonstrated different AI tools to few managers in different departments trying to leverage AI in their processes. Furthermore, the organization has a

division level vice president in charge of AI and technology operations. Naturally, there are managers involved with AI at the business area and group level as well.

Currently, at division X the AI transformation has mostly focused on democratization of general-purpose tools. Thus, many interviewees found that their modus operandi has not fundamentally changed.

“I’d say it [AI] hasn’t changed the fundamental nature of the work itself, but rather certain stages of it. It does, however, speed things up significantly.” Interviewee 2

Thus, large scale change management has not been employed. The IS strategy still emphasizes AI readiness and democratization as key priorities for 2026 indicating that the AI transformation process is still in early stages. Overall, strategic alignment continues to prioritize core operations, with AI gaining significance at higher strategic levels. The implementation, specifically the robust training programs and communication efforts, aligns well with this strategy and is proving effective.

4.1.3 Data and data architecture

The availability of data is imperative for AI adoption. Division X has accumulated a vast amount of internal and external data over the years. Thus, the availability of data is secured, and it has enabled division X to begin the AI adoption process. Furthermore, there still is more unstructured or semi-structured data that could be utilized more.

“AI usage is made possible by the fact that all sorts of data have been accumulated over the years, and that data is relatively organized. However, AI is probably at its best when dealing with unstructured data. After all, you can quite easily create automated reports yourself from pre-structured data that look correct and consistent” Interviewee 1

Division X recognizes the importance of data and particularly the quality of data in their IS strategy. Moreover, interviewees had some mixed opinions about the quality of data. Generally, the quality was determined to meet the requirements to leverage it for AI

purposes. However, the conflicting views stemmed from the data that was leveraged. Data from enterprise systems such as SAP were generally of good quality but unstructured data extracted from emails or PDF files were not as high quality and missed some information leading to poor results. Also, there was deviation between enterprise system data quality with SAP having good quality and extensive data while Salesforce data quality was worse in comparison. Consequently, leveraging and analyzing that data was more time-consuming and difficult.

"Since a PDF is like an image, converting it into structured data can be difficult. Sometimes the AI doesn't understand the layout and mixes up the words, which makes it a bit challenging. Consequently, it's a slightly slower process" Interviewee 6

"Data quality is a classic, age-old problem, but I'd say that you can still generate reports from it. Of course, there will be flaws, and I believe the right way to approach it is to be aware of those shortcomings. You should still go ahead and build that reporting pipeline, but you need to incorporate a feedback loop so that the data, in a way, becomes self-correcting." Interviewee 2

"Even for us, the data quality in Salesforce is probably among the weakest, but it's still quite alright and definitely usable" Interviewee 1

"Generally speaking, our data has been of high quality. It's high-quality because we've always maintained strict standards for whatever is entered into systems like SAP." Interviewee 1

Developers involved in AI adoption also recognized that data is available, reliable, and well-structured before AI adoption. Furthermore, interviewees acknowledge that attaining quality data requires data cleansing, which is particularly common when dealing with unstructured data.

"Yes, before AI adoption, I would say that we must ensure data is available, reliable, and well-structured. Data cleansing is needed for almost everything, I'd say—it is actually essential. You need to verify these things before AI adoption can take place." Interviewee 6

While some data is in 'OK-ish' form, most of it is not in a format that AI can readily use. We actually need to cleanse the data because, for AI to work properly, the input must be complete. If we feed 'garbage data' into an AI tool and expect high-quality results, it simply won't work. As the saying goes: 'garbage in, garbage out.' I would say that while some data is fine, the majority requires significant cleansing and completion. Data completeness is absolutely essential. Interviewee 6

Currently SAP data is cleansed both by a data team by another business area, which provides more generic data tables for all divisions in Finland while division X have also supplemented these tables with their own more business specific ones. The business area data team has fetched that data and provided it to the divisions. In the future business area governing the data, will create business ready SAP data for the entire group which will create both challenges and benefits. The challenge is that division X and its business area's project environment is highly customized and thus unlikely to get prioritization at group level leading to recreating current tables and longer delivery time on getting data. The benefit is that the upcoming change will reduce the need for modeling and maintaining raw data. Essentially, the governance and cleansing of data will become more centralized than before. Moreover, division X will shift to a newer ERP system which will give more data capabilities than the current system while enabling more AI specific needs.

"Right now, another business area is developing a Finland-wide solution to have those tables built in a centralized way. Currently, we've been creating them ourselves for our unit, but we will likely transition to those centralized solutions later on, once they are more finalized." Interviewee 1

The initiative Core and Common Data Products (CCDP) goal is to unify the company data to one system, Snowflake, to create a "Single Source of Truth". The main benefits are a unified data source, better data governance, easier self-service reporting, and improved compliance. Access can be gained through an authorization portal. However, at division X, interviewees believe that the governance of data will become even more bureaucratic than before.

“While centralized execution is beneficial for supporting units without their own technical capabilities, it should not come at the cost of autonomy. It is important to ensure that individual units retain the freedom to manage their data and develop independent projects” Interviewee 7

“Yes, up until now excluding finance and HR data, we’ve practically gained access to everything we’ve requested. At the moment, however, it’s starting to look like the business units might not be as willing to share their data with us as they were before. We’ll have to see how it plays out. At the business level, they might be starting to tighten their grip on data sharing.” Interviewee 2

A challenge which division X has recognized is particularly related to data accessibility when using Snowflake. Currently, the system has access to all data without built-in access control. Consequently, access has been limited to very few as mentioned before. This has limited the potential use cases for Snowflake and its data analysis features. Still interviewees agree that Snowflake does not need to be accessible to all but instead to some who can leverage it more efficiently.

“I would say that as we begin to scale up usage, we’ll obviously need to start considering access control. Snowflake, for instance, is a great tool because it’s built specifically for that—the controls are essentially baked into it. Every user is assigned a specific role, giving them access to certain data rather than everything. Essentially, all of this governs what the AI is able to do and what information it can retrieve.” Interviewee 2

“Our setup is still in its infancy, so to speak. We don’t have proper Row-Level Security in place yet, which is why we can’t allow everyone to access it. We need to get that sorted out first before we can roll it out to a larger group of users.” Interviewee 1

Data silos are a common issue for many companies trying to adopt AI systems and leverage data. At division X operational data does not have many silos but there are some exceptions such as financial and HR data which naturally are not widely accessible. As with data quality, the existence of data silos depends on the perspective. Although operational data is widely accessible and not siloed, some try to protect their own data and are unwilling to share it with other departments, as was mentioned previously. Thus, the

challenge is to break all remaining meaningful data silos in the future and cultivate a culture where data silos do not reappear.

*"There might not be many silos left with operational data anymore, especially on our end. We are able to integrate all of our operational data quite effectively."
Interviewee 2*

The accessibility of data and low amount of data silos is facilitated by Snowflake which essentially acts as both a data warehouse and data lake. It can house vast amounts of data regardless of format (unstructured, semi-structured, structured). At division X it combines most enterprise systems such as SAP and Salesforce, providing a single database where data can be accessed and analyzed. Currently however, Snowflake is one way only meaning that it cannot alter data in the enterprise systems it is connected to but in the future, this might be available too in some systems.

"For many people, the real benefit would come from making the communication two-directional, allowing AI to execute workflows that feed data back into systems like SAP or update statuses there. That side of things is still largely out of play, but with Jira, for example, it should technically be quite possible. Jira has an API that allows you to feed information back into the system, making that kind of integration significantly easier to implement than, say, an integration with SAP." Interviewee 2

Furthermore, having business areas and divisions controlling their own data leveraging methodologies such as data mesh, could be beneficial. Particularly, when the company is moving towards more centralized data governance, extracting real business value and insights is more efficient when data is closer to the end user.

Finally, data flow is mainly executed by existing ERP systems while Snowflake enhances it by tying together most systems. However, as mentioned it is not widely available and therefore data flow could be improved by having robust access control enabling wider implementation leading to increased data flow.

The vision of the business area is data-driven culture where democratized data is available, easy to use and secure, enables transparency and control to improve and run the business. Some aspects of it have been accomplished as mentioned above but still conflicting needs of the group company, business areas, and divisions hinder the vision of data-driven culture. While the adoption of DDDM remains partial, one interviewee highlighted that Snowflake has been instrumental in this transition, providing the capability to conduct complex analysis on significant datasets. The IS strategy aims to roll out the strategy with customer focused, skilled people that innovative culture. Despite some presented challenges, both the strategic objectives and the steps implemented align effectively with the broader organizational vision.

Lastly, the organization, particularly the developers, have had some hurdles when implementing new data analysis tools. Namely, analyzing data from different enterprise systems without clear relationships. The developers have tried to solve this problem with a semantic layer which explains and standardizes business terms and identifiers from different systems. Additionally, they have manually created shared keys that join data tables together and give the AI system a clear path.

"Usually, the solution is to add a new field to the system and instruct that, from now on, you need to enter some identifier we need. It is very difficult to link data without such a factor—unless you can do it computationally or if there is another joining table available. For example, if you have Table A and Table B, you can use Table C as a bridge to connect them." Interviewee 2

"We've had to build these kinds of keys to be able to link the data." Interviewee 1

Privacy and data security is built upon reliable systems, safety culture, and external reviews. At division X privacy and data security is ensured through external certifications and active awareness campaigns particularly on phishing. In the IS strategy, resilient security and compliance is recognized as one of the priorities for 2026. Moreover, security is divided into 6 focus categories: network, endpoint and hosting, vulnerabilities and resiliency, consultancy services, awareness and education, and a public key infrastructure. The prioritization of cyber security demonstrates that the organization recognizes the

importance of it and will take actions to strengthen it. In terms of AI, a key factor in cybersecurity is using approved tools. Division X primarily recommends two tools: their proprietary general-purpose tool and Microsoft Copilot. To guide in the responsible use of available GenAI tools, division X has developed a matrix. Interviewees were generally aware of the GenAI matrix; however, the contents and the location of the matrix were not well known among the interviewees and there were some misconceptions.

“Since those other systems aren't as secure, you have to be very careful about what information you put into them. However, since this [proprietary tool] one can handle slightly more sensitive data, I don't have to worry about data privacy that much.” Interviewee 3

“Yes, I was aware of it [GenAI matrix], but I didn't actually know the details very accurately” Interviewee 5

The matrix consists of all the available GenAI tools, and the confidentiality classification related to them. For instance, the proprietary tool can analyze up to confidential information. Interestingly, Microsoft CoPilot when used in the work tab with a license can analyze even strictly confidential information which has caused the misconception.

Division X has also highlighted the importance of external certifications and consultancy services in the strategy. For instance, division X completed the ISO 27001 certification which specifies the requirements for Information Security Management System (ISMS). The standard addresses IT, personnel, and processes, essentially strengthening the organization's safety culture

4.2 Summary of the findings

The findings show that many components are needed to adopt AI systems including aligning the strategy to enable the process and technical elements such as data architecture. The components were mostly taken into consideration, however since the case company is a division of a large multinational company, their unique requirements and business landscape does not fully align with the priorities of the larger organization. The fundamental goal of the strategy regarding AI is democratization of general-purpose AI

tools including proprietary and third-party tools. Democratization is enabled by frequent training sessions and awareness through internal communication systems. The adoption of more purpose fit tools such as Snowflake are still smaller scale and happening from the bottom up by active personnel.

Since there are multiple strategies varying from group level to division level, the priorities are naturally different as well. The business area strategy mentions AI and digital as priorities for 2030 and the division level strategy for division X does not see AI as a priority instead focusing on core business activities. This emphasizes the centralized approach to general-purpose AI tools while leaving more advanced tools such as Snowflake to be developed by those interested. The baseline work functions for the majority of the workforce have seen little shift. Consequently, there has been no immediate perceived need for large-scale change management initiatives. Instead, a bottom-up approach has emerged, with developers attempting to demonstrate the strategic benefits of AI adoption to upper management.

The findings do however indicate that that more active role of immediate managers would be welcomed to drive AI adoption since change agents are absent. More active role from immediate managers could decrease the barriers to execution and which were noted as the main challenges in the engagement survey. This approach could significantly increase adoption of the proprietary AI tool, as current low usage is not due to a lack of resources, but rather because existing communication and training have failed to capture employee time and attention. Moreover, possibly indicative of an incumbent industrial firm, the process of gaining management's support for adopting specialized analytical AI tools like Snowflake has been more challenging than in other sectors according to the interviewees. A factor which was most notable in the attitudes of upper management and allocation of resources such as hiring specialists. At division X, employee tenures tend to be relatively long. Consequently, the infusion of experience from firms further along in AI adoption is limited, which underscores the critical importance of recruiting external specialists.

The culture was overall accepting of change and new technologies despite some cases where work products and data were not shared with other departments creating data silos. Collaboration and innovation were still at the core of the organizational culture at division X. This is best demonstrated by the Snowflake initiative where active personnel independently adopted and began to develop the tool to meet their needs. The interviews and internal messaging did note however that the upcoming changes to data architecture to move toward a more centralized approach will likely cause some challenges along with positive changes. The centralized model is likely to be more cost-effective and standardized than the current one. However, as data governance moves further from the users, it may hinder the extraction value from data due to the slower and more bureaucratic approach. Consequently, the IS strategy noted that due to the upcoming change some work will need to be redone to capture value from data. Moreover, contemporary approaches such as data mesh and fabric, or a hybrid model could be beneficial to ensure data can be leveraged where needed without delay.

The interviews also found that the integration of multiple enterprise systems into one data analysis tool has caused some challenges where the tool has not always understood the relationship between data from various sources. To mitigate this issue, developers have employed a semantic layer to explain business terms and enterprise specific identifiers to the tool. Furthermore, they have created keys that combine data tables to others which allows the tool to understand relationships between the tables.

Regarding data architecture, the findings suggest that data governance is the key challenge facing division X. As the data governance moves toward a more centralized model, data governance and the key elements to data, quality, accessibility, availability, and flow, become challenged. The interviewees and internal documents agreed that data accessibility and relevance to the user will likely suffer as data becomes more general. This development will likely increase the standardization of data management while decreasing the costs but increase the work load for divisions that require specific and tailored data.

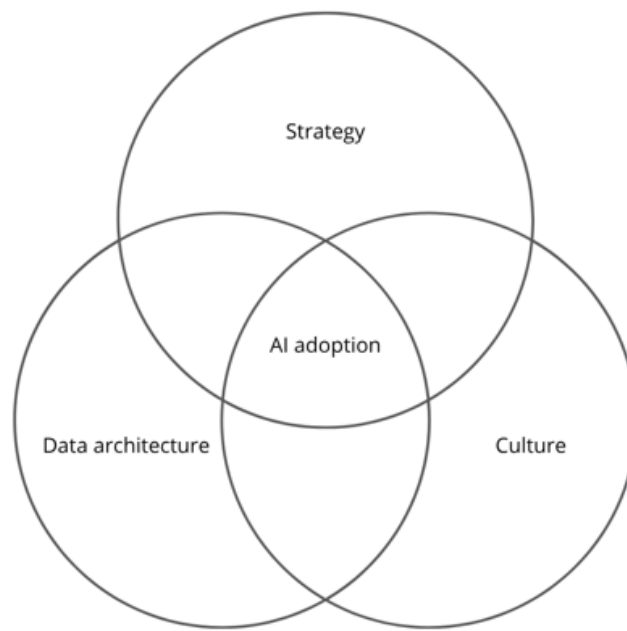


Figure 7. Critical factors of AI adoption

5 Discussion

5.1 Theoretical implications

This study contributes to existing literature in AI adoption and transformation in three ways. First this study complements to literature on AI adoption in incumbent industrial firms and responds to the need to understand different kinds of industrial firms with heavy legacy assets by providing one perspective (Ritala et al., 2024). Within the literature, it is argued that heavy legacy assets and established automation processes can be paradoxical, they represent both a competitive benefit and a potential barrier for incumbent industrial firms (Ritala et al., 2024; Ruokonen & Ritala, 2023). This study suggests that with the right technology which allows to integrate existing legacy systems, AI adoption is not hindered by existing systems, but pace of adoption might increase. Moreover, AI can further automate and optimize existing processes. Thus, confirming the asset augementer characterization defined by Ruokonen & Ritala (2023). Furthermore, this study found that innovativeness and collaboration are key not just among employees but also managers to enable AI adoption complementing Jöhnk et al (2021).

Second, this study argues that recruiting external experts can be the catalyst that begins the AI adoption. The adoption of advanced AI systems happened as a byproduct of recruiting new talent in division X. Long employee tenures are characteristic of many incumbent industrial firms, making the recruitment of new talent essential for driving organizational change. This confirms the findings of Gilch & Sieweke (2021) that renewing an organization's human resource base is crucial in adapting to new technologies. Moreover, existing literature is still scarce on the impact of new experts in driving change. The role of new talent recruitment in industrial firms has not been extensively researched particularly in the age of AI transformation.

Finally, this study extends the literature on the importance of data architecture, particularly data governance. Modern and flexible data governance is crucial for innovation and therefore AI adoption. As established in the literature, data is the fundamental

prerequisite for AI adoption and without high-quality datasets, AI systems cannot operate (Jöhnk et al., 2021; Mikalef & Gupta, 2021). A key finding of this study was the importance of accessibility of data enabled by data governance. Data accessibility and flow facilitate the development and implementation of AI systems (Jöhnk et al., 2021). Currently, literature on AI adoption recognizes the importance of data governance but lacks clear frameworks on how it should be orchestrated. To complement this need, this study suggests that data mesh, a modern socio-technical approach to managing data, could be a crucial factor particularly in established industrial companies where the data architecture is not commonly built to support flexible data governance that innovation and AI require (Blohm et al., 2024).

5.2 Managerial implications

Insufficient resources including money, experts, time, and knowledge were among the most important challenges when initiating the AI adoption process. Somewhat unexpectedly interviewees described a situation where the required technology powered by Snowflake was available to divisions, but its implementation was not deemed important or necessary. Contradictory to the brand image as a technology leader, the case company's upper management seemed uninterested in exploring new capabilities powered by AI. The situation is further complicated by the fact that Snowflake was both accessible and available at no added cost. Therefore, this study suggests management gives adequate resources to AI adoption. Particularly recruiting experts outside the organization with competence in adopting advanced purpose-fit AI systems. Although the case company has made relatively good progress in adopting the Snowflake platform, the pace has been evidently sluggish due to lack of experts, which was also recognized by the interviewees.

Apart from the resources, this study suggests that managers focus on building culture of innovation and collaboration. It was evident that larger scale adoption of Snowflake was only made possible once upper management was convinced that there is business value. Thus, the culture of innovation and collaboration enabled the adoption process.

However, the findings indicate that the perspective on AI development and consequently innovation was person dependent. Therefore, fostering a culture of innovation and collaboration not just among the employees but also the management is imperative to enable AI transformation. The findings also suggest that there is a distinctive difference between adopting general-purpose and advanced purpose-fit AI systems. General-purpose AI is the low hanging fruit which most MNC's can pick up rather easily. The challenge is then the adoption of more advanced systems which require more resources and expertise. The findings also suggest that adoption of more advanced systems require greater cultural change than general-purpose AI. Therefore, this study suggests recruiting experts as developers and managers to act as change agents.

Additionally, the democratization of advanced AI systems such as Snowflake also demands more from privacy and data architecture. The vision of the case company is to roll out the tool to all employees in the future. However, as the findings suggested, the current utilization is still low and robust access control aligned with privacy requirements needs to be established before wider implementation. This is likely to be a common challenge in organizations adopting systems with wide access to data. Therefore, this study suggests that access control is a priority for developers and managers from the start. As the adoption and democratization of the more advanced systems progresses, it requires the same elements as a general-purpose system. Organizations still must communicate, raise awareness, conduct change management, and trainings. The resources needed to democratize advanced AI systems also required more workforce, particularly AI experts.

The findings also found that data governance is a crucial component of AI adoption which can either enable or hinder the process. Data is the single most important element for AI to function. Therefore, this study suggests management includes data governance in the strategy. The findings suggest that complicated and bureaucratic data governance can critically hinder AI adoption. Instead of a centralized model where all company data can be only accessed through portals or tickets and access given by a data team, organizations should strive to adopt a modern approach such as data mesh. The approach

gives data governance to the teams that create it while still allowing for a federated computational governance which maintains universal standards to security, privacy, and data formats. Data governed closer to end user ensures that data is accessible, relevant, and actionable. Instead, when data is governed by a centralized team which manages all data regardless of origin, its value is likely to decrease to the end user as it becomes more generic. Data lakehouse and fabric are also promising and modern approaches to data architecture but still lack proven use cases. Lastly, adopting a data-as-a-product mindset elevates its strategic importance while guaranteeing that data is accessible, high-quality, and actionable.

5.3 Limitations and suggestions for future research

While aiming to provide comprehensive understanding of the elements needed to adopt AI systems, this study has some limitations. First, the researcher was employed by the case company while completing the research. Which might cause some bias caused by the researcher's subjective perspective and little experience in research. Second, the research was conducted as a single case study that examined one division of a listed multinational company (MNC) in a short period of time. Thus, the scope of the research was limited in nature and might not be directly applicable to other divisions globally or generalized in the industry. The findings may have limited generalizability to other sectors, as the case company is an incumbent industrial company. Finally, the findings are influenced by the case company's scale. Its ability to allocate extensive resources to AI initiatives is a strategic advantage not typically available to smaller organizations.

Furthermore, the number of interviewees was limited although selected to represent many departments and seniority levels. The limited number of interviewees reflects the current stage of AI adoption at the case company, which remains contingent on a small group of developers. A larger group of interviewees coupled with a longer time-period could provide further insights. The time constraint also affected the ability to interview more top management due to scheduling difficulties. Lastly, the research focused on

adopting internal AI tools and systems rather than AI products or services offered to customers.

The limitations of the study offer several research avenues for future research. First, a larger multi case study conducted in a longer time-period could offer insights into how different companies manage their AI transformation. A longer period could offer insights that occur only with time. Second, a study of SME's would provide insights that have not been captured in literature so far. They are different in many ways from MNC's and thus further research is needed. Finally, modern data architectures particularly data lake, mesh, and fabric are scarcely researched and lack empirical evidence. Thus, research into organizations that have adopted those approaches should be researched.

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Appendices

Appendix 1. List of interviewees

Interviewee	Role and category	Interview duration
1	Business controller (developer)	58min
2	Process development specialist (developer)	49min
3	Purchasing manager (end user)	33min
4	Project engineer (end user)	45min
5	Project manager (end user)	58min
6	AI and data engineer (developer)	56min
7	Business line controller (AI project founder/developer and end user)	50min

Appendix 2. Semi-structured interview questions for end users

Tools and systems

1. What AI tools/systems have you used? For what purpose?
2. How often do you use them?
3. Do you know what AI tools/systems are available for you?
4. Has AI changed the way you work? If yes, how?
5. How could AI enhance your work? Are there any bottlenecks/time wasters?
6. How well do the current AI tools integrate with the existing tools you use daily?
Does it feel like an add-on or a seamless part of the workflow?

Culture and management

7. Is there a strategy for AI?
8. What AI initiatives are underway in the company?
9. How has management dealt with these new initiatives? (communication, awareness, trainings etc.)
10. Has there been enough training on different AI tools? How have these trainings been facilitated?
11. How should management handle change management?
12. Has the leadership clearly explained *why* AI is being adopted in your specific department?
13. Do you feel like AI could replace people in the workplace?
14. Do you feel like your competence could decrease due to AI? If yes how?
15. Are the resources (time, money, strategy etc.) given to AI adequate?

Data

16. Are you aware of what types of data, including their confidentiality categorization, can be inserted into which tools?
17. Are you aware of how to use AI responsibly? Are there guidelines for responsible use?

18. Beyond data confidentiality, do you feel trained on the risks of AI? For example, knowing how to spot a hallucination or bias.
19. Do you trust AI? Why / why not?

Final thoughts

20. What would you like to add to these topics that have not yet been discussed?

Appendix 3. Semi-structured interview questions for technical specialists

General questions

1. What AI tools/systems have you used? For what purpose?
2. How often do you use them?
3. Do you know what AI tools/systems are available for you?
4. Has AI changed the way you work? If yes, how?
5. How could AI enhance your work? Are there any bottlenecks/time wasters?
6. How well do the current AI tools integrate with the existing tools you use daily?
Does it feel like an add-on or a seamless part of the workflow?

Technology and management

7. Is there a strategy for AI?
8. What AI initiatives are underway in the company?
9. How has management dealt with these new initiatives? (communication, awareness, trainings, resources etc.)
10. What have been the biggest challenges in the AI adoption?
11. What kind of AI systems are used and are they general purpose or process specific?
12. How have you managed to integrate legacy systems and existing data with new AI systems?
13. To what extent do legacy systems (SAP, Teamcenter) limit the scalability of AI deployments?
14. Who are the AI system providers (in-house or external)? (Microsoft, Google, Amazon, Snowflake)
15. To what extent is the AI adoption centralized versus fragmented across different business units?

Data architecture

16. Is the current data architecture suitable for AI? (Collection, Storage, Transformation, Distribution, Use)

17. How is data stored? (data warehouse, data lake, lakehouse)
18. Have you recognized data silos? If so, what?
19. How are the quality and availability of data established before beginning the AI adoption? Has data cleansing been needed?
20. Does the current architecture support real-time data streaming or is it limited to batch processing for historical analysis?
21. How is the relationship between data tables explained to the AI system?
22. How are hallucinations and bias dealt with?
23. In what ways is the security and privacy of the data handled?
24. How is the governance of data executed? Who has access to data?

Final thoughts

25. What would you like to add to these topics that have not yet been discussed?