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The Role of AI in Shaping Competitiveness in Finnish companies

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ABSTRACT:

Yritysten teknologinen ympäristö on nopeasti muuttumassa tekoälyn räjähtävän kasvun takia viimeisten vuosien aikana. Tämä on vasta alkua ja kehitys tulee todennäköisesti kiihtymään ja ihmisten taidot kehittymään entisestään. Sen takia monet yritykset ovat joutuneet miettimään ajankohtaista kysymystä ”Koska me hyödynnämme tekoälyä ja miten?”. Ei ole siis kyse enää siitä, tuleeko tekoäly vaikuttamaan yritysten liiketoimintaan, vaan siitä, kuinka nopeasti ja kuinka syvällisesti vaikutukset näkyvät. Tämän tutkimuksen tarkoituksena on katsoa, kuinka tämä tilanne näkyy suomalaisessa yritysympäristössä. Toiseksi tavoite on ymmärtää, miksi tekoälyn käyttöönotto etenee joissain organisaatioissa nopeammin kuin toisissa sekä mitkä asiat nopeuttavat käyttöönoton prosessia. Tätä kokonaisuutta lähestytään sekä teorian että käytännön näkökulmasta, jotta kokonaiskuva ei jää pelkästään teorian ja mallien tasolle. Tutkimus perustuu asiantuntijahaastatteluihin, joissa eri taustoista ja sektoreilta tulevat henkilöt kuvaavat omia kokemuksia tekoälystä. Haastatteluiden kautta muodostuu kokonaiskuva siitä, missä vaiheessa suomalaiset yritykset tällä hetkellä ovat ja mitkä tekijät vaikuttavat tekoälyn etenemiseen.

Tulosten perusteella tekoälyn hyödyt näkyvät ensimmäisenä melko konkreettisella tasolla. Kuten työ nopeutuu, rutiineja voidaan automatisoida ja osa työtehtävistä helpottuu selvästi. Näillä on suora vaikutus tuottavuuden kasvuun. Pidemmällä aikavälillä merkitys on kuitenkin enemmän strateginen – missä yritykset – jotka pystyvät rakentamaan tekoälyn osaksi omia prosessejaan, päätöksentekoa ja muuttamaan yrityksen toimintatapoja, saavat tekoälystä enemmän irti, kuin ne, jotka käyttävät sitä vain yksittäisenä työkalua osana muuta teknologiaa. Tämä johtaakin työn yhteen keskeisimpään havaintoon, mikä osoittaa monien organisaatioiden työntekijöiden olevan valmiita käyttämään tekoälyä omassa työssä, mutta johto puolestaan suhtautuu sen käyttöönotossa suhteellisen varovaisesti. Tämä johtaa tekoälyn käyttöönottamisen hitauteen, vaikka tekniset valmiudet olisivatkin olemassa. Toisaalta usein datan laatu, osaamisen puute ja epäselvät odotukset investointien hyödyistä nousevat toistuvasti esiin yritysten haasteina.

Tutkimus osoittaa, että tekoäly ei itsessään ratkaise mitään. Hyöty syntyy vasta silloin, kun teknologia yhdistetään toimiviin prosesseihin, osaamiseen ja selkeään sekä tarkasti suunniteltuun suuntaan. Kyse on siis enemmänkin oppimisesta ja muutoksesta kuin yksittäisestä teknologiavalinnasta. Loppujen lopuksi kilpailuetu ei tule siitä, kuka ottaa tekoälyn käyttöön ensimmäisten joukossa, vaan siitä, kuka osaa ja oppii käyttämään sitä paremmin kuin muut.

KEYWORDS: Artificial Intelligence, AI adoption, Competitiveness, Finnish Companies, Digital transformation, Organizational capabilities, AI integration, Strategic management

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1 Introduction

Artificial intelligence is reshaping how organizations compete, make decisions, and create value at a pace that leaves little room for gradual experimentation. AI is already changing the way organizations do business, make strategic decisions, and shape organizational capabilities, as well as how firms create and capture value across industries (Kohtamäki et al., 2025), but the implications of AI are also far-reaching. In fact, it has been shown that the actual value of AI is not just in the adoption of AI by companies, but in the value it brings as embedded in the company´s processes, routines, and decision-making (Wamba-Taguimdje et al., 2020; Gao et al., 2025). The key question for firms is no longer whether to adopt AI, but how deeply and how quickly it should be integrated before competitors move ahead. This is particularly true in Finland, where companies have been experimenting with AI technologies, but where strategic and managerial-level AI adoption remains limited (Solita, 2023; McKinsey, 2025). Understanding the effects of different levels of AI integration on competitive outcomes is both practical and theoretically important.

Finland´s position in the current AI landscape makes this inquiry particularly timely. Though Finland is highly ranked with regard to education, technology, and institutional trust (World Bank, 2019), only 18% of Finnish white-collar workers use generative AI at least once per week compared to the European average of 54% (BCG, 2025). Leadership appears to be one of the relevant factors. Recent poll results show that only 5% of Finland´s top managers expect AI to impact their work, while employee readiness appears substantially higher (Solita, 2023; McKinsey, 2025). This reflects a perception gap between top and lower levels of readiness and competitive AI tools. Furthermore, in terms of TAM (Davis, 1989), this manifests as low perceived usefulness and perceived ease of use among decision-makers, which in turn delays strategic-level integration even where technical capabilities exist. According to McKinsey (2025), organizations whose senior leaders do not invest in AI experimentation risk losing competitive ground to more aggressive peers, both domestically and internationally.

The competitive implications of AI have been approached from several theoretical traditions, particularly Porter´s (1985) strategic positioning perspective and Barney´s (1991) Resource-Based view. These frameworks suggest that competitive advantage comes from superior market positioning or from valuable and difficult-to-imitate resources. However, AI challenges these assumptions by making certain capabilities more accessible and easier to replicate. Moreover, AI can easily replicate functions that once were highly differentiated from their competition, such as decision-making speed, data interpretation, and market sensing, thereby reducing the advantages that were earlier considered durable (Shrestha et al., 2019; Buçinca et al., 2021). Dynamic capabilities theory (Teece, 2007) has emerged as a means of explaining how firms maintain a competitive advantage in times of technological change by sensing changes in their environment, exploiting opportunities, and adapting their resources accordingly.

Despite the growing body of literature, several research gaps remain. First, adoption of AI has been commonly considered to be either present or absent in prior literature, with limited attention to how deep the integration may influence the nature and strength of competitive advantage (Kohtamäki et al., 2025). A firm that employs AI as a standalone tool for productivity may achieve different results than one that embeds it into processes such as decision-making and long-term strategy (Ransbotham et al., 2021). This gap between an enterprise´s surface adoption and its more embedded use has not been thoroughly addressed in the literature. Recent studies have called for greater attention to the organizational conditions through which AI use can be transformed into a durable competitive advantage (Climent et al., 2024; Gao et al., 2025). Second, the Finnish business context has been relatively underexplored in empirical work on AI-driven competitiveness. Finland´s welfare state, cautious investment culture, and regulatory orientation may also affect the adoption of AI in ways that differ significantly from findings obtained in the US or UK (World Bank, 2019; Solita, 2023). Third, while individual tools have received considerable attention through frameworks such as TAM (Davis, 1989), how individual-level technology becomes integrated into broader organizational-level competitive abilities has received limited attention (Kohtamäki et al., 2025; Climent et al., 2024).

The competitive stakes of this adoption cannot be underestimated. As previously suggested, advantages from resources that are easily replicated by your competition will erode rapidly (Barney, 1991; Peteraf, 1993). AI-enabled efficiency gains from automation, process optimization, and predictive analytics are already on the verge of becoming a commodity as the underlying technologies become widely available (Wingate, Burns & Barney, 2025). Early adopters who embed AI in specific routines, data structures, and learning strategies will emerge with advantages that will be difficult to copy. On the other hand, those that try to harness AI using it only to perform a tool without linking AI to strategy or decision-making infrastructure may realize mediocre results. (Iansiti & Lakhani, 2020; Gao et al., 2025). For Finnish companies, the risks are magnified by the fact that they will compete against firms in other regions, such as the United States, China, and Europe, that are further along in this integration process (Accenture, 2025; BCG, 2025).

This study aims to explore how the depth of AI adoption within Finnish companies shapes their competitiveness. To guide this inquiry, the following research question is posed:

"How does the depth of AI adoption influence the competitive practices and outcomes of Finnish companies?"

This thesis examines AI adoption in Finnish companies through a qualitative, cross-organizational perspective. Rather than focusing on a single industry, the study draws on expert insight from multiple sectors to capture how AI is currently used in practice and how its role varies across different organizational contexts.

The structure of this thesis proceeds as follows. Following the introduction, the theoretical background of the study focuses on themes related to competitive advantage, AI adoption, and organizational factors that may influence how AI becomes integrated into practice. Following this, Chapter 3 introduces the methodological choices of the study and explains how the empirical material was collected and analyzed. Chapter 4 then turns to the findings of the study by examining how different levels of AI adoption are visible in organizational practices and how these seem to relate to competitive outcomes. Finally, Chapter 5 discusses the findings in relation to earlier literature and closes the study through managerial implications, limitations, and suggestions for future research.

2 Theoretical background

The theoretical background is structured around three primary focuses. First, it outlines the fundamentals of competitive advantage by using the Resource-Based View (RBV) and Porter's Generic Strategies to explain how firms are historically able to perform better. Second, it examines the Technology Acceptance Model (TAM) to understand why AI is implemented by companies based on its perceived usefulness and ease of use. Third, it links these perspectives to consider how the rapid pace of AI adoption is fundamentally altering the business environment and suggests a two-part process model that distinguishes between operating efficiency and strategic competitiveness.

2.1 Competitive strategy & AI Adoption

At its core, competition determines the success or failure of a firm and, therefore, firms have to innovate, improve their efficiency, and quickly adapt to changes in the market (Porter, 1985). Competitive strategy identifies reasons for a firm's continued competitive advantage, while another fails under environmental pressures. The approach of competitive strategy has been considered from two different perspectives, Porter's (1985) industry view and Barney's (1991) Resource-Based View (RBV).

Porter (1985) believes that a firm can be competitive only by creating value above its cost of production through one of three strategies: cost leadership, differentiation, or focus. According to the RBV, an advantage can be sustained as long as the firm has valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). The advent of AI has begun to shake up these frameworks. For instance, by reducing marginal costs, algorithms enable firms to move from standardized mass production toward hyper-personalized value creation models (Iansiti & Lakhani, 2020). These changes do not render old theories obsolete, but instead, they shift the source of advantage toward firm data, proprietary learning processes, and human-AI interactions.

AI transforms the way these critical business outcomes occur. Cost leadership in the new economy can now be ensured through automation and data-driven optimization. AI saves firms money by reducing costs in supply chains and maintenance. Additionally, AI increases total factor productivity and R&D expenditure, which further promotes firm competitiveness (Sui et al., 2024). However, a key limitation is that as AI becomes more accessible, these gains could become commoditized, since the technology itself can be purchased and replicated more easily. As a result, differentiation increasingly shifts away from the technology itself toward human-centered capabilities such as creativity, brand loyalty, and emotional engagement, which are more difficult for AI to imitate (Wingate et al., 2025). Consequently, a sustainable cost advantage may shift away from the software itself and toward firms with superior data access and the capital to maintain large-scale AI infrastructures.

Differentiation is also tied to the ability of AI to lead to innovation and better customer experiences through personalization. When AI is integrated into an organization's strategy, it can generate more innovative products and services that were otherwise beyond reach (Kitsios & Kamariotou, 2021). Companies such as Amazon and Google have restructured their operating models into scalable AI systems. These systems can leverage data and algorithms to continuously learn, improve, and provide personalized services (Iansiti & Lakhani, 2020).

Lastly, focus strategy enables firms to target micro-segments with high precision through AI, thereby reshaping focus strategies through more accurate customer segmentation and personalization. It achieves a state of "human-AI complementarity," where the speed of algorithms and human expertise create an individual, persistent heterogeneity in niches (Krakowski, Luger, & Raisch, 2022). For smaller firms, the strategic edge is in using targeted AI applications that serve niche requirements, provided the firm is prepared to do so (AlSheibani, Cheung, & Messom, 2020).

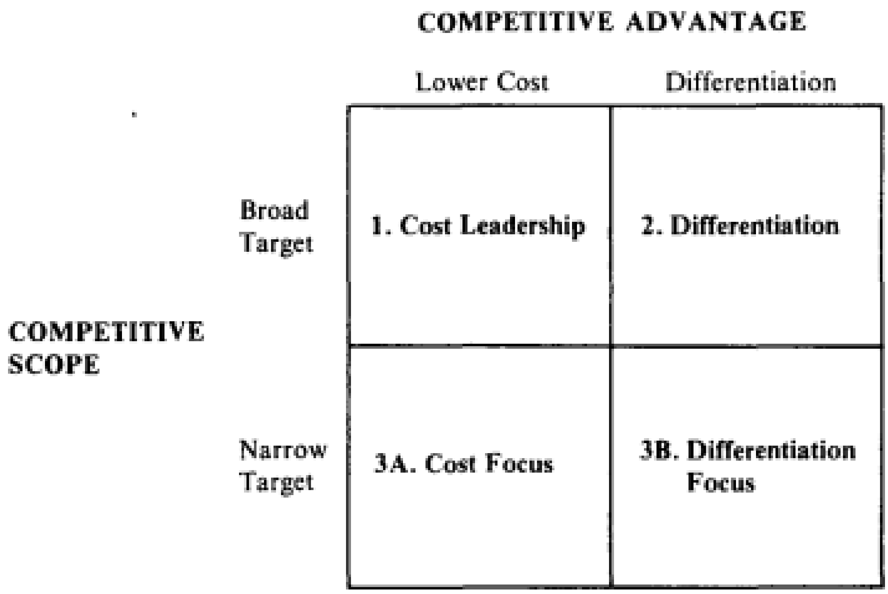


Figure 1. Generic Competitive Strategies (Porter, 1985)

The Resource-Based View (Barney, 1991) identifies resources such as brand equity or patents as the main sources of long-term advantage. In an AI-driven world, having these resources in place does not suffice. The rapid pace of imitation in AI-driven environments increases the importance of continuously developing resources through data-driven processes and organizational learning (Sui et al., 2024; Krakowski et al., 2022).

Standard AI models are increasingly accessible and therefore rarely satisfy the "rare" or "inimitable" criteria of the VRIN framework on their own. Instead, AI becomes a VRIN resource only when integrated with proprietary data and firm-specific human expertise (Kemp, 2024; Teece, 2018). As summarized in Table 1, it is the integration of AI into complex workflows and routines that provides a competitive edge, rather than the acquisition of the technology itself (Wamba-Taguimdje et al., 2020).

Table 1. VRIN and Application in the AI Context.

VRIN Criteria	Explanation	AI & Technology Application
Valuable	Does the resource help a firm improve efficiency or effectiveness.	AI-driven data analytics enables better decision-making.
Rare	Is the resource unique or do many competitors have it.	Proprietary AI algorithms.
Inimitable	Can competitors easily copy it.	AI models trained on exclusive data sets.
Non- substitutable	Can a different resource re-place it.	AI-driven automation vs. human labor (not easily replaced).

As competition moves beyond market boundaries, technology has transitioned from a support tool to a core driver of strategic behavior. Companies are shifting from competing via geographical channels to competing through technological superiority and learning velocity (Iansiti & Lakhani, 2020; Azagury & Moore, 2024). This requires Dynamic Capabilities, defined by Teece (1997; 2007) as the ability to sense changes, seize opportunities, and reconfigure resources.

Digital transformation refers to the integration of digital technologies into organizational processes and decision-making structures, fundamentally reshaping how firms create and deliver value (Veile et al., 2019). In the case of AI, the transformation projects with the highest potential to yield high performance are those that are integrated with management and organizational learning (Wamba-Taguimdje et al., 2020). Technology is an "integrated capability," improving efficiency and flexibility (Sui et al., 2024).

In particular, it is crucial to build a digital core, a structure and infrastructure that ties data and algorithms across the business. Digital cores enable "flywheel effects," where data is gathered, and algorithms are refined, further consolidating the firm's position in the market (Iansiti & Lakhani, 2020). Furthermore, the firms' ability to learn fast within the digital core is now an important factor in defining their competitive advantage (Azagury & Moore, 2024).

Beyond operations, technology is also changing the way companies execute their plans. AI helps overcome the limitation of “bounded rationality” by offering insights that widen human cognition and help firms adapt to uncertainty more quickly (Csaszar, Choen, & Rogers, 2024). This human-AI complementarity represents a departure from viewing technology solely as a labor substitute. Instead, it functions as a cognitive collaborator (Krakowski et al., 2022). But this gain can only be obtained if managers are rational and do not blindly rely on AI for accuracy.

In conclusion, connecting these theories suggests that while Porter and the RBV provide the foundation for competition, their modern payoffs depend on AI-era enablers. Competitive positions endure only when supported by human-AI roles and learning systems that continuously improve. Sustainable performance relies on a firm’s ability to develop renewable technological capabilities that evolve faster than rivals can imitate them (Teece, 2007; Barney, 1991). In this light, technology serves as both the engine and the catalyst for superior adaptability in an uncertain global market.

2.2 Finland´s AI Adoption in a Global Context

While classical strategic frameworks explain how firms achieve and sustain competitive advantage through resources and positioning, emerging technologies such as artificial intelligence challenge these assumptions. The following section explores how AI reshapes traditional sources of advantage and examines Finland’s relative position in adopting these technologies.

2.2.1 Comparative Analysis of AI Adoption

The Technology Acceptance Model (TAM) developed by Davis (1989), is based on the Theory of Reasoned Action (TRA) formulated by Fishbein and Ajzen (1975). Both models try to identify the factors that lead to technology acceptance or rejection by an individual. TRA centers on behavioral intention and its determinants — attitude and subjective norms — whereas TAM has adapted this approach for technology adoption by pinpointing two main beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). PU is the degree to which a person thinks that using a specific technology will improve his or her work performance, whereas PEOU is the perception of the degree to which usage of the technology is easy or requires little effort. These concepts are still very important for clarifying the current organizational decision-making process in terms of AI adoption.

Recent Finnish studies demonstrate the importance of the Technology Acceptance Model (TAM) in shedding light on the slow pace of AI adoption. According to Solita (2023), a survey covering Finland's 500 largest companies found that 83% of them did not use generative AI in their processes. A mere 8% of the people surveyed expected AI to cause a major change in their business, which points to the fact that the perceived usefulness (PU) was very low. Besides, 70% of the top executives did not allow AI to come into their work, and this meant that the perceived ease of use (PEOU) was still low, because AI was treated as something complex, hazardous, or still not a part of the daily managerial routines. The use of daily generative AI among IT management is shown in Figure 2 as being only 31%, while 44% claim not to use it at all; this emphasizes the very limited practical diffusion of AI across roles and hierarchies. Only 60% of the employees in the organizations that have already adopted AI use it daily or sometimes, which again proves that

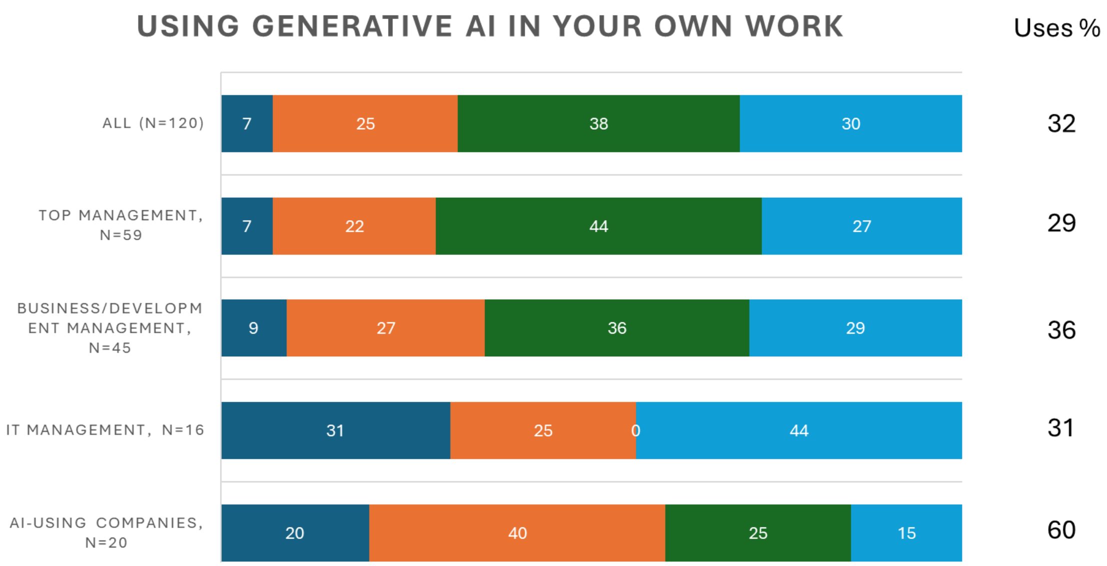
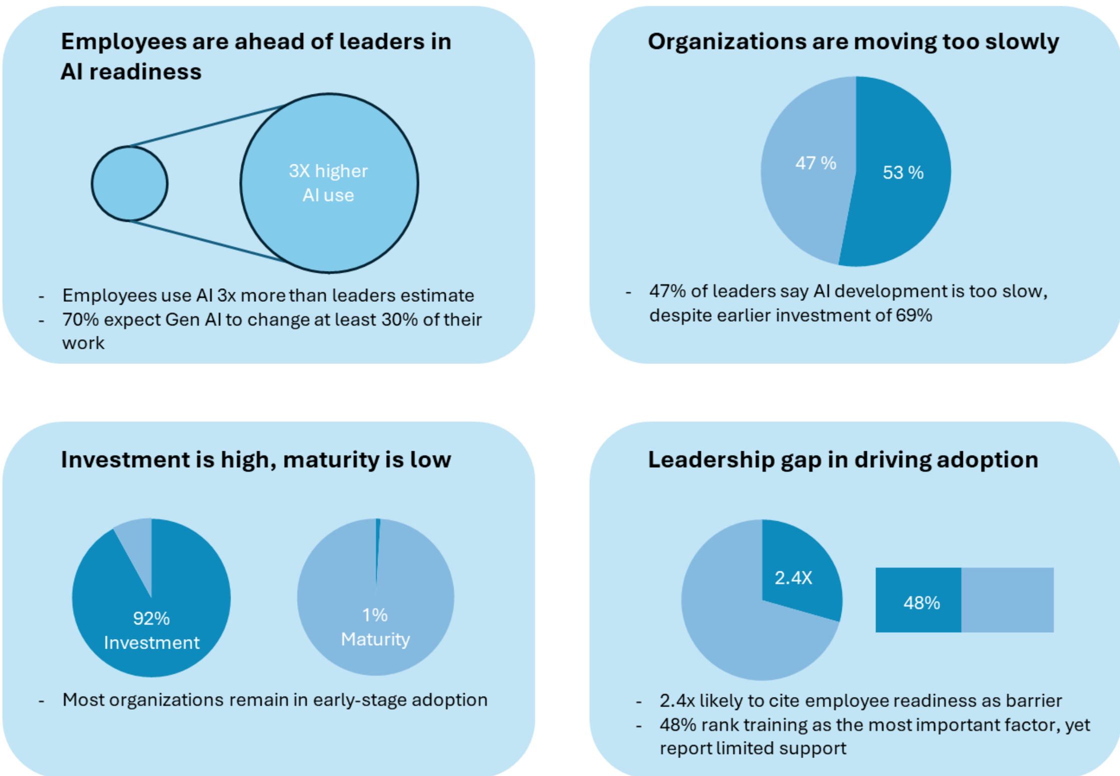


Figure 2. Use of Generative AI Across Organizational Roles (Solita, 2023)

the barriers to adoption result mainly from the management's view of limited usefulness and high complexity rather than from technological unpreparedness.

McKinsey (2025) reports that AI generates significant long-term productivity potential, which corporate use cases can value up to USD 4.4 trillion at its maximum. Still, the short-term effect is, at least, a matter of speculation, particularly for the smaller market of Finland, where the business culture is such that it does not lead the global trends but rather follows them. The document reveals that a mere 19 percent of companies managed to advance their productivity by more than 5 percent due to AI, whereas 39 percent are reporting slight improvements of 1-5 percent. What's more, only 1 percent of companies consider their AI capabilities to have reached the maturity stage. Nevertheless, at this early phase, 92 percent of the organizations involved in the survey are planning to boost their generative AI investments over the following three years (see Figure 3). These results indicate that firms admit the potential of AI, but the vague return on investment and the lack of proper implementation skills are holding back the large-scale

Figure 3. Employee Readiness and Organizational Adoption (McKinsey, 2025)



adoption, especially in the risk-averse markets such as Finland. Foundational and contemporary studies indicate that the Technology Acceptance Model (TAM) is still a valid framework for analyzing such adoption behavior, emphasizing that both perceived usefulness and perceived ease of use significantly influence behavioral intention (Tamilmani et al., 2021).

The attitudes of leaders, according to McKinsey (2025) might be the main reason behind the slow pace of AI adoption. Employees, on the one hand, are much more ready and even positive about the AI technology than their managers, as the survey indicates: 70% of workers anticipate that AI will change about 30% of their tasks soon. In the same vein, Solita (2023) reveals that just 5% of Finland's top managers expect AI to have a great impact on their work processes, whereas 12% of IT professionals think so. The data in Figure 5 further depict that while most organizations are still in the early stages of AI adoption, the participation level of employees in such technologies is much higher than what the executives perceive. The above-mentioned statistics reveal the existence of a perception gap within leadership—top management personnel tend to think that the organization is neither ready for AI nor its potential. In terms of the Technology Acceptance Model (TAM), managers show low perceived usefulness (PU) and perceived ease of use (PEOU) for AI; doing so hampers the adoption of AI in the organization, even though employees are enthusiastic. McKinsey (2025) warns that companies whose top management does not accept AI experimentation and risk-taking may lose their competitive edge to those that are more proactive about AI integration.

Empirical research supports this leadership-driven adoption gap. Ransbotham et al. (2021) reveal that the engagement of employees with generative AI tools is considerably greater than what their managers perceive, with actual usage rates being significantly greater than what the executives expect. This discrepancy reveals that employees have started to use AI already at the operational level, while on the other hand, the leadership's reluctance is retarding the strategic integration and scaling of AI. These findings indicate a persistent managerial perception gap, i.e., between technological readiness and perceived usefulness (McKinsey, 2025 & Ransbotham et al., 2021).

The leadership challenge is also perceived through a theoretical lens. According to Raisch and Krakowski (2022), the automation–augmentation paradox is described, where managers try to find a middle path between speedy automation and fostering human creativity and judgment. This lack of clarity fosters lower PU and PEOU among decision-makers and consequently, the adoption of AI-driven solutions is not very strong. Therefore, any technologically advanced organization can still be at risk of falling behind in competitiveness if the leadership's perception does not change to accompany the change in technology.

2.2.2 AI in decision-making, automation and strategy

While comparative adoption data reveal Finland's position in the global landscape, understanding how AI influences decision-making and strategy within firms is equally important. According to Stone et al. (2020), AI is gradually being recognized as a support tool for decision-making rather than a complete decision-maker, thus helping the management in understanding complex data and making decisions. One of the major powers of AI is to quickly analyze huge amounts of data, which is very important in areas like marketing and customer research, where the data is too much and too fast for humans to process efficiently.

According to Shrestha et al. (2019), the five decision-making conditions that AI can influence are: the specific nature of the decision space, the ability to interpret, the number of alternatives, the speed of decision-making, and the possibility of replicating outcomes. Interpretability, trust, speed, and replicability are the most significant factors from the adoption perspective since they directly affect the managers' perceptions of usefulness (PU) and ease of use (PEOU).

Specificity is the degree to which a decision's parameters and objectives are well-defined. Structured decision-making processes are based on measurable variables and explicit goals, while poorly defined cases rely on human intuition and taking the context into account (Shrestha et al., 2019). For instance, hiring decisions are often a mix of both structured assessments and intuitive judgments about cultural fit. Currently, AI excels in very specific and data-rich contexts, but it has a tough time dealing with non-specific or qualitative aspects of human decision-making. In situations where decision goals are not clear, managers consider AI to be of limited value (lower PU), which hinders its use in difficult, culture-driven tasks.

Interpretability is a term that describes the extent to which people can comprehend the different aspects of decision-making and the resulting outcomes. Humans are able to give reasons for their choices, i.e., reasoning is an integral part of their decision-making and consequently. Human decision-making can be explained; however, AI systems are quite the opposite and, therefore, mostly labeled as “black boxes,” which in turn hinders the detection of biases or logic (Shrestha et al., 2019). The plus side to human decision-making is that it is always reasonable and justifiable; hence, even if AI were somehow to do the same things that humans do, it would still lack the trust that humans need to make decisions. This trust issue has its roots in the fact that AI cannot be questioned or reasoned with. This ultimately leads managers to a non-trustful relationship with the technology as they worry about the reliability of such AI systems. Dependent users have little choice but to take a less trustworthy AI decision even when it is wrong (Buçinca et al., 2021). The interpretation of such decisions may not always cause the problem to disappear. Moreover, in some situations, the so-called “explainability features” even result in the opposite, i.e. more misplaced trust. Cai et al. (2019) maintain that corporate leaders must consider interpretability as a design challenge: by being open about the data used for training, the objectives set for optimization, and possible blind spots, one can not only promote understanding among users but also gain their trust. Therefore, managerial PU is indirectly influenced by AI’s low interpretability and hence slow adoption, whereas proper transparency design can win over trust and boost acceptance.

Speed, Alternatives, and Replicability. The main reason for AI's remarkable dominance in decision-making is its power to analyze different alternatives in a matter of seconds and in a highly organized manner. Human managers are already challenged by their limited mental capabilities, and as organizational complexity increases, they often undergo decision fatigue. AI-powered technologies are relieving the burden by selecting the best options and giving them priority, offering immediate information, and sharing the analytical work among various departments (Shrestha et al., 2019; Purdy & Williams, 2023). Nonetheless, the very same efficiency that allows for quicker decisions also brings about governance issues. When decisions are made on a massive scale through undisclosed algorithms, the effects of biases or model errors can spread faster. To a greater extent, replicability confronts challenges: the decision-making process is a black box, and the changes of training data can lead to different results in different situations, making it unpredictable to apply the same AI model in different organizations or industries (Wirz et al., 2024). For sure, the effective onboarding, explanation mechanisms, and escalation norms (Cai et al., 2019) are the prerequisites to make the automation argument rather than supplant managerial judgment. Therefore, better PU and slower speed across the board replicability come with more stringent governance and model-risk demands, calling for managers to trade-off efficiency for oversight.

Table 2. Comparison of AI-Based and Human Decision-Making (Buçinca et al. 2021)

Decision Making Conditions	AI-Based Decision Making	Human Decision Making
Specify of the decision search space	Requires a well-specified decision search space with specific objective functions.	Accommodates a loosely defined decision search space.
Interpretability of the decision-making process and outcome	Complexity of the functional forms can make it difficult to interpret the decision process and outcomes.	Decisions are explainable and interpretable, though vulnerable to retrospective sense-making.

Size of the alternative set	Accommodates large alternative sets.	Limited capacity to uniformly evaluate a large alternative set.
Decision-making speed	Comparatively fast. Limited trade-off between speed and accuracy	Comparatively slow. High trade-off between speed and accuracy.
Replicability of outcomes	Decision-making process and outcomes are highly replicable due to standard computational procedures	Replicability is vulnerable to inter- and intra-individual factors such as difference in experience, attention, context, and emotional state of the decision maker.

Over-reliance and Human–AI Balance, where over-reliance on AI leads to the erosion of critical human supervision and the deterioration of the process of learning strategically. In their study, Buçinca et al. (2021) point out that the successful integration of AI is fully dependent on keeping the human influence actively involved, which is done through the design of AI systems that advocate the questioning and the validation of AI output rather than the acceptance of it as the truth. The leaders will be able to draw this line by introducing escalated protocols, developing continuous feedback loops for users, and providing training that makes it clear that AI is on the support side and not on the substitution side. A balanced reliance builds up trust and gives further PU by always putting human oversight in the heart of the decision-making process.

The quality of decisions made depends largely on organizational design and governance that either support or make AI difficult to use. According to Ransbotham et al. (2021), out of all the firms that invest in AI, only 11% get extensive financial returns, and those that acquire substantial returns are constantly integrating the algorithms into the formal governance structure, along with the decision rights, escalation paths, and continuous feedback being very clear. In such structures, AI acts as a partner to the strategy by bringing forth the choices, whereas the human experts make the decision after applying their contextual judgment and ethical evaluation. The C-U-E model indicates good governance of AI, resulting in the dual effect of increased efficiency and quality of decisions, which further creates a cultural alignment and technical effectiveness cycle. The process of AI adoption here is no longer viewed simply as a technological upgrade, but rather an organizational learning process that constantly enhances the competitiveness of the business through time.

Furthermore, observation from high AI adopters is that with a higher level of AI adoption, there is an increase in new measures of performance and flexible decision-making processes. In other words, this means that the organization's learning doesn't just become episodic (Ransbotham et al., 2021). Overall, AI governance does not replace human decision-making; it simply increases the ability of the organization to critically examine assumptions and rapidly adapt to changes in the environment.

In conclusion, decision-making effectiveness remains a central determinant of AI adoption. Interpretability, trust, speed, and replicability are not purely technical properties but managerial design decisions that shape perceived usefulness and ease of use. Firms that actively manage these trade-offs, through transparency, governance, and human–AI collaboration, can close the adoption gap more quickly and build dynamic capabilities that sustain competitiveness.

2.2.3 Factors Influencing AI Adoption

Investments are a central determinant of competitiveness, particularly when new technologies reshape industries (Porter, 1985). AI is one such revolutionary technology and hence is gaining massive private and public investments at an ever-increasing pace. Worldwide data reveals that the investment in AI accelerated dramatically during the late 2010s, with venture capital being the major player and funding getting heavily concentrated in the leading economies, of which the United States and China are the most prominent (World Bank Group, 2019). Concurrently, developing countries—barring a few leading instances—obtained just a small part of the AI-related investments, thereby exposing the global disparities in AI capabilities. These investment patterns suggest that leading economies recognized early the strategic importance of large-scale, sustained investment in AI as a foundation for future competitiveness.

Major technology companies, like Google, Microsoft, and Amazon, have put billions of dollars into AI research, training of large-scale models, and commercial applications that include OpenAI's platforms, to name just one, among many such applications. However, even with these gigantic investments, the fate remains uncertain. According to the Harvard Business Review (2023), although 90% of companies were working on AI transformation projects at that time, these projects contributed only 31% of the expected revenue increments and 25% of the cost savings projected. So, it implies that merely pouring money into the project would not yield desired results without organizational preparedness, data strategy, and leadership commitment. According to Forbes (2024) the five elements for effective AI investment are: (1) long-term sustainability and adaptability; (2) measurable financial returns (ROI); (3) cross-functional scalability; (4) accessibility for nontechnical users; and (5) human efficiency enhancement. These factors stress that the window to AI competitiveness opens via the quality and strategic integration of investments, not merely through their volume.

The investment in the public sector has also increased significantly. According to the OECD (2021), government-funded AI R&D saw a rise from about $207 million in 2001 to $3.6 billion in 2019, a very large increase of seventeen times. A number of governments are now granting AI initiatives 10–15% of their total R&D budgets, showing a major change in policy. On a continental scale, the European Commission (2025) is planning to raise €200 billion for AI-related investments, with substantial funding for large-scale computing infrastructure such as AI “gigafactories”. The Commission President, Ursula von der Leyen, describes “AI is a key driver for improving healthcare, boosting research and innovation, and increasing competitiveness,” and the European Investment Bank has also pledged to provide extra funds in order to support AI as a productivity lever. All these actions taken together reveal a very definite policy agreement: AI is no longer considered a regional issue but rather a global competition priority.

Moreover, according to a recent Accenture (2025) report on Europe's AI Reckoning: Reinventing Industries for a New Era, Europe is still falling behind the U.S. and China in terms of private sector AI investment and large-scale commercialization. It is said that if the total AI deployment and capital attraction are not coordinated, the European industries will no longer be able to compete due to the structural risk of competitiveness erosion. Though public funding and regulatory activities are increasing, Europe still has the problem of fragmented data governance, not enough access to risk capital, and a rather conservative business culture. Accenture indicates that among the various industries, manufacturing, healthcare, and public services are the hardest hit because of the slow but sure AI adoption, rather than the fast-paced and disruptive nature of it. This larger European scenario is very similar to Finland's problems, implying that the country's hesitant investment practice and the fragmented funding environment are indeed part of a broader regional pattern and not merely an isolated national issue (Accenture, 2025).

While AI adoption has accelerated globally and promising progress is visible across many European industries, Finland's uptake remains comparatively slow. According to the report by BCG (2025), merely 18% of the Finnish white-collar sector has incorporated generative AI in their daily work at least once a week, while the average in Europe is more than triple, 54%. Training has a strong effect on usage as the trained employees are found to be using GenAI for an average of 3.6 hours a week, in contrast to 1.5 hours for those who have not received any training. This situation suggests a lack of structured learning programs and organizational incentives for AI skill development. Business Finland (2025) supports this finding by stating that while Finland possesses robust research capabilities and top-notch AI expertise, it is still hard to find and keep the best talent. A targeted approach, such as facilitating the hiring of foreign experts, could potentially alleviate this problem.

Finnish firms often approach digital transformation cautiously. Whereas a great number of them are looking for gradual efficiency improvements, only a small number of them arise with radical, transformative AI projects (Business Finland, 2025). This conservative investment pattern gives up high-value opportunities. Additionally, even if the public instruments, such as Business Finland, offer support at the early stage, the larger ecosystem still has a hard time luring large-scale growth capital. Finnish startups are, compared to their peers in other countries, in a much less favorable financing environment, which limits their scaling and commercialization of AI innovations effectively.

Finland is not alone in facing this issue. Similar situations are occurring in other Nordic countries like Sweden, which is among the leading countries globally in AI private investment, gaining approximately $4.3 billion in funding in 2024 (Stanford University, 2025). These countries also have to deal with the same issues, i.e., conservative business cultures and the presence of tight regulatory frameworks. The positive side of these norms is that they help companies to practice and to be ethical and secure with data, and the downside is that they might sometimes slow down the whole process of innovation and experimentation. All in all, the combination of Finland's investment hesitance, lack of talent, and disintegrated funding sector could be the reason behind the slow adoption of AI technology. If Finland wants to turn its research strengths into a substantial competitive edge, it might need to deal with these problems first.

2.3 Strategic Implication and Solutions

Having identified the current AI adoption gap and its underlying causes, it is essential to consider what strategic implications this gap holds for firms and for Finland’s long-term competitiveness. The next section discusses these implications and outlines potential solutions at both the organization and policy levels.

2.3.1 AI’s long-term Impact on competitiveness

Artificial intelligence is rapidly redefining the sources of competitive advantage. It does so by disturbing the existing strategy models and the whole operation, learning, and evolution of companies. On the one hand, AI destabilizes traditional advantages by commoditizing operational efficiency and lowering barriers to entry. It provides high-learning agility companies with a new resource reconfiguration and capability development. According to Teece (2018) and Ransbotham et al. (2021), AI's strategic value is in having the organization dynamic and responsive to change rather than in its static implementation. However, this potential is further complicated by what Kemp (2024) calls the "generic-AI paradox": the very fact that algorithms are explicit, portable, and relatively easy to copy suggests that they should only yield short-term advantages. The paradox is resolved when AI is viewed not as a tool available to everyone but as a capability already built into proprietary data, company-specific routines, and the continual feedback loops between customers and the firm. It is not the mere access to AI that brings about the advantage, but rather how deeply and in what unique way it is integrated into the organization's evolving learning systems (Iansiti & Lakhani, 2020).

While Porter’s and Barney’s frameworks once explained competitive advantage through stable positioning or rare assets, AI challenges these assumptions. In a context of constant innovation, static advantages decay rapidly (Teece, 2007), and firms must now compete on adaptability.

From the resource-based view (RBV) perspective, AI is a resource of a new and distinct nature, data, algorithms, and digital infrastructure, which are quite different from the existing assets. On one hand, physical assets lose value over time, but on the other hand, digital resources often get more valuable due to the use of algorithms, for instance, learn from experience while data gets larger (Kemp, 2024). Nonetheless, these resources become strategic only when they are embedded in firm-specific routines and leveraged through organizational capabilities such as judgment and creativity (Barney, 1991).

The combination of human and algorithmic capabilities is the reason for the birth of what Krakowski, Luger, and Raisch (2022) call the "automation-augmentation paradox." AI has the ability to perform analytical and operational duties with such immense efficiency that it can practically be referred to as a human counterpart; on the other hand, it also enlarges the mental arena where human faculties of creativity, empathy, and strategic interpretation can interact. Companies that exploit AI merely as a means to cut down on costs may get to enjoy a seductive but brief gain, as their competitors will soon be using the same technology and thus adopting the same strategy, ultimately leading to a similar outcome of commoditization. On the other hand, companies that are into the practice of using AI for the purpose of human insight enhancement, for instance, in creative processes, resolving issues, and coming up with new products or services, are gaining the development of mixed competences, which is another way of saying they are creating skills that are not easily copied (Wingate et al., 2025). Using this reasoning, human capital and organizations' learning processes are still the key differentiators, biologically and technologically speaking, even in highly digitized economies.

The dynamic capabilities framework presents a conceptual bridge for comprehending these changes. Teece (2007, 2018) states that in environments subject to change, companies still manage to perform well through three interlinked abilities: the ability to sense possibilities, the ability to take them through prompt investment, and the ability to reconfigure resources so they remain in alignment with the environment. In the AI context, sensing is the same as recognizing the technological changes and the new data-driven opportunities; seizing entails the distribution of capital, talent, and partnerships among the company to make the most of the opportunities. This reconfiguring includes re-training the algorithms, modifying the governance models, and changing the processes as the AI systems and the market are transformed (Warner & Wäger, 2019).

The implementation of AI entirely changes the nature of strategy. The classic approach of strategy formulation was to a set of steps of analysis, planning, and performing. With AI as the competition’s main factor, strategic decision-making becomes a continuous, iterative, and data-based process. The space in making strategic decisions is filled up by almost real-time change, with the help of machine learning systems that are in charge of detecting anomalies, predicting trends, and creating alternative futures (Shrestha et al., 2019). The company's ability to get smarter faster than the rivals becomes the main factor of differentiation, a viewpoint that is in line with the saying "the ultimate competitive advantage is organizational learning speed" (Teece, 2018, p. 43). Importantly, the shift toward algorithmic decision support does not eliminate managerial judgment but rather elevates its role. Managers must interpret machine-generated insights, ensure ethical governance, and align AI outputs with broader strategic objectives (Ransbotham et al., 2021).

For smaller economies like Finland, the implications are particularly pronounced. Finland's historical strengths — high trust, strong education, and digital infrastructure — provide a strong base for AI integration. Yet the country's relatively cautious investment behavior and limited scale of private-sector R&D could undermine its ability to fully develop dynamic capabilities (Business Finland, 2025). Competing in an AI-driven global economy requires not only adopting technologies developed elsewhere but also cultivating domestic learning ecosystems that connect research institutions, startups, and established industries (Accenture, 2025). Nations and firms that institutionalize such learning systems will capture compounding returns from AI, while those that hesitate may face a widening "adaptation gap."

Ultimately, AI challenges firms to rethink what "sustainable advantage" truly means. In the coming decade, advantage will not be sustained by protecting existing resources but by continually renewing them through feedback, experimentation, and human–machine collaboration (Warner & Wäger, 2019). AI does not render strategic management obsolete; rather, it demands a more dynamic, integrative, and human-centered understanding of strategy. As Teece (2018) notes, the defining question for managers in the AI era is no longer "How can we defend our position?" but "How quickly can we adapt, learn, and redeploy what we know?"

2.3.2 Strategies for Accelerating AI Integration in Finland

Accelerating the AI integration in Finland requires a systemic approach that synchronizes technological progress with organizational capabilities, institutional frameworks, and societal trust. Studies in the area of digital transformation have shown that successful implementation is highly dependent not only on the availability of cutting-edge technologies, but also on the combination of human capital, organizational processes, technological infrastructure, and data governance (the so-called People–Process–Technology–Data, or PPTD, framework)(Uren & Edwards, 2023; Kane et al., 2015). In this light, technological capability is considered a facilitator, not the main factor affecting competitiveness. The organizations with the highest performance stand out because of their capacity to create social and managerial capabilities that “raise the floor” for AI to go beyond the pilot stage (Eken et al., 2025; Lavin et al., 2022).

Firm-Level Strategies: Building Organizational AI Readiness

At the firm level, the integration of AI should be considered as a gradual capability-building process instead of a one-off technological project. The studies on dynamic capabilities indicate that organizations should constantly sense the coming opportunities, take them by making resource commitments, and then reorganize their assets to sustain advantage (Teece, 2007; Warner & Wäger, 2019). In Finland, this means constructing an adoption journey that is sequenced to take maturity from one step to the next—from experimentation to scaling and governance. AI transformation empirical studies recommend that data and process gaps should be identified during the early pilots, after which there should be investments made in “industrialization” capabilities such as MLOps, model validation, risk management, and change management (Uren & Edwards, 2023; Lavin et al., 2022).

Finland's large industrial corporations and multinational enterprises, which often face the dual problem of scaling AI initiatives across complicated business units and legacy infrastructures, actually rely heavily on two organizational mechanisms. First, these firms should create cross-functional AI teams that connect the three areas of the business—data science, operations, and strategic management. Such “translator-enabled” teams in large companies help break down structural silos by ensuring a common understanding of problem framing, value realization, and ethical considerations—factors that are always associated with successful transition from prototypes to enterprise-scale deployment (Henke et al., 2016; Davenport & Miller, 2022). The second one is that companies have to prepare their processes by implementing a system of development and governance routines—such as version control, data lineage tracking, and reproducibility checks—that ensure model reliability and auditability throughout the company's multiple divisions (Eken et al., 2025). Without these enterprise-wide processes, scaling beyond pilot projects becomes fragmented, costly, and operationally risky.

People's readiness among the workforce is another important factor that speeds up the process in big companies. Studies on the development of digital capabilities reveal that the adoption of AI, in fact, relies on the literacy and trust of the entire workforce rather than on the small group of the most specialized and technical staff (Kane et al., 2015). In the case of large companies, such end-users who are aware of the basic reasoning, constraints, and malfunctioning of the AI systems, for example, by spotting data drift, recognizing strange model outputs, or having the knowledge when human intervention is needed-will not only be the ones who help making the systems more reliable and efficient but will turn to be the most important ones (Uren & Edwards, 2023). The flow of the skill from the AI teams in the center to the operational units thus not only increases the organization's ability to adapt but also diminishes the resistance to the new digital workflows. International comparisons show that workers in different regions are affected by AI in different ways, and this has led to the need for continuous learning ecosystems that support ongoing reskilling and role evolution within firms (OECD, 2023).

The most distinctive bottleneck remains data readiness, and thus it is the highest-leverage area for intervention. The PPTD framework asserts that well-governed, fit-for-use data are the basis for sustainable AI performance (Uren & Edwards, 2023). The implementation of clear data contracts, metadata standards, and retention policies related to particular use cases enables companies to ensure quality and compliance over time. Since the models change along with the operational conditions, the continuous data curation and quality monitoring should be made part of the standard processes rather than being treated as project tasks (Eken et al., 2025). The OECD framework highlights that privacy protection, accountability, and transparent governance are central for building trust in AI systems and enabling their widespread adoption (OECD, 2024).

Ecosystem-Level Strategies: Strengthening Collective Infrastructure

From an ecosystem perspective, Finland can accelerate to speed up the diffusion of AI through the enhancement of shared infrastructures that will not only lower the entry barriers but also give support to responsible experimentation and learning that is distributed. The open innovation and knowledge-based literatures highlight the significance of collaborative assets, like shared data environments, industry-wide testbeds, and interoperability frameworks, that grant firms the opportunity to access external knowledge, avoid duplicated investment, and build up collective capabilities (Chesbrough, 2020). In Finland, ecosystem initiatives like European data spaces, national AI testbeds, and maturing Gaia-X–aligned infrastructures are platforms where firms can test their models on either synthetic or de-identified data while working on governance procedures in compliance with EU regulations (Sitra, 2025; Gaia-X Hub Finland, 2024).

Shared infrastructures are not just about data-sharing, but they also play the role of coordination and trust-building mechanisms. This is especially the case in Finland, where companies are still reluctant to share data among themselves, usually for the reasons of privacy, competition, and institutional norms. The national maturity model produced by the research organizations (Uren & Edwards, 2023) can be used by the organizations to rate their readiness, discover the systemic capability gaps, and synchronize their steps of development. Such alliances reduce the period of time from trying out new ideas to having them ready for production, thus supporting the whole innovation system that is necessary for the nationwide acceptance of AI.

Public policy plays an enabling role by aligning regulatory clarity with innovation incentives. The forthcoming EU Artificial Intelligence Act establishes risk-based obligations and documentation requirements intended to ensure transparency, accountability, and trustworthy AI (European Commission, 2025). Internalizing these governance mechanisms early allows Finnish firms to treat regulation not as a compliance constraint but as a potential source of competitive differentiation. To support responsible scaling, national programs should emphasize capability readiness by funding translational initiatives that move promising projects from Technology Readiness Levels (TRL) 6–7 to full deployment at TRL 8–9 (Lavin et al., 2022).

Business Finland (2025) and the Ministry of Economic Affairs and Employment (n.d.) have initiated new tools such as innovation-based procurement and AI cluster financing linked to observable PPTD readiness. This strategy is in accordance with the absorptive capacity model, which states that companies need appropriate organizational structures and learning capabilities to adopt and use new technologies (Cohen & Levinthal, 1990). Considering Finland's export orientation, it is necessary that the policy support collaboration across borders with Nordic and EU partners to lessen the fragmentation that is the main reason for Europe being unable to scale AI innovations (Accenture, 2025).

Leadership culture is a very important factor that speeds up the process of AI integration. Research into digital transformation has pinpointed having an executive sponsor who is very clear about what the project is all about, who has the decision-making power, and the trust in the project being experimented on as the main contributors to successful scaling (Davenport & Miller, 2022; Kane et al., 2015). In Finland's decision-oriented managerial environment, empowering product owners and MLOps leads with well-defined authority minimizes the risk of responsibility confusion at the most decisive points (Uren & Edwards, 2023). The implementation of structured data governance practices, such as data lineage tracking, metadata management, and reproducibility mechanisms, enables organizations to ensure the quality of the model and compliance over time. As machine learning systems evolve with changing operational conditions, it is quite important to do continuous monitoring and data curation, which must be integrated into standard organizational processes rather than treated as one-off project activities (Eken et al., 2025).

Finland's advancement to AI competitiveness is not through the application of separate technologies but rather the construction of integrated capability systems. The companies need to have sequential learning paths, interdisciplinary teamwork, and well-established data governance; the innovation networks should be equipped with common infrastructures that would speed up the learning process; the authorities should encourage the development of skills along with the innovation outcomes. There has been a growing empirical consensus that is very explicit: firms that install powerful models do not get the advantage, but those that nurture the socio-technical and institutional conditions, which make these models work reliably even in the intricacy of real operations, are the ones who get the advantage (Teece, 2018; Uren & Edwards, 2023; Eken et al., 2025).

2.4 Theoretical framework

This chapter combines competitive strategy, resource-based view (RBV), and adoption of artificial intelligence (AI) into a unified conceptual framework (Figure 4). The model explains how firms achieve AI-enabled competitive advantage through a process in which internal and external factors influence the level of AI adoption. AI adoption is organized as an evolution from productivity-enhancing tools to processes. But, the advantage in AI is not achieved solely through adoption, but through AI integration, where AI is embedded into business processes, decision-making, and routines of the organization, reflecting the development of dynamic capabilities. This AI integration is achieved through factors like skills, training, data, and infrastructure. The model further notes that the relationship is conditional and that boundary conditions, such as leadership, governance, and clarity about value, also determine whether AI integration leads to improved performance. The model underscores that sustainable competitive advantage in the AI context is dependent upon the effective integration of AI and the organizational conditions under which it is applied, as well as driving the empirical analysis of the study itself.

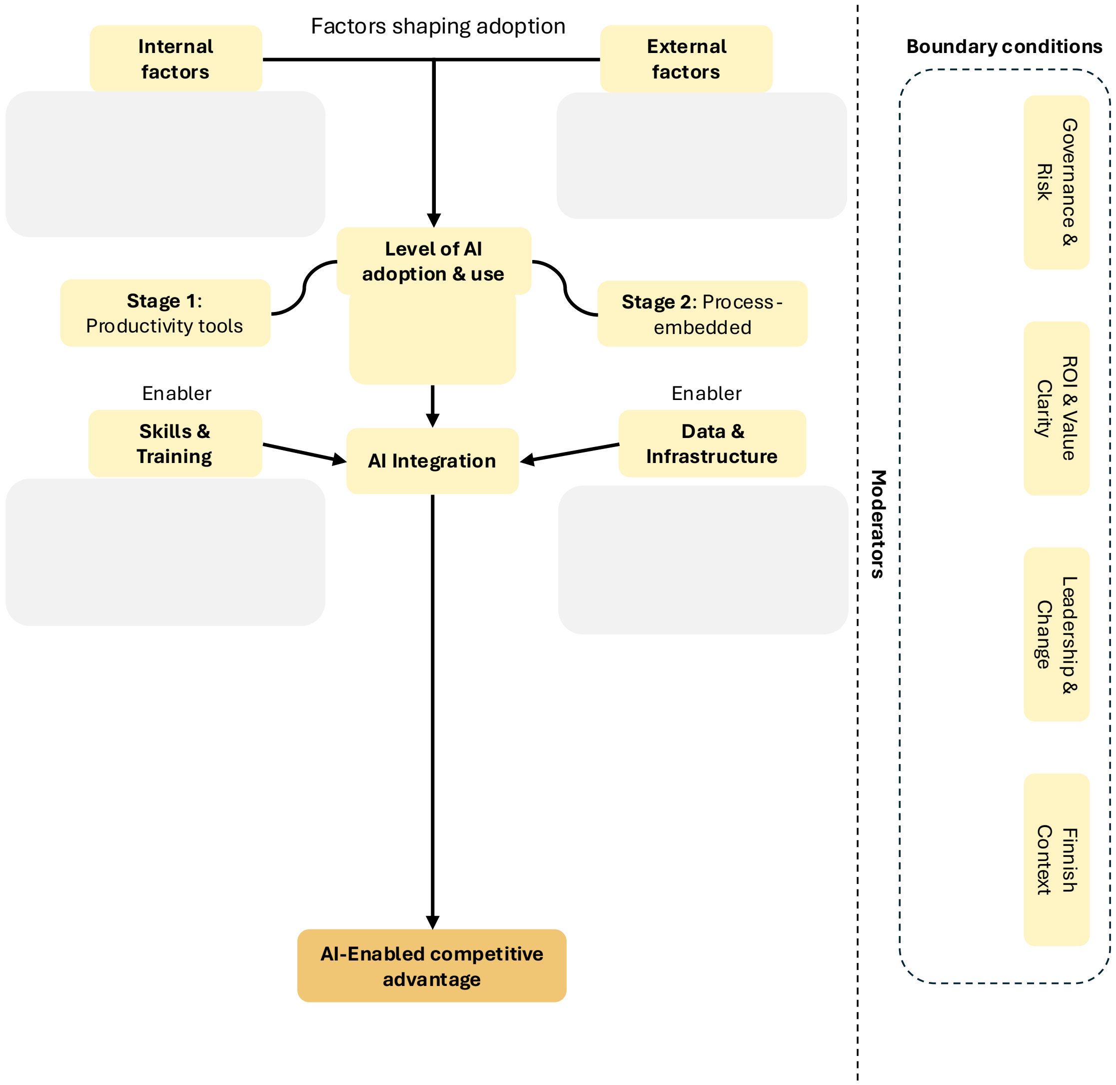


Figure 4. Theoretical framework

3 Methodology

3.1 Research method

Research can be defined as a systematic quest to collect and interpret information to understand various phenomena in our lives (Saunders et al., 2023). In academic work, the approach usually starts with the research question itself (Gioia et al., 2013). Instead of just looking at practicalities, the goal of academic research is often to develop theories that help us to understand a specific topic more deeply (Brannick & Coghlan, 2007). In this study, a qualitative research method is used. This choice is justified because qualitative research is designed to answer "how" questions and build a foundation for understanding connections between different subjects in a changing environment (Gehman et al., 2018).

The justification for this study is both economic and social. As Seppälä et al. (2023) note, the way companies renew their business models through new technology has a major impact on society. Studying how AI affects the competitiveness of Finnish companies is important because, as Gioia et al. (2013) argue, to truly understand a process, one must also understand the landscape around it. The original idea for this research came from the need to see how generative AI might change the strategic landscape for Finnish businesses, where staying ahead is a key driver for long-term success.

To make the research structure solid, this study utilizes the "research onion" model by Saunders et al. (2023). This tool helps to choose and justify the methods by peeling through different layers from philosophy to practical techniques. The logic can be seen in Figure 5, by moving from the outer philosophical assumptions towards the practical techniques of data collection and analysis.

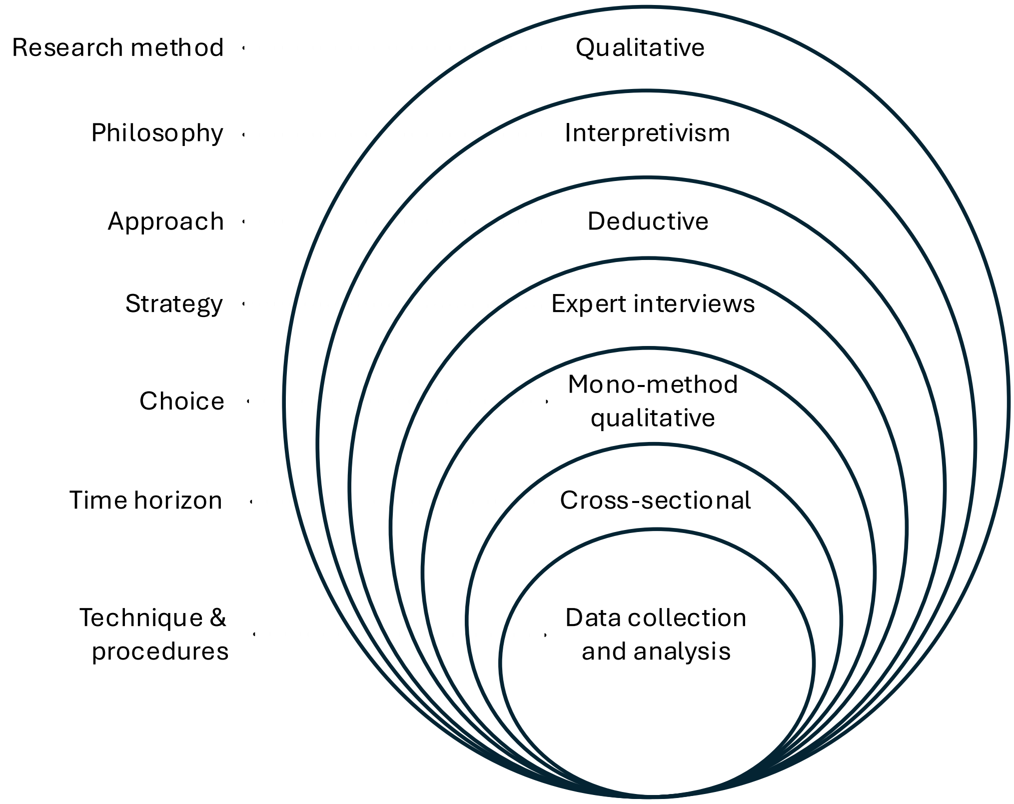


Figure 5. Research onion (adapted from Saunders et al., 2023).

The second layer of the onion is research philosophy. This study follows an interpretive paradigm, as it aims to understand how experts and organizations view future competencies and AI (Saunders et al., 2023). The approach is primarily deductive, by utilizing existing theoretical frameworks to guide the analysis, while also allowing empirical insights to refine and extend the interpretation of the findings (Eisenhardt & Graebner, 2007). For the strategy, this study uses a qualitative multiple-perspective approach. This is fitting when the goal is to build a clear picture of various expert sources. Using expert interviews as the primary sources makes this a mono-method study (Saunders et al., 2023).

The time horizon is the cross-sectional, meaning it looks at the situation as it is right now. This approach is appropriate when examining rapidly evolving phenomena such as artificial intelligence, where current conditions are of primary interest and longitudinal data may be less feasible (Rindfleisch et al., 2008). To avoid biased data, the information is collected from a diverse group of stakeholders, including technology providers, consultants, and ecosystem leads, to ensure a balanced view of the Finnish AI situation.

3.2 Research context and participants

Instead of focusing on a single case company, this study investigates the broader Finnish AI landscape through the insights of key experts. This approach is sometimes called a generic qualitative study, where the focus is on a specific phenomenon across different settings rather than within one organizational boundary (Saunders et al., 2023). By gathering data from various points of view, the research aims to build a more diverse picture of how companies in Finland could approach AI within their organizations.

The participants for this study were selected based on their deep involvement in the Finnish technology and business sectors. To get a holistic view, the participants represent five different perspectives: technology providers, strategic consultants, ecosystems leaders, financial organizations, and large-scale manufacturing companies. As Eisenhardt and Graebner (2007, p. 28) suggest, using a diverse group of knowledgeable informants is a primary way to mitigate bias and ensure the findings are grounded in different realities.

The final list of interviewees consists of professionals with significant experience in software engineering, digital transformation, national AI initiatives, and industrial operations. By combining these five perspectives, the study aims to capture a 360-degree view of the AI transition:

1. **Technology Provider:** Global players who provide the technical foundation and the latest software capabilities.

2. **Strategic Consultant:** Expert who sees the practical implementation hurdles across multiple industries in Finland.
3. **Ecosystem Leader:** Representative from national networks who offer a macro-level view of national competitiveness.
4. **Financial Organization:** Expert representing the investment and risk management side, showing how AI affects banking and capital allocation.
5. **Large-scale Manufacturing:** Two representatives from major industrial companies who provide a view on how AI is integrated into physical production and global supply chains.

All participants and their respective organizations are kept anonymous to ensure that the discussion focuses on strategic potential and practical implementation of AI. This approach allows the experts to share candid insight regarding the operational realities and developmental needs within the Finnish business landscape. By protecting the identity of the informants, the study can better explore the specific strategic actions and innovative solutions that help companies in Finland to leverage AI for increased local and global competitiveness.

Data collection was done until theoretical saturation was reached, meaning that new first-order concepts emerged during the fifth and sixth interviews. The later interviews mainly served to confirm and further strengthen the themes that had already been identified earlier in the process. In total, six informants, representing five different organizational roles, were considered sufficient to provide both breadth and depth for constructing the multi-level framework required by the Gioia methodology (Gioia et al., 2013). This approach is also in line with prior qualitative strategy research, where a smaller number of highly knowledgeable informants is often seen to produce more meaningful theoretical insights than a large sample of less specialized respondents (Eisenhardt & Graebner, 2007).

3.3 Data Collection

Interviews are a very common way to collect data in qualitative research (DiCicco-Bloom & Crabtree, 2006). For this study, the primary data were gathered through semi-structured interviews. This approach was chosen because it allows the interview participants to elaborate on their points if something relevant comes up that wasn´t planned in advance (Gioia et al., 2013). This was essential since many organizations are still in their early stages of using AI, and the discussions needed to stay flexible.

The group of interviewees was gathered through various methods. The most common approach was reaching out to specific employees at selected companies via LinkedIn, where the research idea was presented to the individual. Following this, interview meetings were scheduled with the candidates who agreed to participate. The interviews were held online via Microsoft Teams, which provided a reliable way to record and transcribe the sessions. The digital approach also ensured that the data collection process remained consistent throughout the study.

The interviews took place in Teams, between November 2025 and February 2026. Each session lasted between 35 and 90 minutes. The meetings were done in one-on-one settings, and the interviews were conducted in Finnish and English, depending on what was most natural for the participant. For the Finnish interviews, I translated the key quotes and findings into English, focusing on keeping the original tone and meaning.

Table 3. Overview of Interview Participants and Interview Characteristics

Interviewee	**Role**	**Relevant experience in years**	**Transcript length (pages)**	**Interview length**
1	Team Lead	5	14	41 min 39 s
2	Consultant	13	29	53 min 25 s
3	Community Manager	7	19	35 min 46 s

4	Head of Modern Work	20+	12	22 min 39 s
5	Product Architect	8	26	36 min 2 s
6	Senior Manager	8	12	22 min 15 s

3.4 Data Analysis

The main goal of data analysis is to move from raw information toward building a theory or a clear set of findings (Grodal et al., 2021). After the interviews, the recordings were transcribed by the Microsoft Teams feature. For the interviews, the transcripts were manually checked against the audio recording in order to correct possible spelling mistakes and technical terms that the software may not have captured accurately. Particular attention was given to the accuracy of technical terminology and proper names.

The analysis itself followed the Gioia method (Gioia et al., 2013). This started with data coding, which means breaking down the transcripts into smaller pieces based on similarities (Saunders et al., 2023). I used Microsoft Excel to keep the data organized. In the first phase, I identified "1st Order Concepts" using the interviewees' own words. After this, I grouped these concepts into more abstract "2nd Order Themes" that link the data back to the research questions.

Finally, these themes were refined into findings that explain the strategic integration of AI in Finland. To make the findings valid, I have used direct quotes from the participants throughout the results chapter. This ensures that the theory-building is grounded in what was actually said during the interviews.

3.5 Assessment of Data Quality

To ensure the quality of the academic style of this research, it is essential to evaluate its validity and reliability through established criteria (Saunders et al., 2023; Eriksson & Kovalainen, 2016). The strength of a qualitative study is often argued through construct, internal, and external validity (Gibbert et al., 2008). In this study, construct validity is addressed by providing a clear "chain of evidence" that allows the reader to follow the research process from the initial questions to the final findings. This is further supported by triangulation, as data was collected from five different pillars of the Finnish AI ecosystem. To strengthen internal validity, the theoretical framework was constructed using several recent studies, providing a solid foundation for comparing empirical results with existing literature. During the interviews, research bias was minimized by regularly summarizing the participants' answers to ensure an accurate and shared understanding of the topics discussed.

The challenge of generalizability is addressed through external validity. Since this study focuses on the rapidly evolving field of AI within the specific context of the Finnish business landscape, the results may not be directly transferable to other industries or geographical areas. Therefore, instead of statistical generalization, this study adopts analytical generalizability, aiming to develop theories on AI readiness that can be applied to similar high-tech environments (Gibbert et al., 2008; Yin, 2009). The practical implications are shaped by several variables, such as the interviewees´ diverse experiences and high pace of digitalization, which are explicitly documented to provide the reader with a clear understanding of the study´s scope and boundaries.

The reliability in this research refers to the consistency of the data collection and the extent to which the procedures would produce similar results if replicated (Yin, 2009). To minimize participant error and bias, all the interviewees received a description of the key theme prior to the sessions. Following a consistent semi-structured interview guide and using a unified communication channel (Microsoft Teams) ensured that the process remained stable. Additionally, the participants were informed before the interview that their answers would be treated as anonymous and confidential. This was done to encourage transparency and honesty, which Flick (2018) argues is essential for both research ethics and data quality. By documenting the methodology and analysis steps transparently, the study aims to minimize observer error and ensure that the findings are grounded firmly in the empirical data.

4 Findings

This chapter presents the empirical findings of the study. The research question guiding the inquiry is: How does the level of AI adoption within Finnish companies influence their competitiveness? Findings are based on six semi-structured expert interviews (I1-I6) conducted between November 2025 and February 2026, analyzed through the Gioia methodology (Gioia et al., 2013). Following the inductive logic of the approach, raw first-order concepts were abstracted into second-order themes and those into three aggregate dimensions that together describe the path from AI tool adoption to competitive advantage. The chapter opens with the complete data structure, proceeds through thematic analysis structured by the three dimensions, incorporates a contextual section on the specifically Finnish dimensions of the adoption challenge, and closes with a synthesis that ties the empirical findings to the theoretical framework developed in Chapter 2.

Finnish-language quotations are reproduced verbatim and followed immediately by the researcher's English translation in square brackets. The conventions of the Gioia methodology require that the language of informants be preserved as the analytical starting point; translation is therefore provided for accessibility, not as a substitute for the original expression.

4.1 Overview of Data Structure

The Gioia methodology (Gioia et al., 2013) proceeds through three progressive levels of abstraction, summarized in Table 4. First-order codes preserve the exact language and framings of interviewees, the emic logic of each account. Second-order themes are researcher-constructed conceptual patterns that aggregate and interpret the first-order codes. Aggregate dimensions are the highest-level analytical constructs, representing the overarching processes that the data collectively describe. This three-level structure provides both the analytical rigor expected in qualitative research and the accountability demanded by the Gioia approach: every higher-order claim in the following sections can be traced back to specific first-order utterances in the transcripts.

Table 4. Gioia data structure

First-order concept (illustrative examples)	Second-order theme	Aggregate dimension
"The better the AI, the more efficient"; "twice, three times as long without it"; "essential for competitiveness"; "saves time per week"; "meeting notes automatically"	Productivity and Speed	Dimension 1 — AI Adoption Level and Immediate Competitive Effects
"niche topic — worth making your own"; "find use cases with big impact"; "found own space"; "integrated into the process"; "whole palette from beginning to end"	Use-Case and Process Orientation	Dimension 1 — AI Adoption Level and Immediate Competitive Effects
"everything ultimately goes into data"; "siloed off in many different front lines"; "data is scattered but of poor quality"; "half a million — if you want the data out"; "fragile the way it has been set up"	Data and Infrastructure as Technical Ceiling	Dimension 2 — Enablers of Adoption
"600 info sessions"; "a new standard skill in working life"; "10–15% outside IT"; "people don't have the energy to learn"; "train the executive team and the board"	Skills and Training as Human Floor	Dimension 2 — Enablers of Adoption
"management decisions carry greater weight"; "need to change processes"; "movement from both directions"; "IT is just a very small piece"	Leadership and Change Management	Dimension 3 — Conditions for Scaling and the Adoption Gap
"in accordance with risk management processes"; "sensitive and fragile"; "regulation coming from the ECB"; "a compliance question"; "not possible within the regulatory framework"	Governance, Security and Risk	Dimension 3 — Conditions for Scaling and the Adoption Gap
"30 EUR per person per month — how do you prove ROI?"; "defining the target state is difficult";	Value Demonstration and ROI	Dimension 3 — Conditions for Scaling and the Adoption Gap

"RPA versus GenAI ROI clarity";
"not clear to everyone"

The coverage of each theme across informants is shown in Table 5. The four themes of Dimension 1 and Dimension 2 achieved universal or near-universal coverage, appearing in every interview and typically in the first third of the conversation without prompting. The three Dimension 3 themes were present in five of the six interviews; interviewee 1 is the exception, an interviewee embedded in a technology-native corporation where the question of whether to adopt AI was settled years ago, and the competitive pressure that motivates Dimension 3 concerns does not arise in the same way.

Table 5. Cross-case theme coverage

Theme	**I1**	**I2**	**I3**	**I4**	**I5**	**I6**	**Coverage**
Productivity & Speed	✓	✓	✓	✓	✓	✓	6/6
Use-Case & Process Orientation	✓	✓	✓	✓	✓	✓	6/6
Data & Infrastructure	✓	✓	✓	✓	✓	✓	6/6
Skills & Training	✓	✓	✓	✓	✓	✓	6/6
Leadership & Change Management	—	✓	✓	✓	✓	✓	5/6
Governance, Security & Risk	—	✓	✓	✓	✓	✓	5/6
Value Demonstration & ROI	✓	✓	—	—	✓	✓	4/6

4.2 AI Adoption Level and Immediate Competitive Effects

The first aggregate dimension addresses the most direct form of research question: what competitive consequences does AI adoption produce and how do those consequences scale with adoption depth. The data reveal a two-stage competitive dynamic. In the first stage, even elementary AI tool adoption produces measurable productivity gains that begin to create a gap between adopters and non-adopters. In the second stage, the deepening of the adoption from generic tool use toward process-embedded, use-case-specific deployment produces qualitatively different and strategically more durable competitive positions. The transition between these two stages the key competitive threshold the data identifies.

4.2.1 Theme 1: Productivity and Speed

All six interviewees, without exception and without prompting, identified productivity improvement as the most immediate and universally accessible competitive consequence of AI adoption. The pattern is consistent across sectors: AI tool use reduces task friction, accelerates output, and redirects human cognitive capacity toward higher-value work. Interviewee 1, who has worked with AI tools daily for several years inside a technology firm that actively co-develops AI capabilities, articulated the link between AI quality and individual competitive effectiveness with particular directness:

> *" Often the better the AI you have access to, the more productive you are. If one questions gives you the answer, compared to asking the same thing three different ways, the efficiency gain is substantial " (Interviewee 1)*

Interviewee 1 gave a structural example from daily organizational life: the automatic generation of meeting notes and action items by Microsoft Copilot has fundamentally changed how international meetings function in the corporation. Participants no longer need to dedicate attention to note-taking during calls, and those who miss meetings across time zones can read a structured summary rather than watch a recording. This reduces cognitive overhead not only at the individual level but collectively, across hundreds or thousands of meetings per year. The compound productivity advantage for an organization that has embedded this practice is not trivial.

Interviewee 2, with years of cross-industry consulting experience, placed the productivity theme in a strategic frame. AI tools make it possible for skilled specialists to stop spending time on tasks that should never have consumed specialist time:

> *" It is no longer sensible for engineers with master´s degrees or economists to spend their time manually repositioning images in PowerPoint" (Interviewee 2)*

The competitive implications interviewee 2 identified follow directly: if one organization automates the administrative overhead absorbed by its knowledge workers while a competitor does not, the first organization extracts substantially more high-value work from the same headcount. This is not an incremental efficiency difference, but rather a structural reallocation of specialist human capital that compounds over time. Interviewee 2 described AI as enabling a shift towards what they defined as "more sensible" resource allocation, meaning more rational use of the organization´s human investment. This framing aligns precisely with Porter´s (1985) cost advantage logic applied to knowledge-work economics.

Interviewee 5, whose role is specifically to find and implement high-impact AI use cases in a global organization, provided the study´s most vivid quantification of what productivity gains look like when compounded from individual to organizational scale:

> *" If I was building the solution on my own, I could do it, but it would take me probably twice, three times as long. And also my ideas being flushed out of lot easier with Copilot – I´m thinking different approaches, going back and forth, picking the ones that make sense. So I´m building a cleaner, better quality solution in a much faster time. And if I´m managing to two times my productivity, imagine how that is on a company-wide scale if you could manage everyone else to do the same. "(Interviewee 5)*

This showcases two distinct mechanisms: speed and quality. AI assistance not only accelerates the completion of a task but also improves the process of formulating the task, enabling more thorough exploration of alternatives, better-reasoned choices, and higher-quality output. When both mechanisms operate simultaneously across an organization´s knowledge workforce, the aggregate competitive gain is substantially larger than a simple productivity multiplier would suggest.

Interviewee 4, leading AI tool deployment at a major Finnish financial institution, describes the organizational infrastructure required to achieve meaningful adoption. Over the past year, interviewee 4´s small team organized an extraordinary training effort.

> *"Our team has organized approximatelty 600 different information sessions, presentations, and workshop related to AI and modern work over the past year "(Interviewee 4)*

Internal surveys showed that over 80 percent of employees with AI tool access reported active usage, with the majority reporting measurable time saving per week. However, interviewee 4 emphasized that these productivity benefits did not materialize automatically:

> *"It genuinely does not find its way into daily practice if it is not actively brought there. " (Interviewee 4)*

This observation underscores a critical point. Productivity gains from AI tool availability depend on deliberate organizational investment in training, communication, and change management, not simply on just license deployment.

Interviewee 6, framing the competitive stakes from strategic vantage point of global manufacturer, moved the productivity theme from opportunity language to necessity language, a shift that marks an important conceptual movement in how AI adoption is understood among the most strategically engaged informants:

> *"Just as with internet use in its time – AI utilisation is a new standard workplace skill, the mastery of which is in practice essential for remaining competitive. This is something the everyone would do well to understand " (Interviewee 6)*

This frames AI competence as a baseline skill on the order of digital literacy rather than as an optional performance enhancer; this represents a maturation of the competitive discourse. It implies that the productivity gains of the first stage are not a differentiator for long but rather become a minimum threshold. An organization that does not cross this threshold does not gain a productivity advantage, and it accumulates a productivity deficit. Interviewee 3 confirmed this from the ecosystem level: the Finnish companies that moved early on basic AI tools have built an experiential foundation, familiar employees, adjusted workflows, and basic infrastructure that gives them a compounding head start as AI capabilities evolve. The gap between them is still growing, not static.

Theoretically, this theme connects most directly to Davis´s (1989) Technology Acceptance Model through the construct of perceived usefulness (PU). Interviewee 1´s observation that many employees resist AI adoption precisely because they have not yet personally experienced a productivity gain that justifies the learning investment points to a key adoption dynamic. Because productivity benefits are not self-evident to non-users, organizational conditions that make them visible, such as accessible training, peer demonstration, and use-case galleries, become important determinants of adoption speed.

4.2.2 Theme 2: Use-Case and Process Orientation – From Efficiency to Durable Advantage

While productivity is the most widely experienced competitive consequence of AI adoption, the data converge on a second and more strategically significant observation: the kind of advantage that results from generic productivity tool use is qualitatively different from the kind that results from deep, process-embedded, use-case-specific AI deployment. The former is widely accessible and therefore rapidly replicated; the latter is firm-specific and hence strategically durable. This distinction is the central strategic threshold that the data identify.

Interviewee 1 articulated the build-versus-buy logic most clearly. For standard tasks, like writing, coding, summarization, brainstorming, off-the-shelf tools provide sufficient support, and competitive differentiation comes from how well employees use them rather than from access itself. But when a domain is specific enough, the economics of the decision shift:

> *"If you have a specific niche topic for which you want AI, it is worth considering whether building your own makes sense. The hardware cost of running AI is now relatively low – you just need the right expertise "(Interviewee 1)*

Interviewee 1 developed this point in terms of AI agents, specialist models trained on proprietary data and domain-specific knowledge. The value of such agents is not in the underlying model, which is rapidly commoditizing, but in the combination of model, firm-specific data, and workflow integration surrounding it. This configuration satisfies what Barney (1991) identifies as the conditions for sustained competitive advantage: It is valuable because performance depends on data quality and specificity; rare because the firm-specific accumulation is unique; inimitable because it reflects irreproducible historical learning; and non-substitutable in near term because AI performance degrades without the relevant context.

Interviewee 5 approached the same distinction from a failure-mode direction. The questions of whether AI investments generate returns depend critically on whether they target high-impact use cases or merely generic productivity applications:

> *"Find use cases that provide big impact towards the business, whether that be time saving, cost saving, improving the use interface, the use experience – just making it more easy to work and get things done quicker and adapt to the business environment "(Interviewee 5)*

Interviewee 5 described an internal monitoring system that tracks Copilot license usage at the individual level, classifying users as high, medium, or low. Low-usage individuals receive a polite notification that their license may be reallocated to someone on the waiting list who has demonstrated genuine need. This mechanism functions as an internal market for AI resource allocation: it signals organizational recognition that tool availability is not equivalent to tool value, and that the competitive returns from AI investment are a function of usage quality, not license count. The implication for AI strategy is direct; the objective is not AI deployment but AI-enabled value creation.

Interviewee 4 provided the study´s most precise articulation of the two-stage competitive logic. At their organization, horizontal AI tools provide measurable efficiency benefits at the individual level. But the larger, more strategically significant benefits lie elsewhere:

> *"On one hand, we have these horizontal AI tools, which yield certain efficiency benefits. But if you look at the customer-facing process, that is where the truly large, measurable benefits actually reside. "(Interviewee 4)*

Interviewee elaborated: extracting these benefits requires not incremental optimization of existing processes but fundamental redesign, rethinking the whole palette from beginning to end with AI-native logic. This is qualitatively different from deploying AI within existing workflows. It requires the kind of deep process understanding, governance clearance, and change management capability that most organizations are still developing. But precisely because it is difficult, it produces competitive positions that are hard to replicate quickly. Interviewee 4 also identified the forward competitive frontier within their organization: not process enhancement but entirely new AI-native products and services, new ways of serving customers, new forms of guidance, and new interaction models that only AI makes possible. Interviewee 4 noted that the organization that succeeds in building such a product first may hold a meaningful, if temporary, advantage:

> *"If someone is first to figure out and build such a thing, there may be a significant competitive advantage – at least for a period of time "(Interviewee 4)*

Interviewee 2 introduced a dimension of the use-case theme that concerns platform architecture and strategic data sovereignty. The choice of AI deployment environment is not only a technical decision; it is a decision about the long-term architecture of the firm´s competitive data assets. When an organization´s operational data, such as interaction histories, process logs, and internal documents become deeply embedded in a vendor-managed AI ecosystem, the data simultaneously becomes more accessible to the AI and less accessible to the organization for use elsewhere:

> *"Your own data – your company´s private data – is the gold reserve. But if it has already been embedded in a specific platform, it may not be available for the next one – even if a ten times more powerful model becomes available. " (Interviewee 2)*

Interviewee 2 gave a concrete illustration: extracting data from enterprise platforms can cost hundreds of thousands of euros. An organization that has embedded its competitive data inside a legacy platform may be unable to leverage superior AI models that require access to that same data. This creates a paradox: deep AI adoption through platform integration builds short-term competitive capability but can destroy long-term competitive agility. The strategic implication, design AI architecture with data portability in mind, was not widely articulated by other interviewees, but it represents one of the most consequential long-term considerations of the data surface.

Interviewee 3, speaking from the vantage point of organizational ecosystem observation, provided a macro-level synthesis. The Nordic State of AI survey data showed that the Finnish companies reporting the highest satisfaction with their AI investments were not those with the broadest deployments, but those that had found what interviewee 3 called “their own space”, the specific intersection of AI capability and organizational context where the technology creates irreplaceable value. Interviewee 3 connected this directly to competitive advantage: generic AI use does not differentiate; finding the firm-specific configuration where AI is truly indispensable does.

Theoretically, the use-case and process orientation theme maps to Teece´s (2007) dynamic capabilities framework. The transition from generic tool use to process-embedded AI deployment requires, in Teece´s terms, the simultaneous activation of sensing (identifying high-impact use cases), seizing (committing resources to specific implementations, and reconfiguring (redesigning processes and workflows to leverage the AI capability). Organizations that activate all three functions in sequence develop AI-enabled dynamic capabilities; those that stop at sensing, such as identifying opportunities without making the organizational commitments to seize them, remain in the first-stage productivity mode without crossing into durable competitive differentiation.

4.3 Dimension 2: Enablers of AI adoption

The second aggregate dimension addresses the prerequisite conditions that determine whether and how quickly an organization can move from basic AI tool access to the process-embedded deployment that produces a durable competitive advantage. The data identifies two categories of enablers that function as necessary, though not sufficient, conditions: data quality and infrastructure, which set the technical ceiling of what AI adoption can achieve, and skills and training, which set the human capability floor of what the organization can execute. Without both, even technically available AI capabilities remain unrealized. The relationship between these two categories is complementary rather than substitutable; investment in one without the other produces predictable failures.

4.3.1 Theme 3: Data and Infrastructure as the Technical Ceiling

No theme across the six interviews is expressed with more uniformity or greater emphasis than the centrality of data and availability as the fundamental determinant of how far AI adoption can realistically proceed. The finding is so consistent that it constitutes what might be called the primary empirical law of the study: the ceiling of AI adoption depth and performance is set by the quality and accessibility of the data the AI works with. This pattern emerged spontaneously, without interview prompting, in every interview and was articulated in the first substantive response in the majority of conversations.

Interviewee 3, drawing on observations across nearly 400 Finnish organizations spanning more than 20 industries, offered the most economical summary:

> *“Every conversation ultimately comes down to data: is there anything available, is it usable, is there anything to leverage from it. “(Interviewee 3)*

Interviewee 3 then elaborated on the structural variation in data readiness across organization types. Large manufacturers operating production lines often have sensor data flowing from equipment, but the data was collected for maintenance and quality control purposes, not designed for AI consumption, and frequently exists in formats accumulated across decades of incremental IT investment. Before any AI deployment can process, the data must be cleaned, structured, integrated, and documented. This exercise can consume as many organizational resources as the AI deployment itself. SMEs face a compounded challenge: they may need to build measurement infrastructure before meaningful data even exists. Start-ups have no legacy burden but also no historical depth. The implication interviewee 3 drew is that data readiness is as strategically significant as AI capability itself, and in many Finnish companies, it is the primary binding constraint.

Interviewee 5 provided the study´s most operationally detailed account of data fragmentation inside a large enterprise. At a multinational corporation with operations across many countries, data does not flow freely between systems even when the same organization theoretically controls all of it:

> *"While we have a lot of data, they are usually siloed off in many different front lines. Some front lines use different applications. The ones that are global, the data is probably not as clean as it could be, and then to integrate with it is not easy. "(Interviewee 5)*

Interviewee 5 described the specific case of SAP financial data in vivid terms: it is both sensitive by triggering governance-based reluctance from platform teams and technically fragile, structured in ways specific to local accounting practices across multiple countries, using field names that require domain expertise to interpret. For an AI model to work reliably with this data, a human expert must first explain to the model what each data field means in each national configuration. This requirement combines three rare skill types, which are deep domain expertise in the specific operational process, data engineering capability, and AI architecture knowledge, in a way that few organizations currently possess in sufficient depth. The practical consequence is that a corporation with abundant data and advanced AI tools may still be unable to deploy those tools in its highest-value use cases because the data architecture is too fragmented and too poorly understood to make an AI application feasible.

Interviewee 2 introduced a dimension of the data theme that other informants addressed only implicitly: the strategic architecture risk of vendor lock-in. The organization that embeds its operational data most deeply in an AI-enabled platform ecosystem gains a short-term AI performance advantage but creates long-term data sovereignty risks. When a superior AI capability becomes available from a different vendor, the switching cost can be potentially hundreds of thousands of euros to extract data from the incumbent platform, which might make the theoretically superior option practically unattainable:

> *"If your data is in some platform, say Dynamics, you might maybe get a ten out of it from there. But with a SaaS system there may be restrictions that mean you can´t get the data out. And if you do get it out, it costs this much – in this case it´s half a million. If you want the data from this module out, you get it as some kind of dump. "(Interviewee 2)*

Interviewee 2 described this dynamic as vendor-constructed “moats”: platforms that restrict data exportability are effectively building moats around their customers´ competitive assets. The strategic lesson is counterintuitive: the more valuable your data and the more deeply it is embedded, the more important it is to maintain explicit data architecture governance that preserves strategic optionality. Meaning the ability to migrate to superior tools as they become available.

Interviewee 1 offered a partially countervailing view that reframes part of the infrastructure challenge. While data quality remains a firm constraint, the hardware cost of running AI models has fallen dramatically. The Neural Processing Units (NPUs) now embedded in modern laptops mean that capable, locally run AI models are within reach of organizations that cannot afford enterprise cloud infrastructure. This matters particularly for Finnish SMEs: the infrastructure barrier to AI adoption is lower than it was three years ago and continues to fall. However, Interviewee 1 observation does not dissolve the data quality challenge, as you can run AI cheaply, but you cannot run it effectively on poor-quality, fragmented, or inaccessible data. Lower hardware costs reduce one barrier without touching the other.

Interviewee 6 synthesized the competitive implication of the data theme from a strategic planning perspective that is worth quoting at length because it connects the data challenge explicitly to the research question:

> *“Data is often scattered but of poor quality. And infrastructure – these data infrastructure questions – are now coming to the surface in a completely new way. But this partly relates to what we discussed earlier: it depends on what the expected benefits are, and how much money is invested in data infrastructure.” (Interviewee 6)*

This observation highlights the strategic importance of organizational data quality and infrastructure investment in enabling AI capabilities. The theoretical resonance of this theme with the Resource-Based View (Barney, 1991) is direct. Integrated, high-quality, proprietary organizational data constitutes a VRIN resource: valuable because AI performance is a linear function of training data quality and contextual relevance; rare in that well-curated, firm-specific datasets reflecting unique operational history are not freely available; inimitable because AI performance degrades without relevant, contextualized training data. The competitive implication is that organizations investing in data infrastructure today, even without a specific AI application yet identified, are building the prerequisite for AI-enabled advantages that will compound in value as model capabilities improve. Those that defer data investment until a use case is ready will face a compounded adoption lag, as the use case arrives before the foundational enabler.

4.3.2 Theme 4: Skills and Training as the Human Capability Floor

If data and infrastructure set the technical ceiling of AI adoption, skills and training set the human floor. The data reveal a finding that is consistent across all six interviews and all five sectors represented: the competitive gap between organizations that have AI tools and those that use them well is primarily a skills gap rather than a technology gap. The AI tools themselves are widely available, but the organizational capacity to use them effectively is not.

Interviewee 4 provided the most striking evidence of how seriously this challenge can be addressed at an institutional scale. In describing their organization´s training effort for AI tool adoption, interviewee 4 offered a figure that is remarkable in its magnitude:

> *“We actually have a kind of three-person rollout communication team that mainly handles this, with some additional help from elsewhere in the organization. Over the past year our team has held around 600 different information sessions, presentations, and workshops related to AI and modern work” (Interviewee 4)*

Six hundred events in a single year, from a team of three people, represent an extraordinary investment in organizational AI literacy. Interviewee 4 drew an explicit lesson from this effort: the tools do not embed themselves in daily work through availability alone. Interviewee 4 recalled their earlier consulting career and the conventional approach to major system implementations, such as 'here is the license, here is the software, here is the training manual', and noted that this approach never reliably produced adoption, and does not work for AI either.

Interviewee 4 also described a complementary infrastructure for managing skills development while containing governance risk: the internal chatbot AI, designed for their organization's employees, provides a compliance-approved AI environment that lowers the perceived risk of using AI for sensitive tasks. This design choice does double duty, as it raises the TAM construct of Perceived Ease of Use (PEOU) by making AI interactions feel governed and safe, while simultaneously keeping all the data interactions with organizational oversight. The result, interviewee 4 reported: over 80 percent of employees with AI access reported active usage. This figure contrasts sharply with BCG (2025) data showing Finland´s national average AI tool adoption at approximately 18 percent of white-collar workers, suggesting that organizational investment in training and infrastructure can dramatically accelerate adoption relative to background cultural baselines.

Interviewee 3 highlighted a dimension of the skills theme that is often neglected in discussions of AI workforce development: the urgent need to develop AI literacy not only among operational staff but at the highest levels of organizational leadership. An AI training program designed for senior management teams and boards of directors was developed in response to a recurring pattern observed in the ecosystem: organizations where senior leadership lacks working familiarity with AI tend to make adoption decisions driven by anxiety and misconception rather than strategic insight:

> *"We aim to train executive teams and boards because, both through our history and during this AI journey, we have received direct signals from companies. Leadership asks us to do different things or says that they now want to adopt AI, but often it doesn´t really find a growth path for how to move forward from there" (Interviewee 3)*

This observation confirms in the field the pattern identified in secondary data: Solita (2023) found that only 5 percent of Finnish senior managers expected AI to have a major impact on their own work, and McKinsey (2025) identified leadership´s perception gap as a primary driver of slow strategic AI integration in Finnish organizations. Interviewee 3´s account transforms these survey finding into a lived institutional reality: practitioners in the ecosystem encounter this pattern repeatedly in member conversations and have built their flagship training program precisely to address it.

Interviewee 5 described the within-organization heterogeneity of AI skills in terms that reveal the depth of the challenge in a large enterprise context. Within IT, adoption was estimated at 60-70 percent of employees actively using AI tools effectively. Outside IT, across finance, HR, engineering, and field operations, the estimate dropped sharply to approximately 10-15 percent. The primary obstacles interviewee 5 identified were not lack of access but dual uncertainty. Incomplete understanding of what AI does in the specific work context, combined with concern that demonstrated AI proficiency might accelerate the elimination of one´s role. These two anxieties, cognitive and existential, are distinct in origin but similar in practical effect. Both suppress the experimentation what would, if undertaken, resolve the first and arguably complicated the second.

Interviewee 1 raised an angle on the skills theme that looks beyond the current workforce to a structural, generational horizon. Additionally, interviewee 1 has a background in teacher education as well as technology, observed that educational institutions in Finland have been slow and inconsistent in integrating AI tools into curricula, some even disbanding those, and drew a stark competitive inference:

> *"No matter how much AI improves, it will not change competitiveness until a new generation of workers arrives who are native users of it. That will probably take ten years." (Interviewee 1)*

This is a sobering long-term diagnosis. If the current workforce does not rapidly develop AI competence through deliberate organizational investment in training and practice, the aggregate competitive effect of AI capabilities will accrue substantially more slowly than optimistic adoption forecasts assume. The implication for organizations that cannot wait ten years for generational change, which is all of them, is clear: The deliberate cultivation of AI skills within the existing workforce is not optional infrastructure investment, it is a competitive necessity with a short time horizon.

Theoretically, this theme engages the TAM construct of Perceived Ease of Use (PEOU, Davis, 1989). Interviewee´s observation that employees resist AI adoption precisely because learning investment feels large and the return uncertain points to and adoption dynamic with a specific organizational solution, such as reducing the perceived complexity of AI use through training, peer modelling, and use-case demonstration, while making the productivity benefits visible early enough to justify continued learning investment. It also connects to Teece´s (2007) human capital dimension of dynamic capabilities. The organizational capacity to sense and seize AI opportunities depends on having employees, at all levels, including leadership, with the knowledge and comfort to recognize opportunities and implement responses.

4.4 Dimension 3: Conditions for Scaling

The third aggregate dimension addresses a pattern observed across the Finnish organizations in this study: many organizations that understand AI´s value, have access to AI tools, and employ workers interested in using them nonetheless fail to scale AI adoption beyond individual-level experimentation or isolated pilots. The data identify three interacting conditions that together explain this scaling challenge: leadership and change management (the organizational driver of scale), governance, security and risk (the sector-specific boundary conditions that determine the permissible scope of deployment), and value demonstration and ROI (the investment logic gate that controls whether organizations commit the resources necessary to move from pilot to capability). None of these three conditions is independently sufficient to explain the scaling challenge, their interaction is the explanation.

4.4.1 Theme 5: Leadership and Change Management as the Driver of Scale

Leadership and change management emerged as a critical determinant of AI adoption scale in five of the six interviews. The pattern is consistent: the depth, speed, and strategic coherence of AI adoption is substantially shaped by the quality of leadership engagement, not as a general statement about the importance of leadership. Rather, as a specific finding about the mechanisms through which leaders create (or fail to create) the conditions under which AI investment produces competitive returns.

Interviewee 6, speaking from their organization´s strategy function, was the most analytically precise about the asymmetric influence of leadership decisions relative to individual-level enthusiasm:

> *"I would say that leadership decisions and guidance carry greater weight in the big picture, because the use of AI is heavily influenced by tools, infrastructure, and training. So, leadership has a bigger role in driving it forward in the right way." (Interviewee 6)*

However, interviewee 6 was equally clear that the causation is not simply top-down. Leaders provide structural preconditions and employees provide operational intelligence, the specific identification of where AI creates value in their particular workflow. An organization that activates only one direction faces predictable failure modes. Top-down AI mandates without genuine bottom-up engagement produces tools that are installed but not used and as for bottom-up experimentation without leadership support produces individual productivity gains that never aggregate into organizational capability. Interviewee 6 captured the bidirectional requirement briefly:

> *"To become a leader in AI, you must be able to change certain processes and working practices. This requires movement from both directions." (Interviewee 6)*

By contrast, interviewee 5, working across a similarly large multinational organization, argued that personal level is the primary driver of organizational AI capability.

> *"I think if done well it will drive competitiveness very high, especially if it comes from a bottom-up approach – if the personal usage of it is done well, then you know you can drive your competitiveness and that will spread across the company from down up. But top-down you have to be careful not to overspend and not drive value. "(Interviewee 5)*

Interviewee 5´s account suggests that in their organizational context, the competitive return from AI investment are realized when individuals achieve genuine productivity gains that then propagate through peer demonstration and organic adoption. For instance, not when leadership mandates tools that employees have not yet learned to use effectively. The difference in emphasis between interviewee 6 and interviewee 5 may reflect differences in organizational maturity, sector context, or the specific stages of AI adoption their respective organizations had reached at the time of interview. However, what both have in common is the recognition that neither direction alone is sufficient.

Furthermore, interviewee 4 provided concrete institutional evidence for the leadership dimension, describing their organization rollout as deliberate, leadership-sanctioned, cross-functionally resources program. Interviewee 4 also identified what may be its most important organizational insight: effective AI adoption at scale requires not an IT-centric deployment model but a fundamentally cross-functional coordination architecture:

> *"The adoption of AI requires broad collaboration across the organization. IT is ultimately only a small part of the overall picture. It may handle tasks such as acquiring licenses or implementing technical solutions, but the real transformation happens in the organization. HR must be involved through skills development, along with coaching, communication, risk management, and, more broadly, the organization´s structures and ways of working." (Interviewee 4)*

This observation has direct organizational design implications. Organizations that assign AI adoption to IT as a license-management and security-clearance function, as the conventional default for IT, are structurally misconfiguring the problem. AI adoption is not a technology deployment, it is an organizational change program that requires sustained investment across human resources, communication, risk, and business operations. IT is a necessary but insufficient participant.

Building on this, interviewee 5 articulated the scale paradox that large organizations face: more data, more resources, and a broader range of potential AI use cases, but also a governance and approval architecture that moves more slowly than the competitive window for any given AI opportunity:

> *"In a small to medium company, you use more easy-to-access tools. Their data isn´t as spread. They don't have to go to each country to get permission. They can just go ahead and do it." (Interviewee 5)*

Interviewee 5 describes an approval process that involves IT security, platform architects, country-level legal teams, and ultimately finance, a chain of actions that can require months for initiatives whose competitive value may be measured in weeks. This is not organizational dysfunction, but rather a rational governance in a complex multinational context. But its competitive consequence is real, as smaller and more agile competitors can experiment, learn and deploy more quickly, potentially building AI-enabled competitive positions before organizations have cleared the approval chain for pilot projects. Interviewee 3 confirmed this pattern from their organization´s ecosystem: some of the most AI-advanced member companies are SMEs that have moved more decisively than larger corporations still navigating internal governance processes.

Furthermore, interviewee 3 pointed out to cultural dimension that shapes leadership behavior in the Finnish context. According to the interviewee, a tendency toward caution, consensus-seeking, and “wait-and-see” postures can slow the leadership commitment required for scaling AI adoption:

> *“One word that is perhaps spoken too little is courage” (Interviewee 3)*

This observation connects to secondary literature findings; both Solita (2023) and McKinsey (2025) identify Finnish top management´s limited personal use of AI tools as a primary barrier to strategic AI integration. Interviewee 1 raised a complementary mechanism: Finnish society´s structural safety net and the associated cultural expectation of employment security reduce the urgency signals that drive AI adoption in a more competitive labor market:

> *“In Finland there isn´t really much fear of losing one´s job, even though layoffs and unemployment are discussed. Many people have been able to stay in the same job for a long time without needing to develop their skills.” (Interviewee 1)*

The result is a country-level dynamic where AI´s potential is widely acknowledged but seldom acted on with the speed or commitment the competitive environment increasingly demands.

4.4.2 Theme 6: Governance, Security and Risk as Boundary Conditions

Governance, security, and risk management emerged in five of the six interviews as conditions that set the outer boundaries of what AI adoption can permissibly achieve, regardless of technical capability or commercial motivation. The theme is most acute in financial services (Interviewee 4) and large enterprise manufacturing (Interviewee 5), present in strategic form in industrial strategy (Interviewee 6), and addressed at the systemic level by the ecosystem (Interviewee 3) and consulting (Interviewee 2) perspectives. The finding is not merely that governance is a constraint, but rather that the organization handling governance most thoughtfully is building governance infrastructure as a competitive capability, not just as compliance overhead.

Interviewee 4 provided the most developed account of the governance-as-design principle. In a financial services organization operating under European Central Bank oversight and Finland´s Financial Supervisory Authority frameworks, every AI tool deployment requires documentation, risk assessment, and internal approval as prerequisites. Interviewee 4 describes the initial investment in this “boring paperwork” as the foundation on which all subsequent deployment speed is built:

> *“We have done a lot of groundwork ourselves – to ensure that the tools we are allowed to use comply with our risk management processes. We also have a lot of guidelines, for example about what you are allowed to do with Copilot or what kind of materials you can upload there. And then, separately, what you can do with our own internal AI.” (Interviewee 4)*

The competitive significance of this investment is not immediately obvious, as it is by definition, preparatory and unglamorous. But its effect becomes visible over time: an organization with established compliant AI infrastructure can deploy AI capabilities more quickly than one that must restart the compliance process for each new tool or use case. Governance investment is not only the cost of operating in a regulated environment, as it is an investment in operational AI agility within that environment.

Interviewee 4 also described the architecture of their own AI in terms that illustrate how governance constraints can be turned into design parameters. The chatbot was built with precise, transparent boundaries around what data it can access and what recommendations it can make. Not because their organization is conservative about AI, but because the boundaries reflect an accurate understanding of what the regulatory framework permits and what employees can trust. The result is a tool that employees actually use, precisely because they understand its constraints. Governance, in this account, enhances rather than suppresses the TAM construct of perceived ease of use. Transparency about limitations creates the trust that drives adoption.

Furthermore, interviewee 4 articulated the most striking governance constraint of the data surface. The gap between an ambitious AI vision and what regulation actually permits in the financial sector:

> *"That wild vision – that a customer and we can see everything about them – is simply not possible within current regulatory frameworks." (Interviewee 4)*

This observation establishes an important analytical point. In regulated sectors, the competitive frontier of AI deployment is set not by technology but by regulatory architecture. Competitive differentiation comes not from imagining the most ambitious AI application but from designing the most creative and rigorous applications within the available regulatory space. This is a different competitive challenge from the one that dominates AI strategy literature, which generally assumes that the binding constraint is technical or financial rather than regulatory.

Moreover, interviewee 5 described a specific form of governance hesitation that illustrates how data sensitivity and technical fragility interact in large enterprises. SAP financial data teams at interviewee 5´s organization are reluctant to share access for AI applications, not out of general conservatism but out of legitimate risk calculation. The data is legally sensitive, structured in ways that vary across countries, and technically fragile in ways that require human expertise to navigate. An AI model trained on or fed from this data without careful preparation could produce systematically misleading outputs that are difficult to detect and costly to correct:

"Some teams are really reluctant to give access to the data. It´s sensitive, and the data is kind of fragile. The way it´s been set up, it´s very hard to understand. And then even for a generative AI to take that and rea it, it requires a human to train it: this column actually means this, this means this." (Interviewee 5)

This is rational caution, not obstruction. But its competitive consequence is real: the data where AI could create the most business value, such as operational and financial data at the core of the enterprise, is precisely the data most constrained by governance restrictions. The organizations that invest in data governance infrastructure, meta management, field-level documentation, and access control frameworks not only reduce the risk, but they are building the prerequisites for AI deployment in their highest-value domains.

Additionally, interviewee 2 raised the governance theme at the platform and ecosystem level, extending it beyond internal data management to the structural dynamics of AI vendor markets. As AI platforms mature and accumulate more customer data, platform vendors gain increasing structural power to restrict data portability, creating competitive dependencies that can be difficult to escape:

"The data should be moved to a new platform for use, but it is not necessarily easy anymore. A kind of 'moat' logic emerges as companies try to build protective structures if they notice that others could operate more efficiently using their data, or they restrict it so that the data cannot be taken out. If you think of your company´s private data as a kind of gold reserve, the foundation on which everything operates, it tends to be bounded so that it can be used within your own platform. But if it has already formed within a particular platform or ecosystem, it may no longer be accessible for the next one." (Interviewee 2)

The policy implication points toward the importance of data portability requirements in AI vendor markets, a theme increasingly present in EU digital policy but still underdeveloped in practice. The strategic implication for organizations is to treat vendor selection as a governance decision as much as a technical one, with explicit contractual requirements for data exportability and clear exit architectures before deployment commitments are made.

Lastly, interviewee 3 offered an ecosystem reframing of the governance theme that challenges the common narrative of European regulation as an AI adoption barrier. Finland´s regulatory approach, precautionary but ultimately permissive within established boundaries, may be less of a constraint than it appears. In practice, interviewee 3 observed, there are relatively few uses for AI that are actually prohibited under current Finnish or EU regulatory frameworks. What exists is uncertainty about what is permitted, which creates a tendency toward caution that often exceeds what the frameworks actually require:

> *"Our situation is somewhat restrictive, but there is still a lot that can be done. In many cases it ultimately comes down to how transparent something needs to be or what needs to be documented differently. In reality, there are actually quite few things that are completely prohibited." (Interviewee 3)*

The competitive implication is that organizations investing in regulatory interpretation and governance capability, understanding precisely what the frameworks permit, not merely what they prohibit. Those can deploy AI more aggressively within the available space than competitors that treat regulatory ambiguity as a general prohibition. Governance literacy is itself a competitive capability.

4.4.3 Theme 7: Value Demonstration and ROI as the Investment Gate

The seventh and final theme addresses the investment logic that governs whether organizations make the resource commitments necessary to move from AI experimentation to AI capability. The data identify a consistent and cross-cutting explanation for why many organizations stall at the pilot stage despite technical readiness and employee enthusiasm: the difficulty of articulating, measuring, and communicating the return on AI investment acts as a gate on strategic commitment. This is not merely a measurement problem, but rather a strategic clarity problem whose resolution requires deliberate analytical

Interviewee 5 provided the most direct and vivid articulation of the ROI challenge, rooted in the operational experience of making the investment case of management in real time:

> *"How do you transmit the return on investment of these solutions? Yes, you´re paying for this generative AI, Copilot costs 30 EUR per person per month. How do you tell the management: yeah, this is a good return on investment? Finding the return on investment is still a struggle." (Interviewee 5)*

Interviewee 5 drew a sharp contrast between the ROI clarity of traditional Robotic Process Automation (RPA) and the opacity of Generative AI´s returns. When an RPA bot replaces a human in a specific, repetitive task, the benefit is directly calculable: hours saved multiplied by the relevant labor cost. The investment case is legible, defensible, and auditable. Generative AI´s benefits, accelerated ideation, higher output quality, better decision support, reduces cognitive fatigue – are real and experienced by users, but diffuse in their financial expression. How do you price the value of asking one question instead of three? How do you capture the benefit of a better-quality solution built in two-thirds the time? These are not impossible calculations, but they require a measurement and communication infrastructure that most organizations have not built yet.

Furthermore, interviewee 5 identified feedback mechanisms that amplifies the ROI problem at the individual level: employees who do not understand what AI can do for them are not in a position to request the tools they need, justify the investment to their managers, or investment to their managers, or invest the personal learning time that would make the tools valuable. The absence of an ROI narrative prevents not only corporate investment but also the individual-level experimentation that would generate the evidence for that narrative. This creates a structural cycle: low clarity about value suppresses usage, which suppresses demonstrated value, which suppresses investment, which suppresses deployment, which perpetuates low clarity.

Moreover, interviewee 6 identified a conceptual distinct but practically interrelated dimension of the ROI challenge: not the difficulty of measuring return after adoption, but the difficulty of defining the target state that would justify investing before it. For many

Finnish organizations the question of what a successfully AI-enabled version of the company would actually look like remains unanswered:

> *"Defining the target state is still quite difficult for many companies, because exact realization of AI benefits is not entirely clear to everyone. This affects the kinds of investments companies are willing to make at the moment, and therefore also influences the speed of development." (Interviewee 6)*

This is a diagnosis of strategic ambiguity: not uncertainty about whether AI creates value in general, which the data uniformly affirm, but uncertainty about what specific form that value will take in a given organization´s particular context. Without a clear target state, it is impossible to construct a coherent resource commitment, monitor progress meaningfully, or make the process of redesigning decisions that move from pilot to capability. Additionally, interviewee 6 offered forward looking prediction that frames the competitive stakes of resolving this ambiguity. Over the next decade, interviewee 6 expects the greatest competitive divergence to appear between organizations that successfully specify, measure, and commit to AI-enabled target states and those that remain in the indefinite pilot zone. Interviewee 6 observed that the AI front-runners will typically be software-adjacent companies where the relationship between AI capability and business output is most direct and legible. Traditional manufacturers will follow, but more slowly. Not because AI is less relevant to manufacturing, but because the measurement and specification challenges are greater in a physical production context:

> *"We will see significant impact over ten years for those companies capable of designing processes and IT-data infrastructure and implementing effective AI use cases." (Interviewee 6)*

Lastly, interviewee 2 extended the ROI analysis to a longer competitive time horizon that introduces the technology-obsolescence risk of AI investment. Organizations that have invested heavily in bespoke AI solutions built for specific business functions now face the possibility that new, off-the-shelf foundation models exceed the capability of their proprietary systems:

> *"It was calculated that this would be in use for perhaps ten or twenty years and could then pay itself back. Now three years have passed, and new models are overtaking it entirely." (Interviewee 2)*

This observation generates a nuanced implication for AI investment strategy. It argues against large, model-centric bespoke investment unless the organization is confident that its proprietary data and workflow integration will sustain the advantage even as underlying models improve rapidly. It argues in favor of modular, data-architecture-centric investments, building the data infrastructure and organizational learning that can be paired with successive generations of AI models, rather than betting on a specific model´s capabilities. The competitive moat, in this formulation, is not in the AI model itself but in the data, governance, and organizational knowledge surrounding it. This conclusion aligns with interviewee 2´s earlier observation about data as the ´gold reserve´, the investment worth protecting and building, regardless of which model generation is currently available.

Taken together, the three Dimension themes explain the adoption gap as a compound phenomenon. Leadership failures mean that individual productivity gains never aggregate into organizational capabilities. Governance uncertainties mean that technically capable organizations move more slowly than the frameworks actually require. And ROI ambiguity means that strategic commitments are not made even when the directional case for investment is clear. Each barrier is individually addressable, as its interaction sustains the adoption gap as a systemic challenge that cannot be resolved by attacking any single dimension.

4.5 The Finnish Context: National Dimensions of the Adoption Challenge

While the seven themes above describe competitive dynamics that are broadly generalizable across context, the data carry a consistent thread regarding the specifically Finnish dimensions of the adoption challenge. Three national-contextual observations recur across the interviews with sufficient consistency to warrant explicit treatment before the chapter synthesis.

The first concerns the relationship between structural security and adoption urgency. Interviewee, who has worked in technology organizations for several years and maintains a comparative view from international experience, identified a cultural dynamic in which Finland´s social safety net and strong employment protections reduce the urgency signals that drive AI adoption in more competitive labor markets:

> *"There is perhaps a cultural tendency in Finland not to develop oneself when things are going well. There is less passion for new technology than in many other countries." (Interviewee 1)*

Interviewee 5, speaking from a foreigner´s perspective with four years of working experience in Finland, developed this observation from a comparative structural perspective:

> *"Finland has a really, really good country, a good system, a good process that people like. Why do we need Gen AI? London and the US have that fierce competitiveness – in Finland, it´s not the same pressure. You have government backing, a massive safety net." (Interviewee 5)*

Additionally, interviewee 5 noted a counterintuitive observation that strengthens this argument: Finland´s AI adoption has been slow relative to comparable European countries, yet the country´s unemployment rate has risen among the highest in the EU over the same period. If AI adoption were the primary driver of job displacement, one would expect countries with faster AI adoption to show higher unemployment, not the reverse. Interviewee 5 interpreted this as indirect evidence that AI adoption, far from destroying employment, may create competitive opportunities and jobs. Therefore, making Finland´s relative slowness in adoption a potential contributor to its economic underperformance, not a protection against displacement.

The second Finnish-specific observation concerns sector-level variation in adoption speed. Interviewee 3 identified customer service and manufacturing as the domains where AI adoption had moved most decisively, and healthcare and public administration as those where it remained most constrained. The primary determinant is not AI relevance; AI is arguably more consequential in healthcare than in customer service, but regulatory clarity is. Sectors where the applicable legal and ethical frameworks are relatively settled can move faster; for example, those with overlapping, ambiguous, or evolving regulatory requirements face additional friction that multiplies the governance challenges described in theme 6. Interviewee 3 noted a paradox here: healthcare, where AI has the most profound potential to improve outcomes and reduce costs, is also the sector with the most complex regulatory environment, creating a situation where the highest-impact applications face the highest adoption barriers.

The last observation concerns the opportunity represented by Finland´s collaborative infrastructure between private enterprise, government, and research institutions. Interviewee 3 described this as an underutilized asset: the national network of companies, universities, research institutes, and public bodies that Business Finland and the Lumi supercomputer consortium represent could, if more fully mobilized, provide Finnish SMEs in particular with access to AI development capabilities that would be prohibitively expensive to build independently. The European hyperscale infrastructure question goes as follows: whether Finnish organizations should depend on US cloud providers or invest in sovereign European AI infrastructure is a strategic and policy question that interviewee 3 expected to become increasingly salient as AI capabilities continue to advance.

4.6 Synthesis: A Process Model of AI-Enabled Competitive Advantage

The seven themes identified through the Gioia analysis describe a sequential, conditional process through which AI adoption translates into competitive advantage or fails to do so. Taken together, they constitute an empirical process model of AI-enabled competitiveness for Finnish companies. This synthesis articulates the architecture of that model and connects its components to the theoretical framework developed in Chapter 2.

This all begins in Dimension 1, where the competitive effects of AI adoption first become visible. Even at the basic levels of adoption, AI tools usage produces productivity gains that begin to create a competitive difference between the early adopters and non-adopters. This first stage competitive signal is the most universally accessible form of AI-enabled advantage, as it does not require proprietary data, specialized infrastructure, or deep organizational change. It requires only that employees actually use the tools available to them. However, this accessibility is also its strategic limitation, because productivity-level AI benefits are available to any organization that deploys the same tools. Therefore, these tools do not generate sustainable competitive differentiation. They generate what interviewee 6 described as a minimum competitive threshold, a baseline from which any serious competitive strategy must begin, but on which it cannot rest.

Durable competitive differentiation emerges at the second stage of Dimension 1, when AI is embedded in specific, high-impact use cases integrated with proprietary data and redesigned processes. This is the strategic threshold, the point at which AI adoption changes qualitatively rather than quantitatively. The resulting competitive positions are harder to replicate because their value resides not in the AI technology itself, but rather in the unique combination of firm-specific data, organizational learning, and process re-design that surrounds its implementation. Interviewee 2´s concept of proprietary data as the “gold reserve”, interviewee´s logic of building specialist agents for niche domains, and interviewee 4´s vision of AI-native financial services products all express this threshold from different vantage points.

Movement across this threshold depends on two categories of enablers described in Dimension 2. Data quality and infrastructure set the technical ceiling, for the maximum depth of AI adoption any organization can achieve is bounded by the quality and accessibility of its data. Skills and training set the human floor, the minimum capability required to identify high-impact use cases, implement AI solutions, and extract ongoing value from AI investments. Investment in one category without the other is insufficient. Superb data architecture with an under-skilled workforce cannot generate competitive value, and excellent training without quality data cannot produce the process-embedded AI applications that differentiate. Both enablers must be developed in parallel, and both require sustained, deliberate investment rather than one-time deployment.

The adoption gap, the persistent divergence between AI´s acknowledged potential and its realized competitive deployment in many Finnish organizations, is explained by the three boundary conditions of Dimension 3. Leadership failures translate into individual-level productivity gains that never aggregate into organizational AI capabilities, because structural preconditions (tools, infrastructure, training investment, process redesign, authority) are never fully provided. Governance uncertainty makes technically capable organizations more cautious than the regulatory frameworks actually require, leaving available competitive space unclaimed. ROI ambiguity prevents strategic resource commitments from being made because neither the target state nor the return on the investment required to reach it is clearly enough defined to clear the investment approval threshold.

The Finnish context adds contextual specificity to the model without fundamentally altering its underlying logic. The structural stability provided by Finland's welfare institutions may reduce the sense of urgency that often accelerates AI adoption in more competitive or unstable environments. In addition, sector-level regulatory differences create uneven adoption conditions, where industries with clearer governance frameworks may scale AI initiatives more rapidly than more heavily regulated sectors. Furthermore, Finland's collaborative infrastructure between private, public, and research institutions represents a potentially underutilized asset that could accelerate the transition from isolated productivity tools toward process-embedded competitive capabilities.

Table 6. Summary of findings

Theme	Competitive mechanism	Theoretical anchoring
Productivity & Speed	Immediate competitive effect: efficiency gap widens between adopters and non-adopters; becomes minimum competitive threshold over time	Porter (1985) cost leadership; Davis (1989) TAM — Perceived Usefulness
Use-Case & Process Orientation	Strategic threshold: process-embedded AI creates firm-specific, durable differentiation; generic tool use does not	Teece (1997, 2007) dynamic capabilities; Barney (1991) VRIN; generic-AI paradox (Kemp, 2024)
Data & Infrastructure	Technical ceiling: data quality and accessibility set the upper limit of AI adoption depth; proprietary data is a VRIN resource	Barney (1991) RBV; Iansiti & Lakhani (2020) digital core; Teece (2018)
Skills & Training	Human floor: organisational AI competence at all levels determines execution capacity; generational dimension adds structural urgency	Davis (1989) TAM — PEOU; Teece (2007) human capital; dynamic capability sensing
Leadership & Change Management	Scaling driver: bidirectional leadership engagement converts individual tools into organisational capabilities through cross-functional investment and process redesign	Teece (2007) seizing and reconfiguring; Ransbotham et al. (2021); Wamba-Taguimdje et al. (2020)
Governance, Security & Risk	Boundary condition: regulatory frameworks set scope of deployment; sophisticated governance infrastructure is itself a competitive capability	Institutional theory; Cai et al. (2019); TAM — trust and PEOU in regulated contexts
Value Demonstration & ROI	Investment gate: inability to specify target state and measure AI value prevents commitments needed to scale; creates self-reinforcing adoption cycle	Barney (1991) durability of competitive advantage; strategic ambiguity (Teece, 2018); Kemp (2024)

Figure 6 shows the revised theoretical framework incorporating the conceptual model from Chapter 2 with the empirical results of this study. This new framework builds on the previous model by describing the main mechanisms, enablers and boundary conditions through which AI adoption may lead to competitive advantage. It also explains the conditionality of this relationship and accounts for the Finnish context in which the elements are implemented.

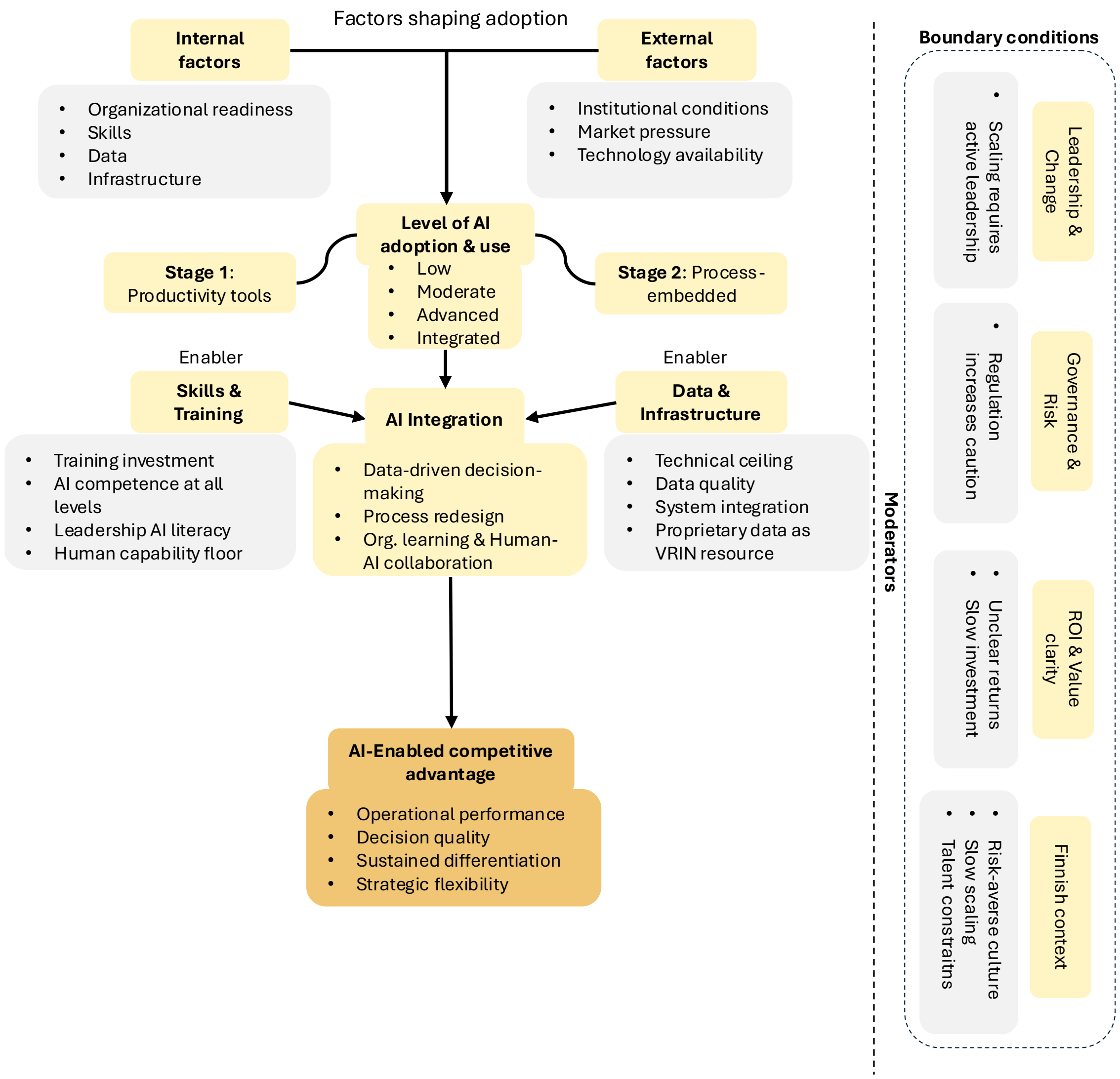


Figure 6. Revised theoretical framework

5 Discussion

The final chapter of this study consists of the discussion of the study´s findings. The chapter begins with theoretical contributions focusing on AI adoption and competitive advantage in Finnish companies. This is followed by managerial implications that aim to serve as practical guidance for organizations implementing AI to improve their competitiveness. The limitations of the study are then discussed, followed by suggestions for future research directions.

5.1 Theoretical contributions

This research was initiated to address three critical gaps in the understanding of AI and competitiveness. With its Stage 1 and Stage 2 framework, the study provides an interpretation of the “generic-AI paradox” through qualitative analysis. The findings suggest that, while adoption of a horizontal tool (Stage 1) is critical to remain competitive, it will not be sufficient for VRIN to recognize competitive advantage until AI is embedded in the organization's processes and decision-making (Stage 2).

The second aspect of the study is to contextualize each stage within the context of the Finnish business environment. The results suggest that the perceived slowdown in integrating a strategy is not caused by technical problems, but rather by a perception gap in leadership that few leaders see the effect on the organization in the long run. By incorporating leadership as a driver of scale in the process model, the study provides a context-specific explanation for the slow adoption and scaling of AI.

Third, the model bridges the individual-organizational divide by illustrating those individual motivations, such as perceived usefulness, that need to be matched by organizational infrastructure and managerial alignment. This allows AI to move from supporting firm productivity to supporting firm dynamic capabilities. It responds to Kohtamäki et al. (2025) in their request for research connecting micro-level technology use to macro-level strategic outcomes.

This study set out to examine how the depth of AI adoption influences the competitive practices and outcomes of Finnish companies. The results indicated that the depth of integration is the major determinant of the type and enduring advantage that AI could have provided. Organizations adopting AI as a productivity tool can see substantial efficiency gains but these gains quickly degenerate into imitations as the technology becomes available in cheaper forms. Organizations that embrace AI as a process, use case-specific tool embed their organizations create qualitatively different and strategically more durable competitive advantages. This distinction between adoption as access and adoption as organizational embedding is the main finding of the study and may have implications for both theories of competitive advantage, technology acceptance, and dynamic capabilities in this new age.

Extending the competitive advantage theory to the AI era. The results confirm that Porter’s (1985) and Barney’s (1991) theoretical formulations are still relevant today, but they need to be rethought in the light of our empirical findings. Porter’s differentiation logic still applies, but the source of differentiation has changed. In each of the organizations, differentiation is no longer attributable to owning AI software (which is available today), but to how AI is integrated into their own processes, workflows, and customer interaction. According to Wingate et al. (2025), AI does not generate sustainable competitive advantage by itself, but the findings add a new explanation: that advantage emerges once AI integration becomes sufficiently firm-specific to satisfy the VRIN criteria defined by Barney (1991).

An empirical precision to an assertion that previous work had expressed in principle but not shown. Here, we show that not raw data is a VRIN resource in AI, but rather the infrastructure that makes data AI-usable: accessible systems, structured formats, governed pipelines, and routines that maintain data quality over time. This extends Iansiti and Lakhani's (2020) concept of AI factories and shows that the factory infrastructure -data architecture, governance, and the integration layer that connects AI with business processes -is even more valuable than the raw materials that are processed. AI models for general applications fail the rarity and inimitable criteria when evaluated in combination with proprietary data and in the context of the firm, a finding consistent with Kemp (2024) and Teece (2018) but now grounded in empirical organizational evidence from Finland.

A theoretically significant finding is that AI adoption does not produce a single type of competitive advantage but rather two qualitatively distinct pathways depending on integration depth. The first pathway, Stage 1, is characterized by gains in operational efficiency through horizontal tool adoption. These gains are real and quantifiable — organizations that have yet to reach the stage attain an ever increasing productivity gap with those that have, but it is also temporary because the same tools are available to all competitors. The second path, Stage 2, creates a more durable advantage through process changes, AI-enabled decision-making, and learning. This distinction is important for theory because it resolves the seemingly incompatible contention among the prior literatures that AI provides a competitive edge (Wamba-Taguimdje et al., 2020; Gao et al., 2025) and those that AI can be easily replicated to sustain advantage (Wingate et al., 2025). Both are valid but describe different stages of adoption rather than competing claims about AI's strategic role.

The three aggregate dimensions emerging from the empirical data map coherently onto Teece's (2007) sensing-seizing-reconfiguring framework, providing an empirical demonstration of dynamic capabilities theory in the AI adoption context that prior research had theorized but not shown through organizational data. A first step in identifying value in AI is to find out how, and to invest in it; second, ROI and value clarity represent seizing: only when the value logic is sufficiently concrete that decision makers act, and not having clear value is the single largest reason organizations fail to scale. Third, leadership, change management, and governance are reconfiguring: whether human, process, data, and decision rights can be reorganized around AI capabilities to maintain competitive advantage over time. This supports Teece's (2018) point that, in an AI-era scenario, the key competitive question is no longer how to defend a position, but how quickly one can adapt and redeploy what it knows.

Although Davis's (1989) Technology Acceptance Model explains the individual's use through perceived usefulness and perceived ease of use, the results indicate the organizational factors that prevent the individual's use from leading to firm-level competitive advantage, which was an earlier gap identified theoretically but not empirically. The data confirm that AI adoption is at least as much a human capital challenge as it is a technological issue. The workforce development needed to take organizations from the experimental to the routine use of AI is far greater than had been previously suggested. This adds empirical validation to Kane et al.'s (2015) digital transformation model by testing for the people readiness dimension of readiness and adding another variable: generational gaps in workforce ability mean that organizations cannot rely on employees to renew themselves, but must invest in the development of workers, including leadership.

Further challenges to the traditional models of change management emerge from the findings that suggest that adoption of AI by employees is not a two-way street. Both in the organizations being examined, leaders determine what needs to be done to adopt AI (i.e., infrastructure, tools, training, governance), while employees and staff test the most effective use cases themselves. This contrasts with traditional top-down or bottom-up transformation and demonstrates that AI adoption requires a coordination model that provides both strategic and operational learning as well. As a result, AI transformation is in fact more of an organization design than a technology implementation problem, a question that can be addressed by firms (Ransbotham et al., 2021; Henke et al., 2016).

A result that challenges the current thinking in practitioners and academic literature is that, when invested in proactively, governance can be a competitive feature and not a compliance overhead. Organizations that create clear AI governance models that clearly document use, access, and approval levels to a risk tier create a set of existing compliance procedures that can be used repeatedly. Especially in regulated industries where competitors must also navigate institutional barriers, governance literacy emerges as a dynamic capability (Teece 2007): it enables the organization to move faster than competitors who think they can do without it. This builds on institutional theory by arguing that the competitive advantage in a restricted environment is not found in circumventing the constraints but in better understanding the constraints than competitors. This reverses the notion that governance is a barrier to innovation: well-designed governance is a condition for scaling innovation responsibly and competitively.

The results extend competitive advantage theory to national institutions in ways not examined empirically before for the Finnish country. The results reveal what can be viewed as a welfare state adoption paradox: Finland's strong social safety net, high trust, and standards of employment security, all genuine positive features of society, reduce the competitive urgency associated with the adoption of AI in market economies where displacement risks are a big motivator. While only a small fraction of Finnish top managers believe that AI will significantly affect their work (Solita, 2023), the response of workers is significantly higher in all the organizations studied. This suggests that the perception gap between top executives and employees is not just psychological but institutionally shaped. It adds to the different types of capitalism literature that there is a positive effect of coordination in market economies during periods of rapid change in general-purpose technology.

While the Technology Acceptance Model (TAM) explains adoption mainly through Perceived Usefulness and Perceived Ease of Use, this study suggests that in Finland, these factors are shaped by what could be called a "consensus-driven subjective norm." Compared to the more aggressive competition seen in markets like the US or UK, Finnish firms tend to approach adoption more carefully and with a stronger emphasis on collective agreement. In practice, this means that even if managers believe AI could be useful, the intention to actually implement it is often delayed until there is wider organizational acceptance around it. The issue is therefore not really infrastructural, since Finland already has strong digital foundations, but more psychological and structural. The relatively high level of social security and economic stability lowers the sense of urgency that usually pushes companies in more competitive economies to adopt technologies faster. Because of this, the "Finnish Gap" seems to reflect strategic hesitation rather than technical inability. Many firms appear to prefer a “wait-and-see” position, where the cultural risk of being first is considered larger than the competitive risk of adopting later.

Together, the findings of this study suggest that the complexity of adoption determines the nature of the advantage, enabling factors are needed but insufficient when several organizational conditions are present. The Finnish institutional context moderates the relation between integration and advantage in observable ways. This is a more nuanced and empirically based model for AI-enabled competitive advantage than the binary models that have dominated previous literature.

5.2 Managerial implications

The results suggest several practical tips for companies interested in turning AI experimentation into competitive advantages. The biggest implication is that AI adoption should be considered an organizational change, not a technology deployment project. Typically, organizations that leave the adoption of AI to IT departments as a license management function get stage 1 productivity gains, but fail to fully reap the process benefits of stage 2. It is not just technical teams that need to coordinate on AI pilots. Cross-functional collaboration between HR, communications, risk management, and business operations, rather than just technical teams, is essential so that AI pilots can take full advantage of the organization’s capabilities. This has immediate implications for the structure, governance, and funding of AI programs.

What’s more, the results show that organizations have to decide between adopting AI for the efficiency benefit and investing in training for the differentiation benefit. For the efficiency benefit, there are cost savings associated with both actions. For the differentiation benefit, there should be process re-design before selecting an AI tool: competitive advantage is provided by the process change, not by the AI tool. Organizations choosing the latter path without clarifying the process change they want to implement will inevitably have a tool that is not delivering the promised benefits, leading to the uncertainty of ROI that holds off further investment.

Large organizations may want to consider a two-tiered governance model where the application risk matches the level of governance. For horizontal applications, using a quick-start process with self-service approval (until explicitly prohibited) allows the organization to quickly try new things. For business-critical or customer-facing AI applications, full governance is recommended and, when done properly, may be an advantage rather than a burden to the speed of deployment. Organizations in regulated sectors may want to upgrade the governance system before deploying AI, considering it a strategic decision, not a cost of compliance.

This is a lesson for SMEs. Focus and speed are the main competitive advantages they may be able to exploit. Rather than copying the strategies of large enterprises, SMEs should focus on one or two specific use cases where AI can be applied in real time to make a difference and rapidly move to deployment. Participating in the infrastructure of ecosystems, such as shared testbeds, industry networks, and public AI initiatives, can provide access to computing power and peer knowledge that would be too expensive to build by themselves, and those businesses in the study who participate in these ecosystems learn faster.

Leadership teams should demand firsthand experience with AI tools before making investment decisions. From the analyses, the conclusion is that the leadership perception gap, in which executives underestimate their own readiness for the tool and its immediate effects, closes most quickly when these leaders have direct experience as opposed to reporting on or showing the benefits. Leaders who have experienced the impact of AI at work are more likely to commit the time and money needed to scale up. This addresses the perception of low usefulness by top leadership that TAM identifies as the largest barrier to adoption of AI.

Finally, firms should move away from generic promises for AI and shift toward concrete, outcome-driven targets. Unable to specify the state of the target in business terms is cited as one of the reasons ROI remains unclear, and investment decisions stall. Connecting investment in AI to measurable performance outcomes, time horizons, and responsible owners transforms the ROI question from a speculative undertaking to a manageable accountability question.

5.3 Limitations

Although the study provides rich empirical evidence on AI adoption and competitiveness, it is not without limitations. As with any qualitative study, the generalizability of findings is subject to certain constraints.

First, the study is based on expert interviews conducted in Finland between November 2025 and February 2026. While participants were selected to represent diverse roles from different organizations, they are concentrated in large organizations and knowledge-intensive sectors. Five of six informants work for multinational or nationally prominent organizations. This creates potential selection bias toward organizations with relatively high AI maturity. True micro-enterprises and organizations in less digitally intensive sectors are absent from the sample. The study´s findings about organizational enablers and scaling conditions may underestimate barriers facing organizations without dedicated IT teams, formal training budgets, or access to ecosystem resources.

Second, research bias should be considered. As a graduate student studying AI adoption while technology is rapidly evolving, the researcher´s own learning about AI may have influenced the interpretation of adoption challenges. The qualitative methodology and Gioia analysis approach help mitigate this through systematic data structure development, but interpretive choices remain inherent to the method.

Third, the temporal scope presents limitations. Data collection captured AI adoption dynamics at a specific moment in the rapidly evolving technology landscape. The findings reflect early-stage generative AI adoption, primarily ChatGPT, Copilot, and custom chatbot deployments. As AI capabilities evolve with more advanced reasoning models, multimodal capabilities, or agentic systems, specific barriers and opportunities identified may shift. The “data quality as ceiling” finding may become less binding if future AI models demonstrate stronger capability to work with unstructured data. Conversely, governance challenges may intensify as AI systems gain greater autonomy.

Fourth, while AI adoption and its potential impact are at the core of this study, the subject is covered in general terms. What is considered as AI includes a spectrum of different technologies, some overlapping and some very different from each other. A more focused approach on specific AI technologies like machine learning or large language models could provide more detailed insights. However, the decision to discuss AI on a general level was driven by the novelty of the subject and organizations´ current stage, where most are experimenting with multiple AI technologies simultaneously.

Finally, the Finnish context introduces both strengths and limitations. The study´s findings about welfare state structures, cultural caution, and regulatory ambiguity are nationally specific and may not apply to other Nordic countries or broader European contexts. However, Finland´s position as a technologically advanced yet cautious adopter makes it an interesting case for understanding barriers that may emerge in other similar contexts.

5.4 Suggestion for future research

As the limitations section suggests, there are multiple avenues for future researchers to explore. The first logical direction would be longitudinal validation of the three-dimensional framework developed in this study. Future research should track cohorts of organizations over 3–5-year periods to test whether organizations that invest early in governance infrastructure achieve faster deployment later, whether the productivity-to-process redesign pathway holds across sectors, and at what point governance investment reaches diminishing returns. Such longitudinal embedded case studies would validate or refine the framework with temporal evidence.

Researchers could also conduct comparative Nordic studies to test the “welfare state adoption paradox.” Parallel studies across Nordic countries, Sweden, Denmark, Norway, using common interview protocols could compare adoption speed, leadership commitment, and urgency perceptions while controlling for firm size and sector. This would test whether the findings are Finland-specific or Nordic-wide and identify other institutional or cultural factors that moderate technology adoption.

Another promising direction would be sectoral deep dives in healthcare and public administration, which were identified as domains where AI adoption remains most constrained. Future research should investigate whether the three-dimensional framework applies to highly regulated, mission-driven contexts or whether fundamentally different adoption pathways emerge. Particular focus on how governance requirements function differently in sectors where errors have life-or-death consequences versus commercial consequences would be valuable.

Due to the qualitative methodology of this study, quantitative validation through large-scale surveys would strengthen the findings. Researchers could develop measurement scales for AI process integration depth, data infrastructure quality, organizational AI readiness, leadership AI commitment, and governance maturity based on this study´s themes. Large sample survey research testing the three-dimensional model across multiple countries would provide statistical validation.

Intervention studies testing the policy recommendations would also be worthwhile. Do leadership training mandates increase organizational adoption? Can standardized ROI frameworks resolve strategic ambiguity? Do regulatory guidance publications increase deployment in ambiguous regulatory spaces? Quasi-experimental designs comparing organizations or regions pre- and post-intervention would validate recommendations empirically.

As we advance in AI capabilities and adoption, it would also be intriguing to understand how the competitive dynamics evolve. Will early movers sustain advantages or will fast followers catch up as AI tools commoditize? How do different national contexts affect competitive outcomes from AI adoption? A comparative study examining AI adoption and competitiveness across different countries and regions could provide insights into whether there is a common global narrative or whether approaches, investments, and attitudes differ significantly between, for example, Nordic countries, the United States, and Asian markets.

Finally, as AI systems become more capable and autonomous, future research should examine the human-AI collaboration models that emerge in practice. This study captures early-stage adoption where AI primarily assists humans. As agentic AI systems develop, the nature of work and competitive advantage may shift fundamentally. Research examining how organizations manage increasingly autonomous AI systems while maintaining human oversight and ethical governance would be valuable.

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Appendices

Appendix 1. Semi-structured interview guide

Background information

1. Could you briefly introduce yourself and your role in your organization?
2. What are your main responsibilities in your current position?
3. How long have you been working in your current role or industry?
4. To what extent does your work involve automation, data, or artificial intelligence?

Artificial intelligence in organizations

1. How do you see the current role and importance of AI in companies, particularly in Finland?
2. How has the use of AI developed in your organization in recent years?
3. What kinds of AI tools or technologies are currently used in your organization?
4. How widely are AI tools adopted among employees in your organization?

AI and daily work

1. How do AI tools influence your daily work or decision-making?
2. In what ways has AI improved productivity or efficiency in your role or organization?
3. What kinds of tasks are currently supported or automated using AI?
4. Do you see AI mainly supporting employees, or replacing certain tasks?

AI implementation and organizational adoption

1. How was AI introduced or implemented in your organization?
2. What role does leadership play in adopting AI within the organization?
3. Do employees receive training or guidance on how to use AI tools?
4. How have employees reacted to AI adoption (e.g., enthusiasm, skepticism, resistance)?

Organizational challenges and barriers

1. What challenges have you encountered when implementing or using AI in your organization?

2. Are there concerns related to data security, governance, or regulations when using AI?
3. How do organizational structures or collaboration between teams affect AI adoption?
4. Do larger organizations face different challenges compared to smaller companies when adopting AI?

AI and business value

1. What kinds of benefits has AI brought to your organization so far?
2. How does AI contribute to productivity, efficiency, or innovation?
3. How do companies measure the value or return on investment (ROI) from AI solutions?
4. Do you believe AI can strengthen the competitiveness of companies in the future?

Future outlook

1. How do you see the role of AI evolving in organizations over the next few years?
2. What kinds of new opportunities or applications of AI do you expect to emerge?
3. What capabilities or skills will employees need in the future to work effectively with AI?