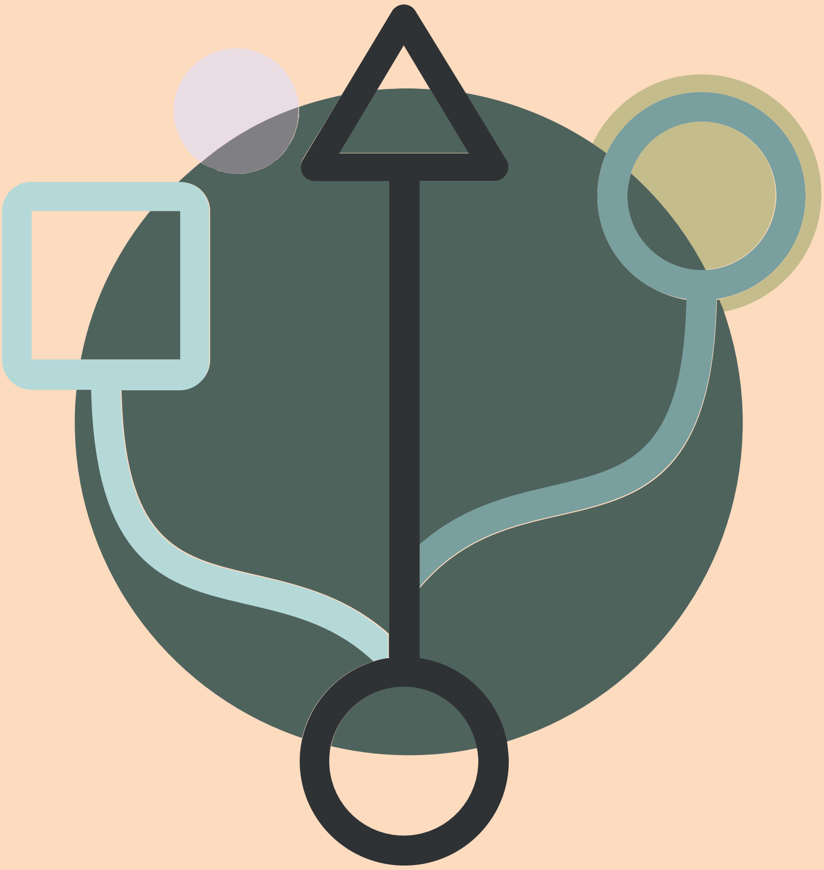

Rapport 2021:07

Drivers of AI adoption

A literature review

This paper examines the literature and identifies the drivers of AI adoption. The main results are synthesised in a conceptual framework that highlight the AI capabilities needed to impact firm performance and deliver competitive advantage.

This subreport is part of the program titled "How is AI transforming businesses, and what is the role of public policy?"

Tillväxtanalys
Myndigheten för tillväxtpolitiska utvärderingar och analyser

Dnr: 2020/250
Myndigheten för tillväxtpolitiska utvärderingar och analyser
Studentplan 3, 831 40 Östersund
Telefon: 010 447 44 00
E-post: info@tillvaxtanalys.se
www.tillvaxtanalys.se
För ytterligare information kontakta: Irene Ek
Telefon: 010-447 44 79
E-post: irene.ek@tillvaxtanalys.se

Foreword

The Swedish Agency for Growth Policy Analysis (Growth Analysis) has been instructed by the Swedish Government to analyse and evaluate Swedish growth policy. This knowledge helps the Swedish government design and implement evidence-based and effective growth policies.

Guiding policy-makers in complex areas of sustainable growth requires in-depth studies that cover different perspectives. After a dialogue with the Swedish government and key stakeholders, we present a yearly analysis and evaluation plan that outlines the two-year programs that we will study. Within the scope of these programs, we continuously produce subreports, but our conclusions and policy recommendations are presented in a final synthesis report.

This report is the second subreport of the program titled "How is AI transforming businesses, and what is the role of public policy?" The study was written by Irene Ek. Peer review was performed by Joakim Wernberg, Swedish Entrepreneurship Forum and Alistair Nolan, of the OECD.

We would like to thank the advisory group for their valuable comments. In addition, we acknowledge the excellent contribution of leading AI researchers and experts who have taken their valuable time to comment on the manuscript during three working paper seminars. Special thanks to discussant Patrick Mikalef, Associate Professor at the Norwegian University of Science and Technology.

Östersund, October, 2021

Peter Frykblom, Head of Department, Internationalisation and structural change

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Sammanfattning

Drivkrafter för ökad användning av AI - En engelsk litteraturöversikt

Trots det stora intresset för och förväntningarna på att utvecklingen av artificiell intelligens (AI) ska driva företagens digitala transformation och förändra verksamheterna i grunden, misslyckas många företag med att integrera AI i kärnverksamheten. Enligt en internationell studie med 2 500 företagsledare anser nio av tio att AI kan leverera affärsnytta. Samtidigt medger många att de flesta AI initiativ inte leder till just det (Ransbotham, Shervin, Fehling, LaFountain, & Kiron, 2019).

I den här studien utforskar vi vad som hindrar och driver företagens användning av AI utifrån följande frågeställningar:

- Varför använder företag AI?
- Vilka är drivkrafterna bakom användandet?
- Vad hindrar företagen att använda AI?
- Finns det forskningsresultat som visar att AI skapar affärsnytta?

Företagens syfte med att använda AI

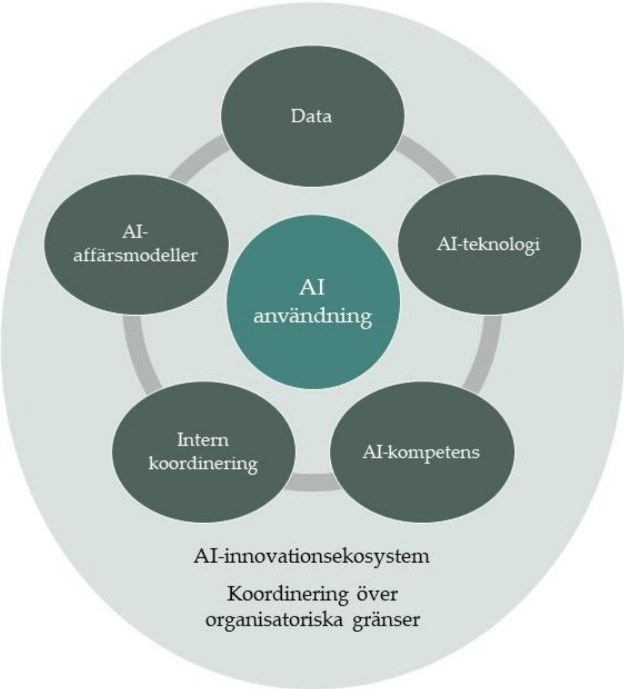
Några exempel på vad företagen förväntas uppnå med AI är att optimera produktionen, optimera globala värdekedjor, utveckla nya innovativa affärsmodeller, utveckla nya och förbättra existerande produkter, förbättra kundkontakter och skapa helt nya företag.

Drivkrafterna bakom användandet av AI

Trots att många företag ser möjligheter med AI visar offentlig statistik att endast fem procent av de svenska företagen använder AI idag. I litteraturen framträder sju drivkrafter som tillsammans kan öka företagens användning (se figuren nedan):

1. **Data**: AI-modeller behöver ofta stora mänger data.
2. **AI-teknologier**: Företagen behöver AI-modeller och nya teknologier för att samla, spara och bearbeta relevant data.
3. **AI-kompetens**: Företagen behöver teknisk spetskompetens för att utveckla och implementera AI-system samtidigt som företagsledningen också behöver förstå AI och vilka AI-relaterade beslut de behöver ta.
4. **Intern koordinering**: När AI interageras i kärnverksamheten behöver företagen ofta arbeta gränsöverskridande över funktionella silon.
5. **AI-affärsmodeller**: Företagen behöver kunna skapa affärer runt AI.
6. **Koordinering över organisationsgränser**: Samarbete mellan olika företag behövs eftersom många företag t.ex. inte har kompetens att själva utveckla AI och därför köper externa AI-leverantörer.
7. **AI-innovationsekosystem**: AI-innovationer utvecklas ofta i samarbete mellan forskningsfinansiärer, AI-forskare på universitet och företag i ett så kallat AI innovationsekosystem.

Figur Drivkrafter för att accelerera AI-användning i företag



Upplevda hinder för användning av AI

Det största hindret för svenska företag är kostnaden för att köpa externa AI-tjänster och teknologier för att till exempel samla in, spara och bearbeta data. Företagen upplever också att AI-strategi och anställdas kompetens är stora hinder. Ett sätt att hantera upplevda hinder är att:

- Välja ett avgränsat och strategiskt affärsdrivet problem
- Ta ställning till om AI är rätt verktyg för att effektivt hantera problemet
- Sätta AI-specifika mål och mäta framgång
- Lista vilken data AI-systemet behöver
- Identifiera vilka resurser och vilken kompetens som behövs
- Precisera eventuella hinder kopplade till exempelvis tvingande reglering som GDPR och den kommande AI-förordningen.

Vetenskapliga studier om affärsnyttan med AI

Studier som kan underbygga att AI verkligen skapar affärsnytta är en bristvara idag. Ett undantag är en tysk studie som visar att AI-innovationer ökade försäljningen med 16 miljarder Euro (Rammer, Czarnitzki, & Fernández, 2021). Det motsvarar 18 procent av det tyska näringslivets totala försäljning för innovationer som är nya för världen.

Abstract

Artificial intelligence (AI) has attracted significant attention in the academic literature and in businesses in the last decade. To gain business value, managers of private firms increase the adoption of AI systems. However, research on the drivers of AI adoption is still scarce, and knowledge needs to be systematised. In this context, the present study aims to fill this gap by providing a literature review to identify the drivers of AI adoption by firms. Research articles on AI adoption are analysed. In addition to gaps for future studies, a conceptual framework is proposed and discussed according to the drivers, i.e., the AI capabilities that firms need to gain a competitive advantage from their AI investments. This study identifies and describes seven AI resources that can drive AI adoption: (i) data, (ii) AI technology, (iii) AI skills, (iv) intrafirm coordination, (v) AI business models, (vi) AI innovation ecosystems, and (vii) coordination across organisational boundaries. These findings contribute to both theoretical and managerial perspectives, with opportunities for generating novel theories and new forms of management practices.

1. Introduction

In the last decade, AI has attracted significant attention in the academic literature and in businesses. As with electrification, AI is viewed as a general-purpose technology (Bresnahan & Trajtenberg, 1995; Trajtenberg, 2019) disseminated throughout all sectors, e.g., telecommunications (Balmer, Levin, & Schmidt, 2020), energy (Ahmad et al., 2021), health care (Borisa, Singh, & Rathore, 2020; Cruz & Wishart, 2006), real estate (Changro, 2021), education (Renz & Hilbig, 2020), manufacturing (Demlehner, Schoemer, & Laumer, 2021), retail (Paolanti, Liciotti, Pietrini, Mancini, & Frontoni, 2018), and journalism (Miguel Túñez-López, Fieiras Ceide, & Vaz-Álvarez, 2021). AI technology is expected to drive business transformations across the economy (Dwivedi et al., 2020; Zhang, Pee, & Cui, 2021). Furthermore, a growing body of literature finds that AI is changing firms' operating models (Ruiz-Real, Uribe-Toril, Torres, & De Pablo, 2021).

In a recent study, Zhang et al. (2021) argue that despite heightened interest, integrating AI into firms remains a challenge. An international survey of 2,500 executives shows that 9 out of 10 believe that AI represents business opportunities for their firms (Ransbotham et al., 2019). However, the same survey showed that most AI initiatives fail to deliver business value and that 40% of firms that made significant investments in AI did not report any business gains. Despite widespread understanding of the potential of AI, this potential is not fully understood (Chen, Li, & Chen, 2021). This lack of understanding prevents firms from adopting AI and extracting business value from their AI investments. Research on the drivers of AI adoption is still scarce and needs to be systematised. This paper aims to help fill this gap by reviewing the literature on the drivers of AI adoption in firms. The insights generated are synthesised in a new conceptual framework that identifies seven capabilities that can drive AI adoption. These findings highlight opportunities for generating novel theories and new management practices.

This paper begins with an examination of why firms use AI and illustrates the expected business benefits. The next section explores the uptake of AI in firms today and identifies the drivers of AI adoption, followed by a discussion of the barriers to adoption. The subsequent section reviews current evidence on the links between AI adoption and firm performance. Based on the reviewed literature, a conceptual framework is proposed that synthesises the elements that shape and drive the adoption of AI adoption by firms. Several limitations in the current evidence base are also noted, such as the diversity of AI adoption metrics and an overreliance on small samples and practice-based studies from consultancy firms. Based on the review, the most promising paths for future research are identified.

1.1 Method

1.1.1 Research questions

Given the challenges involved in obtaining business value through AI, this study addresses the following research questions:

RQ1 – Why do firms adopt AI?

RQ2 – What are the drivers of AI adoption in firms?

RQ3 – What are the main barriers to AI adoption?

RQ4 – What empirical research exists on the connection between AI adoption and firm performance?

1.1.2 Selective literature review

To answer these questions, it was necessary to identify and summarise the literature on AI adoption. The search for relevant research articles was performed and redefined between May 2020 and August 2021. Initially, research articles were identified by searches in the Ebsco and Jstor databases. The search term "artificial intelligence" was used in combination with "use", "adoption", "firm performance" and "drivers" in the title and/or in the abstract. The search terms were extracted from the numerous AI definitions explored by Montagnier and Ek (2021). In the first screening phase, 20 research articles were selected for full-text review based on the following eligibility criteria: (1) the article did not focus on the AI technology itself, i.e., overly technical research articles were excluded; (2) the article addressed AI adoption in firms; and (3) the AI article was in the business, economics, information systems or engineering domains. Another fifteen AI studies were added based on input from international AI experts/researchers during three seminars.

There are several structured literature reviews on artificial intelligence in areas such as AI in supply chains (Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021), the strategic use of AI (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021), COVID-19 as a driver of intelligent automation (Coombs, 2020), AI and sustainable business models (Di Vaio, Palladino, Hassan, & Escobar, 2020), and big data and dynamic capabilities (Rialti, Marzi, Ciappei, & Busso, 2019). These related bodies of knowledge identify general themes in the literature yet provide little in-depth understanding of how firms successfully adopt AI.

1.1.3 Data on AI adoption in Sweden

From the existing literature, it is apparent that the evidence on AI adoption is mixed. For example, an international AI adoption survey performed by McKinsey (2019) shows that 58% of firms use AI in some form, while official AI statistics in seven countries show that between 2% and 14% of firms use AI (Montagnier & Ek, 2021). There are several limitations in the current evidence base on adoption, such as the diversity of AI adoption metrics, overreliance on small samples and the drawbacks of practice-based studies from consultancy firms. To complement the existing literature with quality-assured official AI statistics, this study also contains a section that describes Sweden's AI adoption data.

Figures 1, 2 and 3 are based on Swedish firm-level data on AI adoption for 2020. These AI data are part of Swedish official statistics and are internationally comparable as part of Eurostat's annual survey of ICT usage in enterprises. The sample encompasses 7,739 firms of all sizes, as well as all Swedish firms with more than 200 employees. As this data collection is part of official government statistics, the survey response rate is a high 82 percent.

1.1.4 Explaining differences between different AI surveys

As previously pointed out by Montagnier and Ek (2021), different AI surveys generate very different results. The authors indicate possible reasons. First, the target population was surveyed both in terms of coverage and in terms of firm size. While surveys conducted by consultancy firms have merits, they also have some drawbacks, especially in regard to coverage. A common problem with surveys conducted by consultancy firms is a lack of a proper sampling frame, which calls representation into question. A possible reason why surveys conducted by consultancy firms show higher AI adoption rates may be that they capture only customers who are more digitally mature than the average firm. Ideally, the results of AI surveys could be used to guide practitioners and policy-makers. However, it is difficult to make generalisations from surveys when the firms included are not selected randomly from a target population or when the response rates are unknown or low. In many cases, the data are not open to other researchers, whereby the results cannot be replicated. Official AI statistics also have drawbacks. In Japan, firms employing fewer than 100 employees are not surveyed, which clearly pushes the AI adoption rate upward. Second, the heterogeneity of the definitions of AI and the varying scopes of survey questions may also partly explain the differences. Third, AI is often a part of a firm's digital transformation journey and is combined with other technologies such as big data analysis, IoT and cloud computing. The uptake of those complementary technologies may contribute to explaining differences between surveys. Generally, consultancy-based surveys show much higher rates of AI adoption than official AI statistics.

AI measures are a new and evolving area whereby there is no one agreed-upon AI definition. Consultancy firms and statistical offices struggle with a clear-cut measurement definition of AI. Agreeing on a common definition takes time, which is a challenge in a fast-moving area such as AI. Additionally, the definition of AI may change as AI use patterns change. Furthermore, AI-based systems are not all directly measurable, although their existence often needs to be inferred, as they can be software (e.g., voice assistants, image analysis, search engines, and face recognition) or systems embedded in hardware devices (e.g., robots, autonomous cars, drones or IoT applications). Selecting a definition is complex, as AI often is not a standalone technology but coexists and is embedded in other technologies. Statistics Sweden, for example, provides the survey respondent with examples of what AI applications can consist of (Montagnier & Ek, 2021). This was necessary, as cognitive tests indicated that it was difficult for respondents with limited previous AI knowledge to know when AI was actually embedded as a component of a larger system; they needed examples to guide them. Depending on what is included in the AI definition, the results can vary significantly, which makes comparisons more difficult.

2. Why do firms use AI?

Many firms can see how AI could deliver business benefits. A previously mentioned survey collaboration between MIT and BCG, covering more than 2,500 executives worldwide, shows that 9 out of 10 respondents believe that AI represents new business opportunities for their firms (Ransbotham et al., 2019). At the same time, most firm-level

AI initiatives have thus far failed to deliver business value. According to Ransbotham et al. (2019), 90% of surveyed firms made at least some investment in AI. However, of the firms that invested in AI, fewer than 2 out of 5 reported any business gain. This number improved to 3 out of 5 when focusing on firms that made significant investments in AI. Nevertheless, 40% of firms that made significant investments in AI did not report benefits.

Is it a problem suited for AI?

Executives in all sectors talk about AI. Nevertheless, to avoid engaging in AI for the sake of AI, firms need to pinpoint the problems they have that are suited for AI solutions. A practice-based strategy report by MIT and Sloan Management Review highlights that the problems most likely to benefit from AI typically share a number of characteristics (MIT, 2021). The authors propose that benefits are more likely if AI problems are rooted in business rather than technology. They argue that the problem needs to be meaningful and complex enough to justify the use of AI. The authors use quotes from business executives to highlight that problems that are a good match for AI are generally those that are core to the firm’s business, rather than problems that can be addressed with quick fixes or tasks easily completed with existing tools. It is also argued that problems suited to AI are well structured and have clear boundaries, with relatively controlled input. Finally, as AI is costly, the authors suggest that it makes sense to avoid using AI for one-off projects and instead focus on problems that occur at a scale that makes an investment worthwhile.

Expected business benefits vary

The expected business benefits of AI include optimising production (Demlehner et al., 2021; Haenlein & Kaplan, 2021), optimising supply chains (Baryannis, Validi, Dani, & Antoniou, 2019; Toorajipour et al., 2021; Tripathi & Sachin, 2020), business model innovation (Burström, Parida, Lahti, & Wincent, 2021), new product development (Borisa et al., 2020), engaging with customers, pursuing new markets, and establishing new start-ups (Garbuio & Lin, 2019).

3. AI adoption

Successful AI adoption is about much more than investing in AI technology. According to Davenport (2018), AI may be the technological force with the greatest disruptive potential. It is even suggested that AI may change the nature of the firm itself. Building on Coase’s theory of the firm (Coase, 1937), Wagner (2020) theoretically explores how AI may impact the firm. On the one hand, the author proposes that firms will benefit from AI systems, which can act more rationally than humans. On the other hand, AI applications can result in unintended and undesired outcomes.

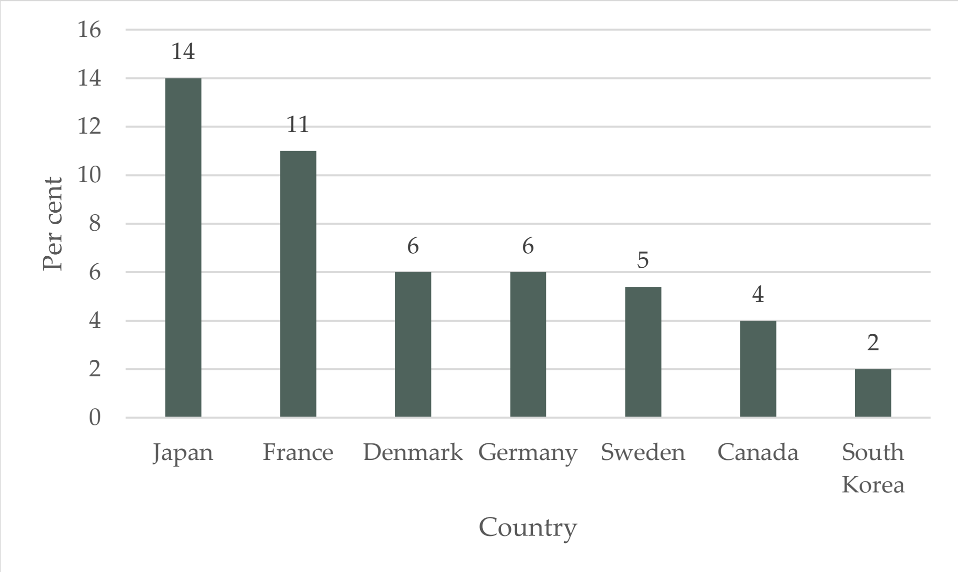
Traditionally, much production and innovation occurred within the firm’s boundaries. The boundary of the firm, as conceived by Coase (1937), is the limit within which a firm can lower transaction costs more efficiently than markets. Wagner (2020) challenges this assumption and argues that AI may be able to make the boundaries of the firm less rigid. When AI is provided as a service, an external AI provider penetrates the firm’s organisational boundaries, potentially resulting in the rents from AI machine labour being expropriated by the external provider. In this case, the AI service provider obtains business benefits. To understand AI adoption, it may be essential to recognise that it can be both a boundary-spanning and boundary-altering activity.

To obtain an idea of how many firms have adopted AI today, the following sections present empirical data on how AI has been disseminated to date. These results demonstrate a baseline from which AI adoption can accelerate.

3.1 Empirical evidence on AI adoption today

AI application in actual use is still at low levels. According to official Swedish statistics, only 5% of Swedish firms use AI. An international overview of quality-assured official AI statistics, provided in the figure below, shows that firms are adopting AI but that this figure ranges between 2 and 14 percent.

Figure 1 International overview of AI adoption in firms as a percentage of all surveyed firms

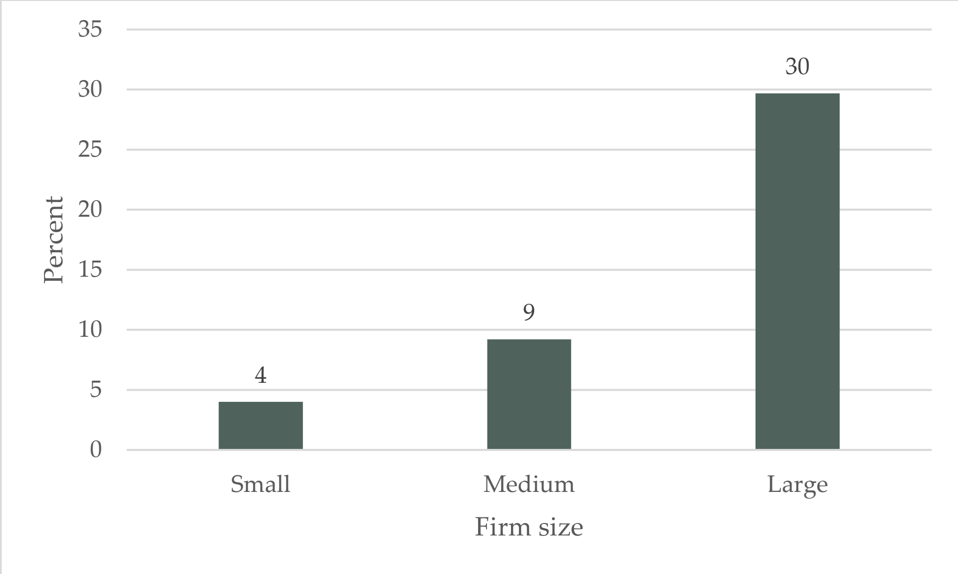


Source: Statistics Sweden ICT usage in Enterprises 2020, Montagnier and Ek (2021) and Rammer et al. (2021)
Note: The figure from Germany is based on the Community Innovation Survey (CIS) from 2018.

Differences in results between countries may come from various sources. Montagnier and Ek (2021) show that when larger firms are surveyed, the results tend to be higher. Japan, for example, only surveyed firms with more than 100 employees and has the highest AI adoption figure at 14 percent.

Many studies regarding AI adoption have been published, but they are primarily focused on larger enterprises (Hansen & Bøgh, 2021). However, small firms are considered the economic backbone of many countries. That is why it is increasingly important that these kinds of firms also have easy access to AI technologies and the opportunity to make them operational. Figure 2 presents official Swedish statistics and shows that 4% of small firms use AI, while 30% of large firms have adopted AI.

Figure 2 AI adoption in Sweden according to firm size, as a percentage of all surveyed firms, 2020



Source: Statistics Sweden ICT usage in Enterprises 2020
Note: Small firms 10-49 employees, medium 50-249 employees, large 250+ employees

This small firm-large firm disparity in AI adoption holds true with most digital technologies, from cloud to supercomputing (Calvino & Criscuolo, 2021; OECD, 2020).

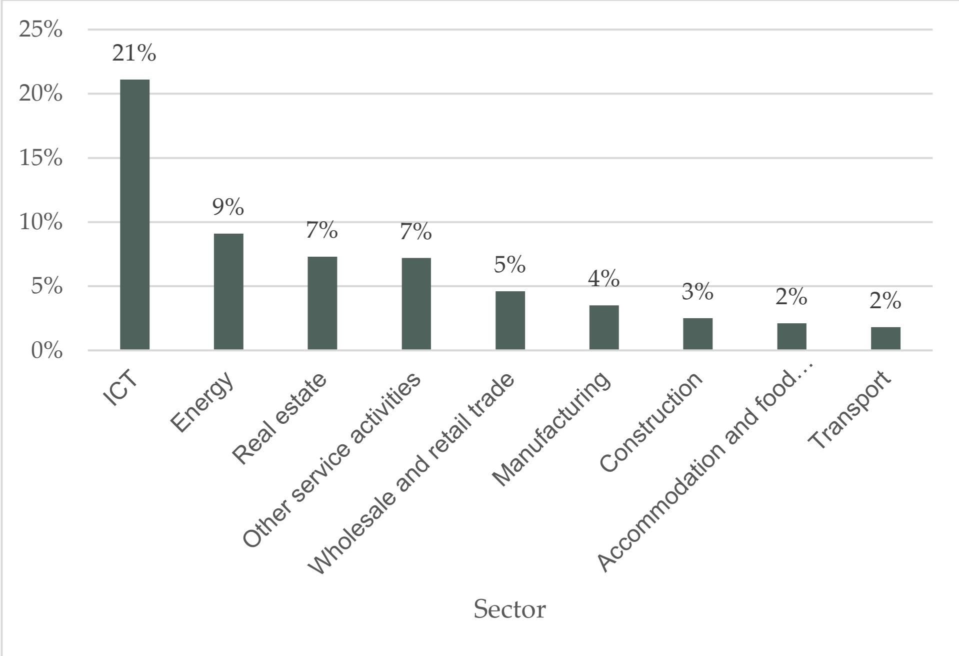
It is interesting to note that official AI statistics and reports from practice-based consultancy firms yield very different results. Whereas official AI statistics show that between 2 and 14 percent of firms have adopted AI, an international AI survey by the consultancy firm McKinsey finds that 58 percent of firms use AI (McKinsey, 2019).

3.1.1 Sectors

Like electrification, AI can be seen as a general-purpose technology (Bresnahan & Trajtenberg, 1995; Trajtenberg, 2019), meaning that AI can be adopted in most sectors. Previous research supports the view that AI is adopted in various sectors, e.g., telecommunications (Balmer et al., 2020), energy (Ahmad et al., 2021), health care (Borisa et al., 2020; Cruz & Wishart, 2006), real estate (Changro, 2021), education (Renz & Hilbig, 2020), manufacturing (Demlehner et al., 2021), retail (Paolanti, Liciotti, Pietrini, Mancini, & Frontoni, 2018) and other services such as journalism (Miguel Túñez-López et al., 2021).

Although all sectors adopt AI, Swedish data show that the extent of AI adoption varies across sectors. As shown in figure 3, 21 percent of firms in the ICT sector use AI, the highest rate of AI adoption. The transport sector is lagging, with only 2 percent of firms using AI.

Figure 3 AI adoption in Swedish firms according to sector, by % of all surveyed firms (2020)



Source: Statistics Sweden, ICT usage in firms 2020

Two sectors are especially interesting to explore further: ICT and manufacturing. The ICT sector is intriguing because it is leading AI adoption in Sweden. The manufacturing sector is interesting because it encompasses firms with complex and cost-intensive production processes that can offer incumbent firms opportunities to use AI.

3.1.1.1 AI in the ICT sector

The ICT sector benefits from AI. The advent of the 5th generation of mobile networks will boost the role of AI in the ICT sector (Li, Xu, & Zhao, 2018). Large international telecom firms such as AT&T and SK Telecom in South Korea have embedded AI into their business strategy (Chen et al., 2021). AT&T is investigating how to use AI algorithms to enable drones to check and repair base stations. SK Telecom uses machine learning to analyse network traffic to detect anomalies and strengthen network operations. Other examples of AI adoption in the ICT sector include virtual assistants to support customer service, intelligent customer relationship management systems and network operation monitoring and maintenance. Nevertheless, most AI initiatives are still at the stage of academic research and exploration (Chen et al., 2021).

3.1.1.2 AI in the manufacturing sector

AI is seen as a promising technology for car manufacturers that have a complex and cost-intensive production process, entailing the assembly of up to 30,000 different components for a market-ready car (Demlehner et al., 2021). A Delphi study by Demlehner et al. (2021) provides an overview of where AI can and should be adopted in car manufacturing and identifies 20 AI use cases. Delphi experts assess these AI use cases according to their estimated business value and realisability, i.e., how easily the AI use case can be set up and implemented. The ranking of the AI use cases by business value reveals four leading applications: predictive maintenance, visual quality control, object labelling and tracking, and optimisation of car sequencing. The ranking of realisability finds six leading use cases: object labelling and/or tracking, the reduction of energy consumption by both robots and on the factory floor more generally, visual quality control, the prediction of the paint bath's chemical composition over time, and the reduction of cut-out waste.

3.1.2 Business functions

Business functions are increasingly digitised, presenting growing opportunities to introduce AI systems. Researchers explore AI in purchasing, research and development (Hartmann & Henkel, 2020), production, marketing (Overgoor, Chica, Rand, & Weishampel, 2019), sales (Xueming, Shaojun Qin, Zheng, & Zhe, 2021), human resources (Meijerink, Boons, Keegan, & Marler, 2021) and accounting (Petkov, 2020).

3.2 Drivers of AI adoption – getting AI capabilities right

The literature highlights that AI technology alone cannot drive AI adoption. AI technology needs to be combined with other AI-specific resources. A few empirical articles use a resource-based view of the firm to identify the AI-specific resources that jointly create AI capabilities (Mikalef & Gupta, 2021; Zhang, Pee, & Cui, 2021).

Previous digitalisation studies show that firms gain competitive advantages by building unique and hard-to-imitate capabilities. These capabilities are developed by combining and deploying several complementary firm-level resources (Bharadwaj, 2000; Gupta & George, 2016). Building on the resource-based stream of research, AI technologies are viewed as one such resource, which is necessary but insufficient to develop an AI capability (Mikalef & Gupta, 2021; Zhang et al., 2021). AI technology alone is unlikely to deliver competitive gains. Mikalef and Gupta (2021) suggest that AI technologies are easily acquired in the market and, thus, easy to replicate. In addition, the data used to fuel AI models alone are insufficient to create AI capabilities. The first empirical result from a study of leading AI firms highlights that firms require a unique blend of physical, human, and organisational resources to create an AI capability that can deliver business value. Mikalef and Gupta (2021) describe AI capability as the ability of a firm to select, orchestrate, and use its AI-specific resources.

Building on resource-based theories (Barney, 1991; Grant, 1991; Penrose, 1995) to explore digitalisation (Ghasemaghaei, 2021) and now the AI domain (Chatterjee, Rana, Tamilmani, & Sharma, 2021; Gurusinghe, Arachchige, & Dayarathna, 2021; Mikalef & Gupta, 2021; Zhang et al., 2021), this paper discerns the resources that jointly constitute AI capability.

Extending the relevant AI resources described in the existing literature, especially the work of Mikalef and Gupta (2021) in combination with the information systems literature (Chen et al., 2021), this study identifies seven AI resources that can drive AI adoption: (i) data, (ii) AI technology, (iii) AI skills, (iv) intrafirm coordination across organisational boundaries, (v) AI business models, (vi) AI innovation ecosystems and (vii) coordination across organisational boundaries. By putting a greater emphasis on external collaborations, these findings highlight opportunities for generating novel theories and new forms of management practices.

3.2.1 Data

Data with which to train AI models are key to achieving the potential of AI (Ghasemaghaei, 2021). Many firms today capture large quantities of data from multiple sources and in different formats (Kersting & Meyer, 2018). Netflix, Google, Airbnb, Amazon and Uber are examples of firms that have been able to process large amounts of data to create new products, markets and services (Iansiti & Lakhani, 2020). However, these are a unique set of firms, unrepresentative of most.

Information systems connect to an increasing number of devices with sensors. Diverse data are generated not only from within firms but also from public, proprietary and purchased sources at unprecedented rates. This phenomenon is known as big data. Big data encompasses structured data such as transactional records stored in traditional databases and unstructured data such as text documents, web content, videos, audio, images and sensor data. According to McAfee and Brynjolfsson (2012), big data are characterised by volume, velocity and variety. Volume refers to the ever-growing magnitude of data. Velocity captures the speed at which data are generated and continuously updated. Variety means that data come in diverse formats, ranging from structured to unstructured.

A recent study by the OECD (2021) deepens the understanding of data characteristics, including the origin of the data how they are collected. There are also technical characteristics such as data structure and whether the data are personal, proprietary or public. In addition, data quality and appropriateness are two important data characteristics. Mikalef and Gupta (2021) also note that the quality of the data fed into the AI model is key to successful applications and achieving business value. A related issue receiving increased attention is accurate data labelling of the data used by the AI model (Roh, Heo, & Whang, 2021). Skewed or inaccurate data labelling, followed by model training, can bias results in important ways and in some cases, yield socially unjust outcomes (AI HLEG, 2020; Larsson, 2021).

It is important to understand the characteristics of the data the AI model trains on and where it comes from. Machine learning models, for example, are trained on a specific dataset to perform one task and need to be partially retrained to solve even a related task (Humbird, Peterson, Spears, & McClarren, 2020). To develop responsible AI (Dignum, 2019), firms also need to know and document where the data come from, e.g., to decide if it is sensitive personal data. For European firms, data are becoming a heavily regulated area where it is specified that firms must be regulatory compliant with GDPR, the Schrems II ruling and the proposed AI act (EC, 2016, 2021). Firms that are not regulatory compliant can face large fines.

Previous research argues that the ability to process big data could have several advantages for firms (Davenport & Harris, 2017; Ghasemaghaei & Calic, 2019a). Nevertheless, gaining a competitive advantage from data is not an easy task (Grover, Chiang, Liang, & Zhang, 2018).

3.2.2 AI technology

AI technology refers to the technical capabilities needed to develop and implement AI systems. Mikalef and Gupta (2021) argue that AI requires an underlying infrastructure and new technologies to bring large, fast-moving and complex data sources to life. The authors find that new technologies are needed to store, process, transfer, connect and secure data through all stages, from data gathering to training and model implementation. The data storage requirements can fluctuate depending on the data needs of the AI model. Apart from flexible data storage, investments in processing power to run complex algorithms are also needed.

Algorithms are the core of any AI model (Polson & Scott, 2018). In a recent case study, Zhang et al. (2021) explore the types of algorithms Alibaba uses in one of its e-commerce warehouses in China. Alibaba uses algorithms for sales forecasting, location recommendation and route planning (see fact box below).

Examples of Algorithms Alibaba uses in the warehouse

- A sales forecasting algorithm uses historical sales data to plan work in the next few days.
- A location recommendation algorithm enables goods with correlated sales to be co-located.
- A route planning algorithm is used to shorten the robot's route when picking up goods.

Source: Zhang et al. (2021)

In a survey of over 340 Chinese telecom firms, Chen et al. (2021) find that it is easier to adopt AI if the technology is compatible with existing IT systems. This evidence is in line with arguments made by Brynjolfsson, Rock, and Syverson (2017) that AI often fails to deliver productivity gains because managers do not know how to effectively integrate AI with existing processes and IT systems.

3.2.3 AI skills

3.2.3.1 Technical AI skills

In line with Mikalef and Gupta (2021), technical AI skills refer to skills necessary to develop and implement AI models, i.e., algorithms. An empirical analysis of online AI job postings in Canada, Singapore, the United Kingdom and the United States for the 2012–18 period illustrates which AI skills firms seek (Squicciarini & Nachtigall, 2021). The results show that in 2012, a considerable part of the skillset required for AI jobs was related to software engineering and operating systems. By 2018, however, software engineering and operating systems seemed to have lost relative importance, while skills such as natural language processing and deep learning had become predominant. Skills related to big data constitute a considerable part of the skills profiles of AI-related jobs in all countries.

An MIT Sloan Management Review report of a practice-based survey performed by the consultancy firm Accenture finds that AI will create new roles such as AI trainers, AI explainers and AI sustainers (Wilson, Daugherty, & Morini-Bianzino, 2017). AI trainers teach AI models. AI explainers will bridge the gap between AI technologists and business managers by explaining to a nontechnological audience how AI systems work. AI sustainers will ensure that the AI system operates as expected and that problem areas such as biases (AI HLEG, 2019) are addressed appropriately.

3.2.3.2 Managerial AI skills

Several studies show that managers frequently do not know where and how to adopt AI. Davenport and Ronanki (2018) point out that one in three managers does not understand how AI technologies work. Based on the results from McKinsey AI surveys, Fountaine, McCarthy, and Saleh (2019) argue that AI failures are often caused by the lack of a foundational understanding of AI among senior executives. This is problematic, as it is the senior executives that lead AI implementation. The authors note that to ease the way for successful AI launches, managers need to explain to employees why AI is important to the business. In line with previous research, it is noted that AI is not a plug-and-play technology and managers need to budget as much for integration and adoption as for AI technology. Fountaine et al. (2019) also note that managers need to decide where AI capabilities should reside within the firm: in a centralised hub embedded in business units or distributed across both options. Nevertheless, the literature remains silent on the fact that managers have to make complex forward-looking decisions about whether to build in-house teams with the required AI skills or to rely on external AI providers. This decision is all the more complicated in a world where technology is changing rapidly. Chen et al. (2021) recently surveyed over 340 Chinese telecom firms and empirically supported a direct connection between managers' AI skills and firms' ability to successfully adopt AI.

3.2.4 Boundary spanning intra- and interfirm coordination

The capability to coordinate AI resources across intra- and interfirm boundaries arises because of a need to conduct boundary-spanning activities within and between firms. Intrafirm resources are needed to digitise and connect different business functions, such as purchasing, production and sales. The importance of intrafirm coordination is noted in a recent study that shows that functional silos often prevent firms from deriving business value from AI investments (Chui & Malhotra, 2018). It is argued that data that are not shared between functional silos constrain the AI solutions that are being developed.

3.2.5 AI business models

AI business model capabilities refer to firms' ability to identify and manage business models around AI. A new study explores how four incumbent manufacturing firms have regenerated their business model around AI (Burström et al., 2021). The results support the view that AI makes it possible to fine-tune and extend traditional value-creation, value-delivery, and value-capture processes. In these four firms, AI-driven forecasting to generate reports and insights from customers is a first step in utilising AI for commercial gains. Most products were installed with sensors and have generated a large amount of data. In most cases, these data had not been used to generate customer insights due to data messiness and the lack of appropriate analytical models. However, with AI, these firms were able to generate new insights. The empirical evidence also shows that the second step towards AI adoption in these firms encompasses the monitoring and control of business applications. This meant an increasing capacity for the firms to develop improved routines for checking their equipment once it had been installed on the customer premises. It is proposed that customers use products unevenly; thus, AI optimises the use of the equipment. These manufacturing firms have also used AI optimisation features to provide contracts for prescriptive maintenance.

Nevertheless, not all of the firms were able to move quickly up the maturity ladder of the AI system. Doing so depended on how well the firms were able to align the development of AI with business applications. However, the firms that had adopted AI claim that they have a better revenue flow with an AI-regenerated business model (Burström et al., 2021).

3.2.6 AI innovation ecosystem

Firms apply AI in ways that have brought and will continue to bring a substantial wave of business innovation (Kane, Young, Majchrzak, & Ransbotham, 2021). AI innovation capabilities refer to the ability of a firm to innovate but also to perform AI innovation in collaboration with external stakeholders in AI ecosystems.

In a recent study of the Chinese AI innovation ecosystem, Arenal et al. (2020) explore the interaction between firms that develop and use AI, AI research at universities and governmental AI policy instruments. The authors find that the relationships between these stakeholders are characterised by the flow of venture capital to AI investments, AI talent, AI knowledge production and data. An analysis of 35 Chinese AI projects illustrates how the AI ecosystem works (Arenal et al., 2020). The AI projects launched leverage the momentum of the Chinese government's AI plan to move beyond outcomes that the market alone could provide. Next, the practical development of AI projects is usually undertaken by firms in partnerships with universities. AI projects are based on a trial-and-error approach that allows room for experimentation. Depending on the success of the projects, they are either discarded, modified, or scaled up. In addition, the government adopted a more traditional role of AI regulators.

China's AI ecosystem covers both large existing firms and AI start-ups (Arenal et al., 2020). The authors find that large established firms such as Alibaba and Huawei play a leading role in the Chinese AI ecosystem. They posit that there are only a limited number of top AI firms in China and that investors tend to bet on two to three dominant firms. As a consequence, large leading AI firms usually capture most of the emergent start-ups to ensure the continuation of their dominant positions. These results are in line with Agrawal, Gans, and Goldfarb (2020), who argue that AI leaders can generally build a sustainable competitive advantage and raise entry barriers against latecomers. Nevertheless, most of the technology that drives AI in China comes from U.S. firms, e.g., AI software from Google's TensorFlow(Arenal et al., 2020).

Building on AI innovation ecosystem mapping by the (Arenal et al., 2020) government at different levels contributes AI strategies, AI regulations, practical support, venture capital and access to data for AI innovations. Firms led by tech giants such as Alibaba are building research centres, deploying applications, and hiring available AI talent. Universities provide AI education and conduct AI research.

3.2.7 Coordination across organisational boundaries

Interfirm coordination refers to the need to coordinate across organisational boundaries. Many firms do not have enough AI skills in-house to develop AI technology or manage its implementation in existing IT systems; for this reason, AI adoption is often associated with the use of external providers. In their survey of more than 340 Chinese Telecom firms, Chen et al. (2021) find that partnerships with external AI providers directly influence the ability to adopt AI. The authors argue that external AI providers are needed because they can create good algorithms and develop the experience needed to implement AI successfully. It seems to be assumed that external AI providers, with state-of-the-art technical and implementation skills, might develop better algorithms than the firm itself.

3.3 Orchestrating AI resources to develop strong AI capability

Orchestration refers to a firm’s ability to combine AI-related resources. AI must work alongside other existing IT systems and processes. Zhang et al. (2021) analyse successful AI applications at Alibaba’s e-commerce warehouse in China. The findings indicate that data, AI algorithms, and robots are the key AI resources in developing AI capabilities. In this case study, AI consumed vast quantities of data from various sources. Data played a vital role when Alibaba developed algorithms that delivered forecasting capability, planning capability, and decision capability in the warehouse. This is in line with prior studies that also show that the value of AI often depends on the availability and reliability of data (Coombs, 2020; Ranjan & Foropon, 2021).

Collecting data and developing AI algorithms were expensive for Alibaba. To keep total costs down, Alibaba used AI-enabled robots to perform repetitive tasks in the warehouse. However, there is a growing consensus in the literature that simply owning data and good algorithms generates little value (Foster, McLeod, Nolin, & Greifeneder, 2018; Mahroof, 2019; Sinha et al., 2020). This Alibaba case suggests that it was the orchestration of all AI resources along with other non-AI resources that led to the development of a strong AI capability (Zhang et al., 2021). For instance, in the goods storing process, data, algorithms and warehouse facilities were coordinated to optimise the robots’ route in the warehouse. Goods that were usually ordered at the same time were collocated in the warehouse and picked up simultaneously.

3.4 Harnessing the power of AI – a checklist to get started

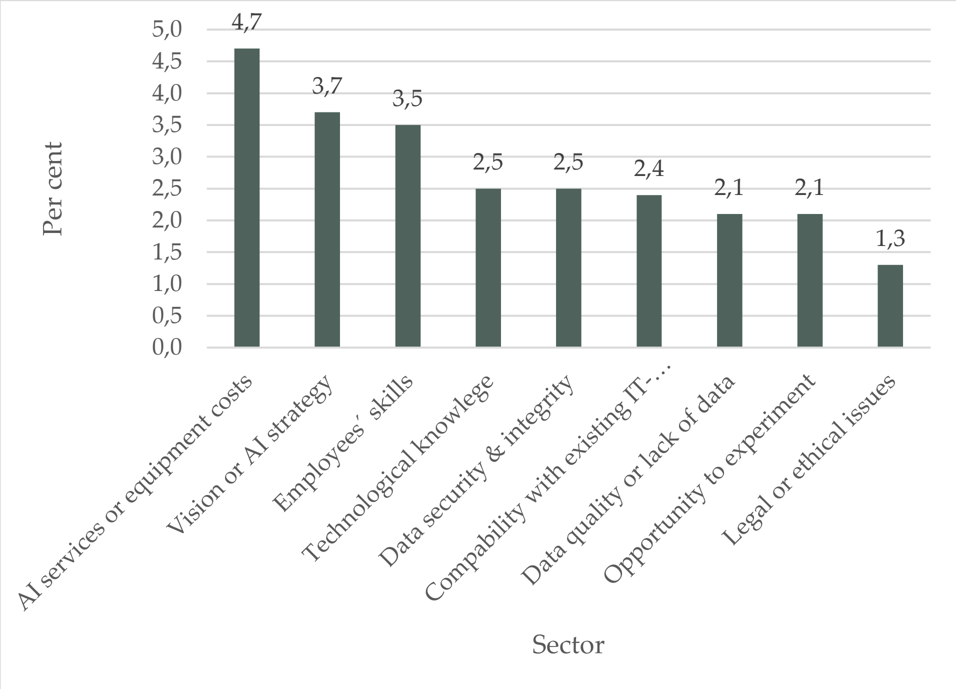
While some studies highlight the potential business value that AI can deliver, firms that are beginning to adopt AI face numerous challenges that may prevent them from realising performance gains. Building on previous studies (MIT, 2021; Sanders & Wood, 2020; Tse, Esposito, Takaaki, & Goh, 2020; Walsh, 2020), the following checklist can help address some of these challenges.

- Pick a problem that is small but strategic
- Make sure that AI is the right tool for the job
- Set AI-specific objectives and metrics for success
- List the data requirements
- Identify the resources and competencies needed
- Pinpoint potential challenges, e.g., regulatory compliance

4. Barriers to AI adoption

Official Swedish statistics show that the cost of purchasing AI services or equipment is the main reason why firms do not use AI. The second major barrier is the lack of an AI vision or AI strategy. Employee skill levels are the third-largest barrier. Swedish firms acknowledge that employees' skills will have to change to adopt AI. Other studies support the view that AI-related skills represent a major barrier. In a survey of 3000 executives, Brock and von Wangenheim (2019) find that skills are the main barrier that prevents firms from adopting AI. With the increasingly complex AI regulatory landscape (EC, 2021), it is nevertheless surprising that only 1.3 percent of Swedish firms view legal or ethical issues as a barrier. Barrier-related questions were addressed to all 7,739 firms, although only five percent of firms in Sweden use AI.

Figure 4 Barriers to AI adoption in Sweden 2020, as a % of all surveyed firms



Source: Statistics Sweden, ICT usage in firms 2020
Note: The figure represents firms that responded that it is a large obstacle out of all firms that responded; only 5% of firms actually use AI.

It was surprising that only 1.3% of firms view legal and ethical issues as a major barrier. Nevertheless, one-third of Swedish firms reported that they do not know if legal or ethical issues are a major barrier. It may also be interesting to note that this study was conducted before the EU AI ACT (EC, 2021) was launched.

Governments can help remove some of the barriers to AI adoption in firms and increase firms' absorptive capacity (Cohen & Levinthal, 1990) by addressing AI skills needs, implementing effective AI innovation policies (Fatima, Desouza, & Dawson, 2020) and developing well-framed AI regulations (Larsson, 2021).

Although it has not yet been empirically explored, barriers to AI adoption, while having commonalities across sectors, may also have some differences. Manufacturing, for example, often operates at such high levels of precision that error tolerance is far lower than, for example, AI-enhanced marketing. As a result, AI models need to be trained so they deliver nearly perfect results each time, which takes time and costs more money. In AI-enhanced marketing, it does not matter as much if a recommendation is perfect every time. Consequently, cost may be a larger barrier for manufacturing firms than for marketing firms.

5. AI and firm performance

A recent study of the German innovation survey by Rammer et al. (2021) finds that AI generated additional sales with world-first innovations valued at 16 billion euros. This figure corresponds to 18% of the total sales of world-first innovations in the German business sector. The authors also show that firms that developed AI by combining in-house resources and external AI providers obtained significantly higher innovation results. The same was true for firms that applied AI broadly and had several years of AI implementation. Nevertheless, as this is the first time AI questions are incorporated in the German innovation survey, it is difficult to talk about causation. What if it is the already profitable digital frontrunners that implement world-first AI innovations?

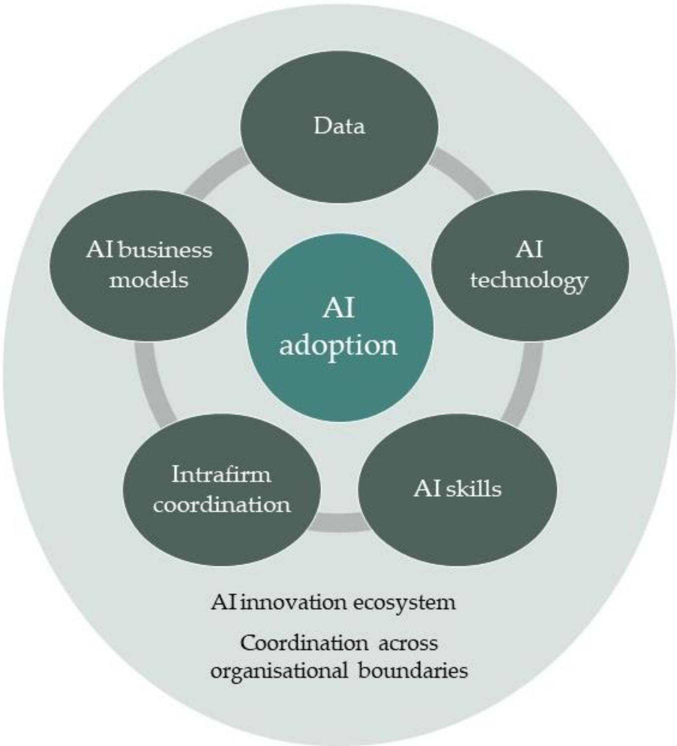
It has been previously established that AI is typically implemented and used with other advanced digital technologies. In a survey of over 3,000 executives worldwide, Brock and von Wangenheim (2019) find that firms with stronger digital skills anticipate stronger AI-induced business impacts than firms with weaker digital skills. This observation was stable across industries and global regions. Previous research seems to indicate that a firm's digital maturity is likely to impact AI success. In this context, it is interesting to note that a previous Swedish microdata study finds that digital maturity correlates with productivity and that digital skills were the main driver of the correlation (Ek, Mattsson, Ouraich, & Li, 2019).

Although there are signs that firms increasingly adopt AI, it may take time to see its full impact reflected in productivity metrics. Brynjolfsson et al. (2017) highlight what they perceive to be a modern AI productivity paradox. The authors argue that the main reasons AI has yet to deliver productivity gains are implementation and restructuring lags. AI adoption is often a time-consuming process. Chen et al. (2021), for example, explore AI in the Chinese telecom sector and show that although some telecom firms have introduced AI, these initiatives are often at the conceptual stage and have not yet generated commercial value.

6. Towards a conceptual framework

After examining the literature on the drivers of AI adoption, the main results are now synthesised in a conceptual framework, as illustrated in Figure 5. The synthesis of existing research reveals that the leading drivers of AI adoption are a) data, b) AI technology, c) AI skills, d) intrafirm coordination, e) AI business models, f) AI innovation ecosystems and g) coordination across organisational boundaries. The proposed conceptual framework divides the drivers into two units of analysis: within-firm resources and boundary spanning resources created in collaboration with the environment. Within-firm resources cover data, AI technology, AI skills, intrafirm coordination and AI business models. Boundary spanning resources cover AI innovation ecosystems and coordination across organisational boundaries.

Figure 5 The capabilities that drive AI adoption



This paper contributes to the AI adoption literature. A resource-based view of firms usually focuses on within-firm units of analysis. However, this study highlights a higher unit of analysis that also considers collaborations between organisations. The results of this study can be capitalised on by practitioners who want to adopt AI and researchers exploring the challenges that firms face when adopting AI.

7. Discussion and conclusion

The current literature is increasingly exploring how AI can deliver benefits for businesses. Several studies report that most firms perceive that AI can deliver business opportunities. At the same time, official AI statistics show that only between 2 and 14 percent of firms use AI today. In addition, it seems that investments in AI technologies do not automatically generate a competitive advantage. A number of AI-relevant resources need to be precisely combined and orchestrated to drive firm performance.

By extending the existing literature, especially the work by Mikalef and Gupta (2021) in combination with the information systems literature (Chen et al., 2021), this study identifies and describes six AI resources that drive AI adoption: (i) data, (ii) AI technology, (iii) AI skills, (iv) intrafirm coordination, (v) AI business models, (vi) AI innovation ecosystems and (vii) coordination across organisational boundaries.

This study contributes to research on AI adoption in several ways. First, the resource orchestration perspective offers a useful theoretical lens to identify the drivers of AI adoption, i.e., AI resources, and to understand how they can be orchestrated to accelerate AI adoption in such a way that it generates business value. All AI resources must work together. Second, the findings also offer practical insights into what drives successful AI adoption in firms. Despite the high failure rate of AI projects observed in the literature, there is initial empirical evidence that AI can generate business value when the AI resources identified in this study are orchestrated in such a way that they work together.

7.1 Research gaps for future studies

There is a consensus in the research literature that the following areas have not yet been sufficiently addressed:

- How does AI adoption impact firm performance? (Calvino & Criscuolo, 2021)
- How do firms' digital transformation efforts align with their AI efforts (Brock & von Wangenheim, 2019; Calvino & Criscuolo, 2021; Ruiz-Real et al., 2021)
- How can AI effectively be managed in organisations, and how can it be scaled most efficiently? (Demlehner et al., 2021)
- How are the relationships between organisations organised in AI ecosystems in different socioeconomic contexts? (Ruiz-Real et al., 2021)
- Governance of AI and infusing responsible practices and regulatory compliance (Ayling & Chapman, 2021; Larsson, 2021)
- Contextualisation of drivers and barriers (Mikalef, van de Wetering, & Krogstie, 2021)
- Which skills does a firm need to successfully procure external AI providers? (Rowan, 2020)

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Tillväxtanalys
Myndigheten för tillväxtpolitiska utvärderingar och analyser

Tillväxtanalys
Studentplan 3, 831 40 Östersund
Telefon: 010-447 44 00
E-post: info@tillvaxtanalys.se
Webb: www.tillvaxtanalys.se