Technological change and regional inequalities

Spatial diffusion of Artificial Intelligence across Danish regions

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TECHNOLOGICAL CHANGE AND REGIONAL INEQUALITIES:

SPATIAL DIFFUSION OF ARTIFICIAL INTELLIGENCE ACROSS DANISH REGIONS

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Technological change and regional inequalities:
Spatial diffusion of Artificial Intelligence across Danish regions

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Summary (English)

This dissertation examines the mechanisms driving the geographical diffusion of Artificial Intelligence through four papers.

Despite the significant attention that Artificial Intelligence has received in recent years and its prominence in both public and research discourse, there are still many aspects of Artificial Intelligence where we lack the necessary knowledge. There is a generally established consensus that the *diffusion* of new technologies, which refers to their geographical spread and adoption among companies and individuals, has a stronger societal impact than the *invention* of new technologies. However, researchers and policymakers primarily focus on the latter, leaving a significant knowledge gap regarding the mechanisms underlying the potentially uneven diffusion of Artificial Intelligence.

This dissertation aims to address this knowledge gap by examining the following research question: How does the regional context influence the rate and direction of the diffusion of Artificial Intelligence across regions??

The dissertation focuses mainly on traditional/statistical Artificial Intelligence, typically used to create algorithms to make predictions, recommendations, and decisions from outside a given data set.

The dissertation approaches how AI technology diffuses spatially from an evolutionary economic theoretical perspective. This entails that how individuals and firms in different regions learn about and ultimately adopt new technology is geographically path dependent, meaning that technology adoption is influenced by several local factors - e.g., regional institutions, resources, capabilities, and the technology already in use - that are self-reinforcing over time. The existing resources in the region, such as worker skills and their experience working with different types of technology, influence the knowledge and learning about new technology that firms can engage with, which in turn affects the demand for diverse resources, experience, and knowledge related to adopting and using the new technology, and thus the mutual relationship continues. The dissertation tests this assumption in the dissertation's four papers focusing on the Danish case.

Paper A serves as a preliminary study for the thesis as it develops a new

regional classification used as the regional scale for the remaining three articles. The main contribution of the article is the use of long time series of different economic and demographic variables related to regional development combined using clustering analysis to develop a more nuanced picture of regional groupings that account for development trends and, thereby, the mechanisms that create different long-term regional development.

Article B is coauthored with Jacob Rubæk Holm and examines regional differences in Artificial Intelligence adoption using data from the TASK survey on AI usage among Danish firm employees. It demonstrates, firstly, that there are regional differences in the degree to which companies adopt Artificial Intelligence and, secondly, that these differences can be explained, among other things, by regional differences in how companies learn and innovate. These characteristics can be described as the firms' so-called "innovation modes". Specifically, the paper finds that Old industrial regions fall behind the metropolitan regions, likely because they, among other things, are influenced more by the innovation mode based on internal experience generation.

Article C studies whether regional institutions and regional adoption of Artificial Intelligence co-evolve over time. Specifically, the article examines regional informal institutions in the form of regional technological discourse in news media and their mutual evolution with the regional adoption of Artificial Intelligence. The article draws on newly collected data on different regions' consumption of newspaper articles about Artificial Intelligence. It measures the characteristics of the regional informal institution through the tone and angle in the articles via sentiment analysis. The article demonstrates first that there are regional differences in how Artificial Intelligence is described and, second, that the newspaper article coverage co-evolves with the regional adoption of Artificial Intelligence over a period of almost twenty years.

Article D zooms in on small and medium-sized enterprises within the manufacturing sector outside the metropolitan areas and examines their absorptive capacity concerning Artificial Intelligence. The article is the dissertation's only qualitative study and uses semi-structured interview data with SMEs in the process of adopting Artificial Intelligence. The article finds that manufacturing SMEs outside the metropolitan regions face particular challenges when they wish to start implementing Artificial Intelligence. Some of the main challenges are a mixture of the lack of relevant skills and difficulties in attracting qualified labor, making AI less abstract and easier to introduce in their business models, overcoming conservatism in the organization, finding inspiration from like-minded companies, and finding information about both new technologies and grant opportunities. However, the firms develop methods to overcome resource scarcity by building on their existing capabilities.

Overall, the dissertation contributes to our understanding of factors that influence an uneven geographical spread of Artificial Intelligence technology. The dissertation demonstrates, by studying the Danish case, that there are barriers to adopting Artificial Intelligence specific to different regions. Different regions have different resources but also cultures, traditions, and institutions of innovation and technology adoption. The dissertation also demonstrates that Artificial Intelligence is not a homogeneous technology, as it has typically been treated in previous studies. This means, as discussed in the Synopsis and illustrated in the various articles, that the observed patterns differ depending on how we treat and define Artificial Intelligence. Still, the conclusion that Artificial Intelligence takes on an unequal geographical spread pattern remains. The dissertation finally argues for greater focus among politicians developing technology policy to take into account that AI technology usage and the driving mechanisms behind it, are, as shown in this dissertation, regionally specific. The dissertation furthermore argues for continued research efforts among researchers to untangle the mechanisms behind the spatially uneven distribution of AI.

Resumé (Dansk)

Denne afhandling undersøger mekanismerne bag den geografiske udbredelse af kunstig intelligens i Danmark gennem fire artikler.

Kunstig intelligens har modtaget meget opmærksomhed i de seneste år og er blevet et fremtrædende emne både i den offentlige og i den forskningsmæssige diskurs. Der er dog stadig mange aspekter af kunstig intelligens, hvor vi endnu ikke har den nødvendige viden. Der er en generelt etableret konsensus om, at *spredningen* af nye teknologier, som her refererer til den geografiske udbredelse og implementering af teknologi blandt virksomheder og individer, har en stærkere samfundsmæssig indvirkning end *opfindelsen* af nye teknologier. I dag er fokus blandt forskere og politikere dog hovedsagligt rettet mod det sidstnævnte. Dette efterlader mangel på viden om de mekanismer, der ligger til grund for en potentielt ulige spredning af kunstig intelligens.

Denne afhandling forsøger at reducere denne mangel på viden ved at undersøge følgende forskningsspørgsmål: Hvordan påvirker den regionale kontekst spredningen af kunstig intelligens?

Fokus for afhandlingen har hovedsagligt været på traditionel/statistisk kunstig intelligens, der typisk anvendes til at skabe algoritmer med det formål at lave forudsigelser, anbefalinger og beslutninger ud fra et givent datasæt.

En central antagelse i afhandlingen er, at de geografiske forskelle i teknologiadoptionen udvikler sig evolutionært. Den evolutionære tilgang skal forstås som, at måden hvorpå enkeltpersoner og virksomheder i forskellige regioner lærer om og til sidst adopterer ny teknologi, bestemmes af en geografisk stiafhængighed, der påvirkes af flere forskellige faktorer - f.eks. regionale institutioner, ressourcer, kapaciteter og teknologi - og som selvforstærkes over tid. Dette betyder, at de eksisterende ressourcer i regionen påvirker viden og læring om ny teknologi, hvilket igen medfører forskellige ressourcer, erfaringer og viden om den nye teknologi, og dermed fortsætter den gensidige relation. Afhandlingen tester denne antagelse i afhandlingens fire artikler.

Artikel A fungerer som en indledende undersøgelse for afhandlingen og udvikler en ny regional klassifikation, der anvendes som den regionale skala for de resterende tre artikler. Artiklen bruger lange tidsserier, forskellige

udviklingsvariable og klusteranalyse for at udvikle et mere nuanceret billede af de mekanismer, der skaber forskelligartet regional udvikling på lang sigt.

Artikel B, med Jacob Rubæk Holm som medforfatter, undersøger regionale forskelle i brugen af kunstig intelligens. Artiklen bruger TASK-spørgeskemaet og viser både, at der er regionale forskelle i, i hvilken grad virksomheder adopterer kunstig intelligens, og at disse forskelle kan forklares, blandt andet ved regionale forskelle i virksomheders læring og innovation med hensyn til såkaldte "innovationsformer". Tidligere industriregioner sakker bagud i forhold til storbyregioner og påvirkes i højere grad af, blandt andet, innovationsformer baseret på intern erfaringsgenerering.

Artikel C fokuserer på, om forholdet mellem forskellige regionale institutioner og regional adoption af kunstig intelligens udvikler sig over tid. Artiklen undersøger specifikt regionale, ikke-formelle institutioner i form af regional teknologisk diskurs og dets gensidige udvikling i forhold til adoptionen af kunstig intelligens. Artiklen måler forskellige regioners forbrug af aviseartikler om kunstig intelligens og analyserer den regionale tone og synsvinkel i artiklerne ved hjælp af sentimentanalyse. Artiklen viser, at ikke kun at der er regionale forskelle i, hvordan kunstig intelligens beskrives, men at måden hvorpå avisartiklerne beskriver kunstig intelligens udvikler sig sammen med den regionale adoption af kunstig intelligens over en periode på næsten tyve år.

Artikel D indsnævrer sig på små og mellemstore virksomheder inden for fremstillingssektoren uden for storbyområderne og undersøger deres absorpteringskapacitet i forhold til kunstig intelligens. Artiklen er den eneste kvalitative undersøgelse i afhandlingen og bruger interviewdata med små og mellemstore virksomheder, som er i processen med at implementere kunstig intelligens. Artiklen konkluderer, at fremstillingsvirksomheder udenfor storbyregionerne står over for særlige udfordringer, når de ønsker at implementere kunstig intelligens. Nogle af de største udfordringer inkluderer en kombination af mangel på relevante færdigheder og vanskeligheder med at tiltrække kvalificeret arbejdskraft, even til at gøre kunstig intelligens mindre abstrakt og lettere at implementere i deres forretningsmodeller, at overvinde konservatisme i organisationen, at finde inspiration fra lignende virksomheder og at finde information om både nye teknologier og tilskudsmuligheder. Dog udvikler virksomhederne metoder til at overvinde deres ressourceknaphed ved at bygge på eksisterende kompetencer.

Afhandlingen bidrager til en bedre forståelse af nogle af de faktorer, der påvirker den ulige geografiske udbredelse af kunstig intelligens. Afhandlingen viser, at der i Danmark er forskellige barrierer for den aktuelle adoption af kunstig intelligens i forskellige regioner. Forskellige regioner har forskellige ressourcer, men også kulturer, traditioner og innovationsinstitutioner. Afhandlingen viser også, at kunstig intelligens ikke er en homogen teknologi, som tidligere studier ofte har antaget. Dette betyder, som de forskellige artikler i afhandlingen også påviser, at virkningerne er forskellige afhængigt af, hvordan vi behandler og definerer kunstig intelligent. Men konklusionen om, at kunstig intelligens antager et ulige geografisk udbredelsesmønster, består på tværs af studierne.

Afhandlingen argumenterer endelig for et større fokus blandt politikere, der udvikler teknologipolitik, for at tage højde for, at brugen af kunstig intelligens og de drivende mekanismer bagved er regionalt specifikke, som påvist i denne afhandling. Afhandlingen argumenterer desuden for fortsatte forskningsindsatser, blandt forskere, for at afklare mekanismerne bag den geografiske skæve fordeling af kunstig intelligens.

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Preface

A love-poem to Randers

As a child, I grew up in a town deeply influenced by its industrial, cultural heritage. My daily walk to school was filled with various experiences, ranging from the smell of hops emanating from the production of the locally renowned Blå Thor beer (which, according to urban legend, won a gold medal in an international brewing contest in Brussels in 1964), to observing workers cycling to their jobs at Scandia, a train manufacturing factory that employed over 1,500 out of the population of only 50,000 people at its peak, or to Randers Rope, known for its controversial and perhaps bleak slogan: "*Don't get hung up on trifles. Hang yourself from Randers Rope*".

In the 1990s, Randers was in the midst of a transformation phase. It had ceased to be the thriving manufacturing hub it once was in Denmark, but it had yet to establish a new identity. Many old manufacturing facilities closed between the 1980s and early 2000s, leaving empty architectural reminders of Randers' industrial past, which had shaped the town's identity. The 1970s structural reform, which centralized governmental powers and led to Randers losing administrative status and many jobs to its larger neighbor, Aarhus, only complicated the transformation process.

Today, Randers is a town that, while not in decline, is experiencing economic stagnation. I believe it has been unable to recreate the sense of community from when many residents, with varying education levels and skills, were employed by the same big company. Large corporations have been replaced by small and medium-sized enterprises, which come with their own set of advantages and disadvantages. However, it is essential to note that the story of Randers is more nuanced than what news outlets and outsiders often depict. Although facing challenges, positive developments are taking place. Urban areas are undergoing impressive landscape architecture transformations, and more young families are moving to Randers due to the affordable housing market, good connectivity to larger cities, a growing job market, access to green spaces, and a thriving cultural scene.

The story of Randers is not unique. It serves as a reminder that discussions about regional development should not be black and white; the regions in-between development stages (the "grey mass" regions) require more nuanced attention. However, regional inequality is rising in many Western countries, and numerous industrial towns have encountered similar obstacles as Randers.

These towns seem to face further challenges in the context of Industry 4.0, where they often lack the path-dependent capabilities necessary to participate in digital transformation. Reflecting on my upbringing in Randers, I believe it has ignited my interest in exploring the significant industrial and technological dynamics that shape regions, cities, and towns and the geographic aspects of the "Dark Side of Innovation". Because what can be done about the rising regional inequality that negatively affects entire countries? What can be done for towns consistently disadvantaged in national policy processes, globalization, and in the face of new technologies? How will the new industrial revolution impact the future of towns that share a similar fate as Randers?

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In the process of writing my Ph.D. dissertation, I have been fortunate enough to have received an immense amount of support from colleagues, friends, and family. I have furthermore been lucky enough to have been able to discuss ideas and work with minds far beyond my capabilities through my everyday life and seminars at my research group, IKE, at Aalborg University, stays at other research institutions, international seminars, conferences, Ph.D. courses, and informal coffee chats. In this section, I will not be able to do justice to all the contributions I have benefited from in my network, but I will try to mention a few of the most important.

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All errors remain my own.

Sigrid Jessen
Dragsmur, July 18, 2023

List of acronyms

AGI = Artificial general intelligence

AI = Artificial Intelligence

ANI = Artificial narrow intelligence

DESI = Digital Economy and Society Index

DRUID = Danish Research Unit for Industrial Dynamics

DST = Statistics Denmark

DUI = Doing-Using-Interacting based innovation mode

EEG = Evolutionary economic geography

EPO = European Patent Organization

FTE = Full-time equivalent employee

GDP = Gross domestic product

GPT = General purpose technology

GVA = Gross value added

I4.0 = Fourth Industrial Revolution

ICT = Information and Communication Technologies

IDA = Integrated Database for Labour Market Research

IKE = Innovation, Knowledge and Economic Dynamics research group

IoT = Internet of Things

ISCED = The International Standard Classification of Education

LAU = Local Administrative Units

LQ = Location quotient

ML = Machine learning

NACE = Nomenclature statistique des activités économiques dans la Communauté européenne (Statistical classification of economic activities in the European Community)

NUTS2-4 = Nomenclature of territorial units for statistics 2 - 4

OLS = Ordinary least squares

PCA = Principle Component Analysis

PIAAC = Programme for the International Assessment of Adult Competences

R&D = Research and development

RIS = Regional innovation systems

SME = Small and Mediumsized enterprises

SST = Social shaping of technology

STI = Scientific and technologically-based innovation mode

TASK = The Technology and Skills Survey

UHDI = The Foreign Trade Statistics Register

WCSS = Within-Cluster Sum of Square

Part I

Synopsis

Synopsis

1 Introduction

How does diffusion of Artificial Intelligence (AI) vary across space? This dissertation set out to answer this question by investigating the mechanisms and drivers behind the unequal spatial distribution of AI in Denmark. The study employs quantitative and qualitative methodologies to identify and discuss the drivers of this spatial inequality concerning technological change. The dissertation makes both empirical and theoretical contributions by offering a wide set of measurements of unequal AI use and application in Danish firms across regions and combining frameworks from the geographical perspective of innovation and technological change with evolutionary economic geography (EEG).

* * *

Technological change creates new opportunities for new industrial paths, economic growth, and wealth (e.g., Solow, 1957). However, technological change can also destroy skills, jobs, and industries (e.g., Freeman & Perez, 1988). This conflicting paradigm has resulted in a substantial body of literature on technological change and the resulting economic importance of technological change in the fields of economics and economic geography going as far back as the 18th century (e.g., Smith, 1776). The interest has only increased in recent years following the development of Industry 4.0 (I4.0)-related technologies. Although there exists a strong consensus within economic geography, economics, and innovation studies that technological change and its ramifications are heterogeneous across space (e.g., Hägerstrand, 1967; Kemeny & Storper, 2020), data limitations and methodological challenges cause the literature, while providing important insights, to often take on empirical assumptions of a spatially homogeneous nature.[1]

[1] See, e.g., the literature on impact of new technologies on the workforce in terms of wage development (Bessen et al., 2020), institutions (Aghion et al., 2019) and employment rates (Acemoglu et al., 2020; Autor & Salomons, 2018; Dauth et al., 2018; Dixon et al., 2020).

Technological change can differ regionally in several ways. First, technological change differs in intensity and pace of technological diffusion(e.g., Schumpeter, 1939). Some regions become regional technological leaders, while others become regional technological laggards. Studies on regional innovative creation have found that path dependency reinforces trends of who has the capabilities to adopt new technology (e.g., Balland & Boschma, 2021). Second, technological change varies in terms of consequences. Some regions are more likely to experience the dark side of technological change that includes the destruction of skills, jobs, and in some more seldom cases, entire industries. In contrast, others are more likely to experience economic and productivity gains (Muro et al., 2019). An example of this phenomenon is the rapid decline of the "rustbelt" regions of the United States and Europe due, among other things, to technological change (Boschma & Lambooy, 1999; Trippl & Otto, 2009).

Literature has long linked spatially unequal access to new technologies as well as the unequal consequences of new technologies to the rising interregional inequalities, which have been observed in most developed countries since the 1980s (Freeman, 2011; Storper, 2018b). Empirical evidence from the previous industrial revolutions has, among other things, shown that new technologies create enhanced regional divides, and the regional divides reinforce an uneven distribution of new technologies (Kemeny & Storper, 2020). Interregional inequalities have in recent years received a substantial amount of attention due to their linkage to the rise in populism (Rodríguez-Pose, 2018) and that it is challenging social cohesion and hindering economic development on a national level (Iammarino et al., 2018).

Scholars have argued that the geographical impact of the diffusion of technologies is much higher than that of the creation of the same technologies and that academia and policy-making should start to emphasize diffusion rather than innovation creation (Mokyr et al., 2015).In a similar line of argumentation, Kitson, (2019) argued that to minimize the increasing spatial, economic, and innovative divides, innovation policies should focus on diffusion rather than emergence since there are higher economic gains from diffusion compared to innovation clusters. The argument is that the widespread distribution throughout society will impact firms and the economy to a larger extent than the innovation hubs, where only a few might be impacted.

A recently emerged technology that has sparked a large amount of interest both in academia and in the public discourse is AI. OECD OECD, (2019), p. 5 defines an AI-systems as: "... *a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It does so by using machine and/or human-based inputs to: i) perceive real and/or virtual environments; ii) abstract such perceptions into models through analysis in an automated manner (e.g., with ML, or manually); and iii) use model inference to formulate options for information or* *action. AI systems are designed to operate with varying levels of autonomy"*. AI has, in recent years, become rapidly diffused across many different types of industrial sectors, causing scholars to go as far as classifying AI as a general-purpose technology (GPT) (Bresnahan & Trajtenberg, 1995). Some scholars have argued that AI will be the cause of major societal changes expected to occur in the near future, as it has the potential to both automate many jobs and create large potential economic and productivity gains for AI-adopting firms e.g., Brynjolfsson and McAfee, (2014). The rapid growth and increasing economic importance of technologies related to AI during the 2010s-2020s have made it an often-studied subject in various fields of economics and economic geography. However, due to, among other things, data limitations, studies on AI have tended to take on a national perspective and less often a regional one. Data limitations furthermore cause the few studies attempting to take on a regional perspective to have a strong focus on the creation of AI, e.g., by focusing on patents rather than the use and subsequent diffusion of the technologies.

This means that, as of yet, the literature knows very little about the mechanisms behind the spatial diffusion of AI. However, a few studies on I4.0-related technologies (I4.0), e.g., Machine Learning (ML), Internet of Things (IoT), robotics, and AI, indicate that these new technologies increase and accelerate regional disparities (Greef & Schroeder, 2021). One of the main arguments for fear of increasing regional inequalities associated with the arrival of I4.0-related technologies is that preliminary results showcase regional spatial patterns both in the creation and the adoption of these new I4.0-related technologies (e.g., Muro et al., 2019). Furthermore, at large, has the adoption of I4.0-related technologies been associated with employment growth, productivity increases, innovation boosts, and higher salaries in the workforce (e.g., Acemoglu et al., 2020; Autor & Salomons, 2018; Cockburn et al., 2018; Domini et al., 2022). The argument is that if regions cannot access these new technologies, they might miss out on economic development. Therefore, this dissertation argues for the importance of unraveling the enablers and barriers of I4.0 and, in the case of this dissertation, AI, specifically.

Although the literature on diffusion, and especially diffusion of AI, has been largely lacking, the literature on technological change and the role of diffusion has a long scholarly tradition behind it. Technological change is generally defined as the process of introducing and diffusing new technologies in the market. This concept emphasizes that technological change involves more than just technical inventions; it encompasses the commercialization of technologies and their actual implementation for productive purposes. This definition draws heavily on Schumpeter's work and his differentiation of *1) invention*, *2) innovation*, and *3) diffusion*. As per Schumpeter's definition, *invention* pertains to the initial creation of a new production process or product, while *innovation* encompasses the subsequent introduction and initial economic utilization of the invention. *Diffusion*, on the other hand, refers to the introduction of the invention by buyers or competitors. The diffusion process often leads to additional innovation, as both developers and users contribute to further improvements and adaptations.

Thereby, *diffusion* should be understood as the spreading of something more widely. However, exactly what is meant by the term *diffusion* differs in the scholarly discussion on the subject. However, several overlaps in the definitions exist. According to Dosi and Nelson, (2010), there are three major stylized facts regarding the process of diffusion of innovations, which are based on a substantial innovation scholarship (e.g., Griliches, 1957; Hägerstrand, 1967; Katz et al., 1963; Mansfield, 1961; Rogers, 1962; Rosenberg, 1972, 1976). These are: i) the diffusion process is characterized by its time-consuming nature. ii) The rate of diffusion differs significantly among technologies and countries. iii) The diffusion of successful innovations typically exhibits S-shaped profiles, however, they are still often asymmetric in nature. However, as noted by Dosi & Nelson (2010), there is a fourth factor to consider: a considerable proportion of innovations, despite initial adoption by some, ultimately fail to diffuse.

This dissertation defines the process of diffusion according to Katz et al., (1963), who, in their definition, manage to include all of the stylized facts, including the discussion of diffusion channels discussed by, among others Hägerstrand, (1967); Rogers, (1962). Katz et al., (1963) defines diffusion process as the "*(1) acceptance, (2) over time, (3) of some specific item - an idea or practice, (4) by individuals, groups or other adopting units, linked to (5) specific channels of communication, (6) to a social structure, and (7) to a given system of values or culture*" (Katz et al., 1963, p. 1).

The thesis adopts an evolutionary view of technological change (Dosi, 1982) to analyze the determinants of the spatial diffusion of AI in Danish regions. The evolutionary view of technological change is particularly suitable for this research endeavor due to its core assumption of ubiquitous heterogeneity across entities in an economic system. In the context of the diffusion of innovations, the literature suggests that potential adopters exhibit heterogeneity on various dimensions that impact their willingness and ability to adopt new technologies and innovations. These dimensions range from firm size (Penrose, 1959) to *absorptive capacities* (Cohen & Levinthal, 1990).

The process of diffusion of innovations is commonly divided into two sides: the supply side and the demand side (Dosi & Nelson, 2010). This dissertation focuses on the demand side of the diffusion process. Regarding the demand side, it is argued that different levels and opportunities for learning are important factors contributing to heterogeneity in diffusion.

The literature on evolutionary technological change is grounded in substantial scholarship that posits, among other things, that geographical settings varyingly tend to agglomerate specific skills, capital, institutions, and technologies, which stimulate conditions for the local developments of knowledge and opportunities for learning. Conversely, these local developments of knowledge and opportunities for learning shape the regional accumulation and development of skills, capital, institutions, and technologies over time (Lundvall, 1992). Similarly, firms accumulate knowledge and learning opportunities in a path-dependent manner, which requires them to adjust the routines of the firm correspondingly over time (Nelson Winter, 1982), which leads to differentiated levels of absorptive capacities for technology adoption (Cohen & Levinthal, 1990). This scholarship has explored various factors known as retardation factors (David, 1990; Silverberg et al., 1988; Soete & Turner, 1984), which create differentiated opportunities for firms and regions to adopt new technologies at an aggregated level.

Regional variations in learning and innovation have been a key subject of investigation (e.g., Doloreux & Shearmur, 2023; Jensen et al., 2007; Lundvall, 1988; Maskell & Malmberg, 1999). Notably, the differences in learning-by-doing have a powerful influence on differentiated levels of innovation adoption, particularly when the innovation is intended for production purposes (Dosi & Nelson, 2010). Within the framework of the Innovation Modes approach, Jensen et al., (2007) delineate various "forms of knowledge and modes of innovation" and establish a clear differentiation between different types of innovation modes. The initial mode, denoted as "Science, Technology and Innovation" (STI), encompasses innovation modes characterized by the usage and development of codified scientific and technical knowledge, also referred to as the "know-what" or "know-why." In contrast, the second mode, termed "Doing, Using and Interacting" (DUI), revolves around experiential learning and embodies the practical knowledge of "know-who" or "know-how." In the original paper, Jensen et al., (2007), they argue, in the case of Denmark, that a mixture of the STI- and DUI-innovation modes have the greatest impact on innovation outcome. Newer studies have showcased that the impact of innovation modes on innovation outcomes differ regionally and depends on the already existing knowledge base of the region, in terms of, e.g., how technologically advanced the region is(Doloreux & Shearmur, 2023; Parrilli et al., 2020). Literature on technological change as an evolutionary process generally agrees that technology adoption and knowledge transfer are more effective if the knowledge base between the technology and the recipient are similar, or "related" (e.g., Boschma, 2017).

Thus, this dissertation is grounded in four distinct yet intertwined features of the evolutionary perspective on technologies, specifically related to spatial enablers and barriers to the diffusion of AI: (1) the path-dependent and cumulative nature of regional variations, leading to (2) differences in how regions learn and innovate, (3) differences in regional capacities to absorb new technologies, and (4) differences in regional institutional contexts that shape the regional ability to learn, innovate, and absorb.[2]

To sum up, due to a large body of literature from the previous industrial revolutions, there is a significant amount of existing knowledge on the drivers, mechanisms, and consequences of technological change, especially regarding the creation of new technologies. Due to data limitations, however, less is known about the spatial patterns of regional diffusion of a new technology, which has been predicted to likely impact society significantly: AI. By taking the point of departure from the evolutionary perspective on technological change, this dissertation aims at shedding some light on some of the drivers and barriers of spatial diffusion of AI in the case of Denmark.

1.1 Aim and main research question

This thesis aims to advance our understanding of the regional variations in barriers, opportunities, enablers, and consequences of AI diffusion by taking a point of departure in the case of Denmark. Based on the introductory discussion, the main question driving the research is as follows:

> **RQ:** ***How does the regional context influence the rate and direction of the diffusion of Artificial Intelligence across regions?***

The investigative questions that guide the research are as follows:

> *RQ1: How can regional inequality and left behind regions be classified?*
>
> *RQ2: How do regional variations in innovation modes affect the AI diffusion?*
>
> *RQ3: How do regional informal institutions co-evolve with AI adoption rates?*
>
> *RQ4: How do manufacturing SMEs in non-metropolitan regions perceive and develop their absorptive capacities to adopt AI?*

The investigative questions will be motivated for in greater detail in Section 2 and especially Section 2.3

1.2 Contributions to the literature

By investigating these research questions, the dissertation aims to contribute to scholarly discussion on the interplay between technological change, taking the point of departure on AI, and regional economic development in the following ways:

[2]Needless to say, this dissertation neglects certain elements of the evolutionary perspective on technological change that likely impact the regional diffusion of AI. This opens up interesting avenues for future research, which will be discussed in greater detail in Section 5.

1. Theoretically, the dissertation showcases the relevance of the evolutionary economic geographical perspective in relation to the diffusion of AI, by showcasing the importance of regional differences in types and impacts of and by AI-related learning.

2. The dissertation provides empirical evidence for spatial diffusion of AI in the early stages of the life-cycle of AI. The dissertation demonstrates that "retardation factors" (David, 1990; Silverberg et al., 1988; Soete & Turner, 1984) for AI adoption are largely spatially dependent. The dissertation, e.g., builds on the work of Doloreux and Shearmur, (2023) and shows regionally varying frequencies and impacts of firm internal DUI innovation modes on AI diffusion. Furthermore, by building on the literature on co-evolution between technologies and institutions (e.g., Freeman, 1995; Nelson, 1994), the dissertation provides empirical evidence for varying impacts of the differing informal institutions on import of AI-related technologies. Lastly, the dissertation, by taking the point of departure in the discussion on *absorptive capacities* (Cohen & Levinthal, 1990), qualitatively showcases that non-metropolitan manufacturing SMEs suffer from internal social and economic resistance, reinforced by their geographical setting.

3. The dissertation showcases the nuances and variations of the mechanisms behind AI behind by adopting a range of data sources and empirical strategies. This contribution aligns with the arguments of Acemoglu and Restrepo, (2020); Ciarli et al., (2021); Marcus and Davis, (2019), who argues that AI is an intangible study object, which makes it even more important to discuss what type of AI is being observed, The dissertation finds that although aligning results, different empirical strategies add nuances to the picture of the diffusion pattern of AI. The dissertation argues that the future literature needs to carefully differentiate the different types of AI and not treat AI as a homogeneous whole.

4. The dissertation provides a new proxy for regional informal institutions based on technological discourse in newspapers. The paper follows recent attempts to untangle previously intangible phenomena, e.g., informal institutions, by using text-data (e.g., Heiberg et al., 2022; Kayser, 2017; Ozgun & Broekel, 2021, 2022a, 2022b; Peris et al., 2021; Rosenbloom et al., 2016). Paper C showcases its relevance through an analysis of co-evolution between and the spatially differing impacts of technological discourses on the import of AI-related technologies.

5. Lastly, the dissertation responds to the call from Martin et al., (2021) and provides a new regional classification system acknowledging regional growth trajectories as long-term and path-dependent. The paper

benefits from the arguments of Boschma, (2018) for the need to incorporate more geographical wisdom as well as Henning, (2019) for the need to incorporate more temporal wisdom in research, especially on the research on economic development.

1.3 Dissertation outline

The dissertation is composed of four papers and an introductory synopsis. The introductory synopsis aims to contextualize and synthesize the papers and clarify the dissertation's overarching theoretical and methodological considerations. The papers included in the dissertation are:

- Paper A: Jessen, S. (2023). The role of time and space in the identification of left behind regions: A case-study of Denmark. In R&R at Cambridge Journal of Regions, Economy and Society.
- Paper B: Jessen, S. & Holm, J. R. Spatial variations in AI diffusion: Employee-level evidence from Denmark on the role of internal DUI. (an unpublished manuscript)
- Paper C: Jessen, S. Informal institutions, information, and innovation: Regional co-evolution of technological discourses and AI investments in Denmark (an unpublished manuscript).
- Paper D: Jessen, S. Regional barriers and trajectories of technological change in Danish manufacturing SMEs: A qualitative case study of early AI adopters (an unpublished manuscript).

2 Theoretical points of departure

This section aims to provide a theoretical framing that embeds and links the four papers of the dissertation. The section first introduces the literature on differentiated regional growth trajectories. Then it introduces the literature on technological change, specifically emphasizing the role of spatial variations in the diffusion of innovations. Lastly, the section introduces the current state of the literature on factors acting as enablers and barriers to the spatial diffusion of AI, sheds light on the knowledge gaps in the literature, and motivates the research questions employed in the dissertation.

2.1 Why do regions grow differently?

How regions grow and what can be expected about the long-term trajectories of regional development can largely be divided into two opposing views (Henning et al., 2022; Rodríguez-Pose, 1999)[3]. The first is founded in neoclassical equilibrium economics (e.g., in Mankiw et al., 1992; Solow, 1956). It posits that regions will *convergence* on similar regional growth paths over time within the integrated national system. The foundation for this literature is a set of models in which long-run economic development is determined by technological change that was not characterized further but simply assumed to exist and generally be available for all economic actors in the economy (Romer, 1994). Differences in long-term trajectories exist only due to differences in capital and labor inputs. Because capital and labor are assumed mobile within the competitive economy, regional disparities are unlikely to persist in the long run as changes in prices and wages will move capital and labor to where they are scarce (Martin & Sunley, 1998). This left technological change an important but underdeveloped place in much economic literature despite prominent contributions by, e.g., Schumpeter, (1961); Schumpeter, (1939); Schumpeter, (1942) who argued that radical technological breakthroughs were the vital mechanism driving economic dynamics and growth.

The second set of theories suggests that economic development is a process driven by cumulative causation and increasing returns that can ultimately lead toward regional economic *divergence* (e.g., Lucas, 1988; Myrdal, 1957; Pred, 1966; Romer, 1986, 1990; Young, 1928). The concept of cumulative causation (Myrdal, 1957) explains how initial advantages or disadvantages can trigger self-reinforcing processes, resulting in virtuous or vicious spirals that perpetuate and even exacerbate spatial inequalities. The concept of cumulative causation contradicts the idea of stable equilibrium in the neoclas-

[3]Both of the two opposing views largely take the point of departure in national contexts, however, both theoretical approaches have applied in the subnational level, especially regarding the second, the "endogenous growth theory" (e.g., Acs & Sanders, 2021)

sical economic theory, where disturbances to a system are believed to trigger reactions that restore a new state of balance (Myrdal, 1957). Myrdal attributes variations at the regional or national level to cumulative processes in which, e.g., regions and/or nations that initially develop advantages will further strengthen and extend them through the attraction of labor, capital, trade, and technologies, often causing disadvantages to other regions or nations.

The idea of cumulative causation is integral to the perspective of "learning processes" within the literature on economic growth, which emerged in the 1960s and 1970s and emphasized virtuous circles of specialization and technical progress (Arrow, 1962). However, incorporating cumulative causation into mainstream economic theory has been challenging due to difficulties in modeling "increasing returns," which are inherent to the concept of cumulative causation. *Increasing returns* is a concept used by *endogenous growth* theorists (pioneered by among others, Romer, 1986) to explain long-run economic development through knowledge or technological accumulation that arises from economic actors' choices about investment in, e.g., capital, research and development, or human capital (Lucas, 1988; Romer, 1990). Young, (1928) and Kaldor, (1966) argued that increasing returns primarily arise from the division of labor and specialization in production, resulting in cumulative expansions in both market size and productivity. (Krugman, 1981) further formalized this idea in his model of uneven industrialization driven by increasing returns, capital accumulation, and cost reductions. The idea of increasing returns is, therefore, an important element to the self-reinforcing, cumulative causation in economic development and has additionally become a primary feature in the endogenous growth scholarship, which explains persistent international inequality. These intertwined mechanisms can result in spatial divides that increase with time and thus hinder geographical economic equalization.

Additionally, the *new economic geography* theory often contributed to Krugman, (1991) also employs the idea of the cumulative causation to explain the spatially dissimilar frequency and type of economic development (Krugman, 1991). As manufacturing activity becomes concentrated in regions or countries with similar initial conditions, a pattern emerges where a prosperous core and a disadvantaged periphery begin to differentiate endogenously. This concentration of manufacturing activities in areas with larger markets attracts additional firms and workers, thereby fueling further clustering and agglomeration effects. These models emphasize the significance of historical factors and minor socioeconomic changes in shaping spatial disparities in development, creating self-perpetuating asymmetrical geographical configurations.

2.1.1 Variations across time: Path-dependency and evolutionary economic geography

So, as per the endogenous growth models (Romer, 1990), which are complemented by new economic geography models that emphasize the influence of initial circumstances on regional outcomes (Krugman & Venables, 1995), and empirical evidence of increased inter-regional disparities in European and North American regions since the 1980s (Storper, 2018b), it is widely recognized that economic growth exhibits spatial heterogeneity.

A literature that is similar to cumulative causation and increasing returns and yet with distinct variations and that also builds on the assumption of path-dependency is evolutionary theory. The evolutionary theory can, roughly, be described as a theory trying to understand how society or the economy learns as an evolutionary process (Dosi & Nelson, 1994). The evolutionary theory emphasizes the importance of random events, e.g., discoveries and opportunities, and how distinct time-specific events impact these. Therefore, the evolutionary theory contrasts the equilibrium-focused neoclassical perspective. Evolutionary theory has branched into many subgenres, including, and most relevant for this present dissertation, Evolutionary Economic Geography (EEG) (Boschma & Frenken, 2006).

According to EEG, regional inequality arises due to several interconnected factors related to knowledge accumulation (Henning et al., 2011). According to Boschma and Frenken, (2006), first and foremost, path dependency shapes a region's economic development trajectory. Certain regions may have enjoyed early advantages e.g., natural resources, infrastructure, or established industries, which create a path dependency that perpetuates their economic dominance. This can lead to a self-reinforcing cycle where successful regions attract more resources, talent, and investment, further widening the gap with less fortunate regions. This factor is then associated with the second factor, the "agglomeration effects", which is the concentration of economic activities and firms in specific regions that can generate positive externalities and agglomeration effects. These effects include knowledge spillovers, access to specialized suppliers and skilled labor, and the formation of industry clusters that promote innovation and productivity. Regions that benefit from strong agglomeration effects tend to attract more businesses, talent, and investment, resulting in a concentration of economic activity (Marshall, 1890), exacerbating regional inequalities. These agglomeration externalities, among other things, allow for a strong specialization, which further reinforces the agglomeration processes. Specialization can further allow for lock-in effects. Economic activities and industries can become locked into certain regions due to factors such as, e.g., specialized skills, infrastructure, and supply chains. This creates barriers for other regions to enter or compete in those industries, reinforcing regional disparities. However, regions also risk becoming too specialized, where transitioning to new industries or technologies may be difficult for regions heavily dependent on declining industries, further deepening regional inequality (Isaksen, 2014).

A pivotal aspect of the literature on EEG revolves around the significance of economic diversification, particularly concerning the emergence of new industries. This diversification is widely regarded as a fundamental determinant of long-term economic success, both at the national and regional levels (Frenken & Boschma, 2007; Neffke et al., 2011a; Xiao et al., 2018). Within the EEG framework, the development of new industries is conceptualized as a regional branching process, wherein regions tend to forge novel industrial trajectories that are intricately linked to their existing economic structures (Boschma & Frenken, 2011; Frenken et al., 2007). A growing body of research substantiates the notion that regional diversification is significantly influenced by path dependency (e.g., Essletzbichler, 2015; Neffke et al., 2011a; Tanner, 2016). This implies that a region's historical path traversed is vital in shaping its future diversification. Furthermore, the predominance of path dependency implies that a region's inadequate possession of related capabilities hampers its potential for engaging in subsequent waves of diversification.

According to EEG, institutions are a key feature of the development of differentiated regional trajectories (Boschma & Capone, 2015; Cortinovis et al., 2017). Regional inequalities can be influenced by institutional factors, e.g., regulations, government policies, and governance structures. Some regions may have more favorable business environments, supportive policies, and better infrastructure, which attract investment and stimulate economic growth. In contrast, regions with weak institutions, inadequate infrastructure, or unfavorable policies may struggle to attract investment and experience slower development, leading to widening regional disparities. This theoretical assumption is, however, notoriously difficult to measure due to the intangible nature of the institutions.

In conclusion, spatial variations in growth trajectories are path-dependent, reinforcing processes that are influenced by multiple factors and result in growing regional divides (Henning et al., 2013; Martin & Sunley, 2006). The concept of cumulative causation and EEG incorporate this idea and underscore the importance of initial conditions and historical factors in shaping spatial inequalities in economic development.

2.1.2 The role of technological change

The co-evolution between technological revolutions and economic growth paths has subsequently been a core subject within economic geography, especially EEG, innovation studies, and economics (Dosi, 1982; Dosi & Metcalfe, 1991; Freeman & Soete, 1997). E.g., Kemeny and Storper, (2020) who linked the different waves of technological revolutions to the different waves of interregional inequality or Schumpeter, (1939) who argued for innovations being a key driver of economic growth. Mewes and Broekel, (2022), additionally, link the technological complexity and regional economic growth by economic growth, showcasing that the regional growth largely originates in the regional ability to produce and utilize complex technologies.

As described in the previous section: the present-day understanding of regional economic dynamics is rooted in the concepts of cumulative causation and increasing returns (Fujita et al., 1999; Krugman, 1991; Lucas, 1988; Myrdal, 1957; Romer, 1986, 1990), which are closely linked to a region's capacity to generate innovation, effectively utilize external ideas and technologies, and diversify into new industrial and technological specializations (Boschma & Lambooy, 1999; Jaffe et al., 1993). This dynamic capacity plays a crucial role in shaping a region's ability to effectively leverage technological advancements and respond to transformation pressures, ultimately influencing its competitive performance at the regional level.

Therefore, the next section dives into the literature on innovation diffusion as a spatial process and clarifies why technologies spread differently across space.

2.2 How do technologies diffuse?

As mentioned in Section 1: technological change is generally recognized as diffusion of new technologies in the market (Schumpeter, 1939), making market diffusion a fundamental aspect of technological change (e.g., Dosi, 1991; Freeman & Perez, 1988; Perez, 1983; Soete & Turner, 1984).

The literature on the diffusion of innovations has long built on the theoretical arguments made in the seminal papers by Griliches, (1957) and Mansfield, (1961); Mansfield, (1968) that perceives diffusion patterns as an S-shaped 'epidemic' diffusion curve. Since then, the static nature of these diffusion models has been challenged, and various alternative diffusion models have been presented to build upon these diffusion models (e.g., Metcalfe, 1981, 1982; Stoneman & Ireland, 1983) in which both the economic characteristics of the innovation and its diffusion environment have been made endogenous to the diffusion process. These latter models, in particular, allow for an interpretation of the diffusion of technology in a broader macroeconomic growth and structural change perspective (Soete & Turner, 1984).

Currently, there is a widespread consensus that the forces driving technological change and shaping the development of technological foundations of different industries develop cumulatively and exhibit a spatial unevenness nature (Metcalfe et al., 2006). This consensus is based on the key assumption that technology is not freely available; rather, it is characterized by varying degrees of appropriateness and uncertainty regarding technical and commercial outcomes. Technological advancements are cumulative, following patterns of innovation and the exploitation of technical knowledge and hardware. Moreover, knowledge and expertise underpinning innovative activities are often tacit and embedded in individuals and organizations, requiring specific learning processes, e.g., knowledge search activities, which are based in technology-specific knowledge bases. These bases encompass information that is publicly available, e.g., scientific findings, but also include localized and tacit skills, experience, and problem-solving strategies (Cohen & Levinthal, 1989; Pavitt, 1984; Silverberg et al., 1988).

2.2.1 Channels of diffusion of innovations

Literature has argued for and identified some main channels where information and knowledge about different innovations and technologies diffuse (Cameron, 1975). These main channels of innovation diffusion include:

1. Personal communication and face-to-face interactions are one of the most common channels, where individuals or organizations share information about innovations directly with others through face-to-face interactions, meetings, conferences, or informal networks (e.g., Bathelt et al., 2004; Dahl & Pedersen, 2004; Østergaard, 2009). This channel allows for detailed explanations, demonstrations, and the opportunity for immediate feedback and clarification. A common branch of this literature investigates labor mobility as being a strong factor in enabling personal communication and face-to-face, supporting the diffusion of knowledge and technologies (e.g., Holm et al., 2020; Østergaard & Dalum, 2012).

2. Media and mass communication are also commonly explored channels of diffusion. Diffusion through television, radio, newspapers, magazines, and online platforms enables the dissemination of information about innovations to a wide audience, creating awareness and generating interest among potential adopters (Hägerstrand, 1967; Rogers, 1962). Literature has, among other things, showcased the importance of media portrayal for the successful diffusion of innovations.

3. Intermediaries or opinion leaders are individuals or organizations with high expertise, credibility, or influence within a specific domain. They play a vital role in disseminating information and promoting innovation adoption. Their endorsement, recommendations, or testimonials can influence potential adopters' decisions and accelerate diffusion. Related here are the social networks, which play a crucial role in innovation diffusion. People within networks share information, experiences, and opinions about innovations, influencing others' perceptions and decisions. Innovations can spread rapidly within tightly connected social networks, where trust and credibility play a significant role in adoption decisions (Caragliu & Nijkamp, 2016; Rekers, 2016; van Eck et al., 2011).

4. Institutions and organizations, e.g., government agencies, industry associations, research institutes, and universities, can act as channels for innovation diffusion. They often have established networks, resources, and platforms that facilitate the dissemination of innovation-related information and provide support for adoption and implementation (Kanger et al., 2019; Pred, 1975).

5. Market mechanisms, including competition and market demand, can drive innovation diffusion. When innovations offer clear advantages, e.g., cost savings, improved performance, or new functionalities, market forces can incentivize adoption and encourage competitors to adopt similar innovations to remain competitive. An often explored channel here is trade and import (Boschma & Iammarino, 2009; Caselli & Coleman, 2001; Jaffe & Trajtenberg, 1999; Keller, 2001).

It is important to note that the channels of innovation diffusion are not mutually exclusive, and multiple channels can work together to facilitate the spread of innovations. The effectiveness of each channel varies depending on the technological, organizational, and geographical context.

2.2.2 Variations across space: Innovative receptiveness and innovative retardation factors and absorptive capacities

As touched upon in the previous section, literature at large acknowledged that the spatial diffusion of technologies and innovations is more complex than the traditional linearand epidemic models of diffusion. The spatial context matters for potential adoption because the diffusion of technologies and innovations is not homogeneous across space.

Literature has coined the forces that create uneven and cumulative delays in technology adoption *innovative retardation factors* (e.g., David, 1990). These retardation factors explain the ubiquitous heterogeneity of potential adopters on a range of dimensions, from size of the firm to different *absorptive capacities* (Cohen & Levinthal, 1990) causing varying levels of firms´ abilities to utilize new technologies.

One of the core thinkers in the literature on the diffusion of innovations as a spatial process is Torsten Hägerstrand. In 1953, Hägerstrand first published his work on the diffusion of innovation as a chorological and chronological process (Hägerstrand, 1967). He argues that innovation spreads as a hierarchical, fan-shaped diffusion pattern, originating from the creation center of the innovation. However, Hägerstrand claims that spatial barriers to the diffusion of innovation exist, and these, first and foremost, depend on two intertwined factors: *i)* the (accumulation) of accessible information for the adopter and *ii)* the innovative receptiveness of the adopter.

Firstly, Hägerstrand proposes that the adoption of innovations is primarily influenced by a learning or communication process, where the effective flow of information plays a crucial role. According to Hägerstrand's conceptualization, information mainly derives from mass media and/or previous adopters and is disseminated through personal messages within the previous adopters' social communication network. The communication network is shaped by social and physical barriers, including natural geographical obstacles like forests and lakes and geographical distance.

Secondly, Hägerstrand argues that the level of resistance to adoption varies among individuals, and higher resistance requires a greater amount of information for adoption to occur. This dichotomy of resistance can be attributed to social factors, e.g., conflicting values with adoption, which is referred to as "social resistance", or practical obstacles that create difficulties and/or even make adoption impossible, referred to as "economic resistance".

The social factor impacting the innovative receptiveness of individuals and firms as a crucial factor for the successful diffusion of innovations and technologies has been investigated in multiple studies since Hägerstrand, (1967). Williams and Edge, (1996) have, in their writings on 'the social shaping of technology' (SST), argued for how design and implementation of technology are characterized by a range of "social" and "economic" factors and different "technical" reflections. Rekers, (2016) argues that spatial diffusion of innovations is a highly social process and that the local intermediate organizations that impact a product's reputation influence whether an innovation will be adopted. Similarly, Feldman et al., (2015) found that cognitive, spatial, and social proximity are strong predictors for the diffusion of rDNA techniques. In a similar line of argumentation, Kanger et al., (2019) argue for the significance of a societal embedding framework, highlighting this through the examination of two case studies on automobile diffusion in the United States and the Netherlands spanning the period from the 1880s to the 1970s.

Absorptive capacities

Related to the idea of innovative receptiveness is the scholarly discussion of "absorptive capacities", which is a notion introduced by Cohen and Levinthal, (1990). The literature on differentiated levels of absorptive capacities has engendered a substantial body of literature. It is today among the core of multiple academic disciplines, from organizational studies to innovation studies and EEG. Absorptive capacities have been applied in many discussions, from knowledge assimilation to innovation adoption. Absorptive capacities are operationalized in many different types of units of analysis ranging from the individual and firm to entire regions or even countries.[4]

[4] Please see, e.g., the Ph.D. dissertation by Leusin, (2022) in-depth discussion on the question of AI development and absorptive capacities.

According to Cohen and Levinthal, (1990), absorptive capacities refer to the firm's capacity to recognize new knowledge and its value, assimilate the new knowledge, and apply it within the organization. The capacity is assumed to correlate with the level of R&D and is largely influenced by the firm's prior knowledge and how this prior knowledge connects to new knowledge. Cohen and Levinthal, (1990) base their argument on prior research exploring cognitive structures and their influence on learning (e.g., Bower & Hilgard, 1981). For instance, Ellis, (1965) illustrates how experience in a particular task can positively affect and strengthen the capacity to undertake similar learning tasks in the future. According to the Cohen and Levinthal, (1990) and subsequent literature on absorptive capacities (e.g., Zahra & George, 2002), absorptive capacities play a crucial role in technological diffusion in the following ways:

- Knowledge acquisition: Absorptive capacity enables organizations and regions to actively seek and acquire new knowledge and technologies from external sources, e.g., research institutions, collaborations, and networks. This involves recognizing the value of external knowledge, identifying relevant sources, and accessing them effectively.

- Knowledge assimilation: Once new knowledge and technologies are acquired, absorptive capacity helps organizations and regions to understand and internalize the knowledge. This involves interpreting and integrating the new knowledge with existing knowledge structures, organizational practices, and capabilities.

- Knowledge exploitation/application/transformation: Absorptive capacity facilitates the application of new knowledge and technologies to improve products, processes, and services. It involves transforming and adapting the acquired knowledge to fit the specific context, utilizing organizational resources effectively, and implementing appropriate innovation strategies.

Overall, the literature on absorptive capacities emphasizes that organizations and regions with higher absorptive capacities are more likely to effectively absorb and utilize new knowledge and technologies, leading to faster and more successful technological diffusion. Building and enhancing absorptive capacities within the organization, organizations, and regions can strengthen their ability to adapt to technological changes, foster innovation, and improve their competitiveness.

The literature on absorptive capacities has, as mentioned, been adopted in many scholarly disciplines and has, as will be discussed in Section 2.3.3, been applied as a main explanatory variable regarding the spatial differences in diffusion of AI and other I4.0-related technologies.

Where neither Hägerstrand, (1967) nor Cohen and Levinthal, (1990) explicitly argue for evolutionary dimensions in their description of the spatial diffusion of innovations and absorptive capacities to adopt innovations, the prominent roles of time and the cumulative and path-dependent understanding of the learning process, make it natural to embed both of the writings within the larger literature of evolutionary economics and especially the subdiscipline of evolutionary, economic geography (EEG).

2.2.3 Variations across time: Path-dependent and evolutionary perspectives

The past decades have resulted in a substantial scholarship on the EEG dimensions of technological change and technological diffusion (Castaldi et al., 2009; Essletzbichler & Winther, 1999). According to evolutionary theory, a key determinant of a potential adopter's successful adoption of a new innovation is the ability to learn how to utilize and implement new technologies. A fundamental assumption is that potential adopters act under certain constraints, e.g., *bounded rationality* or imperfect information(Nelson & Winter, 1982), which impact their opportunities for learning, searching, and experiencing in relation to new technologies. These factors relate to regionally specific institutions of knowledge and learning, which are innate to the spatial, institutional, and/or organizational context. The spatially dependent learning, knowledge, and behavior additionally shape potential adopters' beliefs, objectives, and expectations (see, e.g., discussions of *cognitive biases* by Dosi and Lovallo, (1997)). These processes involve important collective dimensions related to network externalities, the development of preferences, and knowledge spillovers.

Another fundamental aspect within the literature on technological diffusion and the associated spatial barriers to this process is the phenomenon of technological diversification (Castaldi et al., 2009; Essletzbichler & Winther, 1999; Steijn et al., 2023). Similar to industrial diversification, as discussed in Section 2.1.1, technological resources and capabilities are considered central to a firm's competitive success according to the EEG perspective (Barney, 2001; Peteraf, 1993; Ray et al., 2004). When a new technology emerges, and a firm does not possess it, it needs to undergo a process of technological diversification. The literature identifies various factors that influence this process, with relatedness being one of the key factors (Corradini & De Propris, 2015). Over the past two decades, literature has persistently argued that regions are more likely to diversify into new industries when they already have a knowledge base in related industries. Similarly, firms are more inclined to engage in technological diversification within their existing knowledge base. On the other hand, unrelated technological diversification is more prone to failure and, if successful, entails higher adoption costs (Boschma et al., 2015). Recent research has explored different aspects of technological diversification. For instance, Castellacci et al., (2020) investigate the relationship between e-skills and technological diversification in European regions from 2000 to 2012. They find that e-skills strengthen the dynamics of technological diversification, especially in less-developed regions and those with low levels of relatedness. Santoalha and Boschma, (2021) examine the role of political support in the success of regional diversification into new green technologies. They reveal that related capabilities surpass political support in importance for successful regional green diversification. Interestingly, they also find that national-level political support moderates the role of regional capabilities, whereas regional-level political support enhances it. Balland and Boschma, (2022) develop a regional diversification model demonstrating that regional science-related capabilities within a specific industrial specification are robust predictors of the development of new technologies in that same regional industrial specification.

Consequently, differentiated learning, knowledge, and behavior create differences in the development of capabilities and experiences for the potential adopters that can reinforce their differential opportunities for technological diversification. This entails a cumulative and path-dependent phenomenon where institutions are created that support differentiated opportunities of learning and adopting the technologies (e.g., Boschma & Frenken, 2009; Neffke et al., 2011b).

2.3 Spatial diffusion of Artificial Intelligence: The role of differences in learning

The following sections will discuss the current state of the literature in relation to AI adoption. Furthermore, the text will motivate the three research questions focusing on AI in the dissertation.

A recent technology that has received a lot of attention is AI. AI is thought to trigger a revolution across industrial sectors, and in society as a whole (e.g., Xiao & Boschma, 2022) The previous theoretical discussion in the past sections has taken the point of departure in past technological revolutions. While offering a substantial body of theoretical and empirical knowledge on the diffusion mechanism, it remains an open question of how the mechanisms impact the spatial diffusion of AI. In recent years the research on AI has experienced significant growth.However, as of yet, most of the research tends to focus mainly on the impacts of AI-related technologies, e.g., on employment (Acemoglu et al., 2020; Autor & Salomons, 2018; Dauth et al., 2018; Dixon et al., 2020) and wages (Bessen et al., 2020), and less on drivers, enablers, and barriers to the adoption of AI at the firm-level.

This is unexpected, considering that numerous companies continue to face challenges in implementing AI within their production processes and driving forward its adoption (e.g., Kinkel et al., 2022). As surprising, fewer have dealt with the spatial drivers and barriers to AI diffusion, which is surprising, given that preliminary empirical work suggests that AI diffusion takes on strong spatial divides (Muro et al., 2019). More studies have dealt with the factors related to the broader theme of I4.0-related technologies, although the literature here is still sparse. In the following review, the literature on I4.0 will also be included to paint a fuller picture. The limitations to the drawn conclusion will be disclosed and discussed.

Some scholars have argued that differences in spatial diffusion of I4.0-related technologies first and foremost relate to the industrial structure of the region (Castelo-Branco et al., 2023; Clifton et al., 2020). This argument makes sense for many technologies and innovations, e.g., a tractor is more likely to be diffused to and adopted in regions with an industrial specialization within the agricultural sector than in a region characterized by the finance sector. However, AI is likely different.

Due to its broad applicability, AI has already, by many, been regarded as a general purpose technology (GPT) (Agrawal et al., 2019a, 2019b; Brynjolfsson et al., 2018; Cockburn et al., 2018; Crafts, 2021; Klinger et al., 2018; Trajtenberg, 2019) GPTs was originally coined by Bresnahan and Trajtenberg, (1995) where they describe GPTs as being: *"(...) characterized by the potential for pervasive use in a wide range of sectors and by their technological dynamism. As a GPT evolves and advances it spreads throughout the economy, bringing about and fostering generalized productivity gains."* (p. 84). Therefore, GPTs are path-breaking technologies that stimulate economic growth through their diffusion in the economy. A GPT is not isolated to a single industry or sector but can rather diffuse throughout society and influence it as a whole. Previous GPTs are, among other things, steam power, electricity, and ICT (Basu & Fernald, 2019). Previous studies have also found that whereas other types of I4.0 diffused more selectively industry-wise, with, e.g., robotics being more heavily diffused in the manufacturing sector, AI has, in terms of industry, a broader adoption pattern (Corradini et al., 2021; Gjerding et al., 2020). However, there is a consensus in the literature on the diffusion of AI that spatial variations in adoption rates and adoption ability prevail (Abonyi et al., 2020; Barzotto et al., 2020; Jiang et al., 2022).

The main factors identified in the literature on previous industrial revolutions are the differences in learning opportunities and learning outcomes. Taking the point of departure from the evolutionary perspective, the institutional context, the accumulation of skills, knowledge, and technologies are key factors impacting the diffusion of technologies. In the following sections, the most recent scholarship on the spatial barriers to the adoption and development of I4.0-technology, especially emphasizing AI. The following three sections will additionally describe the gap in the literature and motivate the three research questions employed in this dissertation concerning AI adoption.

2.3.1 Differences in accumulation of technological knowledge, skills, and know-how/know-why: Innovation modes

Firms have varying abilities to learn about new knowledge and new technologies and innovate. This depends on the firm's regional setting and the path-dependent, internalized innovation routines and practices of the firm.

There is substantial literature that argues that the ability to innovate can be distinguished by two innovation modes, the STI, the scientific and technical know-why and know-what, and the DUI, the experience-based know-how and know-who (Jensen et al., 2007). Literature has later distinguished the two types in internal and external groupings (e.g., Parrilli & Radicic, 2021).

Most of the literature on spatial variations in AI adoption today has put emphasis on the STI-types of knowledge generation and, in general, knowledge accumulation within traditional, scientific, and technical domains as being a strong predictor for development within AI and other I4.0-related technologies. The firms and regions that lack the traditional, scientific and technological base will struggle more in their AI adoption is the argument (e.g., Xiao & Boschma, 2022).

In the original study by Jensen et al., (2007), they emphasize the combination of STI and DUI has the greatest impact on innovative activities. In this same line of literature, Baker et al., (2021) examine the factors that foster and act as barriers to regional innovation policy in two regional contexts, Ontario in Canada and Massachusetts in the US, regarding I4.0 (IoT: additive manufacturing, remote monitoring, digitalization and integration of data and workflows, predictive analytics, and multi-disciplinary engineering and automation of controls through ML). They find that industrial clusters, context, collaborations, and network intermediaries are among the greatest influencing factors for I4.0 facilitation. The experiences developed through the collaborative synergies and network intermediaries are elements of the DUI-based innovation modes, making both the often acknowledged STI-innovation mode and the DUI-based innovation modes as primary factors for I4.0 adoption. Additionally, Corò et al., (2021) argue that the adoption of AI and other I4.0-related technologies require a mix of STI and DUI, just as argued by Jensen et al., (2007). Furthermore, they posit that the firms with less labor specialized in the digital domain, located in regions with traditionally Marshallian traits, will lack the digital skills and experience, the know-why, and adoption for these firms in these regions, will, therefore, be associated with the employment of this kind of labor. Interestingly, however, the link between AI adoption and the rise in technical and scientific employment is not statistically significant as the only one of the investigated I4.0-related technologies. This might indicate that it is likely that the role of DUI in the firm adoption of AI matters more than previously acknowledged in the literature, which largely has focused on the role of STI. However, as argued by Doloreux and Shearmur, (2023) and Parrilli et al., (2020), the relation between innovation mode and innovation outcome tends to vary across space. Studies have argued that it is likely that the firms in regions with less accumulated knowledge will depend more on DUI-activities in their I4.0-adoption process (Thomä, 2017). However, DUI, and especially internal DUI, is notoriously difficult to measure, which has often made it down-prioritized compared to the more easily measurable STI (e.g., Haus-Reve et al., 2022).

There is, therefore, a significant body of literature showcasing the importance of path-dependent accumulation of knowledge related to higher technological knowledge bases to develop new I4.0 and AI patents, but also for the diffusion of the technologies. However, how regions differ in the ways they innovate and the role of AI adoption is still a part of the literature that is underdeveloped, especially regarding internal DUI activities. Therefore the second paper of this dissertation investigates the following research question:

How do regional variations in innovation modes affect the AI diffusion?

2.3.2 Differences in institutional contexts: Regulations, innovative openness and innovation cultures

The role of institutions has long been a key feature in spatial variations to technological change. It has been posited that technological/innovative activities and regional institutions co-evolve over time (Freeman, 1995; Nelson, 1994). Literature on institutions within economic geography and innovation studies often distinguishes between formal institutions, e.g., policy, regulations, and quality of government, and informal institutions, e.g., beliefs, norms, regional and industrial cultures (Braczyk et al., 1998).

Although the literature on technological change largely acknowledges that differences in regional institutions are among the most significant reasons for differing regional abilities to adopt new technologies, the literature related to the role of institutions and AI diffusion is somewhat sparse. The studies that act as exceptions to the statement have mostly looked at the role of formal institutions, e.g., policy, regulations, and quality of government. E.g., Sandulli et al., (2021) who show in a study of the Basque Country and Catalonia that regions formulate policies to support the transformation of regional innovation systems towards I4.0. Their conclusion highlights that the effectiveness of promoting I4.0 cannot be achieved by replicating policies from other regions, as the transition to I4.0 is a highly regionally-specific and differing process. Similarly, Aghion et al., (2019) zooms in on the impacts of AI adoption on employment growth and finds that the impact depends to a large extent on institutions and policies. Hervás-Oliver, (2021) investigate how I4.0-related technologies are diffused within a Marshallian industrial district (a Toy Valley district in the Valencia region of Spain) through collective action. The study is built on interview data and finds bottom-up-oriented policy initiatives co-developed by collective actors, local firms, and policymakers, stimulate the I4.0-transition. Muscio and Ciffolilli, (2020) investigates the factors driving capacity to adopt I4.0-related technologies, and they argue that position in research networks, EU funding, and inter-regional cooperation have a significant impact on the effectiveness of the implementation of the technologies. Raj et al., (2020) examines the barriers to the integration of I4.0-related technologies in the manufacturing sector, taking the point of departure in both developed and developing countries. They argue that resource constraints and the lack of strategy for digitalization are among the most influential barriers in both developing and developed economies. Their finding implies I4.0-related technologies could be facilitated by advancements in standards and government regulation in the case of developing countries. In contrast, technological infrastructure is having a greater impact in the case of developed countries. This again indicates that the role of institutions is heterogenous across space.

Whereas most of these studies emphasized the role of regulations and policies as potential enablers and barriers for I4.0 and AI diffusion, prior literature point out the importance of the so-called informal institutions of a region. However, few studies investigate the role of informal institutions in AI adoption.

Some papers touch upon firms' innovative openness (Mewes et al., 2022) as being a determinator for radical innovation implementation, which AI adoption would be for many firms. Atwal et al., (2021), among other things, argue that industrial or regional attitudes, cultures, and traditions impact the likelihood of AI adoption among wine farmers in a French wine region. They argue that a "snobbishness" among wine producers in France is causing a barrier to AI adoption. Ozgun and Broekel, (2021) studies news depiction of I4.0-related technologies in Germany and finds strong spatial differences in the manners in which different regions describe and portray these new technologies. While they do not directly showcase the relationship between news portrayal and innovation adoption, they link the discourse with, among other things, regions traditionally associated with innovative activities, e.g., the capital region in Germany.

This leaves a large gap in the literature on the mechanism behind the co-evolution of AI adoption and informal institutions. The third paper of the dissertation, therefore, sets out the examine the following research question:

How do regional informal institutions co-evolve with AI adoption rates?

2.3.3 Differences in accumulation of absorptive capacities, and the role of size and relatedness

A substantial part of the literature on the adoption of AI, focuses on the role of absorptive capacities (Abou-Foul et al., 2023), referring to the literature by Cohen and Levinthal, (1990) and the ability to absorb new knowledge and/or technology. E.g., Kinkel et al., (2022) looks at absorptive capacities and narrows the study subject to AI (AI: autonomous decision-making procedure, support for the optimization and planning of business operations, and analysis of big data), by investigating the enabling factors for firm-level AI adoption in the manufacturing sector. They use a transnational survey of 655 company representatives from firms on whether they have adopted AI-related technologies in their production and if so what supported their adoption process. They find that absorptive capacities related to different organizational factors, e.g., company size, R&D intensity, and digital skills, significantly affect AI adoption in the manufacturing sector. Similarly, Corradini et al., (2021) investigate the spatial distribution of I4.0-related technologies (big data, the IoT, robots, and 3D-printing) by measuring patent citations in European NUTS-2 regions in the years 2000 - 2014. The paper indicates that geographical and cognitive proximity and regional absorptive capacity act as factors for I4.0 knowledge transfers, however, there are also strong variations among the technologies. Their findings generally reveal that the accumulation of technological capabilities and spatial proximity has a more significant and robust effect on the diffusion of 3D-printing and robotics. In contrast, the IoT and big data are more spatially distributed across regions. This goes well with previous scholarly arguments and empirical findings that AI has a GPT nature. Furthermore, it showcases why it is crucial to differentiate between different types of I4.0.

Literature on diffusion barriers of I4.0-related technologies and specifically AI, generally agree that SMEs struggle more in the adoption processes compared to their larger counterparts (Benitez et al., 2020; Estensoro et al., 2022; Grooss et al., 2022; Matt & Rauch, 2020; Müller et al., 2021; Rauch et al., 2020; Stentoft et al., 2021; Yu & Schweisfurth, 2020). The reasons are, among others, the fewer resources, lack of digital skills, and data availability. E.g., Zolas et al., (2020) argue that advanced technology, e.g., AI, is generally more likely to be adopted in larger and older firms. They claim that adoption patterns are consistent with a hierarchy of increasing technological sophistication, meaning that firms that adopt AI or other advanced technologies will also likely use other, more widely diffused technologies. Buarque et al., (2020), furthermore, examine the development and implementation of AI patents in knowledge spaces of European regions. They find that regions where AI is most ingrained in the innovation landscape are also the regions with the most AI patents. They argue that this finding implies the need to support AI diffusion to increase AI innovations. This goes well with the literature on AI inventions clustered in regions that already had previously obtained capability bases with the ICT domain. E.g., Laffi and Boschma, (2022) argues that the importance of accumulated knowledge related to ICT technologies for developing patents of I4.0-related technologies. Balland and Boschma, (2021), furthermore, state that regions in Europe with experience within I4.0-related technologies are, to a greater extent, able to successfully diversify into I4.0-related technologies. In a related study, Xiao and Boschma, (2022) showcases how a regional knowledge base within ICTs impacts the development of AI-related technologies in regions in Europe. They benefit from patent data and find that ICTs are important in supporting regional diversification into AI-related technologies. This finding is particularly strong for the regions' still catching up regarding the inventions of AI. Cicerone et al., (2023) reverse the question and investigate whether AI fosters diversification in green technologies and find AI knowledge supports the regional specialization in green technologies. However, the results only hold if the regions were already specialized in green technologies previously. In fact, their findings indicate that AI diminishes this capability in regions that had not previously specialized in green technologies.

While these studies provide empirical insights into the path-dependent nature of invention processes, they shed less light on the diffusion mechanisms.

In general, while the literature on the barriers for SMEs is among the more thorough and well-investigated parts of the literature on diffusion barriers for AI adoption, little is still known about the specific spatially based barriers facing SMEs outside the metropolitan regions might encounter when attempting to adopt AI, as most studies either take on a country-level analysis or only looks at the urban centers. Shearmur, (2017) argues that the urban bias in innovations studies might risk leading to flawed policy-making since innovation processes in non-metropolitan regions differ from those the metropolitan regions. Despite the fact that there exist differences among regions in terms of regional capabilities, e.g., regional labor market composition and local knowledge, and that firms differ in how easily the firm can access the existing regional resources, little is still known about the role of the regional context and how firms with fewer absorptive capacities in regions with fewer regional capabilities can overcome the lacking capacities to adopt new technologies, e.g., AI. Literature on the invention side of AI, indicates that building on already existing capabilities eases knowledge development, but what can the firm with fewer of the traditional capabilities, e.g., skilled labor and prior experience, located in the regions with fewer regional capabilities do? As SMEs constitute a growing part of the industrial composition in non-metropolitan regions it is important to untangle the barriers and enablers for non-metropolitan SME. Therefore, the last paper of the dissertation aims to answer the following research question:

> *How do manufacturing SMEs in non-metropolitan regions perceive and develop their absorptive capacities to adopt AI?*

Figure 1 showcases the theoretical framing of the dissertation, emphasizing the role of regional and firm-level capabilities, especially regionally specific learning and institutions, by introducing the individual research questions for each of the dissertation´s four papers´ research questions. The theoretical framing of the dissertation argues that regions differ due to long-term trajectories of regional development, which results from cumulative causation and increasing returns. This causes regions and the firms they host to differ in various ways. The regions develop differentiated capability and knowledge bases, where they, e.g., have different degrees and types of local knowledge, different labor market compositions, and different regional institutions, both formally and informally. The firms differ, e.g., in terms of path-dependently accumulated knowledge and experiences, subsequent absorptive capacities, and innovation modes, giving the different abilities to adopt new technologies.

The next section provides an introduction to the methodological considerations and approaches adopted in the dissertation.

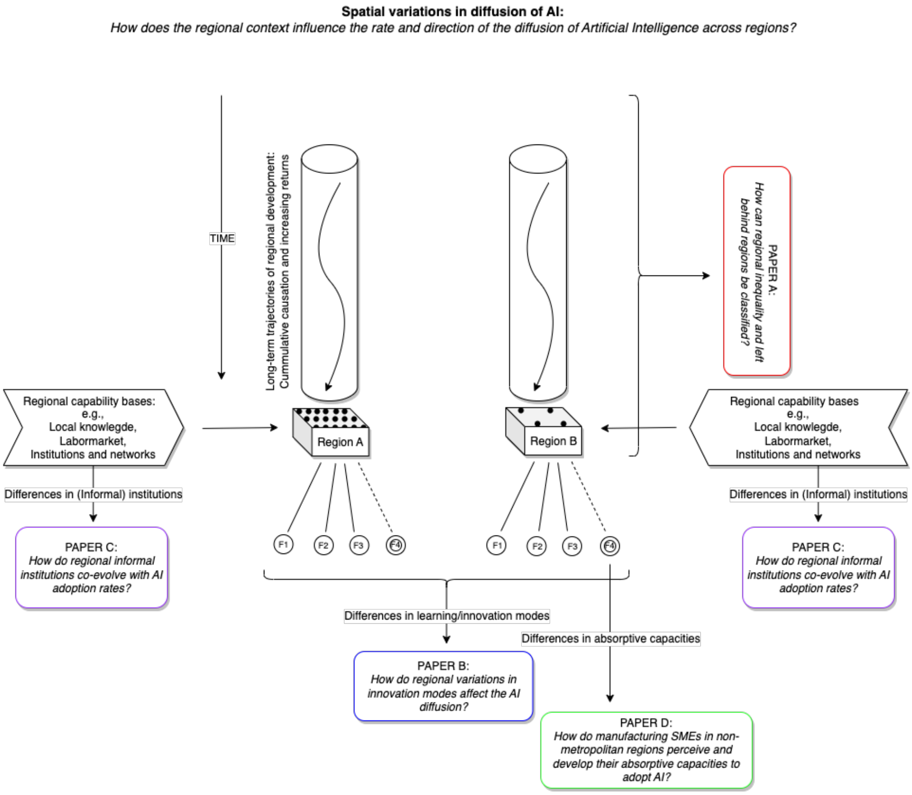

Fig. 1: Theoretical framing of dissertation and link between research questions.

3 Data, methodological considerations, and empirical strategies

3.1 Denmark as an empirical context

All four of the dissertation´s papers are based on Danish data. This section, therefore, gives a thorough introduction to the Danish context, with a specific emphasis on the overall innovative receptiveness of the country and the regional divides.

3.1.1 Danish economy and regions

Denmark is a small Scandinavian country. It is one of the most prosperous countries in the world per capita (OECD, 2023). In 2023 the population of Denmark was approximately 5.9 million, and the population density was 137 inhabitants per km^2 (Statistics Denmark, 2022a). The majority of the population lives in urban regions, with around 1.8 million residing in Copenhagen and the surrounding region (Statistics Denmark, 2018). Since the structural reform of 2007 (Indenrigs- og Sundhedsministeriet, 2023), Denmark has been divided into five administrative regions and 98 municipalities (LAU1). The Danish economy is an export-oriented, knowledge-intensive economy with a large share of inhabitants with higher tertiary educational attainments (Statistics Denmark, 2022b). In terms of income inequality per capita, rising inequality can also be observed. Statistics Denmark, (2021b) could, in 2021, for the first time since 1987, where the development in Gini coefficients have been measured, report a Gini coefficient over 30. The rising inequality is primarily due to the top percentile growing faster than the lowest percentile diminishing.

Furthermore, despite being at the lower end of the specter compared to other countries, Denmark is, as many other Western countries experiencing rising interregional inequality, e.g., in terms of regional GDP per capita and productivity, since the 1980s. Measured in regional GDP per capita, interregional inequalities increased by 17 % between 2000 and 2016 (OECD, 2018).

The rising regional inequality is despite several policy attempts to ensure a fair fiscal, regional distribution. Denmark has a long history of trying to combat regional disparity. It has one of the world's oldest traditions for regional redistribution systems, where the earliest attempts can be traced back to the 1800th century. The idea of municipal equalization was, however, first put into place with the social reform of 1933. Since then, the system has been modified several times. Most significantly in the 1970s with the so-called burden-sharing reforms (Danish: byrdefordelingsreformer) and in 2006/2007 with the structural reforms (Etzerodt & Mau Pedersen, 2019).

The municipal equalization system in Denmark (Danish: Det kommunale udligningssystem)[5] is a system designed to ensure financial equalization among municipalities, aiming to address disparities in revenue-raising capacity and expenditure needs across different regions. In Denmark, municipalities are responsible for delivering, among other things, public services. However, due to variations in population size, economic conditions, and other factors, municipalities may have different capacities to generate revenue through local taxes and fees. Additionally, they may face varying expenditure needs based on factors, e.g., population demographics and infrastructure requirements. The municipal equalization system aims to mitigate these disparities and promote financial fairness and sustainability across municipalities. It works by redistributing financial resources from municipalities with a higher revenue capacity to those with a lower capacity. The system operates in an advanced set of formulas and calculations. It considers variables such as the population's income level, age structure, educational attainment, employment rates, and other relevant indicators. These factors are used to determine the fiscal capacity of each municipality. Municipalities with higher fiscal capacity are expected to contribute more to the equalization pool, while those with lower capacity receive transfers from the pool (Etzerodt & Mau Pedersen, 2018).

3.1.2 Innovation in Denmark and Danish regions

For the past several years, Denmark has been among the leaders in different innovation rankings. E.g., in Digital Economy and Society Index (DESI), which summarizes indicators of Europe's digital performance and monitors the development of European countries on a wide range of different innovation measures, has Denmark either been the highest ranking of the EU countries or among the leaders for the past several years (EU, 2022). Figure 2 showcases the relative progress in the DESI score rankings of each EU member state from 2017 - 2022.

In a study by Atik and Ünlü, (2019), they developed an I4.0 index, where Denmark was ranked in the top among countries in Europe. Surveys on the use of AI in firms continue to place Denmark at the top, with 24 % of firms with more than ten full-time employees (FTE) in 2021 (Statistics Denmark, 2021a). However, just as regarding the regional variations in economic performance and income, the degree of innovative capabilities and activities also vary regionally, with a majority of innovative activities being clustered in the capital region (Jokinen et al., 2020). Caldas et al., (2023), furthermore, showcases regional differences in internet quality using speed tests. They find

[5]There is a long and substantial literature on the Danish municipal equalization system. This section only offers a brief introduction to the system. Please see e.g., Etzerodt and Mau Pedersen, (2018) for much greater detail.

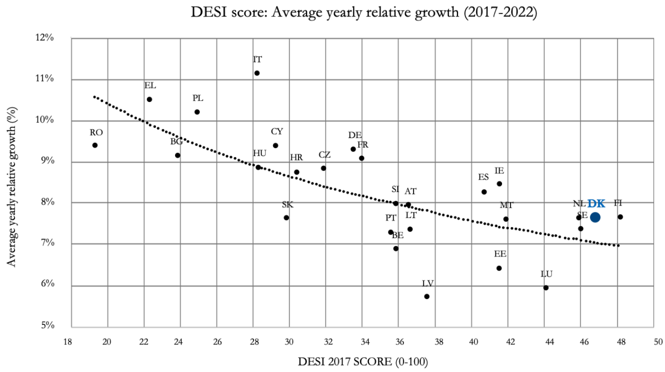

Fig. 2: Digital Economy and Society Index – EU member states' relative progress in the period 2017-2022. Data sources: EU, (2022), European Commission. Layout by the author.

regarding Denmark that despite the small landmass size of Denmark that the quality of the internet deteriorates the further distance to metropolitan regions.

Policy-wise, Denmark has implemented several projects to support AI adoption in Denmark (Danish Ministry of Digitalization, 2019). The national strategy for AI put in place in 2019 is built on four pillars, with the shared goal of making Denmark leading in terms of AI development and AI integration. The four pillars are as follows:

1. "Denmark must have a common ethical basis for artificial intelligence with humans at the center"

2. "Danish researchers must research and develop artificial intelligence"

3. "Danish companies must achieve growth by developing and using artificial intelligence"

4. "The public sector must use artificial intelligence to offer world-class service"

Probably most significant is the fourth pillar, which supports "signature projects" (Danish: Signaturprojekter med kunstig intelligens i kommuner og regioner) in Danish municipalities and regions. (Danish Ministry of Digitalization., 2023b). In the agreement on the municipalities' and regions' finances for 2020, the Danish government, the National Association of Municipalities (Danish: Kommunernes Landsforening: KL), and the national association of Danish Regions (Danish: Danske Regioner) have set up an investment fund that supports the testing of new technologies in the public sector. The investment fund has supported 40 signature projects from 2020-2022 that will test the use of AI in the public sector. Interesting, however, is the urban bias in the distribution of the funding to projects. The four largest city-municipalities (Copenhagen, Aarhus, Odense, and Aalborg), which make up roughly speaking 24 % of the total Danish population, receive 48 % (calculations by the author) of the total funds. While it is to be expected that the greater and more densely populated municipalities receive more funding, since more administrative functions are clustered in and around the urban areas, the skewness in the distribution is still striking since the majority of the funding is assigned to projects within the municipality and not other administrative units, e.g., governmental agencies. 62 of the remaining 94 municipalities do not receive direct funding. Danish policy-makers have, as in many other countries, in recent years put the spotlight on the phenomenon of digital exclusion, where certain population groups within society struggle more with the increasing digitalization of society. Policies are put in place to help citizens who are struggling, e.g., "Thoughtful Digitalization" (Danish: "Digitalisering med omtanke") of June 2023 (Danish Ministry of Digitalization, 2023a). This indicates the political awareness and prioritization to address and combat unequal access to technologies and digital services.

I, therefore, argue that Denmark makes an interesting case for this research endeavor. While the smaller national contexts are a unique case (Freeman & Lundvall, 1988), this study also follows the logic behind the generalizability of extreme case studies: If the diffusion of AI takes on a spatial pattern in Denmark, where there are more minor, although rising, levels of interregional inequality and high ranking in innovation scoreboards, then a similar spatial pattern will likely be found in a larger national context with more significant regional divides and greater technological divides (Flyvbjerg, 2006).

3.2 Data

The dissertation exploits several data sources to investigate the diffusion of AI and regional inequality in Denmark. One of the main reasons for using several data sources is discussed in further detail in the Section on the operationalization of AI. However, briefly speaking, the use of multiple data sources in research with a study object as intangible as that of AI allows for greater validity (e.g., Rowley, 2002). The primary data sources adopted in the dissertation are: Administrative registry data accessed via Statistics Denmark, the TASK survey data, and qualitative interview data. The following section will first introduce the chosen spatial and regional levels and the chosen unit of analysis and then describe the various data sources employed in the dissertation.

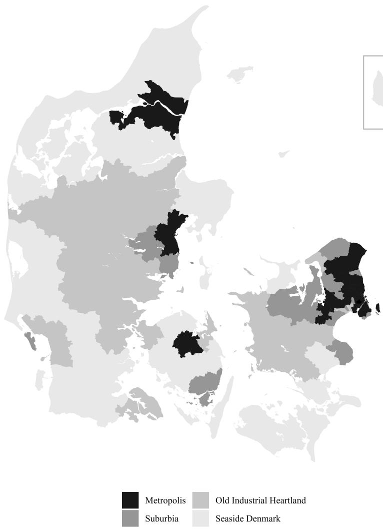

Fig. 3: Map over clusters

3.2.1 Choice of regional and spatial levels

Technological change and diffusion patterns can be examined at several spatial scales (Storper, 1997). Empirical studies on technological change have employed spatial units varying from the national (e.g., Freeman & Lundvall, 1988; Freeman et al., 1987; Lundvall, 1992) to sub-national (NUTS2-4) levels (e.g., Balland & Boschma, 2021; Essletzbichler & Winther, 1999; Rigby & Essletzbichler, 1997; Tödtling, 1992), or even local firms (e.g., Acemoglu & Restrepo, 2019). In this dissertation, the central spatial units are the 98 Danish municipalities grouped into clusters based on the classification developed in Paper A in this dissertation.

This classification employs various variables in longitudinal development trends from 1980 - 2018. The classification results from a K-means clustering process and groups the Danish municipalities into four regional types: The metropolis regions, the suburban regions, the old industrial heartlands, and the peripheral regions/the seaside regions and is depicted in Figure 3.

The regional classification was developed as a part of this dissertation in the pursuit of an appropriate regional classification system that went beyond a binary taxonomy of regional "winners" and regional "losers" in terms of development trends(Lundquist & Olander, 1999; Perrons, 2012), that often only taking the point of departure in regional GDPs and that wasn't purely temporarily static (Henning, 2019; MacKinnon et al., 2022; Martin & Sunley, 2022; Pike et al., 2016), living up to the theoretical framework of the long-term, path-dependent development of regions. The development of the regional classification will be discussed in detail in Section 4 and in Paper A.

3.2.2 Choice of unit of analysis

This dissertation refers to regional variations in the diffusion of AI. Whereas regions do not act themselves, the firms and individuals hosted by the regions do (Boschma, 2004). In general, when this dissertation discusses regional barriers and capabilities for AI adoption, it refers to, respectively, the firms or employees within the region. Other studies have discussed regional dynamics taking the point of departure in industrial sectors (e.g., Balland & Rigby, 2017; Neffke et al., 2011a).

Paper A uses data on the municipality-aggregated (LAU1) level. In Paper B, we benefit from employee-level survey data (TASK - see description in Section 3.2.5) and measure the retrospective changes in AI use and work organization for the employees. The data is linked to registry data (See description in Section 3.2.3), which adds information both on the individual level, as well as the firm of employment. Paper C discusses changes in AI investments on the firm-level 3.2.3 and their co-evolution with discourses and sentiments of newspapers on the LAU1-level. Paper D explores barriers and enablers for manufacturing SMEs in non-metropolitan regions, taking the point of departure in the regional classification system described in 3.2.1.

3.2.3 Statistics Denmark's administrative registry data

Statistics Denmark has collected a large share of register data that is stored by the Research Service and is made available to researchers for research purposes. The registers used in this dissertation are updated (at least) yearly. The administrative data used in the dissertation come from two main types of registers[6]: Individual level registers (e.g., BEF, BFL, IND, AKM, IDAP, IDAN, RAS, UDDA) and firm-level registers (e.g., IDAS and UHDI).

Danish individual level administrative registers

The administrative registers on individual-level data provided by Statistics Denmark provide longitudinal micro-level data on the total population of Denmark from approximately 1980 to 2018. Each Danish inhabitant has a unique identifier, allowing researchers to track individuals across a time-frame of almost 40 years and across a large range of variables, including educational backgrounds, employment, wage, and geographical variables, e.g., location of home residence (Timmermans, 2010). These registers are the

[6]For a full overview of Statistics Denmark administrative registers, please see: Statistics Denmark, (2023)

main data source for Paper A, alongside IDAS, which will be discussed below. Additionally, both Paper B and Paper C also partly benefit from the Danish administrative registers on individual-level data.

Danish administrative registers on individual-level data have several features making them suitable for research on regional development and mechanisms supporting technological change. First, by covering the full population, they make it possible to include statistics on all inhabitants, rather than those covered, e.g. in a survey on the labor force. Secondly, by covering the entirety of this current wave of rising regional inequality (Storper, 2018b), the registers also provide a unique insight into the long-term development of regional development. Thirdly, the many variables allow for detailed insight into the varying mechanisms driving and caused by differentiated regional growth trajectories.

Danish administrative registers on firm-level data

Just as the Danish administrative registers on individual-level data, the Integrated Database for Labour Market Research - Workplaces (IDAS) provides longitudinal records, but instead on the firm level for all Danish firms from 1980 - 2021. IDAS data are used to construct the clusters for the regional classification developed in Paper A. Additionally, it also helps construct control variables for Paper B and Paper C, e.g., on NACE codes and firm size.

For Paper C, the Foreign Trade Statistics Register (UHDI) is one of the main data sources. UHDI covers firm customs records. Just as IDAS, UHDI provides longitudinal records for each firm in each year 1993-2018. Inspired by similar studies, Paper C uses import data as one way of measuring technological change in firms (See, e.g., Abeliansky et al., 2020; Acemoglu et al., 2020; Domini et al., 2022). The operationalization of the approach will be discussed in greater detail in Section 3.3.2.

3.2.4 Newspaper data

For Paper C, newspaper data is used to measure the regional, technological discourse regarding AI. Newspapers have recently become a common data source in studies investigating the discourses over time and space (e.g., Geels & Verhees, 2011; Heiberg et al., 2022; Meelen et al., 2019; Ozgun & Broekel, 2021; Rosenbloom et al., 2016). The regional technological discourse in Paper C is constructed as four different variables, and by combining approximately 17.000 different newspaper articles (national, regional, and local)[7] mentioning AI from 365 Danish newspapers covering all 98 municipalities between 2000 and 2018, as well as data on the municipal newspaper reader share from

[7] For the regressions only regional and local newspapers are included, which are approximately $n = 2000$.

2014. The newspaper articles were found in the Danish written news media database Infomedia. Keywords used for the article search were "AI", "Artificial Intelligence", and "Kunstig Intelligens", which is the Danish translation for Artificial intelligence.

The two datasets are merged based on the municipality level after an extensive data cleaning and geocoding process in which the publishing municipality, news-originating municipality, firms, and/or industrial sectors were identified in the newspaper.

3.2.5 TASK survey data

The Technology and Skills (TASK) survey data is a data set on the use of new technologies, e.g., robotics and AI, and work organization at the individual level. The survey was initiated in 2018 by researchers at Aalborg University with the aid of Statistics Denmark.

The design of the TASK questionnaire was developed with inspiration from Eurofound's European Working Conditions Survey (EWCS) and the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) survey to allow for comparisons. Furthermore, specific questions concerning the utilization and adoption of technology in the workplace were designed exclusively for the TASK survey. Statistics Denmark conducted the data collection for the TASK survey. Following a pilot phase in late 2018, the final data collection for the TASK survey was conducted during the spring of 2019. A sample was created from firm- and employee-level administrative registry data and stratified the sample by region and workplace size. To ensure that the data is representative of the Danish population, post-stratification weights were applied to the dataset, which was derived from registry data provided by Statistics Denmark. The total response rate was 39.9 percent allowing for a final dataset of 1244 observations (Gjerding et al., 2020). The data were subsequently linked with administrative registry data at the individual and firm levels, allowing for more in-depth analysis.

3.2.6 Interview data

Semi-structured interviews were conducted to gain a more in-depth understanding of some of the firm-level aspects concerning technological change and the adoption of AI. Semi-structured interviews are the main data source of Paper D, where the dissertation zooms in on the barriers and enablers for AI adoption in SMEs in non-metropolitan regions. Semi-structured interviews provide detailed insight by focusing on a few specified aspects, and semi-structured setup enables the interviewees to potentially bring in unexpected insights (Longhurst, 2003). The research data comprise nine thematic semi-structured interviews with the informants from Danish SMEs, geographically located outside the main metropolitan regions in Denmark and all participating in the network AI Denmark. AI Denmark is a partnership between the Technological Institute, the Alexandra Institute, Aalborg University, the Technical University of Denmark, Copenhagen University, and the IT-University, and is financially supported by the Danish Industry Foundation. The project aims to inspire and help Danish SMEs to make better use of their data and gain familiarity with AI tools. The project organizes inspiration- and network workshops and connects researchers from the partnering universities with the SMEs in a six-month project taking the point of departure in the firm´s specific context (AI:DK, 2023). The participating SMEs are as majority located in urban settings. I conducted the interviews. Seven were conducted online using Microsoft Teams with only the interviewee and the interviewer present. One interview was held online using Microsoft Teams with a colleague of the interviewer present. One interview was held in person with a colleague of the interviewer present attending. The choice of the informants was based on their geographical location in either the old industrial heartlands or the regionally more peripheral regions. SMEs located in either suburban regions or metropolitan regions were disregarded. Furthermore, the interviewed SMEs had to have a background in manufacturing industries. Most of the interviewed SMEs were traditionally described as low-knowledge-intensive manufacturing, except for two of the firms, which were high-knowledge-intensive manufacturing. The chosen SMEs should have limited prior experience working with AI and could, therefore, not be software SMEs, meaning that firms with NACE-codes 6000 – 7000 as main NACE-code were excluded. The first half of the interviews were conducted in the early spring of 2022. The second half of the interviews were conducted in early fall 2022. The interviews lasted from 20 to 70 minutes, with a mean of 43,78 minutes. A similar set of questions were addressed to each of the informants. During the interviews, various aspects were explored, including the firm's organizational structure, existing barriers, ongoing innovative practices, as well as the potential benefits and challenges associated with adopting AI. Prior to the interviews, the participants received an email providing background information on the topic. The interviews were audio recorded and transcribed verbatim in Danish by a research assistant, with the exception of one interview conducted in English. All eight Danish interviews were later translated into English by myself.

3.3 AI as a study object

Use of and adoption of AI is known to be challenging to measure (Marcus & Davis, 2019). First of all, similar to numerous other digital technologies, a primary challenge in assessing the adoption and diffusion of AI stems from its growing intangibility or inclusion of intangible components. Consequently, acquiring data on the value of transactions associated with accessing AI services or technologies (e.g., software) becomes intricate and challenging to capture (Ciarli et al., 2021).

Secondly, AI is known as being broad technology with many definitions and subgenres making it "fluffy", difficult to study, and difficult to develop a consensus in the literature (Ferrero Guillén & Breckwoldt Jurado, 2023; Hernández-Orallo, 2017; Simon, 2019). The literature on AI has exponentially increased in the last couple of years (Qin et al., 2023). Collins et al., (2021) maps out the evolution of how AI is defined over a 15-year period by analyzing 55 primary papers. They argue that, at large, the literature lacks a consensus on what AI is and how the technology distinguishes itself from other digital technologies. Compared to other technologies, relatively few definitions of AI exist, and those that exist are often more open to interpretation than other technologies. Scholars have furthermore argued that AI is largely a social construct, dependent on the definitions and understandings of various stakeholders (Eynon & Young, 2021). In this dissertation, I work with a somewhat broad definition, where AI is the result of an attempt to develop intelligent machines capable of performing tasks that typically require human intelligence, such as reasoning, learning, understanding natural language, and making decisions. Through techniques like machine learning, natural language processing, and computer vision, AI enables machines to learn from data, adapt to new information, and improve their performance over time. This definition leans on other definitions (e.g., the definition by OECD, 2019, which was described on page 4 in this dissertation), but still encompasses a range of different perspectives of AI that are often not included, which will be discussed further in Section 3.3.1.

Third, AI is a rapidly developing technology. During the time span of this Ph.D., from late 2019 to the spring of 2023, the developments and overall interest in AI from both academia and policymakers have increased exponentially. Among other things, generative AI has become more widely available to a broad audience since November 2022. This causes challenges when attempting to measure AI adoption, which will be discussed in greater detail in Section 3.3.2. In the next section, the history of AI and types of AI will be touched upon, as well as common operationalization practices in the present literature on the adoption of AI.

3.3.1 History and types of AI

The idea of algorithm-based technologies allowing artificial thinking is by no means new. Mathematician Ada Lovelace (1815-1852) is often described as the first computer programmer in the world. Lovelace´s writings on the science of operations, Poetical Science, and the future potentials of computerized creativity, as well as mathematical problems in the form of coding sequences, or algorithms, for Charles Babbage's Analytical Engine, considered the first steam-powered computer, from 1833 are seen as some of the first writings on AI (Aiello, 2016).

During the 1950s, early AI was pioneered by computer science, psychology, and economics researchers, including Allen Newell, Seymour Papert, Marvin Minsky, Herbert Simon, and John McCarthy. They aimed to create intelligent machines that could perform various mental activities. Though mostly still-standing as a field for a few decades, AI as a study object returned in the 1990s, with an object perceived as more realistically obtained: replicating and improving on human intelligence in prediction and pattern recognition, which includes recognizing faces, speech, and abstract patterns in data and making decisions based on past experiences current information (Acemoglu & Restrepo, 2020).

According to Bekamiri, (2023), AI can, roughly speaking, be classified in four different manners. The following text will discuss the four classifications in relation to this dissertation. The four classifications are as follows:

1. By AI technique (Mellit & Kalogirou, 2022): Grouping AI technologies based on the techniques used, e.g., machine learning, deep learning, computer vision, natural language processing, expert systems, and robotics.
    (a) This dissertation uses rather wide AI technique groupings and does, therefore, solely investigate specific techniques of AI. Emphasis is, to a larger extent, put on the AI functionality.
2. By AI application domain (Sarker, 2022): Classifying AI based on the domain or industry in which it is applied, e.g., healthcare, finance, transportation, or manufacturing.
    (a) This dissertation does isolate the analysis to a specific application domain, except Paper D, which zooms in on the manufacturing sector. Instead, this dissertation looks at AI across all Danish sectors.
3. By AI functionality: Categorizing AI based on the functions they perform, e.g., Prediction (optimization, classification, and/or decision-making) and generative creation.
    (a) The main focus of this dissertation is the traditional/statistical AI,[8]

[8]However, as will be discussed later in Section 3.3.2, due to the somewhat open definitions of AI in the different papers, the focus on AI in this dissertation could cover both the traditional/statistical predictive AI and the newer generative AI. Due to the fact generative AI is only being more widely diffused after the empirical analyses of the dissertation have been concluded, is it, however, more likely that the AI being measured in the dissertation is the traditional/statistical predictive AI

which encompasses algorithms employed for prediction, decision-making, and classification. It does not directly encompass the newer generative AI due to the timing of the diffusion of the newer generative AI. In terms of AI functionality, various classification systems exist. One commonly utilized classification, adhered to in this dissertation, categorizes AI as either "Narrow" AI or "General AI" (OECD, 2017). Artificial narrow intelligence (ANI) or "applied" AI aims to tackle reasoning or problem-solving tasks. ANI can generalize pattern recognition, e.g., transfers of knowledge acquired by image recognition to speech recognition. ANI is often contrasted with artificial general intelligence (AGI), wherein autonomous machines possess comprehensive general intelligence. Like humans, AGI can generalize and apply learning on an abstract level in various cognitive operations. AGI exhibits judgment and decision-making abilities, multifaceted problem-solving skills, learning through reading or experience, concept creation, perception of the world and self, inventiveness, responsiveness to unexpected situations in complex environments, and anticipation. While the release of ChatGPT-4[9] in early 2023, broadened access to advanced AI technologies for a wider audience. It is important to note that true General AI does not currently exist as of writing this text (ibid.). Thus, this dissertation refers to ANI when discussing the diffusion and adoption of AI.

4. By AI maturity level (Gartner, 2021; IBM, 2021; Microsoft, 2022): Grouping AI technologies based on the level of advancement and sophistication a company has achieved in adopting, implementing, and scaling AI-enabled technologies to improve its business processes, products, or services.

    (a) This idea of categorizing by maturity level is not directly adopted in the dissertation. However, it serves as an underlying means of analysis in the sense that the very goal of the dissertation is to understand the barriers to AI adoption. several organizations and scholars have offered a wide range of AI maturity models. The models have significant overlaps in the different phases and levels being identified. A maturity model that has gained a large share of positive feedback due to its broad applicability is the Gartner, (2021) maturity model. According to this model, the AI maturity level can be divided into five levels, which are as follows:

        i. The first stage, according to Gartner, (2021), is "Awareness",

[9] Chat-GPT is a Generative AI that creates new content in images, text, audio, and more. In contrast, traditional AI systems are designed to recognize patterns and make predictions.

which refers to the firms, that know about AI but have not adopted it.

ii. Stage 2 "Active" refers to firms that are experimenting with AI.

iii. Stage 3 "Operational" refers to firms that have adopted ML into their day-to-day operations.

iv. Stage 4 "Systemic" refers to using ML in a new way to change business models.

v. Stage 5 "Transformational" refers to the use of ML intensely. ML and information processing is the now the core commodity offered to their customers.

(b) This dissertation is not interested in firms at Stage 5, because emphasis is put on firms adopting AI and not developing AI themselves. However, for Paper B, these firms are not directly excluded in the analysis as they are in Paper C and Paper D.

3.3.2 Empirical strategies for measuring the diffusion of Artificial Intelligence in the dissertation

As discussed in Section 3.3.1 for all three papers dealing with AI in this dissertation, AI mainly refers to the "traditional"/statistical AI, used for data analysis in order to create prediction, decision-making, and orders. However, as will be discussed in the following the empirical strategies allow for a wider definition than that originally intended.

In the literature, there are currently three main ways of operationalizing the use and adoption of AI[10]. Different types of surveys have in recent years been developed and adopted in various studies (e.g., Corò et al., 2021). Studies have also employed import data (e.g., Domini et al., 2022) and interview data (e.g., Matt & Rauch, 2020). The different means of measurement have different strengths and weaknesses. In order to strengthen the analyses of the dissertation, this dissertation adopts all three methods.

In Paper B, coauthored with Jacob Rubæk Holm, we employ the TASK data, which includes indicators for the frequency of using two different types of AI. The two types are as in e.g., Gjerding et al., (2020):

[10] A common measure of AI diffusion and diffusion of technologies, innovations, and knowledge, in general, is patent citations. This methodology, while providing a large data sample and has a substantial scholarship behind it (e.g., Acs et al., 1994; Jaffe et al., 1993; Nelson, 2009; Schmid et al., 2022; Thompson & Fox-Kean, 2005), also has several limitations. The main criticism being raised about using patent citations as a measure of innovation diffusion is that the mechanism being captured is rather biased. This refers to most innovations are not patented, and most innovation adopters do not declare their adoption by citing the innovation in question (Jaffe & Trajtenberg, 2002). For this reason, this dissertation does not take advantage of patent citations

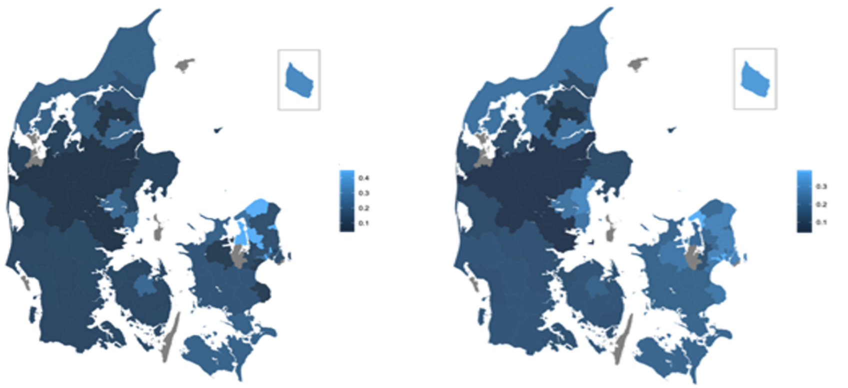

Fig. 4: Change in AI diffusion 2016-2019 according to TASK survey. Source: Paper B in this dissertation. Left: Command AI. Right: Helping

- "receive orders or directions generated automatically by a computer or by computerized machinery"
- "make use of information compiled automatically for you by a computer or by computerized machinery for making decisions or for advising clients or customers"

In Paper B, we refer to these as 'Command AI' and 'Helping AI' respectively. These two ways of using AI are consistent with the model suggested by Agrawal et al., (2019c), which will be discussed in Paper B.

The two dependent variables in the study are binary, taking a value of 1 if the respondent reports an increase in the use of Command AI or Helping AI between 2016 and 2019. Only respondents who held the same job position in both years were included in the analysis, ensuring that changes in AI use were tracked within the same job.

Figure 4 presents the spatial distribution of AI diffusion across Danish regions from 2016 to 2019. Due to limited observations at the municipal level in the TASK survey, the municipalities were grouped into 20 regions based on the administrative divisions of Denmark. Each region is represented in the maps, showing the share of jobs where an increase in AI use was reported between 2016 and 2019. Lighter shades indicate higher diffusion.

The darkest areas in Figure 4 are primarily located in Central and Southern Jutland, as well as the islands to the east of the mainland. This pattern is observed for both Command AI and Helping AI. However, there is a difference between the two forms of AI use. Command AI appears to have experienced significant diffusion in a few municipalities in the eastern part of the country, while Helping AI has spread more widely in large university cities and the northern and northeastern regions.

In Paper C AI is operationalized in two manners. The paper investigates the co-evolution between AI import (AI adoption) and the regional technological discourse regarding AI (the regional informal institutions). First, the informal institutions being the regional technological discourse regarding AI is measured through, e.g., the number of news articles, sentiment analyses, the share of news coming from extra-regional origin, and relatedness of news of extra-regional origin to recipient municipality, on all newspapers concerning AI published in Denmark. As previously mentioned, the keywords used in the search are "AI", "Artificial Intelligence", and "Kunstig Intelligens". How AI is defined for news depiction largely depends on the journalists who authored the different articles. This is part of the argument behind the paper: regional differences in regional, informal institutions might occur. However, at the same time, the definition and understanding of AI might differ from journalist to journalist. E.g., in some newspapers, AI is closer to robotics or ML in other newspapers, it is closer to generative AI, and in some newspapers, it is closer to predictive AI.

AI adoption in Paper C is measured as firm investments in AI-related technologies. Therefore, the dependent variable in Paper C is the relative share of investments in AI-related technologies per municipality in Denmark and is constructed using data from the Danish import registry data, ”Foreign Trade Statistics Register – UHDI”. The method of using trade and import data as a proxy for technology diffusion is in no way novel (e.g., Caselli & Coleman, 2001). In recent years several studies have used import data to capture the firm-level investments in and use of I4.0-related technologies (see, e.g., Abeliansky et al., 2020; Acemoglu et al., 2020; Domini et al., 2022; Humlum, 2022). This paper is interested in the regional level of AI-related technologies and therefore adopts the definitions by Domini et al., (2022), in which AI-related technologies are defined in the HS-2012 codes as:

1. Automatic data processing machines: 847141-847150, 847321, 847330

2. Electronic calculating machines: 847010-847029

So AI adoption in Paper C is the firm investment, measured as the total amount of monetary value in DKK invested in the import of the two before-mentioned HS-2012 codes. This approach covers all 98 municipalities in Denmark, and the variable is constructed using time series from 2000, the first year the codes were included in UHDI, and up to 2018.

Figure 5 showcases the changes in the import of AI-related technologies from 2000 to 2018. As can be observed in the plot, the Metropolis regions are by far investing most in import per capita in the time period, compared to the other regional types. The Old industrial heartlands seem to catch up and surpass the suburban regions in the last four years of the period. The definition employed in Paper C being much more associated with the manufacturing

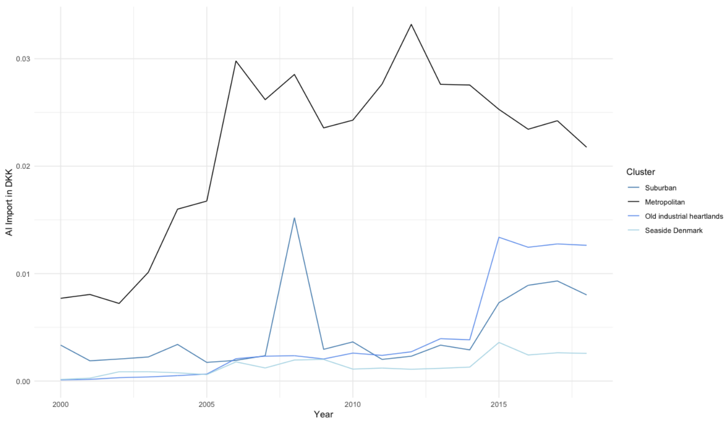

Fig. 5: Development in import of AI-related technologies in Denmark across regions from 2000 - 2018

sector (Domini et al., 2022), it is interesting that the adoption rate for the old industrial heartlands, which still are much more heavily characterized by the manufacturing sector, first started to catch up in the last years of the time frame.

In Paper D, the analysis of AI adoption benefits from qualitative interview data and investigates AI adoption attempts in low-knowledge-intensive SMEs located outside of the main metropolitan regions. The definition of AI adoption is, therefore, dependent on the personal perceptions of the respondents. However, the respondents all participate in the campaign AI:DK, which aims at providing Danish SMEs with tools to begin AI adoption. The AI being applied in the respondent's AI:DK projects is the traditional/statistical AI used for predictions and decision-making. In AI:DK, the firms themselves apply for participation, and here it is also interesting to look at the distribution of participating firms. Figure 6 depicts the distribution of the first three rounds of the campaign and shows a strong urban bias in the participating firms.

In sum, the dissertation employs three different empirical strategies to measure regional differences in and regional barriers to AI adoption. While not adopting all available methods for estimating AI diffusion, the dissertation offers a wide range. This approach allows for a more nuanced picture of AI diffusion patterns. It was based on the idea of method-triangulation to minimize some of the issues when investigating "fluffy" and intangible study subjects to ensure more accuracy. However, there are still drawbacks to this chosen approach.

It is important to keep the differences in the type of investigated AI in mind since, as the papers in the dissertation show, there exist differences in

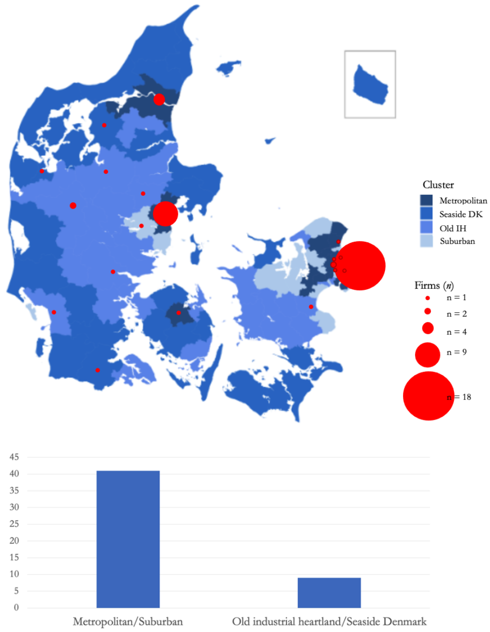

Fig. 6: Spatial distribution of participants in AI:DK round 1-3.

the mechanisms. The difference in results on regional disparities from Paper B to Paper C is likely both the result of the type of AI being investigated, with electronic calculating machines and automatic data processing machines being more likely to be adopted in sectors dominated by heavier machinery and within the manufacturing sector, which would explain the Old Industrial Heartland regions doing relative better in terms of AI adoption in Paper C compared to Paper B, where the definition of AI is much wider. The definition in Paper B should be seen as an overarching definition, which included both the definition of Paper C and Papers D. The definition used in Paper B, is, on the other hand, wide enough to also risk including other types of digital systems that do not necessarily include AI. Furthermore, there is always a risk when using, e.g., survey data, as in Paper B, that the respondents do not understand the questions in the same way they were intended to be understood. Therefore, the definition of AI employed in the dissertation is still, at large, a social construct as argued by (Eynon & Young, 2021), since the definition is dependent on the understanding and definitions of the survey respondents, on the understanding and definitions of the journalists writing the different AI-related newspapers, the understanding and definitions of the SME-CEOs with the help of AI:DK-experts, and the interpretation of my co-author and myself as researchers. The validity of the interpretation is attempted to be ensured by relying on previous definitions and knowledge generated in previous studies and previous official reports.

3.4 Methodological approaches and considerations

This section provides an introduction to the methodological choices made in this dissertation. First, this section introduces the quantitative analyses made in Paper A, B, and C, for then introduces the qualitative analyses made in Paper D.

3.4.1 Quantitative considerations

The quantitative analyses executed in the three quantitative papers in this dissertation can be separated into three main groups. The first group is the descriptive analyses, which are employed in all three quantitative papers. Descriptive statistics shed light on developments over time in Papers A, B, and C. The different papers present the data in tables and figures, where especially maps are commonly used in this dissertation to depict regional variations in the data.

Second, Paper A, B, and C use different types of regression analyses. Respectively the papers adopt ordinary least squares (OLS), logistic regression, and panel regressions to supply evidence for a relationship between the dependent and independent variables in each of the three papers. The different types of regression analyses depend on the research question type and the data used in the analysis. For instance, the binary nature of the dependent variable in Paper B makes logistic regression a suitable choice, and the interest in regional variations in longitudinal import and sentiment trends makes panel regression suitable for Paper C. The different types and choices of regressions will be discussed in much greater detail in the specific papers. These methods are widely used in the economic geography and innovation studies literature.

The third group of quantitative analyses employed in this dissertation is what I refer to as unsupervised ML for categorization. More specifically, I employ cluster K-means analyses in Paper A, principle component analysis (PCA) in Paper B, and textual sentiment analysis in Paper C. These methods help categorize large data samples into different development clusters for Paper A, groupings of related work organizations in Paper B, and, for Paper C, text into either positive or negative sentiments. All three of these methods have been massively popularised in recent years due to the increasing accessibility of tools within ML.

Several limitations regarding quantitative analysis should be taken into account. Section 3.5.3 will discuss these limitations in greater detail.

3.4.2 Qualitative considerations

As mentioned in Section 3.2.6, Paper D benefits from interviews as the main data source. The data consists of nine interviews with owners and employees in Danish, manufacturing SMEs located in non-metropolitan settings, who were participating in the AI:DK campaign and working towards AI adoption. Interviews shed light on the more personalized struggles and enablers for the SMEs in question, which quantitative analyses would struggle to do. The use of interview data, therefore, provides much greater nuance to the dissertation, helps clarify some of the quantitative findings, and verifies some of the mechanisms identified in the quantitative papers. However, also regarding qualitative analyses, several limitations apply. Again, Section 3.5.3 will discuss these limitations in greater detail.

3.5 Limitations of the dissertation

As with most research endeavors, this research also has limitations. This section attempts to discuss some of the limitations and is organized into three themes: the scope of the analysis, theoretical issues, and methodological issues.

3.5.1 Scope of the analysis

1. Technological change and its related diffusion process is a long-term process. This study mainly adopts diffusion time frames ranging from six months (Paper D), to three years (Paper B), to 18 years (Paper C). The length of these time frames is insufficient to capture all dynamics of diffusion of AI. Moreover, the dissertation is written in the earlier life cycles of AI, and if at some point AI reaches a diffusion saturation point it hasn't been reached at the time of writing this dissertation. Therefore the analysis of this dissertation should be seen through the lenses in which it is intended; spatial divides of AI diffusion in the early stages of AI life cycles. Therefore, this dissertation and its studies probably only capture a snapshot of the dynamic characteristics of the spatial diffusion of AI. While it does not go against this dissertation's objective, it warrants more research in the years to come after achieving a more saturated market coverage (Storper & Walker, 1989).

2. As touched upon in Section 3.2.1 and which will be dealt with in further detail in Paper A: Regions can be defined and classified in multiple ways. By taking on different regional classifications results might differ. Furthermore, there is a question of the generalisability of the findings to other national contexts. The analyses in the dissertation are based on the premise that the Danish case is of interest due to its characteristics

of an extreme case study. However, it is still uncertain to what extent the result might be transferred to other national contexts.

3.5.2 Theoretical issues

1. Compared to other technologies, AI is a rather intangible concept (Ciarli et al., 2021; Ferrero Guillén & Breckwoldt Jurado, 2023) that in many studies have had varying definitions. Partly as a result, many different data sources and techniques have been used to measure AI. This results in a somewhat "muddy" literature (Markusen, 1999). Therefore, despite attempts to ensure validity by leaning on previous research traditions in the novel research field of AI and by investigating the diffusion and adoption of applied AI in various manners with different data sources and different empirical strategies, the results of this dissertation might not be generalizable to all definitions of AI used in other studies due to the social constructivist nature of the various definitions of AI employed in the dissertation.

2. This dissertation only focuses on traditional/statistic AI and does not include, for instance, the newer generative AI, which has emerged in the last months of the writing, e.g., Chat-GPT4, StableDiffusion, and DALL-E. While it can be argued that this new generative AI will follow a similar diffusion pattern, due to the complexity of the technologies, it is still uncertain whether this assumption holds. Therefore the results of this dissertation should be seen as specific to the study object of traditional/statistical AI.

3.5.3 Methodological issues

As discussed in Section 3.4.1, the dissertation employs various quantitative analyses, from OLS regression, logistic regression, panel regression, clustering analysis, and sentiment analyses. The goal of this methodological strategy was, among others, to shed light and disentangle some of the mechanisms behind spatial variations of AI diffusion. While quantitative approaches allow for utilizing big data and, e.g., estimating the relationship between different variables of interest, there are also several limitations connected to quantitative analyses that require consideration:

1. Despite attempts to ensure that the chosen data actually capture the mechanism of interest by deductively approaching the data and research questions at hand, it is still not possible to be completely certain. This is often the case in studies on the use of AI. I have attempted to minimize the risk of false positives by adopting different data sources and different methodological approaches.

2. Another limitation with quantitative analyses is the risk of omitted variable bias (Cinelli & Hazlett, 2020), which is false results due to one or more variables being omitted in the regressions. To limit this risk of bias, the quantitative analyses have, e.g., been based on a thorough literature review. Before constructing the models, a review of the existing literature has been conducted to identify relevant variables that have been previously shown to be associated with the outcome or dependent variable of interest.

The qualitative nature of Paper D allows for, as mentioned in Section 3.4.2, a more in-depth understanding of the mechanisms at play. The qualitative analysis took point of departure in semi-structured interviews and iterative analysis by combing inductive and deductive elements (Merriam, 1998). However, also in qualitative research, limitations exist:

1. Representativeness in the sample is often a challenge in qualitative studies. This could have been overcome by securing a large data sample, however, the main motivation for the study in Paper D ended up also being the main problem in the data collection process: There are fewer firms outside the main metropolitan regions adopting AI, and this is especially true for SMEs. The end of the data recruitment was, therefore, a mixture of saturation in the topics raised by the interviewees, emptying out the pool of relevant firms and time constraints.

4 Overview of the thesis chapters, relationship with the research subquestions

The main objective of the dissertation is to investigate the overreaching research question:

> **RQ:** ***How does the regional context influence the rate and direction of diffusion of Artificial Intelligence across regions?***

The section links the research questions of the individual papers to the overall research questions. The section, furthermore, expands on the theoretical context of the research and provides insights into the findings of the papers included in this dissertation.

4.1 Paper A: The role of time and space in the identification of left behind regions: A case-study of Denmark

As discussed in Section 2.1, regional growth patterns are not spatially evenly distributed due to long-term path-dependent processes of cumulative causation and increasing returns. Moreover, there is a general consensus that considering the context is crucial when analyzing regional economic dynamics, encompassing aspects such as structure, system, and policy (Eriksson et al., 2017).

In recent years a large literature has emerged on the topic of rising interregional inequality, the regions and places "left behind" and their political and (socio-)economic consequences (e.g., Davenport & Zaranko, 2020; Grillitsch et al., 2021). The literature often links the rising regional inequality to economic consequences related to lack of national coherence and to the rise in populism through what Rodríguez-Pose, (2018) termed *"the revenge of the places that don't matter"*. Despite the considerable interest in this topic, several scholars have pointed out that the literature lacks a consistent definition of the "left behind"-regions. The criticism focuses particularly on the often unnuanced and dichotomous emphasis on "winner" and "loser" regions (Lundquist & Olander, 1999; Perrons, 2012; Pike et al., 2016) based, often, on regional GDP. Furthermore, most studies tends to take a temporarily static perspective (MacKinnon et al., 2022). Arguably, this unnuanced perspective on regional types carries the risk of making the literature "muddy" and hard to interpret (Markusen, 1999), and in the worst case it risks creating a wrongful basis for regional development policy because regions may be assigned "solutions" that have little to do with their actual temporally and geographically contingent problems(Martin et al., 2021).

With Paper A, I set out to investigate how to create a regional classification system for the identification of left-behind regions, and therefore also other regions, that allowed for both a more robust and nuanced representation of different regions and that incorporates the theoretical understanding of rising regional inequalities as being the result of path-dependent processes driven by cumulative causation and increasing returns. Paper A, therefore, investigates the following research question;

> RQ1: *How can regional inequality and left behind regions be classified in smaller countries?*

First, the paper provides an overview of the state of identification of left-behind regions. Secondly, based on this analysis, the paper develops a new, robust methodology to identify left-behind regions considering the critical elements of time, temporal wisdom (Henning, 2019), and space, geographical wisdom (Boschma, 2017). It emphasizes the long-run development paths that different regions move along when identifying them. The paper finds that, despite increased interest in regional divergence, the method used to classify left-behind regions differs substantially across papers, partly due to dichotomous clustering based on static variables. The alternative method proposed in the paper uses k-means clustering on an extensive range of economic and demographic variables associated with regional development patterns to find those regions that not only appear the most alike at any point in time or within one dimension but over long periods and across many dimensions. The method is exemplified for Denmark using longitudinal data containing various variables from 1980 – 2018, covering the current wave of inter-regional inequality. This is argued to ensure a more robust and nuanced regional classification system, which allows the distinctions to go beyond the merely dichotomous nature of previous classification systems. The resulting regional classification illustrates that left-behind regions may arise based on different mechanisms, e.g., depopulation and de-industrialization, that call for different policy remedies. The robustness of this classification compared to previous methods is illustrated by showing that the clusters are better predictors of regional electoral patterns, a core outcome studied in the recent literature, than traditional methods.

4.2 Paper B: Spatial variations in AI diffusion: Employee-level evidence from Denmark on the role of internal DUI

As discussed in Section 2.2.2, technological change is a primary explanatory variable of differences in regional growth in both exogenous and endogenous growth theory. The main rationale is that technologies do not diffuse across time and space. This is due to different forms of innovative retardation factors and differences in innovative receptiveness. A factor often put at the forefront of most diffusion literature is the cumulative process of learning and knowledge. There is a widespread recognition that knowledge can take various forms, commonly categorized as tacit or codified knowledge (Polanyi, 1966). Codified knowledge is considered to be easily transformed into information and readily transmitted, whereas tacit knowledge is more challenging to transfer due to its intangible nature. Lundvall, (1988) argues that knowledge and interactions result in two types of knowledge: ’know-what’ or ’know-why’ and ’know-who’ or ’know-how’. The former is associated with codified scientific knowledge, while the latter represents tacit knowledge.

Moreover, extensive theoretical and empirical research demonstrates that learning and innovation mechanisms are significant in various sectors, albeit with varying roles influenced by sector-specific characteristics and firm strategies. (Pavitt, 1984; Rosenberg, 1982; Rothwell, 1977; von Hippel, 1976)

Building on this scholarship Jensen et al., (2007) introduced their idea of "Innovation Modes", where they characterize the different "forms of knowledge and modes of innovation," making a distinction between the utilization and creation of codified technical and scientific knowledge. The first mode, referred to as "Science, Technology, and Innovation" (STI), encompasses the "know-what" or "know-why". The second mode, known as "Doing, Using, and Interacting" (DUI), centers around learning based on experience and reflects the "know-who" or "know-how". After Jensen et al., (2007), a substantial body of literature has emerged and divided the two main groups into an external and an internal group, resulting in four subgroups. A recent stream of the literature argues that the innovation modes are not homogeneous across space and that there exist regional variations in the frequency of innovation modes and in the relationship between innovation mode and innovation outcomes (Doloreux & Shearmur, 2023). Recent literature has indicated a relationship between internal DUI and spatial variation in AI adoption, but as yet, limited empirical evidence exists to prove the posited relation (Corò et al., 2021). Furthermore, despite data limitations causing internal DUI activities to be often neglected in research, recent literature has showcased the strong relationship between innovative activities and internal DUI activities (Haus-Reve et al., 2022; Thomä, 2017). Paper B, therefore, investigates the following research question;

> RQ2: *How do regional variations in innovation modes affect the AI diffusion occurring in Denmark?*

Paper B is co-authored with Jacob Rubæk Holm. In this paper, we examine the spatial disparities in the diffusion of artificial intelligence (AI) across Denmark from 2016 to 2019. Our analysis reveals that the diffusion of AI is not evenly spread geographically. The adoption of AI, as a new automation technology, represents an innovation for the adopting firms. Our analysis is based on hypotheses that consider the geographical variations in the relationship between innovation modes and innovation outcomes. We find that firm-internal Doing, Using, and Interacting (DUI) activities partially predict the unequal spatial diffusion of AI.

To conduct our study, we leverage data from a survey conducted in the spring of 2019 at the employee level in Denmark, focusing on technologies and skills. This data allows us to differentiate between two types of AI: Helping AI, which complements labor, and Command AI, which substitutes it. The results indicate that regions with a strong industrial background face greater challenges in the technological transformation compared to both metropolitan regions and spatially peripheral regions that have traditionally struggled in terms of employment and population growth. These differences can be attributed to variations in the quantity and impact of DUI activities. The study contributes to the understanding of spatial variations in AI diffusion during the early stages of Industry 4.0. Additionally, it provides evidence at the employee level, highlighting the regional differences in DUI activities and their predictive ability for AI diffusion

4.3 Paper C: Informal institutions, information, and innovation: Regional co-evolution of technological discourses and AI investments in Denmark

The literature on Regional Innovation Systems (RIS) argues that some spatial variations between innovative activities depend on variations in the specific RIS (Braczyk et al., 1998). RIS consists of "*i) interacting public and private interests, ii) formal institutions, e.g., education institutions, financial institutions, and public authorities, iii) other institutions that contribute to the application and diffusion of knowledge, and iv) informal institutions*"(Drejer & Christensen, 2021). In this context, informal institutions is the unwritten expectations and rules, e.g., tacit customs, habits, or norms (Coenen & Díaz López, 2010). Despite a large body of literature arguing that variations of informal institutions impact innovative activities (Corradini et al., 2022; Lawson & Lorenz, 1999; Maskell & Malmberg, 1999; Saxenian, 1996; Storper, 2018a; Storper & Venables, 2004), as of yet, little empirical literature exists of the regional variations of the informal institution and their relation to innovative activities. Paper C, therefore, aims at investigating the following research question;

RQ3: *How do regional informal institutions co-evolve with AI adoption rates?*

To approach the research question, the paper investigated regional variations in the technological discourse on AI and whether or not it co-evolves with the municipality's willingness to invest in AI-related technologies. In recent years, the literature on regional divides has developed a strong research agenda on the importance and problems of the spatially unequal diffusion of new technologies. A recent branch of this literature focuses on textual data and argues, e.g., that the consumption of newspapers and the focus on the available information are both highly regional processes (Kayser, 2017; Ozgun & Broekel, 2021; Reischauer, 2018). It further posits that these regionally unequal distributions may affect the diffusion of new technologies. However, there is a lack of empirical evidence to support this posited relation. This study attempts to fill this research gap by taking advantage of two data sources; firm-level registry import data on AI-related technologies and newspaper data from more than 17.000 news articles from 375 newspapers with a locally varying readership covering all 98 Danish municipalities between 1985 - 2021. The method of using trade and import data as a proxy for technology diffusion is in no way novel (e.g., Caselli & Coleman, 2001). It has in recent years been used with other I4.0-related technologies (Abeliansky et al., 2020; Acemoglu et al., 2020; Castellani et al., 2022; Humlum, 2022) and with AI-related technologies more specifically (Domini et al., 2022).

The findings contain two main contributions: I) Longitudinal evidence from panel regressions shows that former manufacturing and now stagnating regions fall behind the metropolitan regions over time in coverage of new technologies. This finding supports the arguments in the previous literature that information availability and consumption are spatially unequally distributed. II) Panel regressions and sentiment analyses show a strong co-evolution between the level and tone of the AI news coverage and firm-level AI adoption, implying that regional accessibility of new technology information and the portrayal of the new technology matter for the diffusion rate of technology in firms. Furthermore, the study suggests that the AI adoption of firms in non-metropolitan regions may be more affected by the level and tone of AI news coverage in the region than in metropolitan regions.

4.4 Paper D: Regional barriers and trajectories of technological change in Danish manufacturing SMEs: A qualitative case study on early AI adopters

One of the fundamental parts of the literature on barriers to the diffusion of innovations is the size of the firm (e.g., Penrose, 1959). The argument has long been that smaller firms often will suffer from resource scarcity (e.g., Penrose, 1959). This refers to the lower financial capacities, making it harder for smaller firms to compete on salaries to attract high-skilled labor and perform innovative activities (International Labour Organisation, 2019).

This focus on smaller firms is also clear from the recent literature on barriers to AI adoption. As touched upon in Section 2.3, the challenges of SMEs in digital transformation are a central focus point in the recent literature on barriers to AI adoption. Some papers argue that SMEs have lower degrees of absorptive capacities (Kinkel et al., 2022; Müller et al., 2021), making AI adoption more difficult. Recent reports have also indicated that SMEs, especially with low technological knowledge bases, located in peripheral regions are likely to struggle the digital transformation and lose out on competitive advantages (OECD, 2021; Randall et al., 2020).

At the industry level, the literature has argued that the manufacturing industry has a particularly high level of AI adoption prospect due to the automation potentials in the manufacturing processes (e.g., Kinkel et al., 2022; Stentoft et al., 2021). Despite these emphases in the previous literature on SMEs challenges and the prospect of the manufacturing sector, however, the majority of the empirical studies tend to take on an urban perspective and thereby reinforce the urban bias that exists in innovation studies (Shearmur, 2017).

A different stream of the literature on enablers for innovative activities argues for higher success rates for regions beginning to develop AI-related technologies when they already had knowledge bases within scientific and/or ICT-domains (e.g., Balland & Boschma, 2022; Laffi & Boschma, 2022; Xiao & Boschma, 2022). Zolas et al., (2020) argues the same, just on the firm level. While these studies provide insight for regions and firms already relying on the previously obtained capacities, it is less clear what the firms and regions without previously obtained knowledge bases can do to ease the AI adoption process.

Therefore, Paper D set out to investigate the following research question;

> RQ4: *How do manufacturing SMEs in non-metropolitan regions perceive and develop their absorptive capacities to adopt AI?*

Paper D investigates if the regional context impacts the absorptive capacities of manufacturing SMEs in non-metropolitan regions attempting to adopt AI.

The paper employs the framework on absorptive capacities (Cohen & Levinthal, 1990; Matusik & Heeley, 2005; Zahra & George, 2002), evolutionary technological change (Nelson & Winter, 1982; Rigby & Essletzbichler, 1997), with emphasis on relatedness (e.g., Boschma, 2017). The paper follows the argumentation from Neffke et al., (2018) and sees the region as a bundle of a varying degree of capabilities (Lawson, 1999), which a firm is more or less able to access.

Empirically, the paper builds on in-depth semi-structured interviews with representatives from nine manufacturing SMEs located in non-metropolitan regions in Denmark who are in the process of adopting AI. The paper finds that a mixture of barriers limits the manufacturing SMEs in former industrial regions from adopting AI. These include a lack of relevant skills and difficulties attracting qualified workers, challenges making AI less abstract and easier to adopt into their business models, conservatism within the organization, and limited opportunities for finding inspiration from like-minded firms and finding information about both new technologies and grant opportunities. The firms attempt different strategies to overcome the lack of traditional absorptive capacities by building on already existing capabilities, e.g., drawing on previous collaborations with research institutes, drawing on employees that understand the culture, qualities, and goals of the firm who also have a working knowledge of digital phenomenons, and attempting to create regional buzz and demand.

5 Conclusion

This final section in the synopsis aims at summarizing the findings of the dissertation and their contributions to the literature, which are also represented in Figure 7. The section additionally discusses future research avenues and managerial and policy recommendations.

5.1 Summary of findings and general discussion

The dissertation aimed to contribute to our understanding of the regional variations in barriers, opportunities, and enablers in AI diffusion, by studying the case of Denmark and exploring the research question:

> **RQ:** ***How does the regional context influence the rate and direction of the diffusion of Artificial Intelligence across regions?***

The dissertation has largely been informed by the evolutionary theoretical approach to technological change, where a main assumption is that regions in general are heterogenous across time and space, and that these differences evolve over time in a path-dependent manner where factors impacting the development are reinforcing themselves over time. The literature further states that these path-dependent differences create differentiated abilities to create and absorb new technologies. The dissertation has adopted and developed the following theoretical framework, which has informed the analyses in the dissertation: (1) the path-dependent and cumulative nature of regional variations, leading to (2) differences in how regions learn and innovate, (3) differences in regional capacities to absorb new technologies, and (4) differences in regional institutional contexts that shape the regional ability to learn, innovate, and absorb. This has resulted in four papers, each tackling an aspect of this framework:

1. Paper A investigates the development of regional classification that allows for the theoretical incorporation of the path-dependent and cumulative nature of regional variations

2. Paper B examines the differences in how regions learn and innovate by exploring the role of innovation modes for spatial variation in AI diffusion

3. Paper C focuses on differences in regional informal institutions and how these shape the regional ability to adopt AI

4. Paper D looks at the role of absorptive capacities by examining the AI adoption processes for manufacturing, non-metropolitan SMEs

	Question	Data	Methods	Findings
Paper A	• How can regional inequality and left behind regions be classified?	• Danish administrative registry data	• K-Means clustering • OLS regression	• By taking point of departure in multiple, longitudinal development variables and clustering technique the paper develops a new regional classification system
Paper B	• How do regional variations in innovation modes affect the AI diffusion?	• TASK survey • Danish administrative registry data	• PCA • Logistic regression	• Old industrial regions has a slower AI diffusion rate and these differences can in part be explained by differences in frequencies and impact of internal DUI-activities
Paper C	• How do regional informal institutions co-evolve with AI adoption rates?	• Registry data: UHDI • Newspapers articles on AI • Danish administrative registry data	• Sentiment analysis • Fixed effect panel regression • Granger causality analysis	• Newspapers can be used as a proxy for the technological discourse in regional informal institutions. Regional discourse co-evolve with regional import of AI
Paper D	• How do manufacturing SMEs in non-metropolitan regions perceive and develop their absorptive capacities to adopt AI?	• Semi-structured interviews	• Semi-structured interviews • Iterative analysis combining deductive and inductive reasoning	• The SMEs develop different absorptive capacities in order to overcome their disadvantages in relation to AI implementation in their businesses

Fig. 7: Summary of papers.

The main findings of the dissertation are as follows:

1. **AI takes on spatial patterns, even in small national contexts like Denmark.** In the case of Denmark, the dissertation shows that the highest degrees of applied AI use can be observed in the metropolitan regions by the end of the 2010s. It is less used in the peripheral regions, referred to as Seaside Denmark in the dissertation, and the regions typically characterized by manufacturing specialization, referred to as the Old Industrial Heartlands. An important finding is that the degree of regional variation depends on the AI type being investigated. However, despite variations in the usage of different types of investigated AI, it is evident across the papers that the metropolitan regions are significantly ahead of other regions. Paper B shows that the Old Industrial Heartland regions fall behind the Metropolis/Suburban regions. The differences between Seaside Denmark and the Metropolis/Suburban regions, however, are not statistically significant. Paper C studies a type of AI, which is often closely associated with manufacturing automation. It is, therefore, surprising that The Old Industrial Heartland regions remained persistently behind the Metropolis regions throughout the investigated time frame (2000 – 2018), even though they started to catch up to the Suburban regions in the last four years. It would be expected that the Old Industrial Heartlands, which have a higher share of manufacturing firms, would be more likely to adopt this technology. However, that is not the case. Paper D investigated the non-metropolitan manufacturing SMEs' AI adoption barriers and strategies. The interviewee recruitment process indicated the uneven distribution of AI across non-metropolitan regions. Taken together, the results illustrate that the Metropolis regions are succeeding in the AI-diffusion process to a greater extent than the other regions, especially the Seaside Denmark and the Old Industrial Heartland regions.

2. **Different mechanisms function as barriers and enablers for spatial AI diffusion.** The dissertation investigates the antecedents of uneven spatial AI diffusion by studying the role of factors the previous literature suggests as potential enablers or barriers to previous technology diffusion. These factors include the role of innovation modes, with particular emphasis on internal DUI and work organization, the role of informal institutions, including the regional technological discourse, and the role of absorptive capacities and relatedness, meaning the routines and processes based on the firm's and regions resources that support technology adoption, and firms' experiences using related technologies that can be drawn on in the adoption process. The dissertation suggests that these factors do act as barriers and enablers to AI adoption, that

they are multifaceted, and that many likely develop through mutual reinforcement over long periods.

3. **The impact of the mechanisms is regionally differentiated**. This means that the relationship between the different variables investigated in this dissertation and the adoption of AI is stronger in some regions while being weaker in other regions. E.g., Paper B showcases that the relationship between DUI and AI adoption is stronger in the Old Industrial Heartland regions and the Seaside Denmark regions compared the Metropolitan regions. The same is true in Paper C, where the informal institutions in the shape of regional, technological discourse, measured as newspaper portrayal, are shown to have a stronger relation to AI adoption in the Old Industrial Heartland regions than in any of the other regions. Paper D shows that firms in non-metropolitan regions are likely to develop strategies to overcome the lack of traditional absorptive capacities, which might include workers' digital skills. A key strategy for the firms is to build on the capacities already established in the firm. These strategies are largely dependent on available resources in their regional setting.

5.2 Recommendations for further research

While this dissertation has helped shed light on some of the mechanisms behind the unequal diffusion of AI, several aspects remain unanswered. These unanswered questions provide direction for future research avenues.

First, the dissertation emphasizes the role of the factors acting as barriers and enablers for spatial AI diffusion. The dissertation has especially emphasized the role of learning, including firms' innovation modes, the role of informal institutions, and the role of size in relation to absorptive capacities and relatedness between previously used and the new technology. While interesting and core features of the literature, each theme could have an independent Ph.D. devoted to them, and many aspects of these topics remain to be studied. One example is how related industrial diversification and skill relatedness affects AI technology adoption. This has only briefly been touched upon in Paper B, Paper C, and Paper D despite that the previous literature suggests it could be an important driver of the diffusion pattern. Naturally, there are many more factors that could affect AI diffusion and technology diffusion in general, which this dissertation has not looked into.

Second, there is a question about the generalizability of the findings. While this dissertation argues that the Danish case is of interest due to its extreme case characteristics, discussed in Section 3.1, it is still possible that the findings cannot be generalized to other settings. This warrants more research into the factors studied in the dissertation in different national and institutional contexts.

Third, the dissertation has largely investigated how the relationship and strength thereof, between different variables and the adoption of AI, differs in different regional settings. This means that little effort has been made to investigate the causality of the relationship. While not the goal of the dissertation, this leaves an interesting future research avenue.

Fourth, while this dissertation has mainly focused on traditional, statistical AI, a new wave of generative AI has emerged in the last months of this Ph.D.-project. While I have argued in the synopsis that the social constructivist approach to the definition and interpretations of AI could encompass generative AI if the research had been conducted as this new iteration of the technology became available, the timing of the data collection and analysis implies that the conclusions may not be transferable to generative AI adoption. This opens the question of whether the studied mechanisms function similarly in the diffusion of generative AI as in traditional, statistical AI.

5.3 Policy recommendations

The dissertation advances the understanding of the mechanisms behind the spatially unequal distribution of AI in the early stages of its diffusion process. There are six main policy recommendations for policymakers interested in supporting the diffusion processes of AI across various regions. To mitigate these potential inequalities, I propose that policymakers and stakeholders consider strategies such as:

First, it is crucial for policymakers to incorporate the regional context and to acknowledge that the barriers to the diffusion of AI vary across space, meaning that what works in region X might have different impacts in region Y. In the example of Paper B, whereas internal DUI activities appear to have a substantive supporting role in AI adoption in the Old Industrial Heartland regions and the geographically peripheral Seaside regions, the role seems limited in the Suburban and Metropolitan regions. A policy to support DUI-based AI adoption may, therefore, not be as relevant in the Metropolitan region as in the Old Industrial Heartland.

Second, early evidence presented in this dissertation indicates that it is important to be careful about the definitions of AI, meaning that different types of AI follow different diffusion patterns.

Third, policymakers, especially those in regions with fewer existing technology adoption capabilities, might benefit from redirecting focus from supporting the development and invention of AI-related technologies to emphasizing AI adoption and diffusion. This dissertation argued for the importance of emphasizing diffusion. This is aligned with previous studies that has argued that the positive societal benefits from developing innovation clusters by stimulation of R&D are more limited and challenging to achieve than trying to remove some hindrances to successful spatial innovation diffusion.

Fourth, the dissertation argues for supporting institutions for knowledge and information sharing and development. As pointed out in Paper C, different regions have different ways and points of departure in discussing AI, and this co-evolves with AI-related activities. Furthermore, the findings of Paper D indicate that the interviews SMEs in non-metropolitan regions struggle with their AI adoption, among other things due to the lack of knowledge institutions in a close geographical proximity.

Fifth and finally, the dissertation suggests the importance of a longitudinal development strategy. This recommendation is twofold. First, the dissertation argues that regional AI diffusion, and more generally digitalization, requires resources and capabilities that evolve over more extended periods and that policy, therefore, needs to be based on a long-term strategy. The dissertation arguments suggest that the strategy could emphasize, among other things, A) promoting investment in digital infrastructure to improve connectivity and access to AI technologies in underserved regions. B) expanding access to AI education and training programs to ensure that individuals in all regions have the opportunity to develop AI-related skills. C) supporting initiatives that encourage the collection and sharing of diverse and representative data to prevent data concentration in specific regions. Secondly and more generally, the dissertation, and especially Paper A, argues for the importance of building regional policies on analysis based on longitudinal data and research findings due to their more robust nature.

By addressing these factors and adopting inclusive policies, I believe it would be possible to minimize the potential regional inequalities that may arise from the diffusion of AI.

5.4 Managerial recommendations

The results of the dissertation can give rise to advice relevant not only to policymakers but also to low-technological businesses. This section attempts to provide a few, perhaps rather generic, related recommendations for low-technological businesses, especially SMEs, outside the main metropolitan and innovative centers that aim at implementing AI in their businesses. As this dissertation has argued: AI adoption can potentially be a long and tiresome process if the firm does not already have technological knowledge and experience. The recommendations might ease the adoption process.

The main recommendation based on the findings in this dissertation is to develop incremental and long-term strategies that allow for step-by-step adoption that (1) the firm can commit to, and (2) that builds on the existing and related capabilities the firm already possesses. The recommendation,among other things, includes the following sub-recommendations:

1. Determine the goal of the AI adoption concerning the firm's overall business model.

2. Develop a persistent data strategy, e.g., digitalizing data and records of interest that relate to the AI adoption goal, that the firm can sustain over time.

3. Build on existing partnerships to exchange knowledge and exploit the expertise that exists among other firms in the partnerships.

4. Get hold of a "middleman" who can combine knowledge of the firm's existing organizational strengths and goals, and the technical landscape.

5.5 Final remarks

In 1988 two of the founding members of my research group, IKE, argued for their dissatisfaction with the tendency of the time "to concentrate technology policies exclusively on the supply side and particularly on the stimulation of R&D" (Andersen & Lundvall, 1988). However, 35 years later, not much has changed in the literature and policy-making. Attention is mostly paid to the development and creation of new technologies rather than how we get people to use the technologies.

With this dissertation, I set out to shed light on a small part of the complex and intertwined innovation diffusion processes and the uneven pattern of AI adoption. And though more mechanisms exist and need to be brought to daylight, I hope that, at the very least, this research can help spark a deeper discussion on how and why the diffusion of new technologies is shaped. I am very thankful to you, the reader, for paying interest in this work.

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Part II

Papers

Paper A

The role of time and space in the identification of left behind regions: *A case-study of Denmark*

Sigrid Jessen

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Paper B

Spatial variations in AI diffusion:
Employee-level evidence from Denmark on the role of internal DUI

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Abstract

In this paper, we analyze the spatial variations in the diffusion of artificial intelligence (AI) across Denmark from 2016 to 2019. We show that AI diffusion is spatially uneven. This is in accordance with recent literature, which shows that the diffusion of AI takes on a spatial pattern with regional losers and winners. We build on the literature on innovation modes and put specific emphasis on the role of the firm-internal Learning-by-Doing, Using, and Interacting (DUI) innovation mode. Adopting a new automation technology such as AI is an innovation for the adopting firm, and hypotheses concerning geographical differences in the relationship between innovation modes and innovation outcomes form the starting point of our analysis. We find that firm-internal DUI activities contribute to explaining the unequal spatial diffusion of AI.

We exploit a survey on technologies and skills undertaken at the employee level in the spring of 2019 in Denmark. The data allow us to distinguish between two types of AI: Helping AI, which complements labor, and Command AI, which substitutes labor. Results show that Old Industrial Heartland regions seem to struggle more in the technological transformation compared to both metropolitan regions and spatially peripheral regions traditionally known to struggle in their regional development in terms of employment and population growth. These differences are associated with differences in quantity and impact of DUI activities. This study has two main contributions; i) Showcasing spatial variations in diffusion patterns of AI in the early stages of Industry 4.0 and ii) Providing employee-level evidence on the regional differences in DUI activities and their ability to predict AI diffusion.

Keywords:*Innovation modes, Internal DUI, Innovation outcomes, Regional inequality, Denmark*

1 Introduction

A recent technology that is believed to have monumental consequences for the economy is artificial intelligence (AI). Early studies have shown that AI does not diffuse evenly across space (Muro et al., 2019), and its potential impact on regional inequality is believed to be severe (e.g., Greef & Schroeder, 2021). It is, therefore, necessary to untangle the geographical mechanisms behind firm AI adoption.

The literature on the geography of innovation, among others, states that innovation is a spatially varying phenomenon in terms of the frequency of innovative activities occurring and the mechanisms behind (e.g., Isaksen &

Trippl, 2017).

This paper builds on top of Doloreux and Shearmur, (2023) and connects the literature on innovation modes (Jensen et al., 2007) and literature on the geography of innovations (e.g., Asheim & Gertler, 2006; Audretsch & Feldman, 1996) to investigate regional settings´ impact on the relationship between innovation mode and innovation outcome by taking point of departure in firm-level AI adoption in Danish firms across Danish regions.

Adopting AI in a firm is a process innovation for the firm and, thus an outcome of its innovation process. To understand differences in innovation processes between firms Jensen et al., (2007) developed the concept of innovation modes, and demonstrated their relationship with innovation outcomes. Later researchers have attempted to clarify the varying effects that the STI (Science and Technology-based innovation) and DUI (Learning-by-Doing, Using, and Interacting) innovation modes, respectively have on firms' innovation performance (e.g. Apanasovich et al., 2016; Carrillo-Carrillo & Alcalde-Heras, 2020; Doloreux et al., 2020; Fitjar & Rodríguez-Pose, 2013; Parrilli et al., 2020a; Thomä, 2017). New contributions furthermore introduce a distinction between internal and external innovation modes depending on the main source of new ideas (Doloreux & Shearmur, 2023; Haus-Reve et al., 2022), and have found that the frequency of innovation modes as wells as the relationship between innovation modes and outcomes vary across regions (Doloreux & Shearmur, 2023; Parrilli et al., 2020a).

This paper aims to investigate regional differences in the diffusion of AI at the intrinsic margin, that is, within organizations. This is an incremental innovation entailing increased use of AI among the firm's employees and is thus primarily furthered by the DUI mode of innovation (Jensen et al., 2007), not least internal DUI (Thomä, 2017).

Despite recent attempts in the literature on innovation modes to remedy the gap, internal DUI activities are still by far the most under-investigated due to data limitations (Haus-Reve et al., 2022), especially in the case of regional differences in the relationship between innovation mode and innovation outcome. However, recent literature has implied a relationship between AI adoption and internal DUI activities (Corò et al., 2021).

The paper takes the point of departure in Danish regions. It takes advantage of the TASK survey merged with Danish registry data, which allows us to measure AI adoption and work organization at the employee level from 2016 - 2019. We distinguish between two types of AI, Command AI, which gives orders and directions, and Helping AI, which augments labor by supplying predictions that allow for better decisions. Furthermore, we measure a range of internal DUI activities at the employee level.

The paper finds spatial divisions in the diffusion of AI, with the former industrial heartland lagging behind both the peripheral regions and especially the metropolitan regions. Previous studies on diffusion tend to focus on extrinsic margins. I.e., agents adopting AI. We show that diffusion, in a broader sense explicitly focusing on the intrinsic margin, i.e., increases in the frequency of AI use by agents who have already adopted AI previously, at the employee level but also including the extrinsic margin, is much less dependent on the local industrial structure. Instead, intrinsic diffusion in firms and within jobs depends on the employee and job characteristics. Indeed, we find that internal DUI activities are related to employee AI adoption. Internal DUI activities vary across space in frequency but also in terms of impact on AI adoption, with more substantial impacts in the peripheral regions compared to the old industrial regions.

The remainder of this paper is structured as follows. The next section discusses the regional variations in innovation modes and their relation to AI adoption. The third section will present the data and the empirical strategy, including a discussion of the regional scale. Section four presents our empirical analysis and results, while the paper's final section concludes and discusses policy implications.

2 Theoretical framing

2.1 Regional drivers of technological change

There lies a tremendous economic potential for regions that manage to include the new Industry (I4.0) technologies into the regional context (Boschma et al., 2013). However, if some regions lack the capabilities to adopt I4.0 technologies successfully, then the already existing and increasing regional divides risk being further enhanced (Bailey & De Propris, 2019; Corradini et al., 2021).

The spatial embeddedness of technological change has long been a main point of discussion for innovation scholars (e.g. Jaffe et al., 1993). A large body of literature has resulted in a widespread recognition that innovation and its diffusion are geographically bounded by nature and are caused by the continuous interactions and transfers of knowledge amongst economic, institutional, and organizational actors throughout the regional innovation system (e.g. Freeman et al., 1987; Lundvall, 1992; Storper, 2018). Along this research agenda comes a strong emphasis on the path-dependent elements of technological change, which suggests that spatial diffusion patterns are the result of local capabilities and the related amount of technological resources within the region, creating subsequently differing localized knowledge endowments and opportunities to learn and thus innovate (Martin & Sunley, 2006).

These regional differences in localized knowledge endowments may cause a spatially uneven diffusion of new technology, causing some regions to struggle with technological change. Regions needing to implement more technology-specific knowledge in their preexisting knowledge bases are especially struggling (Castellacci, 2008). Moreover, since the adoption of newer technologies requires a unique form of know-how, regions are expected to implement, explore and pursue technological change bounded by their already obtained technological capabilities (Boschma, 2017), creating regional differences in firms' innovation modes, and subsequently regional differences in the relationship between the innovation modes and innovation outcomes (Doloreux & Shearmur, 2023).

2.2 Innovation modes across regions

Literature has argued that differentiated knowledge bases manifest themselves in the ways firms in regions learn and thus implement new technologies (e.g. Arrow, 1962). These different modes of innovation (Jensen et al., 2007) caused by different knowledge bases lead firms in different regions to innovate differently (Asheim et al., 2011). Jensen et al., (2007) describe the 'forms of knowledge and modes of innovation', differentiating between the STI innovation modes (codified technical and scientific knowledge), and the DUI innovation modes (relying on processes of obtaining learning based on experience).

Recent papers (Doloreux & Shearmur, 2023; Parrilli et al., 2020a) zoom in on regional variations in the frequency of innovation modes and on the relationship between innovation mode and innovation outcomes. In general, firms in metropolitan regions that tend to exhibit strong technological and innovative capabilities are thought to be more likely to adopt the STI-innovation modes (Isaksen & Trippl, 2017). These regions have abundant human capital and display a high absorptive capacity, enabling their businesses to benefit from investment in research and development activities (Cohen & Levinthal, 1990). The innovation modes and the relationship between innovation modes and innovation outcomes outside the metropolitan regions are under-investigated (Parrilli & Heras, 2016). Some researchers have argued that literature on the geography of innovation is skewed in favor of urban innovation (Shearmur, 2017), which is unjustified recent studies have demonstrated that innovation occurs in peripheral regions as well. However, it is worth noting that the outcomes of innovation and the relationship between innovation mode and its outcomes may differ in these non-urban regions compared to urban areas (Eder, 2019; Shearmur & Doloreux, 2021).

Exceptions that try to remedy this gap in the literature include Parrilli et al., (2020a). Parrilli et al., (2020a) investigate potential differences in firms' innovation outcomes concerning their innovation modes in European regions classified according to innovation scoreboard ranking. They find that establishments in the most innovative regions apply both DUI and STI innovation modes, both internal and external modes, with positive results for innovation outcomes. Establishments in moderately innovative regions that are catching up are mostly having success in adopting DUI modes. Lastly, establishments in modestly innovative regions mainly depend on DUI activities but have less impact on innovation outcomes than establishments in moderately innovative regions.

In a similar study, Hervás-Oliver et al., (2021) show that modes of innovation are highly influenced by the innovative, economic, and institutional environment in which the SMEs are located. They find that SMEs in highly innovative regions are significantly influenced by a mixture of various forms of external collaboration, internal R&D, and non-R&D inputs, which greatly impact their innovation outcomes. Conversely, SMEs in less innovative regions rely more heavily on external ties, e.g., firm collaboration.

Doloreux and Shearmur, (2023) builds on top of the literature on the geography of innovation modes by investigating the role of geographical proximity on the impact of innovation modes on innovation outcomes. They find that both external and internal innovation modes have higher impacts on a range of different innovation outcomes in the metropolitan regions compared to the non-metropolitan and central regions. Finally, in central regions, external DUI, such as collaboration with customers or suppliers, is found not to affect innovation outcomes, while internal DUI has a positive effect.

2.3 The role of innovation modes for spatial diffusion of AI

Numerous studies have emphasized the significance of achieving the right combination of know-how and know-why among workers when firms aim to adopt AI and other I4.0 technologies (Bongomin et al., 2020; Brynjolfsson & McAfee, 2014; Janis & Alias, 2017; Raj et al., 2020).

As previously mentioned, Jensen et al., (2007) emphasized that innovation requires specialized labor capable of utilizing new technologies (know-how) and understanding their rationale for innovation and growth (know-why). In the context of AI, the same argument is being put forward. The knowledge profiles of a firm's workforce, encompassing both know-how and know-why, play a pivotal role in the success of AI adoption (Bongomin et al., 2020; Raj et al., 2020). Corò et al., (2021) emphasized the necessity of a workforce with a certain set of technical skills capable of interacting with these new digital infrastructures and the ability to comprehend and apply scientific knowledge based on I4.0 technologies in the strategic decisions related to the organization's production processes, logistics, and activities.

The literature largely emphasizes the importance of STI in relation to AI adoption due to the advanced nature of the technology (e.g., Zolas et al., 2020). The argument is that AI largely is "analytical knowledge" and, therefore, requires intellectual workers with adequate scientific knowledge profiles possessing analytical knowledge (Corò et al., 2021; Grillitsch et al., 2017). However, the relationship may not be straightforward and could be regionally dependent. Corò et al., (2021) found that the adoption of I4.0 technologies, except AI, was associated with an increase in high-skilled labor, particularly technical workers, in industrial districts. The results for AI were insignificant, suggesting that AI adoption may require higher levels of DUI rather than STI in these types of regions.

In conclusion, studies highlight the importance of knowledge workers with critical thinking and intellectual knowledge (know-why) as well as knowledge about organizational applications and methods (know-how) for successful AI implementation (Bongomin et al., 2020; Corò et al., 2021). However, despite acknowledging that innovation generally requires a combination of DUI and STI, literature on I4.0-related technologies tends to emphasize STI in their studies. Recent studies on regional variations in innovation outcomes (Doloreux & Shearmur, 2023; Parrilli et al., 2020b) and the results by Corò et al., (2021) suggest that regions catching up in STI modes may rely more on DUI for AI adoption. However, further investigation is needed to explore these assumptions in relation to AI holds.

2.3.1 Diffusion on the intrinsic vs. extrinsic margins

Until this point in the theoretical framing, the focus has been on the diffusion and implementation of AI and other I4.0-technologies from an extrinsic point of view. I.e., the number of new users of the new technology. This is the common focus in the literature (Sriwannawit & Sandström, 2015). However, we argue that to understand the uneven distribution of new innovations, it is necessary to include both the number of new users and the degree of the use of the new technology, or put differently, the diffusion at both the extrinsic and the intrinsic margin. The full effect of new technology is not observed or experienced the first time the technology is used but when the new technology becomes a pervasive part of different routines across the organization. This is especially true for technologies with widespread potential, such as AI, which may even be new general-purpose technology (Agrawal et al., 2019). When discussing the spatial diffusion of new technologies, it matters whether or not the new users are using the technology every day or if the users only use it monthly. So even though the regions lagging behind the technological transformation might catch up on the extrinsic margin, they might still struggle on the intrinsic margin regarding the degree the technology is being used, causing them to struggle when new technologies should be adopted in the future. The innovation modes of firms are thus crucial for diffusion on both the extrinsic and the intrinsic margin, and (internal) DUI is essential for incremental innovation (Thomä, 2017) and, thereby, intrinsic diffusion of AI.

Working with AI builds AI capabilities at the individual and organizational levels. Further intrinsic diffusion of AI in the organization and jobs may be more likely when AI know-how has been built through experience. Thus DUI learning and forms of work organization that support DUI learning increase the rate of AI diffusion at the intrinsic margin at the job level and at the intrinsic margin at the organizational level, which is likely to include both diffusion at the extrinsic and intrinsic margin among the members of the organization.

The initial observation of the paper is that firms in different regional contexts adopt distinct innovation modes, produce distinct innovation outcomes, and the relationship between innovation mode and innovation outcome varies across these regional contexts. The two core hypotheses of this study are:

1. Regional variation in the diffusion of AI at the intrinsic margin depends on the regional differences in the relationship between internal DUI activities and innovation outcomes.

2. The regions outside the metropolitan regions associated with lower levels of innovative activities are more dependent on DUI mode regarding AI diffusion

3 Methods and data

The key objective of this study is to analyze the spatial divides in AI diffusion across Danish regions with the expectation that innovation modes, e.g., internal DUI, capture important preconditions for this diffusion. Therefore, the following section will introduce the regional categorization employed in this study before introducing the dependent variable and the other control variables.

3.1 Types of regions

When analyzing the regional scale in Denmark, we make use of the regional typology developed in Jessen, (2023). As argued in Jessen, (2023), regional taxonomies distinguishing between periphery and core or using a similar distinction often rely on only one or two variables, are often at least partially subjective, and make the error of categorizing regions according to static level of development. At the same time, it would arguably be more appropriate to rely on relative differences in long term development for categorization (Rodríguez-Pose, 2018).

The classification by Jessen defines four categories of municipalities in Denmark depending on relative development from 1980 to 2018. For each Danish municipality, the analysis takes the development patterns for nine

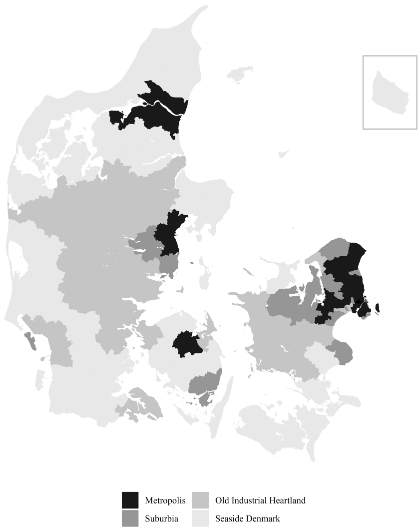

Fig. B.1: Danish municipalities by development category. Source: Figure 6 in Jessen, (2023)

variables. Each municipality is ranked for each variable in both 1980 and 2018, and the change in rank is then used for clustering the municipalities. Figure B.1 shows how the four categories are distributed across Denmark.

The taxonomy distinguishes between municipalities belonging to 1) *Seaside Denmark*, where the level of education has been declining relative to the national average from 1980 to 2018 while relative SME employment has been increasing. Cf Figure B.1 these municipalities are mostly coastal areas 2) *Suburbia* are municipalities close to but not including the major university cities of Denmark. These municipalities are characterized by relative income increase, increasing relative age, relative decline in the share of jobs requiring tertiary education, and a shift away from SME employment. The *Metropolis* are the four main university cities of Denmark: Aalborg, Odense, Aarhus, and Copenhagen, plus several other municipalities near Copenhagen. These have been characterized by strongly decreasing relative age, increasing level of education, and increasing concentration of patenting and of population. The final category is 4) the *Old Industrial Heartland* with a strong relative decrease in manufacturing employment. Interestingly, inhabitants of the Old Industrial Heartlands have not become relatively poorer or older. This underlines the point by Rodríguez-Pose, (2018) that it is not the level of development but the loss of identity associated with de-industrialization, which represents a challenge for such regions. As argued previously, we do not expect a difference in AI diffusion between the metro and suburban regions; these categories are thus merged. Therefore, the variable for the regional classification has three levels, with the Old Industrial Heartland regions as the reference in our analysis.

By adopting the Jessen, (2023) regional classification, we allow for a more robust discussion of regional development trends rather than only observing one point in time. We furthermore allow for a more in-depth analysis of the regional divides rather than only seeing the metropolitan region and the rest of the country as a large grey mass.

By taking Denmark as a case, this study allows a glimpse into a different setting when discussing spatial variations of AI diffusion. Denmark is traditionally perceived as a homogeneous country with little regional inequality compared to larger countries such as the US. This allows for a more extreme case in which it can be argued that if differences in the regional adoption of technologies exist in Denmark, they are like to also occur in countries with greater regional differences (Flyvbjerg, 2006).

3.2 Dependent variable: the spatial diffusion of AI from 2016 - 2019

3.2.1 Types of AI

To understand the diffusion patterns of AI, this study takes advantage of the Danish survey on technologies and skills (TASK) survey by researchers at Aalborg University and Statistics Denmark. The TASK survey is at the employee level and was conducted in the spring of 2019. The survey provides a representative data set on the usage of I4.0-related technologies, e.g., robotics and AI. The survey furthermore provides information on work organization at the individual level. To ensure representation of the Danish population, post-stratification weights were provided by Statistics Denmark, which was derived from administrative registry data. The total response rate was 39.9 percent allowing for a final dataset of 1244 observations. The data offer unique insights into the relationship between the use of technology at work and other job characteristics and is one of the world's first large-scale employee-level surveys on the use of I4.0 technologies, skills, and tasks. More information about the TASK survey can be found in Gjerding et al., (2020).

Furthermore, we merge the TASK data to registry data on the individual level. This allows us to gain detailed and longitudinal data on all employed persons, their workplaces, and firms in Denmark from 1980 onwards.

AI is a broad concept with multiple definitions. AI must therefore be strictly defined when discussing outcomes such as labor market impacts, societal gains, and diffusion patterns. Given the definition of AI, the analysis is further complicated by the multiple applications of AI. It may be argued that it is pivotal to differentiate which type of AI is being analyzed; otherwise, the research and the subsequent policy-making risk being biased (Acemoglu

& Restrepo, 2020).

In this paper, we follow Agrawal et al., (2019), who defines AI as a technology that automates prediction.

In this paper, we differentiate between two types of AI: "Command AI" and "Helping AI". Command AI provides a prediction that makes any further decision-making irrelevant. The employee must simply follow the instructions of the AI. Such AI is labor-replacing and is more useful when tasks are repetitive and in larger firms. Helping AI, which provides a prediction that human labor then uses to make a decision, including decisions on further tasks, requires more skill than Command AI. It is thus more likely to be used in jobs with autonomy and complex tasks. Its diffusion is also more reliant on knowledge flows into the firm. When following this definition, it becomes clear that the potential micro-dynamics behind the adoption of AI might vary depending on which type of AI is being investigated. Command AI does not depend on the know-why but on a greater extent of know-how. Helping AI, in contrast, requires a combination of know-how and know-why.

Over time as AI technologies evolve, the set of prediction tasks that can be automated expands, and the basis for deciding whether to apply AI as Command or Helping AI changes. Our data were collected in 2019, and at that time, an example of a prediction task automated with Command AI is maintenance. The AI predicts the order in which several machines or other units need maintenance, thus taking away the discretion of the maintenance engineer in planning the order of her maintenance jobs. Examples of Helping AI are often found in health services where the AI evaluates data, for example, images, and suggests a diagnosis. In contrast, a health professional undertakes the final diagnosis and treatment decisions. The example highlights two important aspects of Helping AI: one is that while the use of Helping AI entails that the health professional has discretion, the AI nevertheless sets the work pace, and it potentially introduces several routine tasks to other members of the organization in terms of collecting, cleaning and feeding data to the AI. Secondly, the decision of whether to use Helping or Command AI depends not only on the objective quality of the prediction supplied by the AI. Considerations of legitimacy and liability of the ensuing decision task can necessitate a human role. Our data do not allow us to explore these aspects of AI in any detail.

The TASK data contain indicators for the frequency of using two different types of AI. Holm et al., (2021) also using the TASK data leveraged this distinction to explore different impacts of AI on jobs depending on the type of AI. The two types are:

- receive orders or directions generated automatically by a computer or by computerized machinery
- make use of information compiled automatically for you by a computer

Fig. B.2: Change in AI diffusion 2016 - 2019. Left: Command AI. Right: Helping

or by computerized machinery for making decisions or for advising clients or customers

We refer to these as 'Command AI' and 'Helping AI' respectively. These two ways of using AI are consistent with the model suggested by Agrawal et al., (2019) as discussed above.

Our two dependent variables are both binary. They take the value 1 if the respondent reports an increase in the use of Command AI or Helping AI, respectively, from 2016 to 2019. The TASK survey also contains information on job changes from 2016 - 2019, and we exclude all individuals who were not in the same job in 2016 and 2019 so that the reported change in AI use is within a job, which results in a total sample of 796 observations.

Figure B.2 shows the spatial pattern of AI diffusion over the period. The TASK survey does not have sufficient observations to validly estimate diffusion at the municipal level, so in Figure B.2, the municipalities are grouped into 20 groups: the five administrative regions of Denmark, each divided into Seaside Denmark, Old Industrial Heartland, Suburbia, and the study and Metropolis regions. For each of the 20 resulting regions, the maps in Figure B.2 show the share of jobs where an increase in AI use from 2016 - 2019 was reported. A lighter shade indicates greater diffusion.

The darkest areas in Figure B.2 are the regions where the increase in AI use was lowest. These are mostly in central and south Jutland (i.e., mainland Denmark), and to some degree, on the islands to the east of the mainland. This pattern is observed both for Command AI and for Helping AI. One difference between the two forms of using AI, however, is that the diffusion of Command AI appears to have been particularly strong in a few municipalities in the eastern part of the country, whereas Helping AI appears to have diffused more broadly in the large university cities as well as in the northern and northeastern parts.

3.3 Independent and control variables

Our set of independent variables allows us to discuss the factors expected to predict the adoption of AI. The main independent variable is the different contexts described by the regional taxonomy as presented above. This taxonomy describes the context for local capability formation and path dependence. Secondly, a range of independent variables captures the skills and knowledge of the individuals.

3.3.1 Independent variables: Measuring internal DUI

An individual's work organization shows the potential for DUI learning on the job, as work organization can promote the accumulation and diffusion of know-how in the organization.

At the individual level, our main focus is the formal and informal DUI learning processes and experience-building processes that generate know-how in individuals. As argued above, these processes are evident in the organization of work. By affecting the development of know-how and the organization's adaptability, work organization is important for determining costs and opportunities for adopting new technology. Aspects of work organization include the type of tasks in a job and the conditions for undertaking these tasks, such as autonomy. The TASK survey contains data on work organization in 2019 and data on the change in work organization from 2016 to 2019. However, we are interested in work organization in 2016 to explain AI diffusion 2016 - 2019. If an individual report experiencing a given work organization characteristic "always" in 2019 and does not report an increase in the characteristic from 2016 - 2019, then we assume that the characteristic was also highly common in the individual's job in 2016.

Because we rely on the retrospective variables in TASK describing changes from 2016 - 2019, we are limited to five work organization characteristics: solving unforeseen problems, complex tasks, routine tasks, autonomy in choosing own work methods, and autonomy in choosing own work pace.[2] We construct five binary variables that are 1 if the individual experienced the characteristic always in 2019, and this is not an increase relative to 2016. These five binary variables are then condensed in a principal components analysis (PCA) to extract the underlying dimensions of work organization. The result of the PCA has two factors with an eigenvalue greater than 1.

[2]The wording on the survey is: *"Solving unforeseen problems on your own? Complex tasks? Short, routine, and repeated tasks of less than 10 minutes? That you are able to choose or change your methods of work? That you have the option to change your speed of work?"*

	Autonomous problem solving	Complex routines
Problem solving	0.52	0.37
Complex tasks	0.28	0.69
Routine tasks	−0.08	0.80
Autonomous methods	0.82	0.03
Autonomous pace	0.79	0.05

Table B.1: Correlations between the five original variables and the two factors from the PCA

The correlations between these two factors and the original five variables are shown in Table B.1.

Table B.1 shows an interesting result: The variables for complex tasks and routine tasks are captured by the same factor, despite the two original variables having a relatively weak correlation (0.20 - not shown). This shows that complexity and routine are not opposed characteristics of jobs. The automation literature has often emphasized the automation of repeated routine tasks. In contrast, house cleaning is the classic example of a task that is both repetitive and routine yet hard to automate due to requirements of adaptability and dexterity. While house cleaning is perhaps not a complex task, it is a task that changes each time it is performed, which is a characteristic likely to be shared by complex tasks.

A caveat of our data is that they only indirectly measured work organization characteristics in 2016 by inferring them from the 2019 level combined with the change 2016 - 2019. Thus, individuals scoring highly on the second factor had a high routine and high complexity at work in 2016 and a consistently high level over the ensuing three years.

Similarly, individuals scoring highly on the first factor had a high level of problem-solving and autonomy in 2016 and maintained this high level over the ensuing three years.

Formal skills have an ambiguous relation to AI diffusion. On the one hand, formally acquired know-why should support the adoption of new technologies. Still, on the other hand, AI diffuses across various jobs that, at least initially, diffusion does not appear to depend on formal training. Know-how accumulated through experience has a less ambiguous positive relationship to AI adoption, but formal education and the know-why thus accumulated can be a precondition for accumulating experience. There is thus good reason to include formal education, and we distinguish between four levels: At most secondary education, vocational training, at most three years of tertiary education, and more than three years of tertiary education.

3.3.2 Control variables

In addition to the type of region in which the workplace is located, and the work organization and education of the individual, we control for several individual and workplace-level factors.

We control for age, work experience, and occupation at the individual level. Both age and work experience are measured as the natural logarithm of years. For occupation, we distinguish between six different groups: Management, professionals and technicians, clerks, service and sales, crafts workers and machine and plant operators, and elementary occupations.

We control for the size of the workplace measured in the number of employees. The variable is a categorical variable with five different intervals distinguishing between workplaces of ten or fewer full-time equivalent employees (FTEs), more than ten but at most 50, more than 50 but at most 100, more than 100 but at most 250, and above 250 FTEs. Finally, we control for relative specialization. This index is unique to an industry in a region but common to all workplaces with shared industry codes and regions. Relative specialization is intended to capture the important elements of agglomeration externalities, but relative specialization is not agglomeration. A region can be the home of the main specialization of an industry in the entire country. Still, the industry can nevertheless be only a small part of the local economy. Thus the specialization index captures the effect of relative agglomeration, i.e., the effect of being the main national center of the specific industry and hence home to the national frontier of the technologies specific to the industry. Thus AI use is more likely to increase jobs in relatively specialized industries. The location quotient (LQ) describes the industrial specialization level of industry i in region c relative to the total specialization in industry i across all regions. It is given by

$$LQ_{ic} = \frac{E_{ic}/E_{*c}}{E_{i*}/E_{**}}, \tag{B.1}$$

where E_{ic} is employment in industry i in region c, E_{*c} is the total employment in region c, E_{i*} is the total employment of industry i across all regions, and E_{**} is the total employment. The greater the LQ, the more specialized region c is in the industry i compared to the national level specialization in that industry.

Finally, we control for the industry of the individual's workplace. We differentiate between 1) High or medium-high tech manufacturing, 2) low or medium-low tech manufacturing, 3) education and health services, 4) Knowledge-intensive (KI) financial services, 5) High tech KI services, 6) KI market services, 7) Other KI services, and 8) Other services.

3.4 Means and correlations

Table B.2 shows the means of the variables in our regression models for each of the three types of regions.[3] The table shows that the increase in using Helping AI was particularly low in the Old Industrial Heartlands where only 4.9 percent of jobs showed an increase in use compared to 9.1 and 6.6 percent in the Metro-Suburb regions and the Seaside, respectively. The increase in the use of Command AI was also lower in the Old Industrial Heartlands compared to the rest of the country. The two factors for work organization have mean zero by construction, and it can be seen that work organization in the Metro-Suburb regions is close to this average. Jobs in the Old Industrial Heartlands tend to be high in complex routines while low in autonomous problem solving, and vice versa for jobs in the Seaside regions.

	1: Metro/Sub	2: Old Manuf.	3: Seaside
Helping AI	0.091	0.049	0.066
Command AI	0.053	0.037	0.058
Autonomous problem solving	0.001	−0.131	0.115
Complex routines	0.007	0.029	−0.206
Size 1: P<=10	0.084	0.118	0.136
Size 2: 10<P<=50	0.340	0.365	0.501
Size 3: 50<P<=100	0.155	0.233	0.149
Size 4: 100<P<=250	0.146	0.123	0.092
Size 5: 250<P	0.274	0.161	0.121
Specialisation (LQ)	0.347	0.281	0.337
Age (years)	44.872	46.996	48.436
Experience (years)	19.874	21.689	22.372

Table B.2: Averages by region type

A difference in plant size can also be seen. The two smallest size classes are most common in Seaside Denmark, while the two largest size classes are most common in the Metro/Suburb regions. Finally, workplaces in the Old Industrial Heartlands are less often part of relative specializations, and there is a small variation in average years of age and work experience. Both latter variables are here shown in years.

Table B.5 in the appendix shows the correlations between the variables. In Table B.5, age and experience are logged as they enter in the logged form in the regressions. The diffusion of the two forms of AI has a strong but far

[3] To ensure the correct weighting when computing these means and in the other analyses presented in this paper, we have used the survey package (Lumley, 2020). Preparation of the results in tables has been facilitated by Hlavac, (2022).

from perfect correlation (0.491), and neither have a strong correlation with any of the independent variables. Not surprisingly, age and experience have a strong correlation (0.882). The correlation of the size categories with the regional categories shows a pattern where larger workplaces typically locate in the Metro-Suburbs and smaller workplaces are more often found in Seaside Denmark. It can also be seen that larger workplaces tend to coincide with stronger specializations.

The two work organization factors should have variance 1 and correlation zero by construction but they diverge marginally from these statistics because the PCA was undertaken with unweighted data.

3.5 Empirical approach

We estimate separate models for the two types of AI, Helping AI and Command AI. In each case, we attempt to identify predictors of individuals who have experienced an increase in the use of AI. Our dependent variable is binary and we use logistic regression. Continuous variables are mean-centered to facilitate the interpretation of the categorical variables.

In equation B.2, $\Delta AI^a_{i,r}$ is a binary variable taking the value 1 if individual i in region r has experienced increased use of AI type a, for $a \in \{Helping, Command\}$, from 2016 to 2019. In our first model, we include only the categorical variable for region type as an explanatory variable. In the second model, we add the main independent and control variables: work organization, workplace size, specialization, age, and experience. Thirdly, we add interaction terms between a) types of regions and b) work organization, age, and experience. In the fourth and final model, we add additional controls to demonstrate that the results are not affected by including controls for education, occupation, and industry.

The general model in equation B.2 includes all of the models described above. Model 1 contains only the constant and the first term on the right hand. Model 2 adds work organization and the controls in the vector X: size, specialization, age, and experience, while model 3 includes the interaction terms on the right-hand side. Model 4 adds further controls on the vector Z: industry, occupation, and education.

$$\begin{aligned}\Delta AI^a_{i,r} = \alpha^a &+ \beta^a_1 RegionType_r + \beta^a_2 WorkOrg_i + \beta^a_3 X_{i,r} + \beta^a_4 Z_{i,r} \\ &+ \beta^a_5 RegionType_r * (WorkOrg_i + \ln(age_i) + \ln(exp_i)) + \varepsilon^a_i\end{aligned} \tag{B.2}$$

The α and the elements of the five β vectors are the parameters to estimate. The covariates are grouped in vectors, some of which vary at the individual level, i, while others only vary at the regional level, r.

A number of our independent and control variables are categorical. As we also include interactions in some models, we will have a large number of rows in our tables of results. We, therefore, do not report results for variables that neither have a significant effect on the dependent variable nor affect other estimates in the model to a relevant degree. This means that industry, occupation, and education results are not reported. To demonstrate the robustness of our results, we show and compare models with and without these variables.

4 Results

The results from the regression analyses are presented in Table B.4 and Table B.3. We first present the important results in Section 4.1 before summarizing them and discussing them in Section **??**.

4.1 Regression results

Table B.4 shows the results for Helping AI while Table B.3 shows the result for Command AI. As seen in Table B.2 and Table B.5 of means and correlations, individuals in Metro/Suburban regions are relatively more likely to have experienced an increase in the use of Helping AI at work. In contrast, individuals in the Old Industrial Heartland regions are less likely to have experienced an increase. The latter result is also reproduced in the regressions: individuals in the Metro/Suburban regions are more likely to have experienced increased use of helping AI compared to those in the Old Industrial Heartland regions.

In Table B.3, column 2 shows that jobs combining both complex routines and repetitive routines are more likely to have also seen an increased use of Command AI over the period. It appears reasonable that jobs with high repetitiveness are susceptible to automation with command AI, and it also appears reasonable that it is not simple tasks that AI overtakes. When adding interactions to the models (columns 3 and 4), it is found that this is a specific Seaside phenomenon. In Seaside regions, jobs with intense repetitiveness and complexity are automated with Command AI.

When adding interactions to the regression, we also find a relationship between work organization and Helping AI (Table B.4 columns 3 and 4). Again, it is work that combines both repetitiveness and complexity that is the target of AI use. In the Seaside and in the Old Industrial Heartland regions, but not in the Metro/Suburban regions, individuals in jobs with high repetitiveness and high complexity are more likely to experience increased use of Helping AI. As with Command AI, it is reasonable that jobs require repetitiveness for AI to be useful and also that AI is used more often with complex tasks. This result shows that, especially in the Seaside, both types of AI are used when jobs have highly repetitive and complex tasks. AI both automates and enhances humans when jobs are both complex and repetitive.

Table B.3 shows that age is negative for increased use of Command AI while experience is positive. This means that the individuals most likely to increase the use of Command AI are young but also have high work experience. This is somewhat contradictory. Often, variables for age and experience would be expected to capture the same effects, and therefore, only one of these two variables but not the other would be included in a regression analysis. However, in this case, the variables have opposing effects. The positive effect for experience indicates that using Command AI requires tacit knowledge built up over years of work. The negative effect for age indicates that young individuals, who are likely to have recently graduated, are more likely to use AI. In as much as AI skills are relatively novel additions to educational programs, younger workers are more likely to have worked with AI while studying. Thus the two estimates can be argued to both point to the importance of human capital for working with AI. Either human capital from formal education or tacit knowledge created through experience. The fact that the control variable for education is not statistically significant shows that it is not a matter of the level of education but rather of using AI in the specific context of a given educational program.

When adding interactions to the model, the positive effect of experience and the negative effect of age is only observed in Metro/Suburban regions and Old Industrial Heartlands regions. In Seaside regions, the magnitude of the estimated interaction effects cancels out the direct effect showing that in Seaside regions, individuals are equally likely to have experienced an increase in Command AI irrespective of age and work experience.

The relationships between age, experience, and Helping AI are somewhat weaker and only appear when the model includes the interactions. When the interactions are included, it can be seen that more experienced workers in Metro/Suburban and Old Industrial Heartland regions are more likely to have experienced an increase in using Helping AI. In contrast, in Seaside regions, there is no effect. Age is not found to affect the likelihood of increased use of Helping AI.

Individuals in plants of 100-250 employees are less likely to have experienced increased Command AI use compared to both individuals in larger firms and individuals in smaller firms. Individuals working in firms that belong to a regional relative specialization are more likely to experience increased use of Helping AI. This supports that new technologies such as AI are first adopted in headquarters. The result is not very strong.

Table B.3: Models for Command AI

	Dependent variable:			
	$\Delta AI_{i,r}^{Command}$			
	(1)	(2)	(3)	(4)
Old manuf.	−0.381	−0.456	−1.646*	−1.672
	(0.502)	(0.477)	(0.926)	(1.038)
Seaside	0.087	0.196	0.619	0.879
	(0.467)	(0.567)	(0.548)	(0.637)
Aut&Prbl		−0.200	−0.033	−0.066
		(0.207)	(0.212)	(0.269)
Cplx&Rtn		0.272**	−0.141	−0.045
		(0.134)	(0.183)	(0.230)
Size1: P<=10		−0.498	−0.954	−1.095
		(0.795)	(0.753)	(0.935)
Size2: 10<P<=50		−0.239	−0.519	−0.609
		(0.542)	(0.533)	(0.589)
Size3: 50<P<=100		−0.886	−0.940	−0.885
		(0.596)	(0.596)	(0.682)
Size4: 100<P<=250		−1.561**	−1.768**	−1.950**
		(0.698)	(0.764)	(0.859)
Specialisation		0.470	0.284	0.154
		(0.449)	(0.440)	(0.514)
ln(exp)		1.465*	4.021***	4.214***
		(0.810)	(1.147)	(1.442)
ln(age)		−3.942**	−9.931***	−10.682***
		(1.873)	(3.131)	(3.858)
Old manuf.∗Aut&Prbl			−2.008*	−1.689*
			(1.203)	(1.011)
Seaside∗Aut&Prbl			0.270	0.013
			(0.360)	(0.375)
Old manuf.∗Cplx&Rtn			0.324	0.251
			(0.289)	(0.321)
Seaside∗Cplx&Rtn			0.675**	0.753**
			(0.295)	(0.333)
Old manuf.∗ln(exp)			−0.136	0.406
			(1.791)	(2.204)
Seaside∗ln(exp)			−5.117***	−5.094***
			(1.340)	(1.619)
Old manuf.∗ln(age)			0.464	−1.285
			(4.601)	(5.497)
Seaside∗ln(age)			11.839***	12.529***
			(3.435)	(4.397)
Constant	−2.882***	−2.708***	−2.958***	−1.822
	(0.271)	(0.362)	(0.443)	(1.500)
Industry FE	N	N	N	Y
Occupation FE	N	N	N	Y
Education FE	N	N	N	Y
Deviance	310.346	285.848	254.069	228.641
Null deviance	311.52	311.52	311.52	311.52
AIC	315.78	316.25	292.85	298.97
Observations	796	796	796	796
Note:				*p<0.1; **p<0.05; ***p<0.01

Table B.4: Models for Helping AI

	Dependent variable:			
	$\Delta AI_{i,r}^{Helping}$			
	(1)	(2)	(3)	(4)
Old manuf.	-0.663^{*}	-0.727^{**}	-0.942^{*}	-0.892
	(0.380)	(0.367)	(0.538)	(0.563)
Seaside	-0.350	-0.377	-0.256	-0.066
	(0.396)	(0.456)	(0.441)	(0.470)
Aut&Prbl		-0.228	-0.264	-0.277
		(0.191)	(0.203)	(0.220)
Cplx&Rtn		0.158	-0.105	-0.084
		(0.124)	(0.184)	(0.206)
Size1: P<=10		-0.316	-0.425	-0.072
		(0.792)	(0.826)	(0.874)
Size2: 10<P<=50		0.227	0.202	0.451
		(0.404)	(0.397)	(0.444)
Size3: 50<P<=100		-0.521	-0.478	-0.247
		(0.451)	(0.457)	(0.496)
Size4: 100<P<=250		-0.049	-0.007	0.027
		(0.408)	(0.421)	(0.440)
Specialisation		0.712^{**}	0.662^{**}	0.606^{**}
		(0.315)	(0.289)	(0.304)
ln(exp)		0.853	1.362^{**}	1.459^{**}
		(0.533)	(0.593)	(0.616)
ln(age)		-1.325	-1.918	-2.325
		(1.254)	(1.714)	(1.855)
Old manuf.∗Aut&Prbl			-0.120	-0.128
			(0.639)	(0.601)
Seaside∗Aut&Prbl			0.462	0.365
			(0.374)	(0.351)
Old manuf.∗Cplx&Rtn			0.452^{*}	0.493^{*}
			(0.242)	(0.257)
Seaside∗Cplx&Rtn			0.620^{**}	0.710^{**}
			(0.308)	(0.346)
Old manuf.∗ln(exp)			0.159	0.670
			(1.242)	(1.387)
Seaside∗ln(exp)			-1.748^{*}	-1.766
			(1.049)	(1.093)
Old manuf.∗ln(age)			-1.068	-2.302
			(3.048)	(3.696)
Seaside∗ln(age)			1.553	2.259
			(2.529)	(3.072)
Constant	-2.305^{***}	-2.411^{***}	-2.462^{***}	-1.306^{*}
	(0.185)	(0.293)	(0.274)	(0.732)
Industry FE	N	N	N	Y
Occupation FE	N	N	N	Y
Education FE	N	N	N	Y
Deviance	414.959	395.215	382.095	359.139
Null deviance	419.158	419.158	419.158	419.158
AIC	419.57	422.16	424.3	431.01
Observations	796	796	796	796
Note:				*p<0.1; **p<0.05; ***p<0.01

5 Discussion and conclusion

This paper set out to investigate regional variations in the diffusion of AI and which role regional differences in the presence and impact of internal firm DUI mode had on the diffusion process. The core investigative hypotheses were i) that the regional variation in the diffusion of AI is dependent on the regional differences in the relationship between internal DUI activities and innovation outcome. ii) The regions outside the metropolitan regions are more dependent on DUI mode regarding AI diffusion.

Table **??** summarizes the results of the regression analyses. Overall, there is significant variation in our results across the three types of regions. One of the interesting aspects of this variation is the difference in the ability of work organization to explain the diffusion of AI. Work organization was expected to affect AI diffusion in two ways: by facilitating the development of know-how through DUI learning, and by providing the framework where AI is applied. In our results, the second effect dominates. Autonomy and problem-solving at work should promote DUI learning and thus the accumulation and diffusion of experience throughout the organization but we do not find that AI diffusion is higher for workers with high autonomy and problem-solving. Work organization with complex but repetitive tasks involves predictions that can be undertaken by AI and we do find that a higher frequency of complex but repetitive tasks is positively associated with the diffusion of Helping AI in the Old Industrial Heartland regions and in Seaside Denmark. It is also positively associated with the diffusion of Command AI in Seaside Denmark. An unexpected result is the negative relationship between the diffusion of Command AI and autonomy and problem-solving in the Industrial Heartland regions. It is possible that with only five indicators of work organization, our data are not able to disentangle the two effects of work organization. In other words, work with high autonomy and problem-solving may promote DUI learning, but it contains relatively little repetitiveness to facilitate AI use. Our more direct measure of work experience, the log of years employed, does, however, show a positive effect. It is the more experienced individuals who see an increase in AI use across all region types. We can therefore confirm the first hypothesis of the paper. Regarding the second hypothesis of the paper, it is evident from the descriptive statistics of Table 2 that the DUI mode is more present among the respondents from the Old Industrial Heartland regions and the Seaside Denmark regions compared to the respondents from the Metropolitan regions. When looking at the two regression tables, Table 3 and Table 4, it is evident that a large part of the internal DUI mode variables explains some of the regional variances in AI diffusion. However, the different internal DUI variables have differing impacts on the AI adoption. Therefore, the second hypothesis is cannot be outright rejected but requires further qualification. The regions outside the metropolitan regions are, indeed, more dependent on DUI mode regarding AI diffusion, however the impact is not consistently positive.

The paper has two main contributions. *i)* It shows the varying diffusion patterns of AI across Danish regions in the early stages of AI. The paper offers a more fine-grained picture of the diffusion patterns by showing differences in the spatial mechanisms behind the two types of AI, Helping AI and Command AI, with Helping AI having a larger extent of uneven distribution compared to Command AI. *ii)* The paper, furthermore, links the uneven diffusion of AI to regional differences in both innovation mode, but also to the relationship between innovation mode and innovation outcome in relation to AI. The paper shows that firms in the different regions adopt internal DUI activities to varying extents, that different types of DUI activities can predict the adoption of AI to varying extents, and lastly and most importantly, that the impact of DUI activities affect AI adoption different dependent on which regional context the firm is located in. The results add to recent literature investigating the regional differences between innovation mode and innovation outcome. The regional scale adopted in this study combines the geographical (Doloreux & Shearmur, 2023) and innovative (Parrilli et al., 2020a) regional classifications applied in previous studies. The paper also offers new insight on internal DUI activities. Research finding a positive effect of work organization that promotes DUI learning and creation of know-how on innovation is generally at the firm level. Our study is at the level of the individual worker. An individual may have her work organized such that know-how for AI adoption is rapidly accumulated, but AI adoption in her job is likely to be a management decision that takes into account not only the readiness of the individual worker but the organization more broadly.

The implications of this research are severalfold. Helping AI is the type of AI with the strongest regional divides, with the former industrial regions lagging behind both the metropolitan regions and the seaside region. Helping AI has, in previous studies, been associated with labor augmentation and increased productivity (Holm et al., 2021), which can make it desirable to have an even distribution of this kind of AI to minimize regional inequality. The discussion on innovation modes and innovation outcomes, not only needs regional perspectives, but also a more nuanced picture of the types of activities within the classification of innovation mode, i.e., different types of inter DUI activities have different consequences regarding AI diffusion in different regions. It will be necessary from a policy perspective to understand differences in the varying impact of innovation modes on AI diffusion and to address the different regional diffusion patterns to combat regional inequality.

Despite adding new knowledge to both the literature on diffusion of AI and the role of geographical context in the relationship between innovation mode and innovation outcome, this research still leaves questions unanswered for future research avenues. This study has taken point of departure in Denmark. While it has been crucial to understand the regional inequality in AI diffusion from a smaller geographical context, other geographical contexts might cast some light on different mechanisms in the role of innovation mode in the diffusion of AI. Furthermore, this study has focused on the innovation mode which has previously received least attention, internal DUI. However, it would be of utmost interest for future research to try to untangle how different innovation modes are connected and interplay with each other for diffusion of AI.

A Appendix

	Metro/Sub	Old manuf.	Seaside	Help. AI	Com. AI	Aut&Prbl	Cplx&Rtn	size1	size2	size3	size4	size5	Special.	ln(age)	ln(exp)
Metro/Sub	0.250			0.038	0.604	0.626	0.346	0.060	0.032	0.082	0.160	0	0.174	0.010	0.012
Old manuf.		0.209		0.068	0.266	0.030	0.340	0.400	0.664	0.016	0.742	0.014	0.092	0.204	0.176
Seaside			0.148	0.598	0.668	0.104	0	0.210	0.002	0.320	0.086	0	0.674	0.032	0.072
Help. AI	0.068	−0.062	−0.014	0.068	0	0.268	0.148	0.184	0.556	0.104	0.814	0.212	0.014	0.272	0.022
Com. AI	0.019	−0.037	0.019	0.491	0.047	0.338	0.030	0.512	0.548	0.196	0.032	0.074	0.072	0.380	0.502
Aut&Prbl	0.020	−0.074	0.062	−0.040	−0.033	0.984	0.290	0.476	0.616	0.764	0.838	0.172	0.750	0	0
Cplx&Rtn	0.034	0.036	−0.087	0.060	0.087	−0.045	0.960	0.940	0.070	0.770	0.134	0.782	0.206	0.258	0.008
size1	−0.067	0.031	0.050	−0.041	−0.019	0.029	0.004	0.093					0	0.446	0.060
size2	−0.078	−0.016	0.121	0.020	0.024	0.016	−0.065		0.235				0	0.332	0.482
size3	−0.061	0.095	−0.034	−0.054	−0.042	0.011	0.010			0.146			0.084	0.324	0.462
size4	0.052	−0.012	−0.052	0.009	−0.055	−0.007	0.066				0.113		0	0.536	0.156
size5	0.157	−0.083	−0.105	0.049	0.070	−0.044	0.010					0.168	0	0.204	0.266
Special.	0.048	−0.062	0.012	0.095	0.067	−0.012	0.049	−0.129	−0.244	−0.059	0.147	0.319	0.220	0.682	0.896
ln(age)	−0.097	0.042	0.076	0.035	−0.029	0.119	0.033	−0.029	−0.031	0.034	−0.019	0.043	−0.013	0.096	0
ln(exp)	−0.086	0.045	0.059	0.064	0.021	0.152	0.066	−0.071	0.026	0.027	−0.049	0.038	−0.004	0.882	0.742

Notes:
Abbreviated version of variable names. Aut&Prbl: Autonomous problem solving. Cplx&Rtn: Complex routines.
At diagonal: variance. Below diagonal: correlation. Above diagoanl: p-value of correlation
Correlations for mutually exclusive categories are intentionally blank

Table B.5: Pearson correlation table

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Paper C

Informal institutions, information, and innovation: *Regional co-evolution of technological discourses and AI investments in Denmark*

Sigrid Jessen[1]

Working Paper

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Abstract

In recent years, the literature on regional divides has developed a strong research agenda on the importance and problems of the spatially unequal diffusion of new technologies. Literature has argued for a strong correlation between innovative activities and the characteristics of regional informal institutions, such as regional embedded knowledge, common language, norms, and practices. However, no empirical evidence exists to support this posited relation between the regional technological discourse of an innovative milieu and innovative activities. This study attempts to fill this research gap by taking advantage of two data sources; firm-level registry data on investments in technologies related to AI, and newspaper data from more than 17.000 news articles from 375 newspapers with a locally varying readership that covers all 98 Danish municipalities from 1985-2021. The study finds, first of all, longitudinal evidence from panel regressions showing that former manufacturing and now stagnating regions fall behind the metropolitan regions over time in coverage of new technologies and that sentiment is more positive and extreme in the regions outside the metropolitan regions. Secondly, strong co-evolutions in the regional technological discourse and firm-level import of AI-related technologies. Panel regressions and sentiment analyses show a strong relationship between the level and tone of the AI news coverage and firm-level AI adoption. Granger causality analysis further confirms the reinforcing and co-evolving nature of the relationship.

Keywords: *Import of AI-related technologies, News media, Informal institutions, Sentiment analysis, Interregional inequality*

1 Introduction

Increasing regional divergence has been observed in most Western countries (Iammarino et al., 2018). This is expressed in a clustering of human capital (Moretti, 2012; Wheeler, 2001), economic development, and innovative activities (Balland et al., 2020) in urban centers. One explanation for this rising interregional inequality is the uneven distribution of innovative activities (Storper, 2018b). Innovative activities have been linked to regional knowledge diffusion, which constitutes the regional innovative milieu. This concept has been described as the industrial atmosphere (Marshall, 1890), regional culture (Saxenian, 1996), regional zeitgeist (Storper, 2018a), or the regional buzz (Bathelt et al., 2004) or the informal institutions of a region (Coenen & Díaz López, 2010; Cooke et al., 1997). While the literature goes far back, the empirical evidence has mostly focused on the quantitative aspects of the innovative milieu and less so attempted to untangle the content of the innovative milieu.

In recent years have studies adopted newspaper data and other text sources as a proxy for regional innovative milieus as well as to measure accessible (e.g., Geels & Verhees, 2011; Heiberg et al., 2022; Meelen et al., 2019; Ozgun & Broekel, 2021; Rosenbloom et al., 2016) The literature posits that the regional technological discourse may impact new technologies. However, no empirical evidence exists to support this posited relation. Therefore, the objective of the paper is two-fold. i) To understand the regional variations in the development of the technological discourse in the case of AI. ii) To understand the co-evolutions in development in regional technological discourse and the import of AI in the case of AI adoption in Danish regions.

The paper adopts two data sources; firm-level registry data on the import of technologies related to AI, e.g., machinery for processing and analyzing big data, and newspaper data from more than 17.000 news articles from 375 newspapers with a locally varying readership that covers all 98 Danish municipalities from 1985-2021. The findings of the paper showcase; I) Longitudinal evidence from panel regressions shows that former manufacturing and now stagnating regions fall behind the metropolitan regions over time in coverage of new technologies and that sentiment is more positive and tend to be more extreme in the news depiction outside the metropolitan regions. II) Strong co-evolutions in the regional technological discourse firm-level import of AI-related technologies. Panel regressions and sentiment analyses show a strong relationship between the level and tone of the AI news coverage and firm-level AI adoption. Granger causality analysis further confirms the reinforcing and co-evolving nature of the relationship. The contributions of the paper are severalfold. Contributions to the literature count among others that the paper showcases a method using textual data e.g., news paper data, to capture an intangible phenomenon such as informal institutions, which previously has been known to be difficult to measure. Furthermore, the paper provides an empirical proof of the co-evolution between technology and institutions. For the policy-side the paper illustrates that the quality of knowledge dissemination in a region matter for the overall likelihood of long-term technology adoption, as shown in this case of AI related technologies.

The remainder of the paper is as follows: First, the theoretical framing is described putting specific emphasis on the measuring of informal institutions. Second, the data and methodology of the paper are presented. Third, the results of the paper are discussed. Fourth and finally, the paper concludes and discusses potential policy implications.

2 Theoretical background

2.1 Informal institutions: Regionally embedded (tacit) knowledge and innovative milieus

Economic geography, innovation studies, and economics have long linked regional variation in the drive to innovate to variations in knowledge (Lundvall, 1992; Marshall, 1890; Urbano et al., 2019). It is argued that knowledge and its diffusion tend to be ‘sticky’, which gives some regions a competitive advantage and further encourages the clustering of innovative activities (Glaeser et al., 2010).Literature on regional innovation systems (RIS), among others, offers a comprehensive analytical framework to understand regional differences in knowledge, learning opportunities, and their subsequent innovative activities (Braczyk et al., 1998). A RIS has been defined as a system consisting of the following four building blocks; "*i) interacting public and private interests, ii) formal institutions such as education institutions, financial institutions, and public authorities, iii) other institutions that contribute to application and diffusion of knowledge, and iv) informal institutions*" (Drejer & Christensen, 2021). The last building block, the informal institutions, refers to unwritten expectations and rules such as tacit customs, habits, or norms (Coenen & Díaz López, 2010; Cooke et al., 1997). Contrary to codified knowledge, financial capital, and real capital, institutions can not be purchased, and are almost impossible to replicate (Maskell & Malmberg, 1999; Wernerfelt, 1984). This contextual and often regionally-dependent feature of the informal institutions can either impede or promote particular paths of development and innovation (Rodríguez-Pose & Storper, 2006).

The idea of informal institutions and their importance in regional innovation processes have theoretically been expressed in many ways over the years in other works of literature than the literature on RIS. The different theoretical frameworks offer different perspectives and nuances but are, to a certain degree, intertwined and are building on top of each other. Common for many of them is that the regional setting has embedded language, attitudes, norms, and values that create differentiated bases for innovative practices. Marshall, (1890) coined the term the *industrial atmosphere* where the “mysteries of the trade become no mysteries; but are as it were in the air.” (Marshall, 1890, p. 225). In this *industrial atmosphere*, work well done is appreciated, and new inventions and innovations, e.g., in machinery or in the organization and processes of the establishment, have their pros and cons discussed, allowing for new ideas to be generated from the discussion of the previous ideas. The idea of an environment that is distinct and continues to pass on the regional-specific tacit knowledge that then continues to foster the knowledge is also the core idea behind Saxenian’s 1996 discussion of the *regional culture* in Silicon Valley. The regional culture fosters an environment that supports knowledge sharing and a learning culture resulting in the clustering of innovative establishments and activities that Silicon Valley still to this day is known for.

Similarly, in the literature on localized learning, it is argued that the region's specific institutional endowment roots knowledge regionally and empowers further knowledge generation. This endowment takes on a path-dependent nature, which makes the localized capabilities difficult to imitate, and they thereby constitute a competitive advantage over other regions in terms of innovative activities (Maskell & Malmberg, 1999). Scholars in the same stream of literature have also looked at the *regional buzz* (Bathelt et al., 2004). Buzz consists of informal institutions embedded in a given location's social and cultural environment (Malmberg & Maskell, 2002). Buzz compromises a shared language, which fosters *regional collective learning* within innovative milieus (Lawson & Lorenz, 1999). Some places may offer an industrial atmosphere in which discussions related to innovations flourish more easily (Spigel, 2017). Buzz creates an atmosphere in which information, 'know-how', and knowledge related to innovation-related opportunities can be circulated more easily, which as a result, provides a supportive environment for firms interested in adopting new tech (Corradini et al., 2022). In the same line, several scholars (e.g., Boschma, 2004; Gertler, 2003; Lawson & Lorenz, 1999; Pouder & St. John, 1996; Storper, 1995) have attested that co-located firms often have similar logic or as it happens at times get locked into local group think (Grabher, 1993). The literature on industrial lock-in and relatedness, it is stressed that regionally external knowledge flows are important in order to avoid industrial lock-in, but also that relatedness between the two regions is crucial in order for the knowledge to be properly adopted (e.g., Boschma & Iammarino, 2009). Recently, Storper et al., (2015) and Storper, (2018a), have referred to the phenomenon of *regional zeitgeists*. *Regional zeitgeists* (German for the "spirit of the age" in a specific regional context according to Storper, (2018a)) are the approaches to organizing and sharing ideas and practices in a specific geographical setting. The agents who exchange ideas and practices are unlikely to be aware of this process. Storper, (2018a) argues that the regional zeitgeist corresponds to *conventions* by Lewis, (2011), which can be described as the unconscious rules of thumb among the inhabitants in a region, and to North, (1990) and the *beliefs*. A main feature of the conventions, as explained by Storper, (2018a), is that they form societal settings by facilitating a substantial set of agents to have a mutual point of departure and, thus, supporting the organizational ecology of a region.

In sum, literature has long argued that regional institutions are expressed through common languages, norms, and cultures, which require or inhibit regional learning and subsequent regional innovative activities. It is posited that the relationship between these regional informal institutions and technologies is self-reinforcing and evolves together over time. This relationship will be dwelled further upon in the following text.

2.2 Innovative milieus and innovative activities

The relationship between the innovative milieu, technological adoption, and innovative activities reinforces itself path-dependently. The idea that institutions and technologies co-evolve across time is not new (e.g., Freeman et al., 2001; Nelson, 1994; Strambach, 2010). The literature on localized learning describes it as "the social process of joint innovation and tacit knowledge production" (Maskell & Malmberg, 1999). This means that, according to the literature regarding this process, knowledge transfers from technology producers to users are not unidirectional. Instead, users also provide their own tacit knowledge to the producers, among other things, by letting the producers solve users' practical problems with innovative solutions. In return, the producers subsequently share their tacit knowledge with their users through this process. This process takes on a highly regional nature where regional embedded knowledge and regional innovative activities co-evolve over time (Maskell & Malmberg, 1999). In the literature on regional collective learning, it is argued that the routines in organizations in different regions create incremental changes (Nelson & Winter, 1982) that through a path-dependent process create different opportunities for learning and subsequently differences in innovative activities, e.g., technology adoption (Lawson & Lorenz, 1999). Recently, studies showcased the importance of path-dependent knowledge and experience generation in technology creation, by investigating the impact of having regional knowledge bases within Industry 3.0 in the development of Industry 4.0 (I4.0) in European regions (Laffi & Boschma, 2022). This implies that regional-specific knowledge is based on self-reinforcing dynamics that allow for continuing expertise. Furthermore, Hervas-Oliver et al., (2022) show that there exist differentiated strategies to generate awareness and facilitate the widespread adoption of I4.0, and these strategies are the results of unique local 'cognitive structures'. This finding supports the notion of distinct regional cultures and suggests that universal policies for digitization are not feasible.

Therefore, the relationship between these regional innovative environments and technologies is regionally specific. The relationship is self-reinforcing and evolves together over time. This is due to a common routine formation, where experiences and tacit knowledge are created, which influence each other continuously.

2.3 Content of the innovative milieus

The intangible nature of these informal institutions makes them difficult to measure. When scholars previously have attempted measuring informal institutions (Camagni & Capello, 2002), the focus has been on the purely quantitative characteristics of the informal institutions, e.g., the human capital often measured in educational level or labor mobility, research intensity or complexity often measured as R&D-imports or patents, or the characteristics of the network of the innovative milieu. Whereas it all provides an important insight into the characteristics of innovative milieus, little is still known about the more qualitative differences. Glückler et al., (2018) explains further that due to the difficulties associated with the disentanglement of the different features and hence performing econometric estimations thereof(Tomaney, 2014), it remains challenging to provide policy recommendations on informal institutions (Rodríguez-Pose & Fitjar, 2013). This has caused researchers to call for more research on differences among regional informal institutions and different measurement approaches, e.g., qualitative case studies on informal institutions (Bathelt & Glückler, 2014; Bosker & Garretsen, 2009; Gertler, 2010; Pike et al., 2015). In the same line of argumentation, Storper, (2018b) argues for the importance of the content of the local innovative milieu when attempting to untangle the relational infrastructure of places. Storper, (2018b) describes how the difference in the articulation of the content of the visions for San Francisco and Los Angeles tells a story of differences in the regional informal institutions and the regional zeitgeist of the two regions, which in the end, impacted the different development patterns of the regions. The same is argued by Corradini et al., (2022) who showcase the importance of the content of the regional buzz when investigating the entrepreneurial activities in a region. By analyzing Twitter data, they observe that regions with a higher level of engagement in discussions related to innovation foster a more conducive environment for entrepreneurial processes.

So far, there have been empirical attempts to measure the diversity of the innovative environments focused on R&D import, patents, human capital, and network infrastructure and not the content of the regional environments, due to measurement challenges associated with the qualitative characteristics of informal institutions. However, recent studies have implied that the informal institutions' content and discourse could help shed new light on the regional differences in innovation activities. Therefore, it is crucial to understand the regional technological discourse, when investigating the regional processes of technological change.

2.4 Newspapers as a proxy for the regional innovative milieus

Knowledge (spillovers) famously leave behind no paper trail by which they can be tracked or measured (Krugman, 1991). In recent years researchers have attempted to prove this rationale wrong. There has already been a long tradition to use patent data in this endeavor (e.g., Jaffe et al., 1993) and in recent years new methodological tools have allowed for new research avenues by taking advantage of different types of textual data sources ranging from planning documents (Heiberg et al., 2022), Twitter postings (Corradini et al., 2022), press releases (Ozgun & Broekel, 2022a) and newspapers (Ozgun & Broekel, 2021, 2022b; Peris et al., 2021). Newspapers are an increasingly popular data source and have been used to capture regional knowledge, in terms of accessibility and sentiment.

This paper argues with recent papers that newspapers can be used as a proxy for regional technological discourse in the innovative milieu. The argument is well-aligned with the idea of the social life of information. Newspapers mirror the societal context in which it is embedded and the relationship between the receiver and the deliverer. Therefore, newspapers are not solely a record of events on a specific day:

> *"News is not some naturally occurring object that journalists pick up and stick on a paper. It is made and shaped by journalists in the context of the medium and the audience. (...) The newspaper, then is rather like the library – not simply a collection of news, but a selection and a reflection. And the selection process doesn't just "gather news", but weaves and shapes, developing stories in accordance with available space and priorities."* (Brown & Duguid, 2000, p. 185-186.)

Newspapers are strongly embedded in their regional and social context, and the status quo and future development of newspapers can be seen as the result of larger regional structural change due to two intertwined main reasons; i) the local audience: which covers demographic and economic regional change, and ii) the topic, which covers industrial and technological regional change.

Firstly, the local audience covers the demographic and economic regional change. There have long been attempts to understand the relationship between newspapers and economics and demographics (e.g., Reddaway, 1963). The combination of lower inhabitant numbers and continuing depopulation causes many newspapers and editorial headquarters to cluster in the urban centers (Kekezi & Mellander, 2018).

Local newspapers face higher per-copy costs compared to newspapers operating in larger markets due to their smaller operational scale (ibid.) Moreover, these costs require higher efficiency demands, lower wages, and more advertisement, causing the quality of the news to decline (ibid.). The clustering of editorial headquarters also results in the coverage of smaller regions being more likely to be conducted by journalists from larger region settings compared to larger cities (Rosenberg, 2019). The idea is that distant areas are less likely to receive media coverage due to the lack of local coverage (Nord & Nygren, 2002). Kekezi and Mellander, (2018) set out to examine these assumpted correlations on whether the absence of a local editorial office contributes to reduced consumption of "local news", being the non-metropolitan newspapers. Likewise, they also examined whether a decrease in local news consumption is associated with a lower number of local journalists. Their findings indicate that the presence of an editorial office in a municipality does not have a significant correlation with the consumption of local newspapers, but the availability of employed journalists residing in the municipality does.

Studies have furthermore argued that differences in educational levels across regions additionally affect the demand and supply, regarding both the frequency of newspaper publishing, but also the quality of the newspapers provided (Elvestad & Blekesaune, 2008).

The second main reason is the topic, which covers industrial and technological regional change. Newspapers tend to report on news that is of interest to the local community (Brown & Duguid, 2000). That means for one thing that newspaper pieces on the industrial patterns of the local community are more likely to be featured and subsequently consumed within the local community. Research has shown that urban newspapers generally cover more news on innovation and new technologies compared to media outlets in rural areas (Ozgun & Broekel, 2021). The same study finds that regions normally associated with less innovative activities tend to have higher sentiment levels, meaning they generally tend to be more positive in their depiction of new technologies. The authors posit that this counterintuitive finding might be a sign of lesser quality in the news angles and a more sensational, whereas the newspapers in the larger urban regions normally associated with innovative activities tend to remain more neutral in the depiction. This theory is well aligned with empirical studies finding that quality decreases with socioeconomic changes in the region and newspapers outside the main metropolitan regions tend to struggle to maintain the same journalistic standard, among other things due to the increased dependence on commercial advertisements (Kekezi & Mellander, 2018; Reddaway, 1963). Another reason for the more sensational angle on the news depiction of the newer technologies in the rural regions can be that the unfamiliarity with a topic causes more extreme news portrayal. This has been seen with other phenomena, e.g., Islamophobia and crimes, where the depiction in regions less likely to experience both Muslim inhabitants (Hassan & Azmi, 2021) and crime (Wong & Harraway, 2020), tended to be more extreme in their news depiction.

This paper argues that the structural change that has shaped the newspapers results in that newspapers can be used as a proxy for (the discourse of) the content of different regional innovative milieus. Overall, this is not to claim that newspapers make up the matter or infrastructure of regional innovative milieus. However, they provide a suitable proxy for such endeavors.

2.5 The regional co-evolution of technological adoption and innovative milieus

Regional differences among other informal institutions, which are expressed by regional norms, practices, beliefs, and language, are associated with differences in innovative activities. This relationship is self-re-enforcing and path-dependent. Newspapers are, due to them taking on a social life, where they are formed by the regional structural change, causing them to be suitable proxies for the regional technological discourse, which is argued to be a part of the informal institutions of a region. In recent years an increasing interest has been put towards AI, both academically and publicly, which has resulted in larger media attention and more firms investing and adopting AI in the organization. This theoretical background leads to the following hypothesis:

- H1: Regional technological discourse and regional technological imports co-evolve over time and space.

Studies have found that the more extreme and the less neutral the news depiction, the less likely the area is to have a thorough understanding of the topic. This theoretical background leads to the following hypothesis:

- H2: The more extreme the regional sentiment in news depiction, the more likely the degree of technological change is to be weaker

3 Data and methods

3.1 Denmark as an empirical context

This study focuses on Denmark, which is particularly interesting due to its advanced technology level (EU, 2022) and highly educated population (OECD, 2023). Despite its small size and historically low regional economic disparities, Denmark has also experienced increasing regional inequalities (OECD, 2018). The study examines the 98 municipalities (LAU1) resulting from the 2007 structural reform in Denmark. Prior to this reform, Denmark had 271 municipalities, but for this study, they are classified according to the post-2007 standard. The municipalities are categorized according to (Jessen, 2023) into four regional development typologies: Metropolitan regions, Suburban regions, Old Industrial Heartlands, and the peripheral regions, also known as Seaside Denmark regions. These typologies are constructed based on demographic, economic, industrial, and innovative data spanning nearly 40 years. This approach provides a more comprehensive and context-specific understanding of regional disparities over time.

3.2 Data

To understand the relationship between regional technological discourse and regional technological imports, the current paper benefits from three main data sources; *i*) Danish registry data, among others, the Danish import registry data, "The Foreign Trade Statistics Register – UHDI", *ii*) the Danish newspaper database, and *iii*) data on Danish geographical reader shares across Danish regions from the Danish Ministry of Culture from the year 2014. The data allows for the construction of the variables discussed below.

3.2.1 Variables

Dependent variable
The dependent variable is the relative share of import of AI-related technologies per municipality in Denmark. It is constructed using data from the Danish import registry data, "Foreign Trade Statistics Register – UHDI". The method of using trade and import data as a proxy for technology diffusion is in no way novel (e.g., Caselli & Coleman, 2001). In recent years several studies have used import data in order to capture the firm-level imports and use of I4.0 related technologies see, e.g., Abeliansky et al., (2020); Acemoglu et al., (2020); Domini et al., (2022); Humlum, (2022). This paper is interested in the regional level of AI-related technologies. It therefore adopts the definitions by Domini et al., (2022), in which AI-related technologies are defined in the HS-2012 codes as:

1. Automatic data processing machines: 847141-847150, 847321, 847330

2. Electronic calculating machines: 847010-847029

In this paper, the firm import is, therefore, measured as the total amount of monetary value in DKK invested in the import of the two before-mentioned HS-2012 codes. This approach covers all 98 municipalities in Denmark, and the variable is constructed using time series from 2000, the first year the codes were included in UHDI, and up to 2018.

Independent variable
As previously mentioned, newspapers have recently become a common data source in studies investigating the discourses over time and space (e.g., Geels & Verhees, 2011; Heiberg et al., 2022; Meelen et al., 2019; Ozgun & Broekel, 2021; Rosenbloom et al., 2016). The regional technological discourse in this paper is constructed as four different variables, and by combining approximately 17.000 different newspaper articles (national, regional, and local)[2]

[2] For the regressions only regional and local newspapers are included, which are approximately $n = 2000$

mentioning AI from 365 Danish newspapers covering all 98 municipalities from 2000 to 2018 and data on the municipal newspaper reader share from 2014. Keywords used for the search were "AI", "Artificial Intelligence", and "Kunstig Intelligens", which is the Danish translation for Artificial intelligence.

The two datasets are merged based on the municipality level after an extensive data cleaning and geocoding process in which the publishing municipality, news-originating municipality, firms, and/or industrial sectors were identified in the newspaper.

The first independent variable measuring the regional technological discourse is discourse density, the share of AI-related news per municipality per year.

$$N^*_{my} = \frac{N_{my}}{T_{my}} \tag{C.1}$$

where, N^* refers to the share of AI-related news consumed in the municipality or "News Density" of the total amount of published news articles, N refers to the total number of AI-related news articles published in the region, T refers to the total number news articles published in the region, m refers to the municipality, and y refers to year.

The second variable is the sentiment of the discourse, measured as the sentiment on the title basis of each of the 17.000 newspaper articles. Sentiment analysis has, in recent years, become a widely used tool when analyzing the tone of the discourses ranging from Twitter analysis to geographical differences in discourses (e.g., Ozgun & Broekel, 2021). The sentiment is measured by calculating ratio of positive and negative loaded words, given by the following equation as defined by Ozgun and Broekel, (2021);

$$SENT = \frac{(\#POS - \#NEG)}{(\#POS + \#NEG)} \tag{C.2}$$

In this equation, POS represents the total count of positive words, NEG represents the total count of negative words, and the denominator represents the total count of sentiment-bearing words. This paper uses the data package SentiDa (Lauridsen et al., 2019), which is a sentiment program for the Danish language.

The third measure of regional technological discourse is the extra-regional knowledge flows as a dummy. The geocoding allows for identifying the municipality from which the news is originating as well as the municipality in which the news is published. As touched upon in the theoretical section, knowledge is seen as spatially sticky. However, the degree of extra-regional knowledge flows to the region can impact technological innovations by preventing industrial and innovative lock-in. The share of extra-regional news is given by:

$$E^*_{my} = \frac{E_{my}}{T_{my}} \tag{C.3}$$

where, E^* refers to the share of news originating from extraregional context out total of news consumed in the municipality. E refers to the total amount of news originating from extra-regional setting that are consumed in the municipality of interest. T refers to the total amount of news being consumed in the region. m refers to the municipality, and y refers to year.

The fourth and final measure of regional technological discourse is the extra-regional knowledge flows related to existing industrial specialization, measured as co-occurrence relatedness (e.g., Boschma et al., 2013; Hausmann & Klinger, 2007; Hidalgo et al., 2007). Knowledge flows related to the industrial knowledge base are argued to be more easily transferred and impacting the technological activities to a larger extend compared to the unrelated knowledge flows (e.g., Boschma & Iammarino, 2009). The fourth variable is given by:

$$\varphi_{i,j} = \frac{occ_{ij}}{occ_i + occ_j - occ_{ij}} \tag{C.4}$$

where, $\varphi_{i,j}$ refers to the relatedness between each industry i, which is the industry described in the extra-regional originating newspaper, and j, which is the industrial composition in the receiving region. occ_{ij} refers to the total number of times i and j co-occur. occ_i refers to the total number of occurrences of i.

Control variables

The control variables include five commonly used variables. First, the share of SMEs with less than 250 employees in the municipality. Second, the share of the working-age population between 16-64 years of age being unemployed. Third, the population density per square kilometer. Fourth, a control for relative industrial specialization, the location quotient (LQ). The LQ is a metric used to assess the degree of specialization of industry i in region c in relation to the overall specialization of that industry across all 98 municipalities in Denmark. The LQ is calculated using the following formula:

$$LQ_{ic} = \frac{E_{ic}/E_{*c}}{E_{i*}/E_{**}} \tag{C.5}$$

In this equation, E_{ic} represents the employment in industry i in region c, E_{*c} denotes the total employment in all industries in region c, E_{i*} represents the total employment of industry i across all regions, and E_{**} represents the total employment in all industries across all regions. As said, the LQ value indicates the level of specialization of the industry i in region c relative to the national specialization of that industry. A higher LQ indicates a higher degree of specialization in industry i in region c compared to the national average.

Fifth and finally, the regional cluster classification as developed in Jessen, (2023) is included. The regional cluster classification divides Denmark into four regional typologies, i) the metropolitan regions, ii) the suburban regions, iii) the former industrial heartlands, and iv) the rural coastal regions, based on the longitudinal data from 1980 – 2018 on demographic, industrial, and institutional factors.

3.3 Econometric approach

To test if the relationship between informal institutions and AI adoption in fact is re-enforcing and co-evolving, the study first sets out to establish whether or not there is a statistically significant relationship between the two variables. This present paper adopts balanced fixed effect panel regression with regional interaction effects covering the time period from 2000 – 2018 and the model is given as follows;

$$y_{my} = x'_{my}\beta_x + W'_{my}\gamma + \sum_{i=1}^{M}(\lambda_i m_i) + \epsilon_{ym} \tag{C.6}$$

where y_{my} is AI import by firms in municipality m, year y, and x_{my} is a vector of explanatory variables including AI-news density, AI-sentiment, extra-regional knowledge flow, and extra-regional knowledge flow related to the existing knowledge base. The vector W_{my} refers to the control variables firm size, industry, Location Quotient, unemployment rate, population density, and regional cluster classification. Finally, m_i is a municipal indicator variable taking the value 1 if the municipality is i and zero otherwise, and ϵ_{my} is an error term.

The next step is to investigate if the two variables can descriptively predict each other's long-run development. To do so, a Granger causality test (Granger, 1969) is performed. The Granger causality test has been adopted by similar studies (Castellacci & Natera, 2013). The initial focus of the test is to assess the predictive ability of one time series for another by conducting t-tests and F-tests on lagged values of relevant variables. The model is given as follows:

$$y_t = \sum_{j=1}^{J}\beta_j y_{t-j} + \sum_{j=1}^{J}\gamma_j x_{t-j} + \varepsilon_t, \tag{C.7}$$

where y_t and x_t are variables, and y_{t-j} and x_{t-j} are j period lags of the variables. The coefficients β_j on the lagged variable show how previous values predict current values of the variable. In contrast, the coefficients λ_j show whether previous values of the other variable predict the first conditional on having controlled for the lagged first variable. J is the maximum lag considered. If at least one of the coefficients λ_j is non-zero, then the second variable predicts the first. One tests this using a joint F-test for all coefficients being equal to zero. Granger, (1969), p. 319 suggests that the two variables have a feedback relationship if lagged values of the variables can predict the other in this model framework.

3.4 Descriptive statistics

This paper had two main objectives: i) To understand the regional variations in the technological discourse of AI in Denmark, and ii) to understand the co-evolutions in development in regional technological discourse and the import of AI. First, Table C.1 depicts the descriptive statistics of the main variables adopted in this paper focusing on the year 2000, the year 2018 and the change in the variable in the 2000 - 2018 time period.

Figure C.1 depicts the development in import of AI related technologies per capita for each of the four regional clusters: Metropolitan regions, Suburban, Old industrial Heartland and Seaside Denmark. Due to the type of AI investigated in this paper, with larger data processing machinery, one might assume that the Old Industrial Heartland regions would be doing better in the rates of import due it their large share of manufacturing industries compared to the other regional clusters. However, interestingly, it is only in recent years that the Old Industrial Heartlands are beginning to catch up, e.g., to the Suburban regions. The Metropolitan regions have largely dominated in terms of imports and continue to do so.

Regarding descriptive analysis of the regional news depiction of AI-related news, the descriptive analyses showcase strong regional differences in the quantity of regional news on AI, the sentiment of the regional available news, and the share of extra-regional and locally originating news. Figure C.6 in the Appendix shows the regional reader shares by different types of newspaper outlets. Here it becomes evident that there exists a regional skewness. The national outlets tend to be largely consumed in the metropolitan and suburban regions. In contrast, the local and regional outlets are dominated by the former industrial regions and the rural regions. Figure C.2 depicts the development in AI mentions from 1985 to 2021 by paper type. The first mention of AI in Danish newspapers was in 1985, with a steady incline until around 2014, when the Danish media outlets' mentions of AI expanded exponentially after different new AI-related technologies hit the market and made AI more publicly available, e.g., Alexa being released in November 2014. The national and regional outlets largely dominated the growth. However, growth in mentions can be observed across all types of newspaper outlets.

When looking into the tone of news portrayal of AI from the different

Table C.1: Development in main variables from 2000-2018 by cluster

Cluster	Year	Mean	Δ Mean	SD	Min	Max
AI Import in DKK per capita						
Suburban	2000	0		0	0	0
	2018	0.0708	0.0708	0.0706	0	0.2473
Metropolitan	2000	0		0	0	0
	2018	0.0973	0.0973	0.0493	0	0.1702
Old industrial heartlands	2000	0		0	0	0
	2018	0.0951	0.0951	0.0846	0	0.2911
Seaside Denmark	2000	0		0	0	0
	2018	0.0997	0.0997	0.0861	0	0.2914
Number of AI-related news per muni						
Suburban	2000	0		0	0	0
	2018	1.3333	1.3333	1.3452	0	4
Metropolitan	2000	0		0	0	0
	2018	3.0909	3.0909	4.264	0	16
Old industrial heartlands	2000	0		0	0	0
	2018	2.6207	2.6207	4.1526	0	14
Seaside Denmark	2000	0		0	0	0
	2018	4.0312	4.0312	5.227	0	15
Number of extra-regional AI-related news per muni						
Suburban	2000	0.0033		0.0088	0	0.033
	2018	0.008	0.0047	0.017	0.0002	0.0577
Metropolitan	2000	0.0077		0.0251	0	0.1177
	2018	0.0218	0.0141	0.0167	0.0004	0.0509
Old industrial heartlands	2000	0.0001		0.0002	0	0.0008
	2018	0.0126	0.0125	0.0122	0.0001	0.0308
Seaside Denmark	2000	0.0001		0.0006	0	0.0032
	2018	0.0026	0.0025	0.0076	0.0002	0.0394
Relatedness of extra-regional AI-related news						
Suburban	2000	38.7297		7.4882	24.3825	55.0335
	2018	384.1389	345.4092	79.9954	263.065	573.475
Metropolitan	2000	38.1964		9.9583	24.3825	54.3825
	2018	382.3477	344.1513	102.7488	224.5283	565.8953
Old industrial heartlands	2000	26.1841		3.9358	24.0237	35.0335
	2018	252.6106	226.4265	40.7618	225.2598	354.7995
Seaside Denmark	2000	23.1732		6.1014	14.3825	44.3825
	2018	225.3119	202.1387	60.6636	144.2976	455.3076
Sentiment of AI-related news						
Suburban	2000	0.7579		0	0.7579	0.7579
	2018	0.5136	-0.2443	0.0136	0.4993	0.5398
Metropolitan	2000	0.7579		0	0.7579	0.7579
	2018	0.5182	-0.2397	0.0303	0.4929	0.6369
Old industrial heartlands	2000	0.7591		0.0064	0.7579	0.7927
	2018	0.541	-0.2181	0.0389	0.5009	0.6325
Seaside Denmark	2000	0.7579		0	0.7579	0.7579
	2018	0.5421	-0.2158	0.0457	0.5015	0.6332

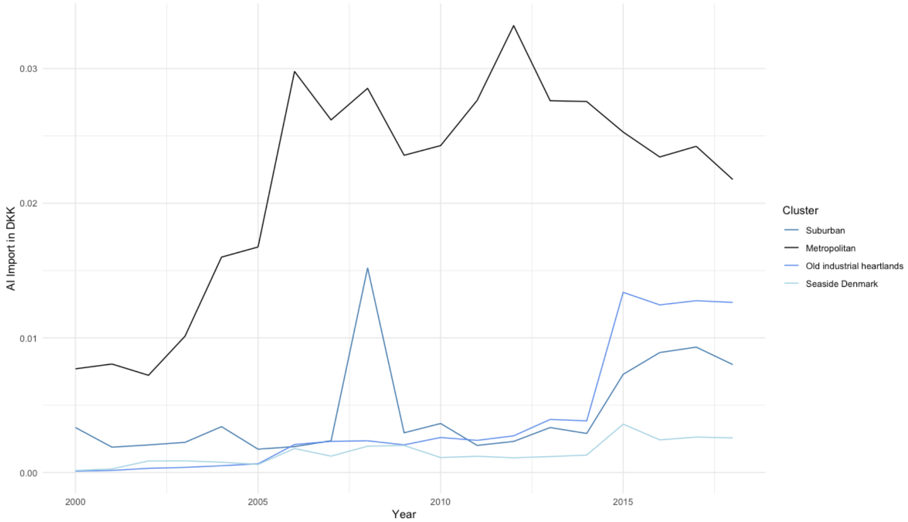


Fig. C.1: Development in import of AI-related technologies 2000 to 2018 across Danish regions

types of news outlets, it is clear that there also are differences in this dimension. In general, the tone of the Danish news media on AI corresponds with the results found by Ozgun and Broekel, (2021) on the tone of the depiction of I4.0 in Germany. The tone is largely neutral. However, the news in the former industrial regions and in the rural regions take on a more positive angle in their news portrayal, whereas the news on AI consumed in the suburban and metropolitan regions remains neutral to a larger extent. The news depiction has more extreme values in the areas outside the metropolitan regions. The explanation is, among other things, based on the regional variations in the type of news outlets being consumed in the different regions, see Figure C.3.

The empirical focus of the news consumed in the different regions takes on a hierarchical nature, see Figure C.4. This means that news consumed in metropolitan regions is about either local news, on the national level, or from abroad. The news consumed in the rural regions is largely on urban firms and to some extent local firms.

As covered in Section 2 on the theoretical framing, due to fewer audiences in the rural regions, rural newspapers incur higher per-copy costs in comparison to newspapers operating in larger markets.(Kekezi & Mellander, 2018). The higher per-copy cost is compensated for by higher efficiency demands, lower wages, and more advertisement, causing the quality of the news to decline (Reddaway, 1963). This goes well with the results with more extremes in the news depiction of the regions outside the metropolitan regions. Furthermore, if the assumption of Hassan and Azmi, (2021) and Wong and Har-

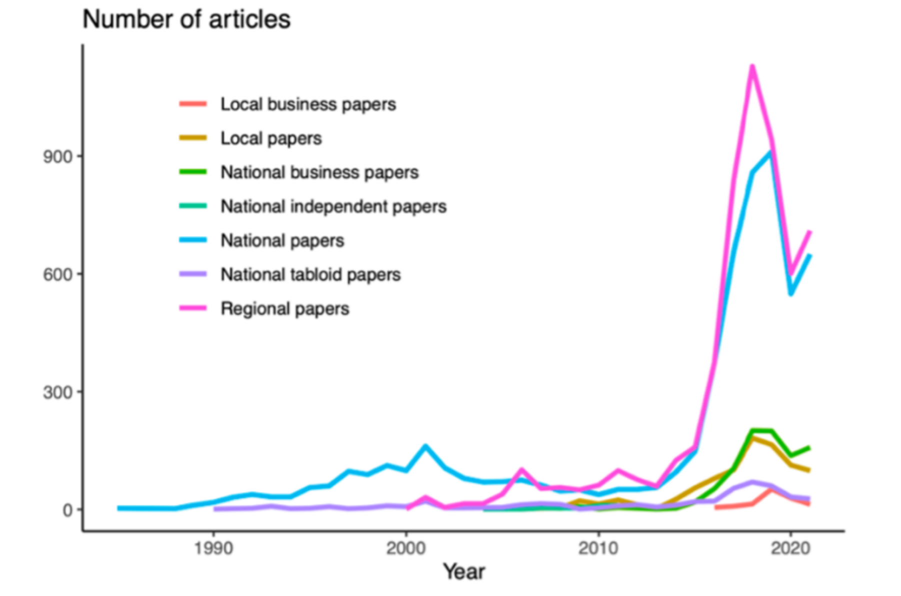


Fig. C.2: Development in AI mentions from 1985 to 2021 by paper type

Paper type	Mean	SD	Min	Pct25	Pct50	Pct75	Max
Local business papers	1.56	2.08	-3.67	0.33	1.17	2.50	7.17
Local papers	1.07	1.83	-7.50	0.00	0.67	2.22	9.17
National business papers	0.82	2.02	-6.66	0.00	0.67	2.00	7.50
National independent papers	1.43	2.40	-2.33	0.33	0.83	2.04	9.00
National papers	0.51	2.24	-35.50	-0.21	0.33	1.58	13.70
National tabloid papers	0.40	1.85	-7.00	0.00	0.17	1.17	9.67
Regional papers	0.82	2.06	-10.50	0.00	0.67	1.83	12.00

Fig. C.3: Sentiment means by paper type

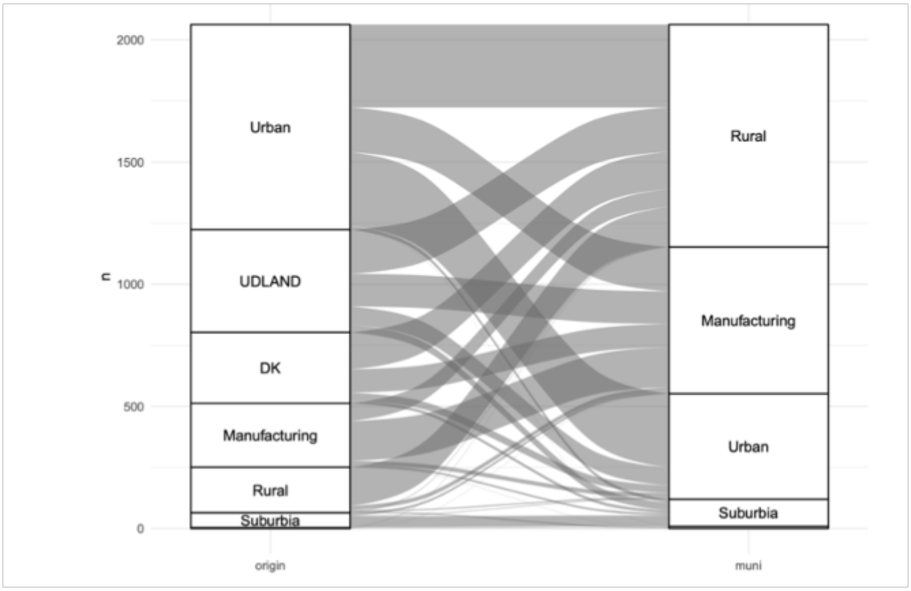


Fig. C.4: Alluvial plot with origin and destination municipality of news consumption on AI

raway, (2020) holds, then the extreme depiction could also indicate a larger extent of unfamiliarity within the region of the topic of AI.

Moreover, as discussed in Section 2 on the theoretical framing, the coverage of smaller regions is more likely to be conducted by journalists from larger regions settings compared to larger cities (Rosenberg, 2019). Due to the absence of local coverage, distant areas face reduced media attention and are less likely to be covered (Nord & Nygren, 2002), as can be interpreted from Figure 4 with the hierarchical nature of the news flows. Another explanation is that the innovative activities clusters in the metropolitan regions (Balland et al., 2020) creating more news material related to innovation (Ozgun & Broekel, 2021). The first objective of the paper was to understand the regional variations in the technological discourse of AI in Denmark. To answer the first objective of the paper, the study has investigated the regional variations in the type of newspaper outlets consumed in the different regions, the regional frequency in the news media portrayal of AI, the tone and sentiment of the news, and the empirical context of the news. It is evident that the urban and suburban regions have a larger exposure to news related to AI, that the news remains more neutral in their depiction of the new technologies, and that is a larger share of local coverage for the urban firms compared to the firms in the rural and former industrial heartland regions.

4 Results

The second objective of the paper is to understand the co-evolution in development in regional technological discourse and the import of AI. The results from the regression Table C.2 show that the higher sentiment or the more positive the regional news is, the lower the municipal import of AI-related technologies. This result holds even after the introduction of lag and control variables. News coming from outside the municipality has a positive relationship with the municipality's AI-related imports. The same is true for news coming from outside the municipality related to the receiving municipality's existing knowledge base.

Table C.2: Fixed effect panel regression on AI-related imports and regional technological discourse, 2000 - 2018

	Dependent variable:				
	AI Import				
	(1)	(2)	(3)	(4)	(5)
Sentiment	-0.308				-0.559^{***}
	(0.187)				(0.157)
News Density		0.003^{***}			-0.001
		(0.001)			(0.001)
Extrareg. news			0.510^{***}		-0.315^{*}
			(0.137)		(0.168)
Relatedness				4.304^{***}	1.591
				(0.998)	(1.165)
Lag (AI Import)					0.748^{***}
					(0.019)
Constant	0.973^{***}	0.572^{***}	0.640^{***}	0.643^{***}	8.856^{**}
	(0.162)	(0.058)	(0.053)	(0.052)	(3.502)
Control	No	No	No	No	Yes
Observations	1,862	1,862	1,862	1,862	1,056
R^2	0.001	0.011	0.007	0.010	0.663
Note:			*p<0.1; **p<0.05; ***p<0.01		

Regression Table C.3 dives into the regional variation in the results by introducing regional interaction variables. Here it becomes evident that the negative relationship between news sentiment and AI imports is largely driven by the former industrial heartlands. This relationship only seems to be reinforced over time, as shown in Table C.5 in the Appendix, where when lags of 1-10 years are introduced the effect size only increases. This same can be seen for the inflow of extra-regional news, however here the significance disappears after the introduction of control variables. The relationship between the inflow of extra-regional news related to the knowledge base of the receiving municipality is strongest for the urban regions. For Suburban regions, the news of extra-regional origin has a negative relationship with AI import, however, if the news is related to the existing industrial structure of the Suburban region, the relationship becomes positive. Table C.5 in the Appendix shows that these relationships hold unto lag year 8.

In order to test the direction of the relationship between informal institutions and AI adoption and if the two variables are, in fact, reinforcing and co-evolving, a Granger causality test (Granger, 1969) is performed. The results of the Granger causality tests are presented in C.4 in the Appendix. The null hypothesis that discourse (all four measures) does not lead to growth in AI-related imports is rejected. In other words, all four measures of the discourse of the newspapers on AI do have predictive power for AI-related import of Danish regions between 2000 and 2018. Only the null hypothesis that the sentiment of the discourse does not lead to growth in AI-related imports is rejected. Meaning that according to Granger causality analysis, informal institutions regarding technological discourse with three of the four measures and import in AI-related technologies are co-evolving. The only of the four variables that measure informal institutions regarding technological discourse where AI import can uni-directionally predict the informal intuitions is the sentiment of the discourse.

In summary, the results imply a co-evolution between the regional technological discourse, measured in this case as AI-related news, and the region's import of AI-related technologies. The relationship seems to be strongest for the former industrial regions. Granger causality analysis seems to confirm the co-evolution of regional technological discourse and AI-related technologies, with the only exception of the sentiment of the discourse, which is unidirectional.

5 Implications and conclusions

This paper set out to investigate the regional variations in the informal institutions, measured here as the technological discourse, and whether the technological discourse on AI co-evolves with the regional investment in AI-related technologies. The paper adopted newspaper data as a proxy for the regional technological discourse. The results of the paper showcase regional variations in the technological discourse in terms of the quantity, the tone, and the empirical content of the news. Granger causality analysis seems to confirm the co-evolution of regional technological discourse and AI-related

Table C.3: Fixed effect panel regression on AI-related imports and regional technological discourse with regional interaction variables, 2000 – 2018

	Dependent variable:					
	AI-related Import					
	(1)	(2)	(3)	(4)	(5)	(6)
Sentiment (Reg. 1)	−0.440				−0.531	−1.032***
	(0.336)				(0.439)	(0.395)
Sentiment (Reg. 2)	0.076				−0.217	−0.252
	(0.281)				(0.367)	(0.329)
Sentiment (Reg. 3)	−0.740***				−0.806**	−0.825***
	(0.244)				(0.318)	(0.286)
Sentiment (Reg. 4)	−0.154				−0.138	−0.187
	(0.243)				(0.314)	(0.282)
News Density (Reg. 1)		0.002**			0.001	0.0001
		(0.001)			(0.001)	(0.001)
News Density (Reg. 2)		−0.001			−0.004***	−0.002**
		(0.001)			(0.001)	(0.001)
News Density (Reg. 3)		0.005***			0.003*	0.001
		(0.001)			(0.001)	(0.001)
News Density (Reg. 4)		0.001			0.00003	0.0003
		(0.001)			(0.002)	(0.001)
Extra-reg. news (Reg. 1)			0.348		−0.144	−0.251
			(0.272)		(0.557)	(0.500)
Extra-reg. news (Reg. 2)			0.439**		−0.765*	−1.043***
			(0.202)		(0.435)	(0.390)
Extra-reg. news (Reg. 3)			0.791***		0.154	0.028
			(0.180)		(0.321)	(0.288)
Extra-reg. news (Reg. 4)			0.107		−0.019	−0.117
			(0.188)		(0.349)	(0.313)
Relatedness (Reg. 1)				2.234	1.473	1.498
				(1.891)	(3.627)	(3.252)
Relatedness (Reg. 2)				3.520**	6.532**	6.280**
				(1.384)	(2.814)	(2.523)
Relatedness (Reg. 3)				5.679***	1.133	0.778
				(1.321)	(2.288)	(2.051)
Relatedness (Reg. 4)				0.739	0.711	0.870
				(1.463)	(2.644)	(2.371)
Lag(AI-related Import)						0.470***
						(0.031)
Control	No	No	No	No	Yes	Yes
Observations	1,824	1,824	1,824	1,824	1,824	1,056
R^2	0.007	0.018	0.015	0.015	0.080	0.261

* *Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

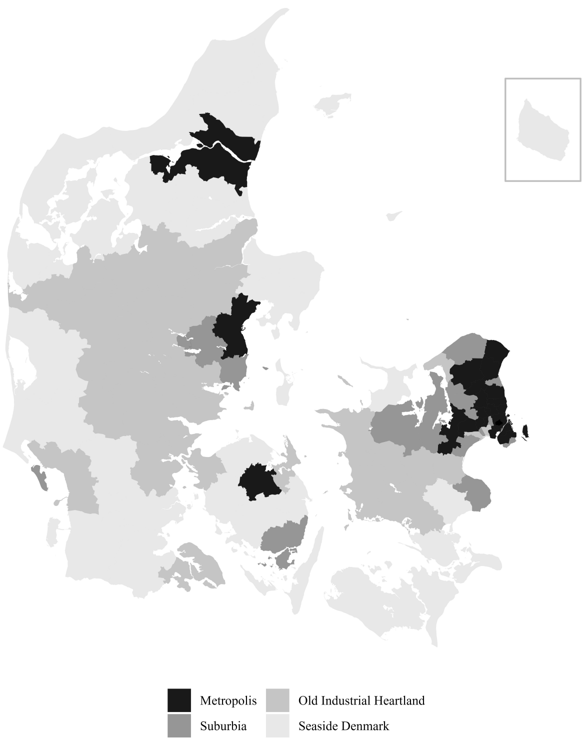
† *Note:* Reg. 1 = Suburban, Reg. 2 = Metropolitan, Reg. 3 = Old industrial Heartlands, Reg. 4 = Seaside Denmark technologies on all measures, with the exception of the sentiment of the discourse. Thereby can the first hypothesis: *Regional technological discourse and regional technological investments co-evolves over time and space*, not be rejected. The paper subsequently shows strong statistically significant relations between the regional technological discourses on AI and the regional investment in AI-related technologies. These results are especially strong for the former industrial regions. The second hypothesis: *Higher regional sentiment in news depiction is likely to be correlated with weaker degrees of technological change*, can also not be rejected.

This study has several contributions. The study provides a new measure of informal institutions, by measuring the regional technological discourse, using newspapers. The study furthermore showcases the relevance of the new measure by providing empirical evidence of the co-evolution and reinforcing nature of regional institutions and technologies, in the case of a recent technology, AI. Despite the contributions made by the study there also are limitations. E.g., the measurement of AI is a crude measure, where only the largest of establishments and their innovative activities connected to AI will be registered. An interesting future research avenue could be a study replicating the results with longitudinal data on the use of AI or other technologies across time and space.

The policy implications of the study are several-fold. First and foremost, the relationship between informal institutions and technologies varies across space both in terms of direction and size of the effect, meaning it is crucial to differentiate between regional settings and industrial histories when addressing (informal) institutional development and endowments related to innovative policy development. Secondly, the development of institutions is a long-term process, that seems to change slowly over time. This might indicate that the policy changes made today are unlikely to have an effect tomorrow. This showcases the importance of longitudinal perspectives in policymaking and planning.

A Appendix

Fig. C.5: Development clusters



Note: Source: Jessen (2023) - Paper A in this dissertation.

Fig. C.6: Municipal readership by paper type and cluster

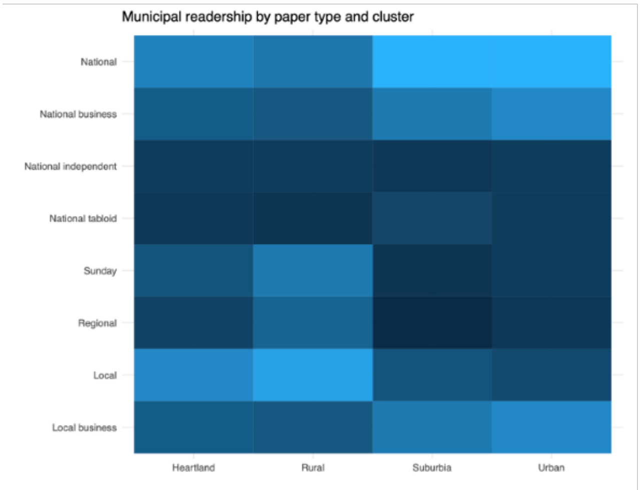


Table C.4: Granger causality analysis - P-value for F-test for joint zero λ_j

Outcome	**Predictor**	**Lag 1**	**Lag 2**	**Lag 3**
AI import	News Density	0.00	0.00	0.00
News Density	AI import	0.00	0.01	0.02
AI import	News Sentiment	0.07	0.07	0.00
News Sentiment	AI import	0.86	0.66	0.17
AI import	Extrareg. relatedness	0.01	0.01	0.03
Extrareg. relatedness	AI import	0.00	0.00	0.01

Table C.5

	AI import				
	(1)	(2)	(3)	(4)	(5)
Sentiment (Reg. 1)	−.768***	−.705**	−.874**	−.984***	−.515
	(.288)	(.304)	(.360)	(.381)	(.407)
Sentiment (Reg. 2)	−.250	−.100	−.441	−.507	−.490
	(.237)	(.251)	(.297)	(.317)	(.335)
Sentiment (Reg. 3)	−.534***	−.541**	−.725***	−.842***	−1.136***
	(.206)	(.218)	(.257)	(.272)	(.280)
Sentiment (Reg. 4)	−.146	−.173	−.159	−.169	−.317
	(.204)	(.218)	(.256)	(.270)	(.276)
News Density (Reg. 1)	−.0001	−.0001	−.0002	.0001	.001
	(.001)	(.001)	(.001)	(.001)	(.001)
News Density (Reg. 2)	−.002**	−.002**	−.002**	−.001	−.0005
	(.001)	(.001)	(.001)	(.001)	(.001)
News Density (Reg. 3)	.0003	.0002	.001	.001	.0005
	(.001)	(.001)	(.001)	(.001)	(.001)
News Density (Reg. 4)	−.0004	−.001	−.0005	.0004	−.0001
	(.001)	(.001)	(.001)	(.001)	(.001)
Extra-reg. news (Reg. 1)	−.232	−.222	−.175	−.247	−.305
	(.423)	(.431)	(.457)	(.479)	(.400)
Extra-reg. news (Reg. 2)	−.842**	−.976***	−1.031***	−.690*	−.513
	(.330)	(.338)	(.357)	(.383)	(.321)
Extra-reg. news (Reg. 3)	.013	.045	.102	.103	.051
	(.247)	(.252)	(.264)	(.275)	(.238)
Extra-reg. news (Reg. 4)	−.133	−.109	−.089	−.071	−.135
	(.265)	(.271)	(.285)	(.296)	(.258)
Relatedness (Reg. 1)	1.108	.998	1.042	1.599	.832
	(2.843)	(2.896)	(3.027)	(3.130)	(2.554)
Relatedness (Reg. 2)	4.482**	4.822**	6.188***	5.199**	3.081
	(2.162)	(2.209)	(2.323)	(2.442)	(1.999)
Relatedness (Reg. 3)	.989	.934	.435	.490	.506
	(1.761)	(1.796)	(1.888)	(1.963)	(1.627)
Relatedness (Reg. 4)	.663	.679	.771	.601	.350
	(2.052)	(2.090)	(2.184)	(2.261)	(1.876)
Control	Yes	Yes	Yes	Yes	Yes
Dep. var. lags	1	1:2	1:5	1:8	1:10
Observations	1,628	1,532	1,246	1,056	864
R^2	.368	.341	.305	.309	.528

Note: *p<0.1; **p<0.05; ***p<0.01
Note: Reg. 1 = Suburban, Reg. 2 = Metropolitan, Reg. 3 = Old industrial Heartlands, Reg. 4 = Seaside Denmark

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Paper D

Regional barriers and trajectories of technological change in Danish manufacturing SMEs: *A qualitative case study of early AI adopters*

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Abstract

This paper investigates the absorptive capacities of manufacturing SMEs in non-metropolitan regions attempting to adopt artificial intelligence (AI). The size of the firm has long the associated as a key indicator of the internal capabilities and resources of firms in terms of technological change. The deindustrialization of many former industrial regions has caused a loss of larger plants and workplaces, which then become substituted with smaller firms and enterprises. While providing employment opportunities for many, it might also at a larger level cause former industrial regions to lag in the technological transformation. However, as of yet, little is known about the AI adoption barriers of manufacturing SMEs outside the metropolitan regions. This paper draws on previous literature on evolutionary technological change and absorptive capacities to build a theory of potential barriers for technology adoption among manufacturing SMEs in non-metropolitan regions. The paper illustrates the empirical relevance of the theory through in-depth semi-structured interviews with representatives from nine manufacturing SMEs located in former industrial regions and rural regions in Denmark, who are in the process of adopting AI.

The paper finds that a mixture of the lack of relevant skills and difficulties attracting qualified workers, making AI less abstract in terms of expected outcomes and making it easier to adopt into their business models, overcoming conservatism within the organization, finding inspiration from like-minded firms, and finding information about both new technologies and grant opportunities are among the main barriers for manufacturing SMEs in former industrial regions when beginning to adopt AI. However, many of the SMEs develop strategies in order to overcome the lack of firm-internal and regional absorptive capacities where incremental changes building on existing and related capabilities prove effective solutions.

Keywords: *Firm absorptive capacities, Regional capability bases, AI, Evolutionary technological change, Manufacturing SMEs, Denmark*

1 Introduction

AI is believed to have the potential to ignite a productivity revolution in firms that will bring about a profound transformation in business procedures, particularly in the manufacturing industry, because of its considerable automation potential (e.g., Kinkel et al., 2022)The recent literature studying barriers to Industry 4.0-related technology - and particularly AI - diffusion generally agrees that SMEs struggle more in the adoption processes compared to their larger counterparts (**MasoodSonntag2020_IndustryAdoptionChallenges**; e.g., Benitez et al., 2020; Estensoro et al., 2022; Grooss et al., 2022; Matt & Rauch, 2020; Müller et al., 2021; OECD, 2021; Rauch et al., 2020; Stentoft et al., 2021). They argue that SMEs are more likely to struggle, among other things, because they have fewer financial resources to invest in adoption, their employees are less likely to have the digital skills necessary to understand and use the I4.0 technology, and they likely have little experience working with technologies related to AI. Zolas et al., (2020), for example, suggest that larger and more established firms are generally more inclined to adopt advanced technologies, including AI. They contend that adoption patterns align with a hierarchy of technological sophistication, wherein firms that embrace AI or other advanced technologies are likely to have already adopted other widely diffused technologies.

Understanding the barriers SMEs face is essential from an academic and policy perspective. These firms account for more than 95 percent of registered firms and more than half of employment in Western societies (EUROSTAT, 2022). As a result, SMEs have aptly been referred to as the "economic backbone" in most Western countries by Neagu et al., (2016). This means that falling behind in AI adoption and productive improvements can have substantial economic consequences for many workers and businesses. This risk is exacerbated by the fact that the share of SMEs is growing in the regions associated with economic stagnation, where the SMEs tend to replace large plants that disappeared after de-industrialization processes (Freshwater et al., 2019). SMEs´ AI adoption challenges, therefore, also end up potentially increasing the rising regional inequality observed in many Western countries during the past 40 years (e.g., Storper, 2018). Nevertheless, existing studies on the adoption of AI in SMEs emphasize urban firms, reinforcing the predominantly urban bias in innovation and technology adoption studies (Shearmur, 2017). Therefore, as of yet, little is known on how non-manufacturing SMEs perceive their and potentially overcome barriers to adopt the new I4.0 technologies.

This paper contributes to the previous literature on AI adoption by studying the barriers manufacturing SMEs in non-metropolitan regions face when attempting to adopt AI. It does so by first developing a theoretical sketch that explains why non-metropolitan SMEs particularly may struggle with AI adoption. The sketch is subsequently informed by a qualitative semi-structured interview study with nine non-metropolitan manufacturing SMEs attempting to adopt AI technology. The interviews were focused on perceived adoption challenges. All nine firms were part of the project AI:DK in which SMEs get help to start their AI adoption from partnering with Danish universities. The interviewees at the firms were either project leaders or had higher-level management positions as firm representatives in the AI:DK project, with positions in the firm ranging from CEOs to innovation managers. The nine cases have had varying levels of success in their adoption attempts and provide insights into the factors influencing AI adoption in manufacturing SMEs outside the metropolitan regions. The interviews have been coded and analyzed in an iterative manner (Merriam, 1998) by combining inductive and deductive approaches, going back and forth between the theoretical framing and the interview data.

The theoretical sketch draws on the literature on absorptive capacity (e.g., Cohen & Levinthal, 1990; Matusik & Heeley, 2005; Zahra & George, 2002) and the idea of knowledge transfer through related diversification (e.g., Boschma, 2017) to explain the AI adoption barriers facing manufacturing SMEs. Here, absorptive capacity roughly refers to firms' ability to adopt and use new technology based on the resources it possesses and its previous technology adoption experiences (e.g., Cohen & Levinthal, 1990). The idea of related diversification has a key feature in economics and management literature (Porter, 1980) and has become a key feature in evolutionary economic geography (EEG) (e.g., Boschma, 2004a; Boschma & Iammarino, 2009; Neffke et al., 2011). Related diversification roughly refers to when, e.g., a company expands into new markets or businesses that are connected to its existing operations, leveraging its strengths and creating synergies. The literature tends to argue the adoption of new knowledge and new technology is more effective if the knowledge or technology is already similar or "related" to the the already existing knowledge base of the firm (Boschma, 2004a). Together these theoretical perspectives encompass and build on the theoretical arguments in the previous AI adoption literature.[2] Additionally, the sketch draws on the argument from EEG and regional studies that available regional resources (Lawson, 1999; Neffke et al., 2018), including the pool of workers with different technological knowledge, and the competition over these vary because of previous economic activity in the regions so that firms in non-metropolitan regions may find it harder to access resources they need to adopt new technologies. This argument explains why firms in non-manufacturing regions may be more likely to face adoption adversity than firms in metropolitan or near-metropolitan regions.

Together, the empirical study and the theoretical sketch suggest that the non-metropolitan manufacturing SMEs with little experience in developing and maintaining large data infrastructures and high technological activities face internal and regional-specific barriers in their AI adoption process. However, SMEs that can build on related activities and existing knowledge, skills, and experiences within the firm and adopt a more long-term step-by-step approach to AI adoption could achieve more successful results.

The remainder of the paper is structured as follows. First, the theoretical sketch is outlined, emphasizing firms' absorptive capacities, related diversi-

[2]Though only a few of these studies mention absorptive capacity (e.g., Kinkel et al., 2022; Müller et al., 2021), their emphasis on the importance of firm resources and experiences can be directly linked to this theory.

fication, and evolutionary foundations for differences in regionally available resources. Second, the study's data collection strategy and research analysis are presented. The third section discusses the findings of the interview data. The fourth and final section concludes with the paper's findings and discusses its implications.

2 Theoretical framing: Technological change as an evolutionary process

In the following, the theoretical argument of the paper will be described. The section first covers the idea of regional capability bases and their theoretical importance for firms' technology adoption, viewing technological change and adoption from an evolutionary perspective, and then moves on to describe the absorptive capacities of firms.

Today a large consensus exists that firm- and regional-level technological change tends to take on an evolutionary nature (e.g., Rigby & Essletzbichler, 1997) characterized by path-dependent change, where development and transfers of knowledge and technologies are more likely to be successful if already related to the existing knowledge base of the firm or region. In this theory, the behavior of firms and their market environments are subjected to simultaneous impacts of dynamic processes (Nelson & Winter, 1982). The evolutionary nature of these processes is based on the notion that path dependence, cumulative processes, and increasing returns are fundamental characteristics of technological change. This is because firms are believed to possess, to varying degrees, internal structures, which allow for organizational memory and learning, and that firms´ actions, behavior, and routines are in part formed by the environment in which they reside (Dosi & Metcalfe, 1991). This relationship will be described in further detail in the following.

2.1 Regional capability bases

The foundation for the evolutionary perspective employed in this article is that regions are heterogeneous across space and time. This study follows Neffke et al., (2018) and adopts the resource-based view of the region. According to this perspective, regions possess capability bases being the unique set of resources, competencies, and capabilities that are present within a specific geographic region(Boschma, 2004b; Lawson, 1999). Regional capabilities stem from resources that multiple firms can adopt but are primarily accessible within the given region (Neffke et al., 2018; Penrose, 1959). They encompass various aspects such as (informal) institutions, local knowledge bases, networks (Asheim & Gertler, 2006; Boschma, 2004b; Cooke & Morgan, 1998), untraded interdependencies (Storper, 1995), access to specialized suppliers, local knowledge, skilled labor (Almeida & Kogut, 1999; Faggian & McCann, 2009; Glaeser et al., 1992; McCann & Simonen, 2005), and localized learning (Maskell & Malmberg, 1999).

The theory also assumes that the degree to which firms can access and rely on regional resources depends on their level of embeddedness in the local economy. The degree of embeddedness is dependent on the economic, social, and trust-based relationships that firms develop with various entities within the region, e.g., institutions, i.e., governments, and other firms (Cooke & Morgan, 1998; Grabher, 1993; Saxenian, 2007; Storper, 1995). The process of developing these relationships may require a significant investment of time, e.g., because firms need to actively nurture long-term connections with local suppliers and knowledge networks in order to secure preferred access (Boschma & ter Wal, 2007; Ghemawat, 1986; Giuliani & Bell, 2005). Similarly, it may be easier to attract the right local workers when the firm can recruit through local social networks (Sorenson & Audia, 2000). It follows that the regional resources become increasingly accessible to the firms as they strengthen their regional presence (Pouder & St. John, 1996; Storper & Venables, 2004).

While it becomes easier for firms to access resources when they become more embedded, how much they need these resources will depend on the firm's characteristics within this theoretical perspective. For instance, larger firms often possess internal resources, e.g., knowledge bases, supply chains, and labor markets, that make them less dependent on immediate regional resources. On the other hand, smaller firms with fewer internal resources may also seek resources in different regions if their social networks facilitate this access (Agrawal et al., 2006; Saxenian, 2007). At the same time, larger firms often have a competitive advantage over their smaller counterparts regarding attracting skilled labor due to their ability to offer higher wages and job security (International Labour Organisation, 2019).

Based on this theoretical perspective, firms in non-metropolitan regions will likely have access to different resources to the extent that the regional capability bases differ with respect, e.g., to the local knowledge-sharing institutions, the skills among the workers participating in the local labor market, and the competition over resources.

2.2 Evolutionary technological change and firms' absorptive capacities

An extensive scholarship has argued that firms have different levels of "absorptive capacity", a term coined by Cohen and Levinthal, (1990). Cohen and Levinthal (1990, p. 128) define absorptive capacities as "the ability of a firm to recognize the value of new external information, assimilate it and apply it for business purposes". A core assumption of absorptive capacities is connected to the evolutionary view of diversification and knowledge transfer: Knowledge is most effectively absorbed if the new knowledge is similar or "related" to the already existing knowledge base of the subject of interest, e.g., firms or entire regions. It follows that absorptive capacities can be related to the evolutionary theory of firms developed by Nelson and Winter, (1982), who argue that firms' knowledge bases are shaped by their prior accumulated knowledge and experience. These can in turn be argued to depend on the geographical location and how well the firm is embedded in the regional setting, and thereby have access to regional resources based as discussed in the previous section.

Since the seminal paper of Cohen and Levinthal, (1990) several papers have proposed different ways of operationalizing the different types of absorptive capacities. Probably most prominent has been the attempt of Zahra and George, (2002), who divided the absorptive capacities into four distinct sorts of organizational routines and processes: (1) acquisition, the capability to acquire new knowledge, (2) assimilation, the capability to include the new knowledge in the firms knowledge base, (3) transformation, the capability to transform the new knowledge so that it becomes useful for the firm, and (4) exploitation, the capability to apply the new knowledge in the firm. They argue that the two former capabilities constitute the firm's potential absorptive capacities, and the latter two the realized absorptive capacities. Matusik and Heeley, (2005) also proposed an extension to the literature on absorptive capacities by classifying the absorptive capacities by dividing them into three groups, which also could be interpreted as three different levels of the unit of analysis: (1) the firms' embeddedness in their geographical setting; (2) the routines and knowledge base of the main value creation group in the firms; and lastly (3) the individual's absorptive capacity.

This paper draws on both these two operationalizations of the absorptive capacity concept to build the theoretical foundation for studying the AI technology adoption of SMEs in the non-manufacturing regions. It draws on the two potential absorptive capacities and the combined realized absorptive capacity from Zahra and George, (2002) to frame the capacities involved in the process of adopting new technology. For all three categories, the assumption that path-dependent processes shape the absorptive capacities and that "relatedness" (e.g., Boschma et al., 2015) works as a driver for effective interfirm learning prevails (Cohen & Levinthal, 1990). It draws on Matusik and Heeley, (2005) to emphasize the role of regional embeddedness of the firm and the internal routines and knowledge bases of the firms. The next section further explains the three types of capacities and the theoretical importance of regional embeddedness.

2.2.1 Capacity 1: Acquisition of new knowledge

The first of the absorptive capacities is the acquisition capacity, the capacity to *"to identify and acquire externally generated knowledge that is critical to its operations"* (Zahra & George, 2002, pp. 189). According to Zahra and George, (2002), the acquisition of new knowledge depends on the firms´ prior level of and portfolio of investments, prior obtained knowledge, and the speed, intensity, and direction of the knowledge acquisition process. These factors will influence the scope of the search, the degree of new contacts, perceptual schema, and the speed and quality of the learning (ibid.).

Firms differ in the capacities to acquire new knowledge (Hägerstrand, 1967). The differences in the acquisition of new knowledge between firms are several-fold. First, the motivation to start searching for technological opportunities might be hindered or motivated by organizational inertia, which forces one to search for new opportunities to avoid lock-in (Hannan & Freeman, 1984). An important component of acquiring new knowledge is the past experiences and the subsequent internalized memory of the firm (Nelson & Winter, 1982). E.g., previous success can hinder the firm´s willingness to do things differently and invest in new technological opportunities. This is also called the "competency trap" (Levitt & March, 1988). March, (1991) described the "competency trap" as the interplay of "exploration of new possibilities" and "exploitation of old certainties". Lawson and Lorenz, (1999) have further explained the phenomenon as "becoming quite good at doing any one thing reduces the organization's capacity to absorb new ideas and to do other things" (Lawson & Lorenz, 1999, p. 311).

Incumbent firms frequently tend to prioritize incremental competency-enhancing improvements over radical competency-destroying innovations (Teece, 2007). Uncertainty of the outcome of acquiring the new technological opportunities further hinders the willingness to act upon opportunities (Lippman & Rumelt, 1982). This uncertainty can result in risk aversion and, subsequently, innovation avoidance (Kahneman & Lovallo, 1993). The uncertainty of the investment outcome can, however, also result in the opposite, with excessive optimism regarding the outcome and subsequently limited or even negative returns.

Moreover, acquiring new knowledge depends on individual employees' technological knowledge, skills, and creativity. The likelihood of success increases when the scanning, interpretative, and creative processes are integrated into the firm's organizational structures (Winter, 2003). However, integrating these processes tends to be more difficult for smaller and less-knowledge-intensive firms, often with lower skill compositions (Müller et al., 2021).

In terms of the role of geographical location for the firms´ acquisition of new knowledge, it is evident that knowledge has strong spatial decay meaning that firms further away from innovative milieus are less likely to get hold of new knowledge regarding technological opportunities (Arrow, 1962) The network in which the firm is located also matters for the accessibility of new knowledge. For example, establishing connections between corporations and universities aids in conducting comprehensive and wide-ranging searches (Teece, 2007). Additionally, leveraging non-local knowledge relationships is a crucial aspect of acquiring new knowledge for firms, particularly those in peripheral regions.

This has, e.g., been showcased in the case study by Boschma and ter Wal, (2007) of the Barletta footwear cluster. Similarly, Baker et al., (2021) investigate the factors that enable or hinder regional innovation policies related to I4.0 (IoT: additive manufacturing, integration of data and workflows, digitalization, remote monitoring, automation of controls through machine learning and predictive analytics, multi-disciplinary engineering) in two cases: Ontario, Canada, and Massachusetts, USA. They argue that context, industrial clusters, network intermediaries, and collaborative synergies are significant influences on facilitating I4.0. This highlights the crucial role of networks in accessing new technological knowledge.

2.3 Capacity 2: Assimilation of new knowledge

The second of the three subcategories of absorptive capacities is the firm's ability to assimilate new knowledge. This capacity pertains to the routines and processes within a firm that enables the analysis, processing, interpretation, and comprehension of knowledge acquired from external sources (Zahra & George, 2002). In recent studies related to the diffusion of I4.0-related technologies and specifically the diffusion of AI, it has been argued that observed adoption patterns are consistent with a hierarchy of increasing technological sophistication, meaning that firms that adopt AI or other advanced technologies are likely also to use other, more widely diffused technologies (Zolas et al., 2020). Similarly, on the regional level have Xiao and Boschma, (2022) and Laffi and Boschma, (2022) showed regional knowledge base of knowledge and communication technologies (ICTs) influences the emergence of AI technologies in the European region. These findings indicate that knowledge is easier transferred and comprehended when related to the existing knowledge base of the firm and that comprehension might risk being severely delayed if the externally acquired knowledge is not related to the knowledge base (Zahra & George, 2002).This absorptive capacity is like the first absorptive capacity, strongly connected to the human resources and their skill sets available to the firm. Because the firm depends on its workers' knowledge and skills, it will also depend on the local labor market that its geographical location allows it to access.

2.3.1 Capacity 3: Application of new knowledge

The third and final of the three subcategories of absorptive capacities is in this paper, the two realized absorptive capacities according to Zahra and George, (2002): Transformation and Exploitation, which in this paper is referred to as "Application of new knowledge". This merged together capacity refers to the firm's ability to refine the routines of the firm by combining existing and newly acquired and assimilated knowledge. This is done by continually redesigning routines and business models. E.g., firms can work toward active learning and upgrading, e.g., through retraining or renewal of relevant skills (Branzei & Vertinsky, 2006).

Regarding AI and the transformation of firm routines and work organization after adoption, studies argue that effects depend on the type of jobs and industry. Holm and Lorenz, (2022) argue that AI can enhance or supplement skills by promoting the adoption of high-performance work practices while also introducing constraints on work pace and reducing employee autonomy. They further argue that the study's results indicate that the diffusion of AI may lead to increased inequalities in the labor market by augmenting skills required in high-skill jobs, albeit with relatively more negative impacts on other types of jobs. If looking at the results through the lenses of absorptive capacities, one could further speculate that the high-skilled jobs could be associated with a higher ability to positively apply AI in the firm.

2.4 Regional barriers and trajectories of AI adoption in manufacturing SMEs: Absorptive capacities of regions and firms

The evolutionary theory of regional technological development and the theories of firm technology absorption can be combined to provide insights into I4.0 technology adoption barriers. The main arguments are that regions differ in regional capability bases, and firms within regions differ in their absorptive capacities partly due to the regional capability bases they can access. It is relevant to study this because AI, as a new technology, is expected to reshape production and manufacturing in the near future through its effects on competitive advantages for adopting firms. However, little is yet known about how absorptive capacities affect AI adoption among SMEs outside the main metropolitan regions, likely due to difficulties measuring AI use in firms and possibly also an urban bias as argued by Shearmur, (2017). The main research questions of this study approach this question about AI adoption with drawing on the theory of absorptive capacity outlined above:

- RQ1: How are the non-metropolitan manufacturing SMEs benefitting from existing absorptive capacities regarding AI adoption?

- RQ2: How are the non-metropolitan manufacturing SMEs overcoming their potential internal and external barriers concerning AI adoption?

The theoretical point of departure is depicted in Figure D.1, where path-dependent processes lead to different regional capability bundles. Firms have different options in competing for regional resources. The more disadvantaged regions make it more difficult for more disadvantaged firms to compete for regional resources because the pool of, e.g., skilled workers is more limited.

3 Methodological approach

3.1 Danish firms and regions as an empirical setting

The empirical component of this study takes the point of departure in Danish firms and regions. Denmark is known as one of Europe's most digitally advanced countries, both in terms of overall technological and digital application in society among citizens and firms, and in terms of employment in the digital economy (EU, 2022). Despite the high level of digitalization for Danish firms, however, recent reports and scholarly papers show that Danish SMEs fall behind the AI adoption and digital transformation in general (Danish Ministry of Finance, 2021; Stentoft et al., 2021; Yu & Schweisfurth, 2020). For the regional classification, this study employs the definition by Jessen, (2023), which benefits from a wide set of development data across almost 40 years. The 98 Danish municipalities (LAU2-level) are divided into four development types in this classification: The Metropolis municipalities, the Suburbia municipalities, the Old industrial heartlands municipalities, and the Seaside Denmark municipalities. The two latter are the regions with the least level of economic and human capital development and are, for that reason, the two regions this study takes the point of departure.

3.2 Research design

This paper investigates 1) how the non-metropolitan manufacturing SMEs are benefitting from existing absorptive capacities regarding AI adoption, and 2) how the non-metropolitan manufacturing SMEs are overcoming their potential internal and external barriers concerning AI adoption. To achieve this aim, a qualitative study that draws on interview data is conducted. Adopting this approach allows for a contextual understanding and in-depth insights into the regional trajectories and barriers at the firm level when SMEs begin to implement AI in their businesses.

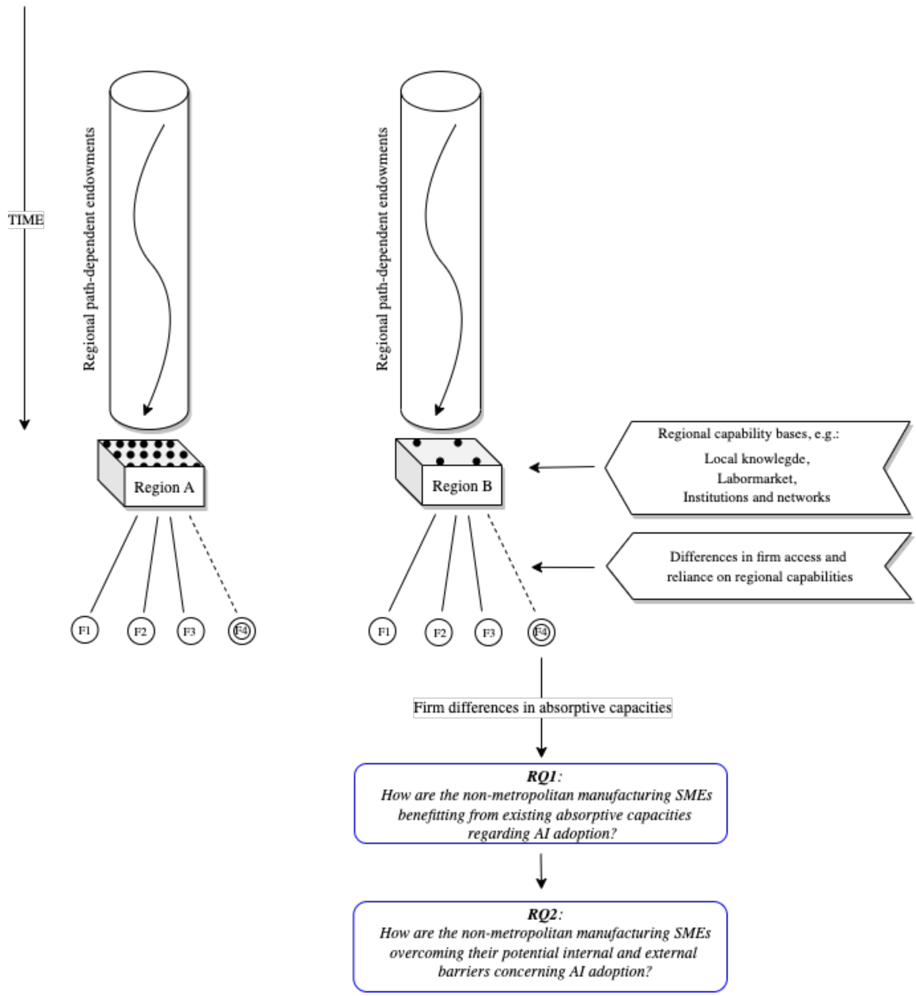

Fig. D.1: Theoretical framing of the current study. Layout by the author.

3.3 Data collection

The study set out to investigate the regional barriers for manufacturing SMEs outside the main metropolitan regions interested in beginning AI adoption. The research data comprise nine thematic semi-structured interviews with the informants from Danish SMEs, geographically located outside the main metropolitan regions in Denmark (see Figure 1 in Appendix) and all participating in the network AI Denmark. AI Denmark is a partnership between the Technological Institute, the Alexandra Institue, Aalborg University, Technical University of Denmark, Copenhagen University, and the IT-University, and is financially supported by the Danish Industry Foundation. The project aims to inspire and help Danish SMEs to make better use of their data and gain familiarity with AI tools. The project organizes inspiration- and network workshops and connects researchers from the partnering universities with the SMEs in a six-month project taking the point of departure in the firm´s specific context (AI:DK, 2023). The participating SMEs are as majority located in urban settings. The author conducted the interviews: Seven of the interviews were conducted online using Microsoft Teams with only the interviewee and the interviewer present. One interview was held online using Microsoft Teams with a colleague of the interviewer present. One interview was held in person with a colleague of the interviewer present. Eight of the interviews were in Danish and one was in English. The choice of the interviewees was based on their geographical location in either the Old Industrial Heartlands or the regionally more peripheral regions. SMEs located in either Suburban regions or Metropolis regions were disregarded. Furthermore, the interviewed SMEs had to have a background in manufacturing industries. Most of the interviewed SMEs were traditionally described as low-knowledge-intensive manufacturing, except for two of the firms, which were high-knowledge-intensive manufacturing. The chosen SMEs should have limited prior experience working with AI and could, therefore, not be software SMEs, meaning that firms with NACE-codes 6000 – 7000 as main NACE-code were excluded. Half of the interviews were conducted in the early spring of 2022. The second half of the interviews were conducted in early fall 2022. The interviews lasted from 20 to 70 minutes, with a mean of 43,78 minutes. The interviewees were all asked similar questions taking the point of departure in the interview guide. The interviews were semi-structured, which allowed to enabling exploration of topics that occurred during the interviews. During the interviews, various aspects were explored, including the firm's organizational structure, existing barriers, ongoing innovative practices, and the potential benefits and challenges of adopting AI. Prior to the interviews, the interviewees received an email providing background information on the topic. The interviews were audio recorded with the permission of the interviewees and subsequently transcribed verbatim by a research assistant. All eight Danish interview transcripts were later translated into English by the author.

3.4 Data analysis

The nine transcriptions were analyzed using iterative qualitative analysis, which takes the point of departure in thematic coding that combines inductive and deductive elements by going back and forth between the data and theoretical framework to inform the analysis (Merriam, 1998). The iterative nature of the analysis refers to the engagement in a continuous, iterative process with the data by revisiting and revising the initial interpretations to develop a comprehensive and nuanced understanding of the research topic. The iterative process adopted in this analysis started with deductive coding, where elements and concepts from the theoretical frameworks were applied. The coding categories and labels were refined and revised as new data was analyzed. The iterative nature of the analysis allows for the emergence of new insights (ibid.). Nvivo was adopted to help organize the different codes in the analysis. The analysis resulted was divided into the three themes: (1) Acquisition of new knowledge, (2) Assimilation of new knowledge, and (3) Application of new knowledge.

4 Findings and discussion

Figure 2 presents the main results of the analysis of the data collected in the nine interviews. The acquisition capacities associated with nonmetropolitan manufacturing SMEs' adoption of AI mainly focus on internal knowledge generation, market scanning, sensing customer trends and behavior, and engaging in collaborations and network activities. The assimilation capacities for the nonmetropolitan, manufacturing SMEs attempting AI adoption depend on data management, the bridging of skills, integration into the main business model, and breaking away from path-dependent routines. Finally, the application capacities require a strategic orientation toward AI implementation. The interview data both emphasized the existing absorptive capacities in the SMEs that supported their AI implementation processes but also highlighted the absorptive capacities the SMEs felt they were missing and what caused barriers in the adoption process, and how to potentially overcome these lacking absorptive capacities.

Interview	Position	Size of firm	NACE	Geographical location	Founding year of firm	Length of interview
J1	CEO	12	289900: Manufacture of other special-purpose machinery n.e.c.	Old industrial heartland	2002	00.50.44
J2	Innovation Employee	37	204100: Manufacture of soap and detergents, cleaning and polishing preparations	Old industrial heartland	1987	00.37.00
J3	Innovation Employee	51	289900: Manufacture of other special-purpose machinery n.e.c.	Seaside Denmark: peripheral region	2016	00.36.26
J4	CEO	226	289300: Manufacture of machinery for food, beverage and tobacco processing	Old industrial heartland	1978	01.10.16
J5	CEO	132	107110: Manufacture of bread; manufacture of fresh pastry goods and cakes	Seaside Denmark: peripheral region	1995	00.19.24
J6	CEO	15	329900: Other manufacturing n.e.C.	Seaside Denmark: peripheral region/Urban region	2016	00.57.20
J7	Innovation project manager	60	463700: Wholesale of coffee, tea, cocoa and spices	Old industrial heartland	1964	00.40.30
J8	CEO	4	283000: Manufacture of agricultural and forestry machinery	Old industrial heartland	2007 (1998)	00.35.42
J9	CEO	135	289900: Manufacture of other special-purpose machinery n.e.c.	Old industrial heartland	1977	00.47.24

Fig. D.2: Interviewee information

	Description	Dimension	Identified codes from interviews
Acquisition capacities	• Definition: the firm's ability "to identify and acquire externally generated knowledge that is critical to its operation" (Zahra & George 2002) • The first of the two potential absorptive capacities	• Prior knowledge and prior investment	• Building on prior partnerships with universities and research institutes • Building on prior obtained knowledge: Understanding the rules of the game/ecosystem • Building on prior experience: Filtering (out) opportunities not relevant for business • Building on already established trust relationships and internal sources, e.g., information from board members • Building on existing external ties, e.g., networks, campaigns, innovation milieus
		• Speed, intensity, and direction of knowledge search	• Intensity of search - Prioritizing AI in a busy everyday and letting AI be an experiment: Time and monetary constraints • Direction of search - The role of sensing customer behavior and trends • Speed of search: Internal knowledge generation and creating the right mindset: the problem of organizational inertia, competency trap and breaking out from path dependent routines
Assimilation capacities	• Definition: The routines and processes within a firm that enables the analysis, processing, interpretation, and comprehension of knowledge acquired from external sources (Zahra & George 2002) • The second of the two potential absorptive capacities	• Understanding	• Lacking labor pool with technical knowledge imagination: New blood and new ideas • Making AI less "fluffy"/abstract and overcoming uncertainty (about the outcome) bias • Competition for regional capabilities (no-show students, Ph.D.s, labor market • Bridging skills - Combining know-how and know-why (technical and business knowledge
Application capacities	• Definition: The firm's ability to refine the routines of the firm by combining existing and newly acquired and assimilated knowledge • The two realized absorptive capacities of Zahra & George (2002) merged together	• Refining and redefining routines	• Radical changes in incremental steps: defining a long-term AI vision and integrating into the business models • Aligning existing internal data and data demands: From data in the head to algorithms • Attracting labor for maintaining data • Creating local demand and buzz • "Shaking the bag": renewal and retraining of laborpool

Fig. D.3: Overview of interview data structure. Layout by the author

4.1 Capacity 1: Acquisition capacities for AI adoption in non-metropolitan, manufacturing SMEs

As touched upon in the theoretical framing, "acquisition" refers to the firm's ability "to identify and acquire externally generated knowledge that is critical to its operation". In the following text the SMEs´ prior knowledge and investments impact on the scope and quality of knowledge searches. Furthermore, the factors impacting the intensity, speed and direction of the knowledge searches will be discussed.

4.1.1 Building on prior knowledge and prior investments

An important building block for the interviewed SMEs in acquiring new knowledge was building upon existing knowledge and prior investments. This allowed the SMEs to overcome some of the uncertainties related to knowledge acquisition regarding AI adoption. It furthermore allowed the SMEs to dive deeper into their searches and widen the scope of the knowledge searches, which several SMEs thought necessary due to their geographical location.

Theme 1: Building on prior partnerships with universities and research institutes
All nine cases highlighted the importance of engaging with universities and research institutes when looking for innovation-related opportunities. Given the common determinator of inclusion in this current study, the engagement in AI:Denmark, this is perhaps not the most surprising finding. However, most of the cases had become aware of the opportunity with AI:Denmark from previous collaboration partners based in different universities, as, e.g., with Company 3: *"We have previously had contact with, for example, Aarhus University and the Technological Institute, where there have also been projects where AI has been a part of it."*.

The previous collaboration with universities and research institutes allowed the SMEs to be seen as innovation interested, and if collaboration had been mutually successful, it is more likely that the collaboration will continue in the future, as Company 7, put it: *"We had like a follow-up call, how we can actually... What's our next project, because we enjoyed working together and that was quite helpful. They suggested to go for the AI:Denmark (...)."*

It furthermore allows the SMEs to have to use fewer resources on the inter-knowledge generation because they are "in the loop", when new and potentially interesting technological opportunities appear in the market. The chance of the new technological opportunities being a better fit is seen as greater and more reliable if the opportunities were made aware of prior collaborators at universities familiar with the SMEs´ strengths, shortcomings, and future goals: *"We had a project running with the Technological Institute, where we had a statistician who helped us make some statistics on some road data we use in some of our systems. And in that connection, we just talked to him far and wide, and he mentioned, "well, we also have a department that is working on this and might be able to help you". And so that way, the contact was made with his colleagues, who then went out and presented to us what it (Ed.: AI:DK) really is."* (Company 4)

Theme 2: Building on prior obtained knowledge: Understanding the rules of the game/ecosystem

A key element of being able to acquire new knowledge is the ability to understand the rules of the game and how the business ecosystem is structured. Both in terms of grants, collaboration partners, suppliers, and keeping on top of the trends in the market. Company 6 expresses how they managed to scan the market for new opportunities like this: *"One of the most difficult things about being an entrepreneur is actually getting an overview of how this entire ecosystem is connected. Because there are so many players, there are so many initiatives, so you can easily get completely confused."* According to Company 6, understanding the business ecosystem is achieved by experience and trial and error, but it takes time to achieve this understanding.

Theme 3: Building on prior experience: Filtering (out) opportunities not relevant for business

One of the main challenges of scanning the market is not the lack of opportunities but instead to achieve the ability to filter out the opportunities not relevant for the business. Many of the SMEs tell stories about being flooded with different offers from campaigns and salespersons with all sorts of more and less relevant new offers. To achieve the ability to filter out the relevant opportunities from the less relevant opportunities again require experience and a constant focus on what the firm seeks to achieve in the future. Company 4 explains how an information email about AI:Denmark caught their eye: *"But the only way that I was sort of made aware of these things here was by receiving some email from somebody, you know, like I get five every day, right? That is, with, "no, now you have to listen", and that was exactly the word that caught me - and AI is so superlative to that (...)And then it really caught my attention because we were already working on similar themes. I pushed for us to do something about it, and that made us get in touch via (...)Technological Institute, otherwise we wouldn't have got it, so we wouldn't have come that way."*. The relevance of the AI:Denmark due to prior experiences and ongoing business goals interested the company in exploring the opportunity.

Theme 4: Building on already established trust relationships and internal sources, e.g., information from board members

A different subsection of the theme "engagement in the collaborations and networks" identified in the interview data is developing internal infrastructure that allows more low-technological firms to search for new technological knowledge more efficiently. This can, e.g., be done by seeking board members that have the technological knowledge that the SMEs internally might be missing, as, e.g., Company 9, who recently got a new innovation interested board member: *"We started it because someone from our board, he works a lot with IT (. . .) He pushed us that way and thought it was something we should consider, and I considered it and applied for participation in the project."*. Company 9 continues to stress the importance of developing capacity in the setting of a non-metropolitan and low-technological manufacturing SME: *"It's abstract and when you don't have a whole arsenal who have experience with a range of different things in your workforce. Because where do you start and end? It's insanely difficult. We wouldn't have gotten started if our board hadn't provided us with the necessary push."* (Company 9)

Theme 5: Building on existing external ties, e.g., networks, campaigns, innovation milieus

Several of the interviewed SMEs points out that due to their size and their geographical location, it is more difficult to get hold of information and to sense new technologies and the validity of the new technological opportunities, which makes collaboration with universities and having a strong network with people having technological knowledge all the more important. One of the more high-technological and younger of the SMEs, who started as a rural located SME for then also opened a metropolitan location, describes their decision to seek towards innovation environment in order to support the phases you are in, like this: *"Yes, so as an entrepreneur, you think you are special, and then you find out, well, the phases you go through, they are very much the same. So the innovation environments, they can, if they do it well, it's really about supporting your needs in the phase you're in. And it can be anything from cooperation with subcontractors to access to students to researchers. And the ones we know, we've had different needs and have had different strengths, but access to, well, how to apply for funds, how to raise investments, and when you start talking to customers, and product development – there are many aspects. And unless you come as an entrepreneur and are relatively well-rounded as a person or have someone in your team, well then you will always have some blind spots."* (Company 6). Company 9 adds on: *"If you don't have your horizons on the possibilities that are there, then it quickly becomes very far away. If you don't have someone around the corner who has tried some of this, it will be really far away, and if you can't get anyone to help you with it, it will be almost impossible."*. If you, as a firm, do not have previously obtained knowledge, have someone in the team or in the local environment who has experience with a similar topic, then the search becomes much more difficult. Company 7 argues that the struggle is to be included in strong networks. It is a time-consuming process, but once these connections are established, the geographical location matters less: *"The barrier I think is to get onboard. Once you are in relevant networks, I think you will get the knowledge."* (Company 7)

4.1.2 Speed, intensity, and direction of knowledge search

The speed, intensity, and direction of the knowledge searches are also dependent of the prior experiences of the firm. Most of the interviewed SMEs see it as a crucial part of their business to watch for market trends and the overall competition and already have that as a internalized routine and practice of the firm. The firm's size is just an increasing incentive for scanning the market for new technologies, as Company 5 expresses it: *"Well, it's... We're a manufacturing business, (...)which means there's very, very fierce price competition. (...) So therefore, we are constantly under pressure to be efficient, so, all such tools that can somehow make us more automated, more efficient, we look at them all the time, so it is a completely natural process for us."* (Company 5)

Being a small company in a global competition means that the SMEs have to come up with ways to compete in terms of productivity with larger scale operations, and here are, being aware of developments in the market regarding automation tools crucial. There are different factors that impact the intensity, speed and direction of the search, as touched upon in the following.

Theme 1: Intensity of search - Prioritizing AI in a busy everyday and letting AI be an experiment: Time and monetary constraints

There are a range of factors that can impact the intensity of the knowledge search. The SMEs face different obstacles compared to their larger counterparts, e.g., in terms of monetary resources: *"It's something we're interested in at (Ed. Company 2), but we are not Novo Nordisk either, who has a huge pool of money you can take advantage of and that you can throw at some experimental, fun projects that you don't know about yet (...)We have a slightly different degree of coverage of our products. It's a sensible business. But it is limited."* (Company 2) Another challenge for more intensely to pursue the search of knowledge related to AI adoption for the manufacturing SMEs is the many everyday obstacles they have to deal with: *"Well, our own internal affairs here make it challenging. We are one in terms of revenue, but we are a relatively small administration, and since we are a very vibrant company, something is happening all the time. (...) Well, it just means that the tasks that are now, well, they are prioritized in the order in which we have the opportunity and capacity to solve them. So it's not because we don't want to use it (...) So it's just everyday with us that something or other is constantly* *happening, you could say. (...) We are completely underwater right now. We really are."* (Company 5) As will be discussed in greater detail under the results for the Application Capacities, one way of overcoming the time constraints, as described by the interviews, is to view AI adoption as a longitudinal, incremental process, starting with a data strategy and implementing it into the SME´s business model.

4.1.3 Theme 2: Direction of search - The role of sensing customer behavior and trends

Several of the SMEs perceived customer demands as a factor setting the direction of the knowledge search. Although many of the SMEs see few customer branding opportunities related to their AI adoption process due to few of the customer bases would be aware of the involvement of AI in the product, however view AI as an unavoidable part of future businesses even if customers are not aware of it: *"But it is something that we must have. In other words, in ten years, we must have it because by then, it is known knowledge."* (Company 8). These positive associations with AI and other technological advances are, however, something some of the SMEs feel is being increasingly requested by the customers. AI will be something they expect will set them apart in a time where the competition in the manufacturing sector is being pressured by global competitors: *"I think so, because it's about having something that the others don't have in such a market here, right? Come up with something that provides some value that none of the others can because otherwise, we're just selling stainless steel, right? And there is someone who can make it cheaper if we can't position ourselves in some way."*(Company 4) It is also pointed out that it is easy to get swayed away by new high-tech solutions, which have little to no effect on the customer. It is important for innovation initiatives to keep focus on how the new initiative will benefit the customer. It will ultimately impact the direction of the knowledge search. Company 9 uses the following analogy to explain the customer sensing technological opportunities; *"It is important to continually remind oneself of the value of all this. I often use the example of my brother-in-law, who purchased a coffee machine with Wi-Fi capability. Fortunately, he finds it completely ridiculous because with this coffee machine, you can make a cup of coffee using Wi-Fi, which is fine. However, the issue is that you must have a cup inside the machine and then activate your phone. But every time you do so, it runs a cleaning program that wastes half a cup of hot water. So, you approach the machine, press your phone, and then insert the cup. Why use so much energy to complicate matters in the first place? What is the benefit for the end user?"*

Theme 3: Speed of search: Internal knowledge generation and creating the right mindset: the problem of organizational inertia, competency trap and

breaking out from path dependent routines
The speed of the knowledge search can impact the front-runner advantage the SMEs might gain. However, many of the SMEs bring up the challenge of getting stuck in a certain way of doing things, that has worked well in generations. This makes it difficult to be open to new opportunities, even if it might benefit the firm, however, there is a need to act swiftly not to get lost behind in the competition. Company 7 expresses it like this: *"When you are in the eye of the storm it seems very quiet and it seems all fine, but everything around you is turning (. . .). So, there's chaos around you, but you fail to understand it because you are in the midst of chaos. You know, so for someone who's in the status quo, it's very easy to be like, "okay, this is fine. Let's just do the business". (...) The problem is that the competition around you might harness the potential that AI, automation, and data-driven learning offer. So, if you are not investigating this and adopting it, you will be left behind in the future. We will probably still be fine selling our (ed. products), but you can see that other companies are doing much better and that you are losing maybe customers."* (Company 7) Another theme being brought up is that many of the SMEs, especially older SMEs, tend to be more person-driven rather than function-driven in their organization and have over time developed strong routines that might be difficult to change: *"We are well-established and well-consolidated companies, where you have some fixed ways...that is, certain ways of doing things, and not least the people who...that is, you will experience, I think, in these companies, it is that a great many functions in organizations are person-driven and not function-driven. (...) Some key people sit and manage the company, who have been there for many years, and who may even own the company, who have generated a good and stable turnover, and who make a good living. And one day takes another. (...) That's why it's damn hard to change things. If you have a start-up company that can be visionary, it is easier to change direction. "*(Company 4) Several of the firms made it clear that the adoption of AI was more distantly related to the existing knowledge bases of the firm, making the process of getting hold of new information more tiresome and less cost-efficient.

A way of overcoming the issues of becoming too good at something was explained in the interviews as either being forced to change and look for new opportunities (e.g., by experiencing changes in supply chains, as seen for many firms during Covid-19, the War in Ukraine and the energy crises in recent years, or by experiencing slow, but steady increasing competition nationally and globally).

4.2 Assimilation capacities for AI adoption in non-metropolitan, manufacturing SMEs

As mentioned in the theoretical framing: Assimilation capacities refer to the routines and processes within a firm that enables the analysis, processing, interpretation, and comprehension of knowledge acquired from external sources. For several of the SMEs, the assimilation capacities are one of the main aspects where the interviewed SMEs struggle due to lower educational composition and lacking digital skillsets in the workforces, making the comprehension of both the potentials and how to about to go about an AI adoption more intangible. However, several firms have developed new strategies to overcome the lack of traditional absorptive capacities and digital skills.

Theme 1: Lacking labor pool with technical knowledge imagination: New blood and new ideas

One of the main perceived barriers to understanding the new technological opportunities among the interviewed firms is often the lack of technological knowledge. Most of the interviewed SMEs were older and established firms (see Table 1) with a large share of family-owned firms. However, interestingly, at least five out of nine SMEs have undergone a large organizational transformation in recent years with, e.g., generational changes and new management, e.g., Company 4: *"We have... So if we have to look at the entire management, the three of us who are the newest in the organization are the brand new factory manager, a brand new development manager, and then myself. I'm not completely new anymore, but in this organization, I'm still considered new - I've been here for six years."* (Company 4). They continue: *"(...) if you have to take a company like ours, what was really needed was a generational change."*

Those who have not undergone a managerial transformation had gotten a new employee with either a new network or new knowledge that made them seek out new technological opportunities. In Company 7, where the organizational knowledge was described as "experience-based" and with a "strong level of know-how", which was the case for most of the SMEs, the respondent was hired rather recently and had a more innovation-oriented background: *"I do hope the colleagues at (ed. Company 7) agree that it was probably a good idea to hire someone like me. (...) So, I think they are like, this is that's at least also the feedback I'm getting like, "okay, it's so cool that you are now here. So we have many more opportunities with you on board".* (Company 7)

The managerial changes toward younger management and with a new network and the hiring of new employers with more innovation-oriented backgrounds are perceived among the respondents as a strong strategy in generating more internal technical knowledge, and that allows for a better understanding of AI and other technologies they had not previously been able to.

Theme 2: Making AI less "fluffy"/abstract and overcoming uncertainty (about the outcome) bias

Several SMEs explained that AI's fluffy and abstract nature made it difficult to properly understand and comprehend the technology and subsequently integrate it into the firm's business models. If the management team has been reluctantly convinced to investigate the opportunities of AI, then it can be challenging to convince them: *"The biggest challenge of the management is that this AI is pretty fluffy. The challenge from my side was that I couldn't say anything at all about what could be expected as an outcome of the investments."* (Company 2)

One of the SMEs argues that one of the ways to make AI less fluffy is to engage in projects e.g., AI: Denmark, but prior to starting the project, have strong alignments of expectations. To both avoid risk aversion, but also to avoid being overly optimistic about the outcome. Some of the firms show that a lack of knowledge about AI made them excessively optimistic about the potentials of AI and made them jump too fast into a process where a greater amount of preparation time and alignment with the business model might have saved them time and energy: *"I feel like we never really got started. We ran ahead and then were kicked back again to start and told in the end, "Well, now you have to sit down and get the commercial part of it under control. Get some research done and fully understand these things before getting started."* (Company 4)

These extended preparation times might also have shown that a more easily implemented solution than AI might have helped the firms achieve their goal just as well and maybe even better than AI: *"I have bitterly learned that sometimes AI is not the solution, no matter how much you think and want it, and how much you are a fan of AI."* (Company 3)

Theme 3: Competition for regional capabilities (no-show students, Ph.D.s, labor market)

Some of the SMEs found it more difficult than others to implement AI. Some of them experienced in AI:Denmark that the university students assigned their project did not show up due to further commuting distances and *"it might not be as exciting to work with AI adoption in a manufacturing SME, compared to the more high tech, urban SMEs"*. This is not a new problem for some of the SMEs, since they previously had struggled to find industrial SMEs and new high-skilled labor, due to size and location. Some of the SMEs mentioned that they had to brand themselves better and make it part of a long-term strategy.

Theme 4: Bridging skills - Combining know-how and know-why (technical and business knowledge)

Many of the SMEs bring up the fact the lack of technological knowledge makes the ability to seize the new technological challenge. Some of the firms argue that since many of the firm's knowledge processes are based on experience-based know-how, and AI is perceived as a high-technological innovation and adoption of AI is a radical innovation for many of the firms, then it is easy to be hindered in the adoption phase. A solution for this problem was getting a middleman of sorts. An employee who might not be a data engineer, but someone who understood the technical side of AI and data but still knew the capabilities of the firm, as well as long-term strategic goals of the firm: *"If it was just me and the guy who talks data, we wouldn't understand each other, which is why it is a must to think project management. There is a must to have an employee who could bridge our two worlds"* (Company 9)

4.3 Capacity 3: Application capacities for AI adoption in non-metropolitan, manufacturing SMEs

As described in the theoretical framing: Application capacities are in this paper the merged, realized absorptive capacities as described by Zahra and George, (2002) and refer to the firm's ability to refine the routines of the firm by combining existing and newly acquired and assimilated knowledge. This is done by redesigning routines and business models. For several of the interviewed SMEs, they acknowledge that the AI adoption is a long-term process. Due to the fact the AI is less closely related to the already existing knowledge bases of the firm as could be desired, then the process then should be in incremental, step-by-step changes, where the firms build on top of the already existing related capabilities within both the firm and the local environment.

4.3.1 Refining and redefining routines: A strategic focus on AI implementation

Theme 1: Radical changes in incremental steps: defining a long-term AI vision and integrating into the business models
A core theme that is repeated multiple times in the interviews is how crucial being able to align AI adoption to the overall business models. Several struggles were explained, and capacities needed to be developed to overcome the challenges. If a manufacturing SMEs does not have the path-dependent experiences and capabilities to introduce innovative activities and products into the organization, "then it is supertankers, and when you turn a supertanker, it takes time before the ship starts spinning" (Company 4). One might be able to successfully implement AI into the organization, but it might take longer than initially expected: "I have no doubt that it will come, but it may be that the push is five or six years instead of two.". A way to successfully achieve AI adoption would be to see the AI adoption as radical changes in the organization that need to be undertaken in incremental steps, e.g., by defining a long-term AI vision: *"Well, I think it's a lot about softening it up a bit*

and saying that you get something very concrete and saying that you could do such and such. So, and then you can just go from there, that is, because it's like eating an elephant. It can be done, it just takes a little time. So I think that instead of starting big projects, maybe have some small ones that can then run once more and once more." (Company 8)

Theme 2: Aligning existing internal data and data demands: From data in the head to algorithms

For many of the firms, the underestimation of the quality and type of data required for AI processes came as a surprise: *"I had tried to correct the worst mistakes myself, and tried to get some data cleaned for it, but there was still an enormously long way from what I thought was a cleaned data set to it being cleaned enough for them to use it in the here mathematical models. (. . .) I think there is an underestimation of how much time and how many resources are needed for the data to be used, how big a task it really is."* (Company 2)

While many of the firms have had a large share of data available, some of the firms had to undertake larger transformations on getting the data paper-based: *"(Ed. The data we have) is not based on academic science. (...) Is there a worn part? Is it a worn part that needs to be changed at intervals? And so on and so on. And it's not at all based on the calculations or anything. (. . .) And then we have recommended... i.e. department lists and everything else, you should have that lying around, but it is purely based on experience. It's not written down anywhere, it's in the minds of the people who work on it."* (Company 4)

Having a data strategy and then maintaining it is important, in order to have the right type of data for the intended purpose. This is crucial that the managerial team supports these efforts: *"If we want to continue with AI, we have to become much sharper about what type of data we collect and what the quality of the data should be. We need a data strategy that needs to be prioritized by the management".* (Company 2)

Theme 3: Attracting labor for maintaining data

Some of the firms express difficulties attracting employees capable of maintaining the AI and related data, largely due to their size and the regional capability base. One of the solutions suggested is to externally source the tasks: *"We are currently investigating whether there is a "babysitter" for these algorithms somewhere that can sit and monitor and store."* (Company 9)

Theme 4: Creating local demand and buzz

Some of the firms who experienced their geographical location as a barrier to AI adoption touched upon the need to create a demand for AI locally: *"We need to create demand, right? I mean, people. . . Companies need to realize that they would be doing better if they made those changes. I think this is probably* *done best through those networks, you know. Food and BioCluster in Aarhus or... Through like classes and a number of networks where they exchange knowledge and collaborate."* (Company 7) They continue arguing that the increased demand would help develop a buzz, where knowledge sharing would be easier and the regional capabilities e.g., the skilled labor market, would come along with the increased demand.

Theme 5: "Shaking the bag": renewal and retraining of laborpool
Others mention that the retraining and renewal of labor in the organization would be part of a long-term strategic focus on AI. None of the firms interviewed for this study expected it to be necessary to let go of employees, but multiple of the SMEs saw it as a necessity to look more strategically at the labor force in the future: *"We have to shake the bag somewhere. And I can testify to how hard it is in a place like this. Because we have many competent and skilled employees who have laid down their lives... Sacrificed their lives for this company, right? And if you have to change it, you simply have to shake the bag."* Most of the SMEs didn't view it as a possibility to retrain the vocationally trained workers but hoped to renewal process would occur as an organic process, with many of the SMEs having larger shares of the employees getting closer to retirement age.

5 Conclusions

This paper set out to investigate the absorptive capacities of non-metropolitan manufacturing SMEs in relation to AI adoption. The paper finds that the non-metropolitan manufacturing SMEs with little past experience in larger data infrastructures and high technological activities in general face internal and regional-specific barriers in their AI adoption process.

Among the most common obstacles is the lack of personnel with technical knowledge, and they struggle to attract qualified workers in their regional setting, which often is sparse in terms of digital skills in the labor force. This impacts both the potential and realized absorptive capacities regarding AI adoption. However, many of the SMEs develop new strategies to overcome these internal and external challenges. The SMEs, e.g., build on past experiences and engage in different sorts of collaborations and networks with universities and other research institutes, which make their knowledge search scopes both wider and deeper. It is also seen that SMEs obtain a more technological-oriented board, which can help sense some of the technological opportunities in the market.

Many of the SMEs express having strong organizational cultures of know-how and strong path-dependent routines in often cases inherited down through generations to the current management teams. However, many of the SMEs have undertaken either generational management shifts or have hired more innovation-oriented employees who open new horizons. Some of the SMEs also express the importance of having an employee who understands the technical world but is also strongly familiar with the capabilities and goals of the firm, and who can bridge the two worlds. This “middle man” can act as a substitute for technical knowledge employees (know-why) due to sparse regional capabilities and difficulties in competing for the regionally available high-skilled labor.

For most of the SMEs, it is important to view AI adoption as a radical change that needs to be implemented in incremental steps that build on and are related to the already existing capabilities of the firm. This is, among other things, done by developing a long-term AI strategy, i.e., a data strategy, and constantly reassuring that the new technological opportunity, e.g., AI adoption, is aligned with the business model of the SME and the future goals of the establishment.

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