Adoption of Artificial Intelligence Technologies in Production: Empirical Insights from the Manufacturing Industry

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Abstract

Artificial intelligence (AI) has developed rapidly in recent years and is now used in many areas of life. Despite promising fields of application and potential for increasing efficiency in manufacturing, the implementation of AI, especially in production, remains cautious. This dissertation aims to shed light on the challenges and prospects of AI adoption in production by examining various factors, influences, and effects on resilience and product innovation. The investigation consists of four scientific journal articles and is supplemented by empirical findings from a systematic literature review (SLR) and quantitative analyses from the German Manufacturing Survey (GMS). This data basis allows for a comprehensive examination of AI adoption in production from different perspectives.

The first article analyzes the current state of research on the adoption of AI in production based on a systematic analysis of the literature. This analysis identifies influencing factors that are important and serve as a basis for subsequent studies. The second article examines the influence of AI readiness on AI adoption in production, taking into account various dimensions of readiness (technological, organizational, and their combination). The results show that organizational, and especially combined AI readiness, have a significant positive influence on the probability of AI adoption, underscoring the particular importance of organizational resources in the implementation of AI solutions in production. The third article explores the influence of AI readiness on the resilience of production systems. The analysis reveals that companies with higher AI readiness are better able to respond to disruptions, such as those that occurred during the COVID-19 pandemic, and recover more quickly. These results highlight the strategic relevance of AI for stability and adaptability in production. In the fourth article, the focus lies on analyzing the influence of AI adoption in production on product innovations. It considers different types of product innovations: new for the company, new to the market, digital-oriented as well as eco-oriented. The analyses show that AI adoption has a positive influence on different types of product innovation, especially digital product innovations.

Professor Dr. Frank Schultmann, Institute for Industrial Production (IIP), Karlsruhe Institute of Technology (KIT) is supervising the dissertation. The intended degree is Dr. rer. pol..

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1 Introduction

1.1 Motivation

German manufacturing firms are currently facing challenges and are confronted with stagnating demand and intense competitive pressure (European Commission 2025; German Chamber of Commerce and Industry 2025). In demanding markets, constant adaptation and improvement are essential for companies to remain competitive (Day and Schoemaker 2016). In manufacturing companies, seamless production processes are particularly important, as errors or defects in operational processes can impair efficiency and productivity and result in high costs (Hassan et al. 2023). Decision-makers must therefore ensure that their production processes run continuously and smoothly to increase efficiency while improving sustainability (Garetti and Taisch 2012), thereby guaranteeing high quality and availability in the future (Shi et al. 2024). Continuous process improvements and the integration of digital technologies can make a contribution to responding flexibly to changing customer needs and maximizing productivity (Kim et al. 2013; Lloréns et al. 2005). In these dynamic markets, flexible production systems are important in order to be able to quickly respond to fluctuations in demand (Slack 1987). In addition to the need for productivity gains and increased flexibility, competitive markets exert considerable pressure on firms to be innovative and develop new products and services that offer customers greater value (Beneito et al. 2015; Vives 2008). To remain competitive, companies must be able to identify trends early on and offer effective solutions (Slack 1987).

Over the past few decades, the vast dissemination of information and digital technologies, as well as underlying infrastructures, has expanded rapidly and significantly transformed the economy (Ghobakhloo and Ching 2019; Nambisan et al. 2019). While new business models have emerged and old ones have been displaced, companies and their processes and products have had to radically change in the digital world in order to survive (Nambisan et al. 2019). With the emergence of Industry 4.0 as a strategic measure in Germany in 2011 (European Commission 2017), German manufacturing companies have also increasingly turned to digital initiatives to achieve digitally connected production that collects data and makes it usable through the use of digital technologies (Ghobakhloo and Ching 2019; Hansen et al. 2024). With the digital transformation, new technologies are spreading rapidly and processes are changing, requiring various adjustments within organizations (Colovic et al. 2025; Redmond 2003). These adjustments require organizational work, that necessitates restructuring and associated changes, including in the processes and behaviors of the actors involved (Colovic et al. 2025; Redmond 2003; Rogers 1962, 1983).

Although the history of AI began many decades ago (McCarthy et al. 1955), in recent years this technology has developed into an outstanding digital innovation that is opening up new opportunities for various industries. AI promises to bring new capabilities to rule-based decision-making, enabling independent learning, pattern recognition, and system adaptability (Jackson et al. 2024; Krakowski et al. 2023). The adoption of AI could therefore be a promising way to increase the competitiveness of German manufacturing firms. Since production processes are a central component of value creation in manufacturing, they are crucial to the survival of companies (Sinha and Noble 2008) and thus a key area for the potential integration of AI.

While AI offers a variety of possible application domains in production processes, such as production scheduling, inventory management or condition monitoring (e.g. Yang and Lai (2024), Alqsass et al. (2024) or Mukund et al. (2024)), it mostly focuses on the technical level. This perspective tends to overlook general influencing factors, the structures and resources necessary for AI adoption, and the effects of AI at the organizational level. This starting point serves as a motivation to examine this topic in a structured manner and to analyze the drivers and implications of AI adoption in production from an organizational perspective.

1.2 Objective and Research Questions

The integration of AI into production processes is increasingly seen as an opportunity to improve efficiency and competitiveness (Pillai et al. 2022; Yang and Lai 2024). This dissertation aims to provide an in-depth analysis of various perspectives on AI adoption in production. To this end, three central research questions (RQs) are formulated to serve as a guide for this work. The aim is to gain valuable insights that are relevant for both science and practical application.

Recent research shows that the use of AI in manufacturing holds promising potential for increasing efficiency and agility (Fosso Wamba et al. 2024; Pillai et al. 2022; Sanchez et al. 2020). At the same time, it is clear that AI is a distinctive technology with numerous unique aspects, such as ethical issues (Castañé et al. 2023; Grote et al. 2024; Krogh et al. 2023; Vlačić et al. 2021), employee attitudes (Lichtenthaler 2020; Pillai et al. 2024; Vlačić et al. 2021), and technical requirements (Krogh et al. 2023; Vlačić et al. 2021). Although AI is discussed in various contexts in the literature (Hussain and Papastathopoulos 2022; Jia et al. 2024; Kinkel et al. 2023), there is no comprehensive overview of the numerous factors influencing the introduction of AI in the specific field of manufacturing. To close this gap and offer guidance for the desire to adopt AI, it is necessary to identify the diverse factors that influence the adoption of AI in production. The aim is to capture a broad spectrum of possible influences at various levels and to present them in a structured manner in order to promote the successful adoption of AI in production. Based on this, the first RQ can be formulated:

RQ1: What influences AI adoption in production?

Moreover, the current state of research shows that the actual use of AI in manufacturing is still limited at present (Kinkel et al. 2022; McElheran et al. 2024; Rammer et al. 2022). In contrast, the consumer sector shows a more advanced adoption of AI technologies, especially since the rise of generative AI (Gupta et al. 2024; Lee et al. 2024). This situation raises questions about the reasons for the rather slow uptake in manufacturing. Initial studies show a connection between companies' readiness to implement AI and the actual use of the technology (Alsheibani et al. 2018; Jöhnk et al. 2021; Uren and Edwards 2023). However, there is a lack of empirical analyses that systematically examine this relationship in the specific context of production.

The underlying factors and available resources within manufacturing companies play a central role for the successful adoption of AI (Horvat et al. 2023). Given this, the readiness of organizations to integrate AI could have a significant impact on the implementation process. The second RQ is addressed by analyzing the following aspect in this dissertation:

RQ2: Are manufacturing firms ready to implement AI?

In addition to the fundamental analysis of the key influencing factors and the influence of AI readiness on the adoption of AI, the third research objective of this thesis is dedicated to a more differentiated level of analysis. Various effects of AI use, such as performance improvements, have already been investigated in different areas of AI application (Al-Surmi et al. 2022; Löwhagen et al. 2025). However, the interplay between AI and the resilience of production systems, i.e., the ability to withstand unpredictable events, such as fluctuations in demand or supply bottlenecks, without interrupting the production flow and being able to adapt processes, has gained attention during the COVID-19 pandemic (Fosso Wamba et al. 2024; Xi et al. 2024). Here, the literature is limited on comprehensive empirical studies that capture the effects of AI readiness on the resilience of production systems (Fosso Wamba et al. 2024). In addition, there are only a few studies that examine the influence of AI on product innovations (Cooper 2024; Gama and Magistretti 2023) and the existing studies do not analyze the specific effects of AI use in production processes on the development of product innovations.

This analysis therefore pursues two perspectives: First, it considers the influence of AI readiness on the resilience of production systems, and second, it analyzes the effects of AI adoption in production on the development of product innovations. The aim is to close this research gap with two studies based on the following RQ:

RQ3: What are effects of adopting AI in production?

The overarching objective of this study is to create a comprehensive framework for the organizational consideration of the introduction of AI in production – both in terms of analyzing the prerequisites and influencing factors on readiness and actual adoption, as well as in terms of the effects of AI.

1.3 Structure of the Thesis

This work is divided into two main parts. The overview of the individual sections of part I is shown in Figure 1. It contains the general research framework of the dissertation, the summarized results, and the implications based on the synthesis of four journal articles included in this dissertation. Part II presents the four papers in their entirety.

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Figure 1: Overview of the structure of the dissertation in part I

Part I begins with an introduction outlining the motivation, research objectives as well as three guiding RQs, and presents the general structure of this work. It then establishes the fundamentals for AI, the concepts of readiness and adoption, as well as AI adoption effects, thereby creating a basis for classification within the theory and background. It also provides a brief overview of the methodological foundations. Section 3 identifies the research objectives based on the state-of-the-art research on this topic. This is followed by a synthesized presentation of the four research articles published in international scientific journals that form the core of this paper. The motivation, methodology, results, discussion, and limitations of each of the four articles are summarized. Section 5 looks back at the identified RQs and summarizes the implications of the entire dissertation. Finally, section 6 presents the overarching conclusions that serve as a final assessment of the work, offering a brief summary, critical reflection on the results, and suggestions for future research opportunities.

In part II, the four selected articles are displayed in their entirety and divided into four sections:

A - Heimberger, Heidi; Horvat, Djerdj; Schultmann, Frank (2024): Exploring the factors driving AI adoption in production - A systematic literature review and future research agenda. In: *Information Technology and Management*. https://doi.org/10.1007/s10799-024-00436-z.

B - Heimberger, Heidi; Horvat, Djerdj; Jäger, Angela; Schultmann, Frank (2025): Exploring AI Adoption in Manufacturing: An Empirical Study on Effects of AI Readiness. In: *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2025.109733.

C - Lerch, Christian M.; Heimberger, Heidi; Jäger, Angela; Horvat, Djerdj; Schultmann, Frank (2022): AI-readiness and production resilience: Empirical evidence from German manufacturing in times of the Covid-19 pandemic. In: *International Journal of Production Research*, *62*(15), 5378–5399. https://doi.org/10.1080/00207543.2022.2141906.

D - Horvat, Djerdj; Heimberger, Heidi; Jäger, Angela, Lerch, Christian M. (submitted): The Innovation Payoff of AI in Production: Evidence from German Manufacturing. Submitted to a scientific journal in December 2025.

2 Theoretical and Methodological Foundations

To conduct a structured analysis of AI adoption in production, this dissertation builds on a theoretical basis to examine the range of relationships between the concepts analyzed. First, in subsection 2.1, a basic understanding of AI, which is the focus of the analysis, is presented. AI is discussed in general, along with various possible applications within the context of production, which serves as the subject of this thesis. Section 2.2 then provides information on the concepts of AI readiness and AI adoption. This includes an explanation of the basis of organizational readiness for change regarding AI readiness, followed by a discussion on the adoption of technologies and its underlying models. Initial conclusions about the connection between AI readiness and AI adoption are also drawn. Section 2.3 provides the background for the effects of AI analyzed in the dissertation, discussing production system resilience and the development of product innovations. Finally, section 2.4 concludes with a brief overview of the methodological principles applied in the analyses.

2.1 Artificial Intelligence

To gain a better understanding of AI in general in the context of this dissertation, section 2.1.1 first provides an overview of the characteristics and challenges of this technology. Section 2.1.2 then discusses the potential applications of AI in production processes.

2.1.1 Understanding AI

The technology examined in this dissertation is AI, which is characterized by a variety of properties: it is self-learning (Berente et al. 2021; Hutzschenreuter and Lämmermann 2025), capable of recognizing patterns (Hutzschenreuter and Lämmermann 2025), and can either make decisions independently or provide decision proposals to other systems or humans (Berente et al. 2021). AI systems thus differ from other digital systems and possess additional intelligence that machines did not previously have (Berente et al. 2021; Hutzschenreuter and Lämmermann 2025). The essential basis for AI functionality is the availability of data. Without data, AI cannot learn and improve (Berente et al. 2021; Hutzschenreuter and Lämmermann 2025; Truong and Papagiannidis 2022). AI can analyze data based on a variety of techniques; for example, systems use natural language processing or image processing to learn from data and make decisions (Berente et al. 2021; Truong and Papagiannidis 2022). Depending on the particular use case, the appropriate AI technology is usually integrated into existing IT systems and builds on the data and infrastructure available there. This makes it possible to expand various tools with additional intelligent functions, opening up a wide range of potential applications (Chatterjee et al. 2021a; Heimberger et al. 2025).

While promising opportunities are known, there are also challenges associated with AI, such as dystopian portrayals that depict AI as a superpower, thereby fueling fears of unpredictable abuse of power (Fallis 2021; Khogali and Mekid 2023; Li and Huang 2020). There are concerns related to the potential loss of jobs due to AI technology, both because of the impact of automation on certain occupations and because of a general shift in the world of work brought about by digitalization (Chiarini et al. 2024; Jackson and Panteli 2023; Khogali and Mekid 2023). In addition, intelligent systems are highly complex and often resemble black boxes, making decision-making processes opaque and difficult to explain (Asatiani et al. 2020; Hutzschenreuter and Lämmermann 2025; Jackson and Panteli 2023). AI bases its decisions on learning data, which raises questions about the bias behind the data and what has been learned, as well as the explainability of decisions (Asatiani et al. 2020; Hutzschenreuter and Lämmermann 2025). All these challenges lead to a noticeable uncertainty (Li and Huang 2020) and public mistrust of AI – both on the part of potential users as well as decision-makers (Glikson and Woolley 2020; Hutzschenreuter and Lämmermann 2025; Jackson and Panteli 2023).

2.1.2 AI in Production Contexts

AI has developed rapidly over the last few years and is now present in many areas of life. In addition to prominent examples from consumer markets (e.g. large language models, such as ChatGPT, that generate texts or images resembling human output (Doshi et al. 2025)), AI also offers promising use cases in the manufacturing industry. In addition to possible applications in areas, such as marketing or supply chain management, AI can support production processes in the manufacturing industry. Within production, this dissertation examines different areas of AI application: production process management, maintenance, quality control, internal logistics, and production process innovation. Table 1 illustrates these areas, the purpose and objectives of adopting AI in each area, and examples of AI applications.

Table 1: Possible areas of application for AI in production-related fields

Possible AI application	**Purpose and objective**	**AI tasks**
Production process management	Process optimization, decision support, and forecasting	AI-based production scheduling for decision support, sales forecasting and production scheduling (Yang and Lai 2024)
		AI-supported decision-making assistance for process planning, production planning, scheduling, and real-time control (Castañé et al. 2023)
Maintenance of machinery and equipment	Condition monitoring, predictive maintenance, and failure prevention	AI-based condition monitoring of industrial robots via sound analysis (microphone as sensor module) (Olsson and Funk 2009)
		AI-supported evaluation of sensor data (such as voltage, current, temperature, humidity, vibration, and noise level) to predict faults in lathes (Mukund et al. 2024)
Quality control	Quality improvement, fault detection and reduction of scrap	AI-based image recognition for analyzing surface scratches in sheet metal forming processes (Li et al. 2022)
		AI-supported quality control using image data analysis to detect surface defects in copper rods for electric motors (Chouhad et al. 2021)
Internal logistics management	Increased efficiency in resource procurement, transportation, inventory management, and demand planning	Autonomous intelligent vehicles in the material transport system for transporting products in a manufacturing environment(Cronin et al. 2020)
		AI implementation to enhance inventory management systems (Alqsass et al. 2024)
Production process innovation/ improvement	Accelerated knowledge generation and knowledge exchange, improved learning and absorption capabilities	Generative AI integration to improve organizational learning in production systems (Wang and Zhang 2025)
		AI as a driver of technological innovation in manufacturing (Liu et al. 2020)

The use of AI in production process management focuses largely on optimizing processes, supporting decision-making, and forecasts. Various AI technologies can be applied in production planning to make informed decisions and generate sales forecasts. Examples include AI-supported systems that serve as decision-making aids for efficient planning, scheduling, and real-time control of processes (Castañé et al. 2023; Yang and Lai 2024).

In maintenance, AI is mainly used to monitor machine conditions, perform predictive maintenance, and prevent breakdowns. Among other applications, sound processing technologies can be used to monitor the condition of industrial robots, or other sensor data is evaluated to predict faults at an early stage (Mukund et al. 2024; Olsson and Funk 2009). However, these applications are only a selection of the many possibilities that AI offers in maintenance.

Quality control can also benefit from AI, where applications aim to improve product quality, detect defects, and minimize waste. In this context, AI-supported image processing stands out as a prominent tool that can be used to analyze surface defects in produced parts (Chouhad et al. 2021; Li et al. 2022).

In internal logistics, AI mostly aims to increase efficiency in procurement, transport, inventory management, and demand planning. Here, for example, autonomous AI-supported vehicles can be used for material transport in production, and AI systems can be applied to optimize inventory management processes (Alqsass et al. 2024; Cronin et al. 2020).

When it comes to innovating production processes, AI has the potential to accelerate the generation and exchange of knowledge by optimizing organizational learning in production systems through intelligent systems. AI can thus increase efficiency by acting as a driver for technological innovation (Liu et al. 2020; Wang and Zhang 2025).

The AI application areas in production listed above represent a selection of possible use cases for AI and aim to provide a better understanding of the application context.

2.2 Readiness and Adoption

At the core of this research, questions concerning AI adoption and AI readiness in organizations are addressed. Therefore, this foundational section 2.1.1 provides background information on the theoretical foundations of organizational readiness for change, leading to AI readiness. This is followed by a discussion of technology adoption in section 2.1.2. Finally, section 2.1.3 integrates the two concepts and examines their interplay.

2.2.1 Organizational Readiness for Change

In rapidly changing environments, organizational leaders are often faced with the challenge of making adjustments to strategies, processes, and corporate culture in order to realize certain goals (Armenakis et al. 1993; Holt et al. 2007). The effectiveness of such changes is influenced by numerous factors, with readiness for change playing a key role (Armenakis et al. 1993). Readiness is expressed in the beliefs, mindsets, and intentions of employees regarding the necessity of adjustments and their ability to implement them successfully (with positive effects on employees and the organization) (Armenakis et al. 1993; Eby et al. 2000; Jones et al. 2005). Furthermore, readiness significantly influences employees' initial support for change initiatives (Holt et al. 2007)

Therefore, readiness is an important indicator of how members will behave toward change initiatives, which can manifest itself in either support or resistance (Holt et al. 2007). The introduction of targeted changes can lead to conflicts as well as differences between managers and members of the organization. To ensure that the changes proceed in the desired direction, it is necessary to resolve these conflicts and ensure that the beliefs and insights of employees are aligned with those of managers (Holt et al. 2007; van de Ven and Poole 1995), i.e., readiness is a state that must be created among the organization's employees (Holt et al. 2007). A strong readiness for change can help minimize resistance and increase the effectiveness of change projects. It is therefore crucial to differentiate between readiness and resistance to change in order to ensure successful transformation processes. By promoting readiness within the organization, the conditions for a smooth implementation of change can be created (Armenakis et al. 1993; Weiner et al. 2008).

Employees' willingness to embrace change plays a key role, as it influences both resistance and support behavior (Armenakis et al. 1993; Eby et al. 2000; Weiner 2009). Before implementing changes, it is important to determine how willing employees are to embrace new circumstances. A thorough assessment of willingness can identify potential gaps between the different expectations of managers and employees (Armenakis et al. 1993; Holt et al. 2007). To prepare the organization for upcoming changes, it is important to dispel any misconceptions among employees while simultaneously developing an engaging vision for the future. In addition, confidence in the possibility of realizing this vision should be fostered (Weiner et al. 2008). This task is the responsibility of managers, who should proactively monitor whether there are any significant discrepancies. If such gaps are not identified and no measures are taken to close them, resistance is to be expected, which can significantly jeopardize the success of the change project (Armenakis et al. 1993; Holt et al. 2007). Therefore, promoting employee readiness is not only important for minimizing resistance, but also for ensuring the successful adoption of change within the organization.

In order to measure readiness for change in certain contexts, both qualitative assessments (e.g., through interviews or observations) and quantitative assessments (usually through questionnaires) are possible. Both types of evaluations of readiness for change have advantages and disadvantages and should be selected based on the specific context (Holt et al. 2007). Qualitative methods (e.g. Rusly et al. (2015), Isabella (1990)) may offer deeper insights into the change process but are usually more complex to conduct and make it difficult to compare different surveys (Holt et al. 2007). On the other hand, quantitative assessments (e.g. Holt et al. (2007)) enable managers to generate a large amount of information in a short period of time, for example across different departments or locations. Here, comparisons are easier to make and the results can be checked for validity and reliability (Holt et al. 2007).

The readiness for change can refer to different change contexts that can influence the environment and conditions in which employees operate (Holt et al. 2007). Technological changes can play an important role here, as they intervene in existing processes and transform them (Holt et al. 2007), which is why a high level of organizational readiness for the associated changes is decisive for the success of adopting technological innovations (Jöhnk et al. 2021; Snyder-Halpern 2001; Weiner 2009). It is therefore assumed that AI, as a technological innovation and due to its unique characteristics, requires organizations to be ready for the changes it entails (AI readiness) to successfully integrate it into existing processes and structures. As part of this work, readiness models are being developed for the respective research context, using quantitative methods to derive the current state of AI readiness and enable comparisons within the manufacturing industry in Germany.

2.2.2 Technology Adoption

The adoption of a wide variety of technologies has been studied in the literature for decades and considers different levels of analysis, including individuals, organizations, industries or markets, society, and politics. Technology adoption is a complex concept that is defined and analyzed in various ways in scientific literature. Adoption generally describes the acceptance or start of use of something new (Hameed et al. 2012; Karahanna et al. 1999). The research approach varies across disciplines and specific questions. In a dynamic process view, adoption is seen as a multi-stage, often contextualized process that is frequently examined using qualitative case studies with small sample sizes. Here, the focus is, for example, on researching transitions and resistance in the adoption process (Langley and Truax 1994; Rogers 1962, 1983). A binary, static perspective, on the other hand, usually views adoption as a one-time event, which is examined using quantitative analyses and large case numbers. This approach allows for greater generalizability and usually examines differences between adopters and non-adopters or the underlying influencing factors (Dahlke et al. 2024; Heimberger et al. 2025; Kinkel et al. 2022). A combination of both approaches, for example through long-term studies, can also provide comprehensive insight into the adoption process by e.g. first identifying the adopters and then analyzing their use in detail.

In academia, several important models and frameworks for studying technology adoption have become established, which form the basis of many analyses. These differ in terms of their object of study, focus and core components, and analyze different factors and perspectives that influence the adoption of technologies. The theory of *diffusion of innovations (DOI)* was developed by sociologist Everett Rogers, who, in his book 'Diffusion of Innovations' (Rogers 1962, 1983, 1995, 2003), examines how new ideas and technologies spread, what reasons there may be for this, and at what pace it occurs. The DOI focuses on analyzing the spread of technologies within a social system, which plays a crucial role as it represents groups of individuals who interact and influence each other. Rogers analyses innovations that differ from existing products or concepts and identifies five key characteristics of innovations that influence diffusion: relative advantage, compatibility, complexity, trialability and visibility. An essential part of this diffusion process are communication channels, which represent the pathways through which information about innovations is disseminated, such as mass media or social networks, and influence the whole innovation-decision process. Social systems, i.e. organizations, play a decisive role, as they represent groups of individuals who interact and influence each other. The diffusion process for technologies takes time and, according to Rogers, can be divided into different phases that do not necessarily occur in a fixed order: knowledge, persuasion, decision, implementation and confirmation. In addition, Rogers categorizes users of innovations into five groups: innovators, a group that is the first to try out new ideas and take a certain risk; early adopters, who act as opinion leaders and quickly accept innovations; the early majority, who accept new ideas after others have tested them; the late majority, a skeptical group who adopt later; and laggards, who are hesitant and accept innovations last (Rogers 2003). Rogers laid the foundation for understanding how new ideas and technologies are adopted by individuals and groups, and his work on the diffusion of innovations theory is widely recognized in various fields (Faber et al. 2017; Sharma and Sharma 2024; Sila et al. 2024).

The *Technology Acceptance Model (TAM)* (Davis 1989) was developed by the information scientist Fred Davis and is based on the Theory of Reasoned Action (TRA) (Fishbein and Ajzen 1975). In contrast to the DOI, the TAM addresses individual user acceptance of technology and aims to explain and predict how users can be motivated to adopt and use a technology. Two factors are central to the intention to use: perceived usefulness, i.e. the extent to which a person believes that a particular system could actually help them improve their work performance, and perceived ease of use, which is based on how much effort a person has to put into the technology. These two main factors influence the user's attitude towards the technology, which in turn influences their behavioral intention to utilize the technology and ultimately leads to the actual use of the technology (Davis 1989). Over the years, the TAM has been applied in a variety of contexts (Chatterjee et al. 2021b; Gündoğan and Keçeci 2024), serves as the basis for many adoption analyses, and has been expanded to include several additional factors (McCoy et al. 2007; Venkatesh and Davis 2000).

The *Technology-Organization-Environment (TOE)* framework (Tornatzky and Fleischer 1990) was developed by Louis G. Tornatzky and Mitchell Fleischer and is another well-established model for analyzing the adoption and implementation of technological innovations. In contrast to the other two models considered, it focuses on the factors influencing technology adoption at the organizational level. The model views the introduction of technologies as the result of the interaction between three main dimensions in the corporate context: The first dimension, the technological context, takes into account various internal and external technologies that are relevant to the organization. These include the availability and characteristics of the technologies. The second dimension, the organizational context, encompasses the characteristics and resources of the organization, such as company size, scope, communication processes and management structure. The third dimension, the environmental context, considers the external environment of the organization, including industry characteristics, market structure and regulatory provisions (Tornatzky and Fleischer 1990). The TOE model, with its various factors on three levels, serves as the basis for many adoption studies in research (Kinkel et al. 2022; Thong 1999) and is often supplemented by additional factors (Heimberger et al. 2024; Marimuthu et al. 2022) or linked to other theories (Chatterjee et al. 2021b).

A number of additional adoption models have been developed to examine technology adoption (e.g. the Theory of Planned Behavior (TPB) (Ajzen 1991) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003)) from different viewpoints. However, analyses of scientific work on technology adoption show that, although many basic models form an important foundation, they usually need to be extended or adapted to the specific research context and the corresponding technological innovation. Therefore, the adoption models outlined here form a solid basis for the present work.

As described above, research into technology adoption often examines a variety of factors that influence it. Depending on the technology and context, there are distinct factors that positively or negatively influence the decision to adopt, which in turn affects the success of the technology adoption (Obal 2017; Wu and Wang 2005). For example, many technological innovations face challenging factors such as financial constraints (Gomez and Vargas 2009; Shehabuddeen et al. 2006), a lack of commitment from staff or management (Koljonen and Chan 2024; Shehabuddeen et al. 2006), or legal concerns (Xiong and Zuo 2022). As with the TOE model, influencing factors can be assigned to certain dimensions or areas that represent thematic blocks and thus cluster factors (Hameed et al. 2012). As each technology encounters a multitude of potential positive and negative influences in a specific context, individual analyses are of great importance. The analysis of the influences of factors on technology adoption is often carried out using empirical analyses based on a large sample size (such as multivariate regression analyses, e.g. Kinkel et al. (2022), Heimberger et al. (2025)).

In this dissertation, the adoption of a AI (as the technology to be analyzed) is examined as its integration into processes within organizations (Dahlke et al. 2024), taking a binary perspective that considers the differences between adopters and non-adopters. AI adoption of manufacturing organizations in the context of production processes is analyzed, with a particularly focus on the group of adopters in order to evaluate influences on adoption and identify the effects.

2.2.3 Interplay Between AI Readiness and AI Adoption

Based on the theoretical principles of organizational readiness for change and technology adoption, it becomes clear that the readiness of the organization plays a key role in the introduction of new digital technologies. This readiness should be established as a basis for ensuring acceptance of the technology to be introduced, as it can otherwise lead to resistance and the failure of adoption projects (Armenakis et al. 1993).

Regarding AI as the digital technology analyzed in this paper, AI readiness is considered an important foundation that is required in order to be able to take the necessary steps in adopting AI. In this work, AI readiness is understood as an interplay of various factors and dimensions that influence the adoption of AI. While some factors are conducive and encourage adoption, others can hinder its adoption. AI readiness models (as developed in sections B or C) can be used to determine the readiness of companies both as a collective measure and with regard to individual dimensions. Based on this, recommendations for action can be derived in order to achieve a higher level of readiness, which in turn prepare firms for AI adoption.

2.3 AI Adoption Effects

Organizations are introducing AI as a technology to achieve various effects. In this dissertation, two effects are analyzed: the influence of AI on production system resilience (section 2.3.1) and the introduction of product innovations (section 2.3.2).

2.3.1 Production System Resilience

Production resilience has gained considerable attention in research and practice in light of the tense economic and political situation and global events in recent years (such as the COVID-19 pandemic) (Alexopoulos et al. 2022; Lerch et al. 2022; Romero et al. 2021). The production resilience of a manufacturing system is defined by its ability to respond to and recover from internal malfunctions and external disruptions (Alexopoulos et al. 2022; Qin et al. 2022). This resilience includes both preparatory measures to minimize the impact of potential disruptions and efficient adaptation and recovery after an incident (Lerch et al. 2022).

Production systems face the challenge of meeting a variety of requirements in order to operate efficiently and effectively. A key requirement for resilience is the robustness of production systems, which describes a system's ability to maintain its performance and functionality even in challenging situations without creating considerable additional costs (Alexopoulos et al. 2022; Qin et al. 2022; Stockmann et al. 2021). Robustness involves proactive preparation for unexpected events and system maintenance (Lerch et al. 2022). This capability encompasses two essential aspects: First, performance has to remain stable, which means that deviations from the original state are minimal. The specific thresholds for acceptable deviations should be set individually for each system. Secondly, production systems must deliver acceptable performance at all times so that all value-adding processes can continue to run even in the event of disruptions (Mondal et al. 2010; Stockmann et al. 2021; Stricker and Lanza 2014). To ensure robustness, forecasting, anticipation, and prevention are key (Lerch et al. 2022).

In addition to robustness, it is crucial that production systems are reactive and demonstrate both flexibility and agility. Flexibility refers to the ability to adapt to changing conditions and respond efficiently (Gerwin 1993; Mishra 2016; Upton 1994). A robust production system needs this flexibility to ensure certain performance even in the face of change, which is why flexibility can be seen as the basis for robustness (Stockmann et al. 2021; Stricker and Lanza 2014; Wiendahl et al. 2007). Agility, which is similar to flexibility, nevertheless differs in some respects: First, an agile system responds more quickly to change (Lotfi and Saghiri 2018), and second, it is capable of fundamentally changing its structure (Santos Bernardes and Hanna 2009;

Stockmann et al. 2021). In contrast, a flexible system remains adaptable within a defined framework (Stockmann et al. 2021; Wiendahl et al. 2007). It is important that the robustness of the production system enables companies to respond agilely in certain situations in order to cope with significant changes without causing instability and performance losses (Stockmann et al. 2021).

Unpredictable events pose significant challenges to production systems, which must be increasingly adaptable. Innovative strategies and the integration of state-of-the-art technologies are required to significantly increase their resilience in such situations (Fosso Wamba et al. 2024; Ivanov and Dolgui 2020). Here, AI can be an important technology that strengthens production resilience and supports informed decision-making through its analytical, preventive, and computational capabilities in processing large amounts of heterogeneous data (Dey et al. 2024; Ivanov et al. 2019; Queiroz et al. 2021). Intelligent systems can help improve key aspects such as the last mile, customization, and agility in production, as well as effectively mitigating disruptions (Dey et al. 2024; Modgil et al. 2021).

By using big data analytics, AI can support forecasting and reasoning to identify risks early on and develop proactive action strategies, enabling companies to respond better to unexpected challenges. In risk management, AI can optimize processes by enabling preventive measures and providing valuable decision-making support (Dey et al. 2024; Grover et al. 2022). In addition, AI can increase production efficiency through intelligent predictions (Dohale et al. 2022). The integration of technologies such as machine learning into production processes (e.g. maintenance) can also improve connectivity and decision-making within dynamic networks which, in turn, have positive effects on process agility as well as robustness by reducing uncertain risks in production environments (Dey et al. 2024; Usuga-Cadavid et al. 2022).

Overall, it is clear that the unique capabilities of AI have the potential not only to increase the responsiveness of production systems, but also to strengthen their ability to respond flexibly and agilely to changing events and challenges.

2.3.2 Product Innovation

In an ever-changing business environment, innovation is considered an essential source of competitive advantage (Crossan and Apaydin 2010; Dess and Picken 2000; Tushman and O'Reilly 1996). Promoting innovation is crucial to the market success and competitiveness of companies (Haefner et al. 2021). This research highlights two types of innovation that are of great importance to manufacturing companies and are interrelated: product innovations and process innovations.

Product innovations refer to the creation and introduction of new or significantly improved products to the market (Bergfors and Larsson 2009; Crossan and Apaydin 2010; Martínez-Ros and Labeaga 2009; Utterback and Abernathy 1975; Wang and Ahmed 2004). This type of innovation is often driven by technological improvements or external market demands and is essential for maintaining competitiveness in the market (Bergfors and Larsson 2009; Utterback and Abernathy 1975). Product innovations aim at improving the effectiveness of product characteristics and performance (Bergfors and Larsson 2009) and are more visible than process innovations (Damanpour and Gopalakrishnan 2001) as they often involve new design approaches, faster design process models, and other framework conditions. However, product innovations are fraught with uncertainty and can lead to failure, which is why effective decision-making tools and user-orientation are necessary (Veryzer and Borja de Mozota 2005).

Process innovations, on the other hand, involve the development of new or significantly improved production processes (Bergfors and Larsson 2009; Crossan and Apaydin 2010; Martínez-Ros and Labeaga 2009; Wang and Ahmed 2004). They are usually intangible and are driven by the need to increase efficiency, reduce costs, and improve quality, service and output (Bergfors and Larsson 2009; Utterback and Abernathy 1975). Process innovations are internal and not visible to customers, but they play a significant role in achieving higher performance in production objectives (Bergfors and Larsson 2009; Cohen and Levinthal 1989; Davenport 1997; Tushman and Nadler 1986). Different technologies can be used to drive process innovation, meeting the specific needs and challenges of the organization by, for example, utilizing real-time data and optimizing production times (Blichfeldt and Faullant 2021). The challenges with process adaptions lie in the need for continuous improvement and adaptation to existing structures and systems (Barras 1986).

Process and product innovations are closely linked and can reinforce each other (Damanpour and Gopalakrishnan 2001; Utterback and Abernathy 1975). Process innovations, such as the optimization of production workflows, can lead to more efficient product development. Conversely, new products can increase the need for innovative processes in order to successfully develop and distribute these products. It is important to drive success in organizations and actively promote both process and product innovation (Martínez-Ros and Labeaga 2009).

Digital technologies play an important role in stimulating both process and product innovation (Blichfeldt and Faullant 2021; Martínez-Ros and Labeaga 2009; Utterback and Abernathy

1975). With its unique characteristics, AI can be an important technology for contributing to the innovative capacity of organizations (Haefner et al. 2021; Verganti et al. 2020). In this work, the focus is on analyzing the effect that the adoption of AI in production processes (i.e., AI as a process innovation) can have on product innovations.

2.4 Methodological Foundation

To research the factors, influences and effects of AI in production, a methodological mix of a SLR (section 2.4.1) and a quantitative empirical research design (section 2.4.2) is employed and explained below.

2.4.1 Systematic Literature Review

To identify and structure the various factors influencing the adoption of AI in production, the results of this study are based on the research method of a SLR. For this purpose, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) reporting guideline (Page et al. 2021) was applied, a well-established method for systematically reviewing studies (Ingaggiati et al. 2023; Liao et al. 2017; Thomé et al. 2016). In order to identify the relevant studies for the desired analysis, the scientific literature published between 2010 and May 2024 was systematically searched in three scientific databases. After several preliminary tests, a search command was defined to adequately cover the topics of this work and identify the desired articles.

The research team opted for different types of publications in English in the final publication phase. Based on the previously defined search command, a list of documents was extracted, which were then subjected to a more in-depth analysis. The research team checked the articles in a double-blind screening procedure and jointly established decision rules for the analysis, supported by pilot searches. The titles, abstracts, and keywords of the selected articles were examined according to the predefined criteria and only selected for further analysis if all three topics were the focus of the publications. This additional review loop allowed the list of articles to be further reduced, resulting in a selection of a subset of papers for which the full texts were obtained. Some articles had to be excluded again if no full texts were available. The full texts were then subjected to a further content analysis, which resulted in the exclusion of additional articles that did not meet the inclusion criteria. At the end of this reduction process following the PRISMA steps (Page et al. 2021), a final selection of papers was made, which were then subjected to content analysis and synthesis.

In order to identify the factors influencing AI adoption in production, a qualitative content analysis following Mayring (2000) was conducted. To this end, all previously identified articles on the topic were first reread by the reviewer team to obtain a comprehensive overview of the existing literature and references to initial influencing factors. Subsequently, a list of factors influencing AI adoption was created for each article. These factors were extracted from the texts and documented. In the next step, the identified factors from all papers were compared and merged if they showed similarities. This allowed for an initial structuring of the data. In addition, supercategories were developed for each of the identified factors in order to systematically organize the multitude of factors and gain a better understanding of key influencing factors. After setting the category system, the articles were reclassified, identifying the factors according to the developed category system. To validate the results, this backward check of the suitability of factors and categories was performed to verify the consistency and relevance of the developed categories and to make adjustments if necessary. The entire process thus proved to be iterative and deductive, with several loops in which the factors and categories were continuously developed and adjusted. This approach ensured openness, which allowed the reviewers to approach the topic without being too restricted (Mayring 2000).

2.4.2 Quantitative Research Design

The findings in this dissertation are supplemented by quantitative data from the GMS, a large-scale survey of manufacturing firms in Germany. It was first conducted in 1993 by the Fraunhofer Institute for Systems and Innovation Research ISI and is conducted every three to four years to capture various modernization trends in production- and technology-oriented companies in Germany. Production managers, technical managers, and managing directors of manufacturing companies with at least 20 employees in Germany are surveyed using an eight-page questionnaire. The aim of this survey is to collect a variety of indicators that are relevant for analyzing production and innovation processes. The topics covered in the questionnaire include structural characteristics of the companies, the implementation of innovative manufacturing technologies and modern organizational concepts, various performance indicators, information on product innovations, human resource management, cooperative relationships as well as general company data. Since 2022, the survey has been conducted in the form of a push-to-web survey, enabling efficient and up-to-date data collection. It comprises a representative sample of around 1,200 to 1,500 manufacturing companies and uses detailed indicators to analyze different innovation fields. In 2022, around 1,300 German companies took part in the survey (Fraunhofer Institute for Systems and Innovation Research ISI 2024).

Since its inception in 1993, the survey has been continuously developed to integrate new topics. Based on the results obtained from the SLR, a set of questions on AI was developed as part of this dissertation for the 2022 survey round, which was incorporated into the survey for the first time. This integration provided valuable insights into the state of AI use in various production-related areas of the manufacturing industry in Germany. This extension of the GMS forms the basis for the results in studies B and D of this thesis.

Bivariate and multivariate methods were applied for the empirical analyses based on the GMS data in this study. First, bivariate analyses were performed to descriptively capture initial correlations between the variables under investigation. Second, multiple regression analyses were used to test the hypotheses. Several independent variables were included in the models simultaneously in order to estimate their effects on the respective dependent variable while controlling for other variables (especially variables capturing the structural characteristics of the manufacturing companies).

3 Research Objectives

This dissertation pursues a series of research objectives, which are presented below and addressed in the main articles. These research objectives are based on the RQs presented in section 1.2 and aim to fill existing gaps in the literature. Three key research gaps are discussed: the driving factors for AI adoption, the influence of AI readiness on AI adoption, and the impact of AI on production processes. For each research objective, additional sub-RQs are derived to serve as a guide for the articles included in this work.

All studies conducted (A, B, C and D) and their interrelationships are illustrated in Figure 2 and summarized in section 4. The full articles of the studies listed here can be found in Part II of this dissertation.

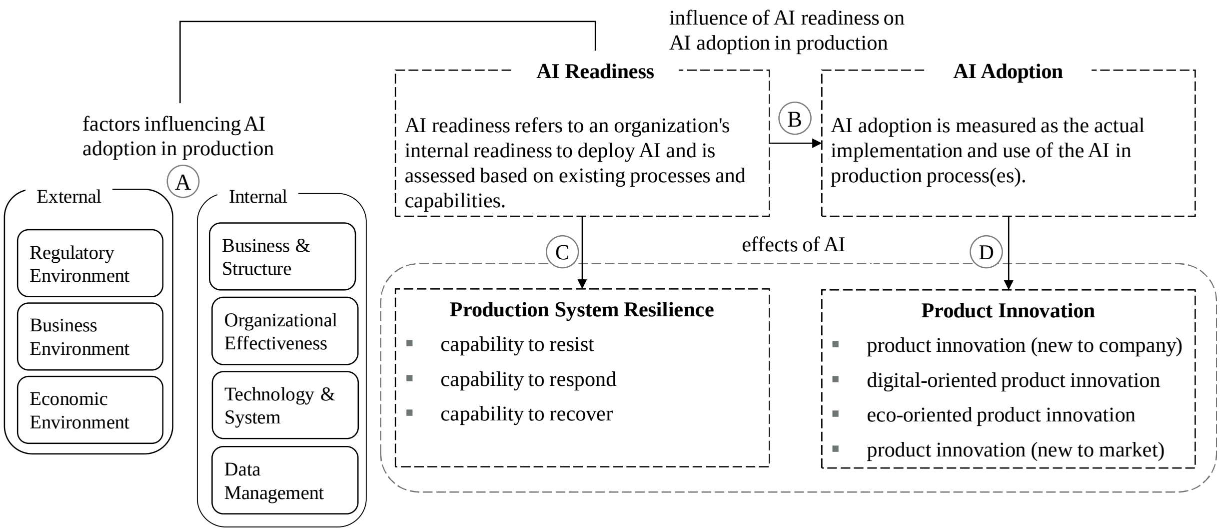


Figure 2: Overview of the research concept and the conducted studies

3.1 Factors Driving AI Adoption

The specific research context of this dissertation underscores the need for a systematic investigation of the factors influencing the adoption of AI in production contexts. The characteristics of AI and the possible applications in production contexts described in Section 2.1 illustrate the complexity of the field of application. Despite the existence of numerous technology adoption models that identify general adoption factors, each technology and application context is unique (Obal 2017; Wu and Wang 2005). The production environment in particular has specific requirements and challenges that are often not adequately addressed in existing models (e.g., with regard to the complexity of processes, the variability of machinery and procedures, or the interdisciplinary nature of the actors involved (Kara and Kayis 2004; Schmidtke et al. 2014; van

Veen-Dirks 2005)). It is therefore crucial to identify factors that are specifically relevant to AI adoption in production.

Furthermore, there is a lack of consolidating research examining the actual adoption factors in production contexts. While theoretical approaches and models exist (e.g. Merhi and Harfouche (2023), Chatterjee et al. (2021b) or Kinkel et al. (2022)), it remains unclear which factors actually tip the scales in specific scenarios. A systematic investigation should close the gap between theory and practice and provide valuable insights for the implementation of AI in production. This brings me to the first sub-RQ within the scope of the first research objective:

RQ1.1: What factors influence the adoption of AI in production?

Other key issues include the challenges and risks associated with AI adoption in production. These aspects are often not sufficiently addressed, especially with regard to AI-specific factors such as employee acceptance and the ability to integrate data from existing systems (Cheng et al. 2023; Hangl et al. 2023). Understanding these challenges for manufacturing firms is crucial for developing appropriate strategies for the introduction and use of AI.

In addition, there is a lack of systematization that structures the current state of the scientific basis for AI adoption in production and identifies open RQs. This leads to the second sub-RQ for the first research objective:

RQ1.2: What research topics are of importance to advance the research field of AI adoption in production?

The SLR in study A, which was conducted to answer the sub-RQs listed here, therefore aims to close these identified research gaps and create a solid foundation for future research. By identifying relevant influencing factors and investigating significant research topics, the discussion on AI adoption in production can be enriched.

3.2 Influence of AI Readiness on AI Adoption

This dissertation also highlights the need for an empirical analysis of the link between AI readiness and AI adoption in manufacturing companies. The fundamentals presented in section 2.2 emphasize that readiness for change plays a central role in the success of change processes. Although a few models for measuring AI readiness exist in the literature (e.g. Jöhnk et al. (2021) or Kalleparambil and Akoum (2025)), the specific necessity of organizational and technological readiness, as well as their combination and their influence on AI adoption in production, remains largely unexplored.

An important issue is that existing studies often consider either the readiness for AI or the adoption of technology in isolation, without analyzing the influence of readiness on adoption. This research gap is particularly relevant because a high readiness for change may have a positive influence on the acceptance of new technologies. The question of how different readiness dimensions interact and influence the likelihood of AI adoption in production processes remains unanswered in the existing literature.

Furthermore, there is a lack of comprehensive empirical studies that assess AI readiness and identify the specific influencing factors that affect both technological and organizational readiness. This leads to the need to develop a structured model that brings together the resources and factors important for AI readiness and integrates an effective measurement concept.

In summary, this research objective aims to address the identified research gaps by examining the need for considering organizational AI readiness, technological AI readiness and combined AI readiness (the combination of organizational and technological AI readiness), as well as their influence on AI adoption in production. The sub-RQs that arise for the second research objective are:

RQ2.1: How does a company's technological readiness for AI influence the likelihood of AI adoption in the production processes of manufacturing companies?

RQ2.2: How does a company's organizational readiness for AI influence the likelihood of AI adoption in the production processes of manufacturing companies?

RQ2.3: How does a company's combined readiness for AI influence the likelihood of AI adoption in the production processes of manufacturing companies?

The broad empirical analysis of the manufacturing industry in Germany conducted to address these RQs (study B) not only measures AI readiness and AI adoption in production but also examines the influence of AI readiness (at the respective levels) on AI adoption.

3.3 Effects of AI in Production

This dissertation aims to shed light on various effects that AI can have in a production context. These analyses aim to gain valuable insights into the relationship between AI readiness, AI adoption, and their effects on the resilience of production systems and the development of product innovations.

As discussed in section 2.3.1, research on production resilience has gained importance in recent years due to increasing global uncertainties, such as the COVID-19 pandemic (Alexopoulos et al. 2022; Lerch et al. 2022; Romero et al. 2021). Although there are theoretical foundations for analyzing the ability to respond to and recover from internal and external disruptions, there is a lack of empirical studies that specifically examine the influence of AI readiness on this resilience.

AI readiness encompasses various dimensions that together determine a company's ability to successfully implement AI. A company that is well prepared for AI may be able to anticipate and cope with unpredictable disruptions more effectively. However, it remains unclear to what extent this readiness actually influences the resilience of production systems. The central sub-RQ in this context is:

RQ3.1: How does AI readiness influence production system resilience?

The analysis conducted to address this research objective (study C) collects detailed empirical data that systematically captures the influence of AI readiness and the ability to cope with unexpected events.

In a dynamic and competitive business world, innovation is a crucial factor for the long-term success of companies (Crossan and Apaydin 2010; Dess and Picken 2000; Tushman and O'Reilly 1996). The ability to develop and bring new products to market is often seen as the key to competitiveness (Haefner et al. 2021). While the role of AI in promoting innovation processes is discussed in the literature (e.g. Gama and Magistretti (2023) or Liu et al. (2020)), empirical studies that examine the direct influence of AI adoption in a production context on the introduction of product innovations is missing.

The link between the use of AI as a process innovation and the likelihood of developing new products is a research area that has been little researched to date. In particular, it remains unclear how the adoption of AI technologies influences the likelihood of developing new products. The central sub-RQ to address this is:

RQ3.2: How does AI adoption in production influence the probability to introduce product innovations?

The empirical analysis conducted for this purpose (study D) aims to provide empirical evidence showing how AI adoption in production influences the innovative capacity of companies. By conducting these two empirical analyses on the effects of AI, the dissertation aims to close existing research gaps on the effects of AI in production and provide valuable insights for practical application.

4 Summary of the Conducted Studies

This section provides an overview of the four papers included. For each article, the motivation and methodology, results, discussion, and limitations are summarized.

4.1 Study A: Underlying Factors for AI Adoption in Production

This subsection summarizes the paper entitled 'Exploring the factors driving AI adoption in production - A systematic literature review and future research agenda', written by Heidi Heimberger, Djerdj Horvat, and Frank Schultmann, published in 'Information Technology and Management' in 2024.

4.1.1 Motivation and Methodology

Study A examines the current state of the literature on AI adoption in the context of production. The focus is on identifying and aggregating the factors that influence AI adoption in this specific area and pointing to important research directions. In doing so, we address the existing research gap (as discussed in section 3.1), which is a missing overview on AI adoption in production and provide a comprehensive overview of relevant influencing factors that have not yet been fully evaluated. Although some studies analyze the specific context of AI adoption in the manufacturing industry, they do not address all relevant factors and therefore do not provide a comprehensive overview. For production research, the derived factors are intended to help decision-makers identify the crucial aspects of AI implementation and make adoption a success.

To derive these factors, we applied the SLR method. First, we selected relevant literature by searching three databases (Scopus, ScienceDirect, and Web of Science) for defined keywords ('artificial intelligence' AND 'production or manufacturing' AND 'adopt*') in the period from 2010 to May 8, 2024. Our analysis included conference articles, journals, reviews, book chapters, conference papers, and books in English. We identified a total of 3,833 documents. In the next step, we reviewed the titles, abstracts, and keywords of these documents for their suitability for analysis. Working in a team of two to three researchers, we conducted a detailed analysis and subjected only those articles to a full-text analysis that covered all three relevant topics (focus on AI, technology adoption, application in a production context). This reduced the number to 300 articles, with three articles excluded because the full text was not available. Using a double-blind review process, we ultimately analyzed 297 articles and reduced this number by a further 249. For the qualitative content analysis of the remaining 47 articles, we developed a coding system to identify key ideas, categories, and connections. This iterative process led to the central findings of our paper, including the identification of influencing factors and future research directions.

4.1.2 Results

The results of our SLR are threefold. First, our analysis shows that the number of publications on the topic of AI adoption in production has been increasing, especially since 2018. Qualitative journal articles by authors from several countries dominate, with strong industrial countries like the USA, Germany, and India being particularly active. These results illustrate that the topic has gained relevance and is increasingly attracting attention in research.

In the second part, which identifies the influencing factors, we were able to derive a total of 35 factors from the content analysis of the 47 studies that were analyzed. We have assigned these factors to various supercategories in two organizational environments (internal and external environment) as visualized in Table 2.

Table 2: Overview of factors and supercategories influencing AI adoption in production

Organizational environment	**Supercategory**	**Factors**
Internal environment	Business and structure	Performance measures, investment, company size, product complexity, batch size, R&D complexity
	Organizational effectiveness	Trust, change management, managerial support, strategic promoter, strategic orientation, skilled workforce, education and training, innovation culture, mindset
	Technology and system	IT infrastructure, security, user-friendliness, system compatibility, safety
	Data management	Privacy, data availability, data consistency, data governance, data interoperability, data processing, data analytics, data storage
External environment	Regulatory environment	Ethical guidelines, laws and regulation
	Business environment	Cooperation, government support, environmental dynamism
	Economic environment	Industrial sector, country

Source: Table published in Heimberger et al. (2024)

In the third part, we derived a research agenda for the most frequently mentioned factors (in at least half of the 47 articles). We assume that these factors are particularly important for AI adoption in a production context. The research agenda formulates open questions on key topics such as skills, data availability, ethics, and management support, which are especially important for future research directions regarding AI adoption in production.

4.1.3 Discussion and Limitations

With regard to the research objective of the paper, which is to provide a comprehensive overview of the state of research, influencing factors, and future RQs on the topic of AI adoption in production, we were able to answer all open questions. Our results show an emerging interest in this topic in academia, which is consistent with practical experience in industry. Practitioners are increasingly addressing questions about the adoption of AI in production and can use our findings to analyze important factors and take them into account when introducing AI. In addition, our results enable the topic to be classified in terms of future research opportunities that require in-depth analysis, particularly regarding the most relevant factors.

Nevertheless, there are some limitations to our analysis. As with all research that considers a specific time frame, AI is a very current topic and new, relevant papers have certainly been published that could expand our findings. We had to define a fixed framework and select the most relevant literature databases, which limits the research content to a certain extent. Future analyses may include the new articles since May 2024, which were not considered here.

4.2 Study B: Impact of AI Readiness on AI Adoption in Production

This section presents the findings of the paper ‘Exploring AI Adoption in Manufacturing: An Empirical Study on Effects of AI Readiness’, published in 2025 by Heidi Heimberger, Djerdj Horvat, Angela Jäger, and Frank Schultmann in the ‘International Journal of Production Economics’.

4.2.1 Motivation and Methodology

Current research now covers various possible applications of AI in a production context well, and the potential that can arise from adoption is clear. Nevertheless, the actual use of AI in production is still relatively low. This raises the question of whether companies are ready to implement AI and to what extent this readiness influences the actual adoption of AI. We are therefore attempting to link the two concepts of AI readiness (i.e., the readiness of the organization at various levels to use AI systems) and AI adoption (actual use of AI) in order to close the research gap identified in section 3.2. The aim is to find out to what extent readiness, based on the existence of certain resources within the firm, is important for adoption and what companies can do to increase it. For science, we are thus combining two theoretical concepts that are closely related but have not yet been examined in conjunction with AI in production. With a view to practical application, we seek to offer support that further analyzes readiness and shows companies possible courses of action for increasing it.

As part of this study, we are drawing on the GMS. In the 2022 survey round, a set of questions on AI was developed and integrated as part of this dissertation that covers areas of application in four production areas (production management, quality control, maintenance, and internal logistics) and addresses a wide range of production- and innovation-specific issues for companies in the manufacturing sector in Germany. Based on different factors, we have developed an AI readiness index that can measure both technological and organizational AI readiness (as well as their combination). We analyze the connection between AI readiness and AI adoption using descriptive statistics, bivariate group comparisons, and multiple logistic regression analyses based on 1,130 manufacturing companies from the GMS. AI adoption serves as the dependent variable (in the form of a binary variable), and we have established the three AI readiness indices (technological AI readiness, organizational AI readiness, combined AI readiness) as independent variables. In addition, we control for structural variables and production characteristics: company size, sector, product complexity, batch size, and value chain position.

4.2.2 Results

The results on AI readiness show that the majority of companies in the manufacturing industry have medium (49%) or high (40%) technological AI readiness, while high organizational AI readiness is lower at 28%. Around 25% of the manufacturing companies have no or only low combined AI readiness, while around 60% have medium and only 17% have high combined AI readiness. In addition, large companies have higher AI readiness than small firms, which often have either no or only low readiness.

Data on AI adoption shows that only 14% of German manufacturing companies use AI in at least one of the four application areas examined, indicating that AI adoption in production is not yet widespread. Large companies with more than 500 employees use AI significantly more often than smaller ones, and the automotive industry stands out in particular, with almost a third of these companies using AI applications. Regarding production characteristics, 20% of manufacturers of complex products use AI in production, while only 8% of manufacturers of simple products do so, with smaller differences in terms of batch size and value chain position.

Table 3: Results of the three regression models on the explanatory power of AI readiness

Variables	**H1 Technological AI readiness**		**H2 Organizational AI readiness**		**H3 Combined AI readiness**	
	OR	Sig	OR	Sig	OR	Sig
Firm and production characteristics						
Firm size						
(Log value of the # of employees)	0,45	**	0,48	*	0,43	**
Squared log value	1,09	**	1,08	**	1,09	**
Sector		**		**		**
(Reference: Machinery)						
Metal industry	1,76	*	1,82	*	1,82	*
Food and beverage industry	1,95	*	2,20	*	2,17	*
Chemical and pharmaceutical	0,68		0,65		0,66	
Rubber and plastics industry	2,55	***	2,44	***	2,48	***
Electrical/electronics industry	0,96		0,93		0,93	
Vehicle construction	3,19	***	2,98	***	3,02	***
Others	1,67		1,67		1,64	
Product complexity		***		***		***
(Reference: simple)						
Medium	1,75	**	1,71	*	1,69	*
High	3,37	***	3,20	***	3,04	***
Batch size						
(Reference: single lot)						
small/medium lot	1,30		1,30		1,24	
big lot	1,77	*	1,82	*	1,69	
Value chain position						
Supplier (system-, part-)	1,20		1,21		1,20	
AI readiness						
Technological AI readiness		*				
(Reference: low)						
no	0,60					
medium	1,22					
High	1,99	*				
Organizational AI readiness				**		
(Reference: low)						
no			0,98			
medium			1,33			
High			2,11	**		
Combined AI readiness						***
(Reference: very low)						
no					1,65	
low medium					1,28	
high medium					1,99	**
high					3,04	***
Constant	0,139	*	0,12	**	0,16	*
Log Likelihood/sig.	840,73	***	840,05	***	834,25	***
Cox & Snell R^2	6,0%		6,1%		6,6%	
Nagelkerke R^2	10,9%		11,0%		11,8%	
Explanatory contribution of AI (ΔLog Likelihood)	7,81	*	8,49	**	14,29	***
n=1,130; Significance levels: *** p<0.01; ** p<0.05; * p<0.1						

Source: Based on Heimberger et al. (2025)

As visualized in Table 3, the analysis of the link between AI readiness and AI adoption indices shows that high achievements in all three indices (technological, organizational, and combined AI readiness) are significant factors influencing the likelihood of AI adoption in production processes. Combined AI readiness in particular has the highest explanatory power, showing that companies with high combined AI readiness are three times more likely to implement AI solutions than those with low readiness. The results also indicate that high organizational AI readiness doubles the likelihood of AI adoption, while technological AI readiness has limited contribution to adoption (significant only at 10% level). In addition, structural characteristics such as company size, industry, and product complexity are crucial for AI adoption, with larger companies and the automotive industry being particularly highlighted. The analysis suggests that the differentiation between high and medium levels of AI readiness is relevant, while lower levels show no clear influence on adoption. Overall, the results highlight the need to view AI readiness as a multi-layered concept including various dimensions.

4.2.3 Discussion and Limitations

This study makes an important contribution to the state of research on the relationship between AI readiness and AI adoption in the manufacturing industry by highlighting the importance of various resources and their combinations. This enabled us to fully address our RQs highlighted in section 3.2 and, with the help of the developed framework, take into account both the technological and organizational aspects of AI readiness, which is highly relevant for theory and practice. The results show that companies striving for combined AI readiness are more likely to successfully implement AI solutions. At the same time, the identified structural differences, especially company size and product complexity, highlight the challenges and opportunities associated with AI adoption.

Limitations of the study relate to the one-sided consideration of factors influencing AI readiness and adoption, as it is limited and e.g. ethical and social aspects as well as the interaction of technological and organizational resources were not taken into consideration. Future research could integrate these dimensions and also examine the influence of external factors such as competitive strategies or management support. In addition, a broader analysis of AI applications in different production areas and the relationship between AI adoption and business performance could provide valuable insights in the future. Finally, an international comparative study could help to increase the generalizability of the results and help understand the dynamics of AI adoption in different contexts better.

4.3 Study C: Impact of AI Readiness on the Resilience of Production Systems and Operations

Here the findings of the paper 'AI-readiness and production resilience: Empirical evidence from German manufacturing in times of the Covid-19 pandemic' by authors Christian Lerch, Heidi Heimberger, Angela Jäger, Djerdj Horvat, and Frank Schultmann, published in 2022 in the 'International Journal of Production Research' are summarized.

4.3.1 Motivation and Methodology

In study C, we examine the output side of AI readiness among manufacturing companies. Our focus is on the effect that high AI readiness can have on production resilience in order to address the research objective derived in section 3.3. Production resilience is of central importance because production systems and processes are exposed to numerous influences, and unpredictable events in particular place high demands on them. In our study, we examine this relationship using empirical analysis during the COVID-19 pandemic. The aim is to measure the effects of high AI readiness (understood as the presence of strong technical and digital foundations) on three dimensions of resilience: (1) the ability of companies to withstand restrictions, (2) respond appropriately to them, and (3) recover after restrictions. Our contribution thus addresses an existing research gap regarding the relationship between AI readiness and production resilience. This is relevant for both research and practice, as the introduction of intelligent technologies not only brings classic effects such as efficiency and productivity gains, but also potentially strengthens the overall resilience of production systems, an aspect that has hardly been investigated in the context of production processes to date.

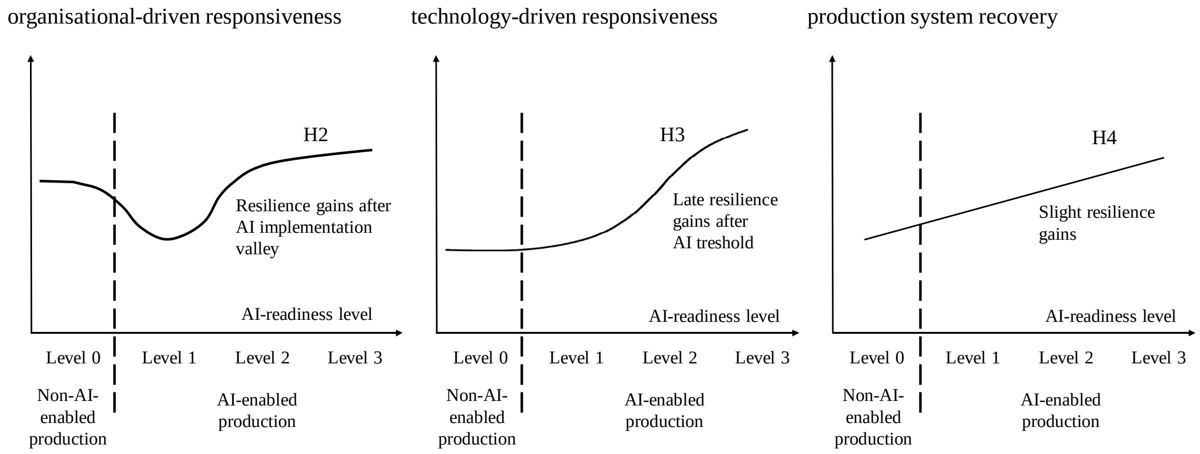
For the empirical study, we draw on two data sets: First, we use the GMS from 2018, which, with a response rate of 1,256 replies, is representative of the entire manufacturing sector in Germany and contains information on different industries, company sizes, and production characteristics. Second, we use a second survey on the topic of COVID-19, which was conducted in September 2020 to capture the specific circumstances of the pandemic period. A total of 237 companies participated in this additional survey. After combining both data sets, our analysis is thus based on a total of 228 companies that participated in both the GMS 2018 and the additional COVID-19 survey. This data includes production, innovation, and structural data from the companies as well as information on the effects and impacts of the COVID-19 pandemic. This combined data set enables a unique analysis of the experiences of manufacturing companies in dealing with unpredictable events, using the coronavirus crisis as an example.

For the empirical analyses, a technical AI readiness index was developed based on six dimensions that map various AI-enabling technologies considered key prerequisites for implementing AI systems. The index serves as an indicator of a company's technological maturity in terms of the use of AI and thus measures AI readiness. Based on this indicator, the companies were divided into four groups: no, low, medium, and high AI readiness. Various aspects of production resilience are considered as dependent variables in the analyses. These include (1) the impact of operational restrictions during the COVID-19 pandemic, (2) the measures taken to overcome these restrictions (through production reorganization and the introduction of digital solutions), and (3) the ability of companies to ramp up production again after the restrictions. To test the underlying hypotheses, bivariate analyses were first performed to identify correlations between AI readiness and the individual resilience indicators. In a second step, multiple regression analyses were applied to statistically test the influence of AI readiness on production resilience while controlling for other relevant company characteristics.

4.3.2 Results

The results indicate that 79% of companies were affected by lockdown measures. The classification into AI readiness groups showed that 9% of the companies had no AI readiness, 38% had low AI readiness, 33% had medium AI readiness, and 20% had high AI readiness. The analysis also revealed that companies affected by production restrictions tended to have higher medium and high AI readiness, but this difference was not statistically significant. When reorganizing production processes during the lockdown, 56% of companies with low or no AI readiness took measures, compared to 74% of companies with medium or high AI readiness, which was considered statistically significant. With regard to the implementation of digital solutions during the lockdown, 25% of companies with low AI readiness and 55% of companies with high AI readiness stated that they had implemented such solutions. In terms of production output after the lockdown, no company without AI readiness recorded an increase, while 5%, 8%, and 13% were recorded for low, medium, and high AI readiness, respectively.

Figure 3: Relationship between AI readiness and production resilience



Source: Figure published in Lerch et al. (2022)

Figure 3 illustrates the positive effects of increased AI readiness on production resilience. The results of our multiple regression analyses show that companies with higher AI readiness were significantly better able to reorganize their production processes during the COVID-19 lockdown. Companies with low AI readiness showed the least organizational-driven responsiveness, while companies with moderate or high AI readiness demonstrated the best reorganization capabilities. In this context, it is evident that when transitioning to AI-enabled production, companies initially enter an ‘AI implementation valley’ in which their organizational responsiveness temporarily declines before significant progress can be made.

In terms of implementing digital solutions, companies with higher AI readiness were able to introduce them more effectively. The analyses show that technology-driven responsiveness initially stagnates until a critical ‘AI threshold’ is exceeded. Only after reaching this threshold did a consistent increase in responsiveness occur, leading to slight gains in resilience. These early gains in resilience illustrate that while the introduction of AI-enabling technologies can be challenging at first, it leads to a noticeable improvement in responsiveness and recovery capabilities once companies reach a certain level of AI implementation.

The analysis of the ability to recover shows that a higher level of AI readiness increased the likelihood that companies were able to achieve increased production output after the COVID-19 lockdown. Companies with higher AI readiness demonstrate an improved ability to recover from disruptive events, leading to slight gains in resilience. The results confirm the positive relationship between AI readiness and resilience with regard to the recovery of production systems, with the sector also playing a decisive role.

4.3.3 Discussion and Limitations

The results of this study illustrate that the relationship between AI readiness and production resilience is complex and multifaceted. While the initial assumption that a higher level of AI readiness reduces the likelihood of being affected by Covid-19-related production restrictions could not be confirmed, the subsequent results show that companies with higher AI readiness were better able to respond to lockdown restrictions. In particular, the ability to reorganize production processes and implement digital solutions was significantly higher in companies with moderate or high AI readiness. These results suggest that AI-enabling technologies increase the responsiveness of companies in crisis situations, but do not necessarily improve their robustness against such disruptions. This highlights an important aspect of production resilience: AI readiness strengthens companies' agility, but not their ability to respond proactively to disruptive events. This leads to the proposition that AI-enabling technologies in production primarily promote reactive capabilities, but do not act as a protective mechanism against external disruptions.

Despite the valuable insights, the study has some limitations that may stimulate future research. First, the relationship between AI readiness and production resilience was examined on the basis of theoretical concepts without analyzing the specific processes of capability enhancement through AI technologies in greater depth. Future studies should examine the influence of AI on the development of both reactive and predictive capabilities in more detail, possibly through qualitative case studies or long-term analyses. Furthermore, measurement methods for AI and resilience in manufacturing are currently limited due to the low implementation rate of AI. Future research could benefit from the broader application of AI technologies in industry to more comprehensively determine their impact on resilience. The analysis is also limited geographically and temporally, as it focuses exclusively on the German manufacturing industry during the first Covid-19-lockdown in spring 2020. Future work could also examine resilience across multiple lockdown phases or over longer periods of time to develop a better understanding of how companies can respond to repeated disruptive events and improve their robustness.

4.4 Study D: Impact of AI Adoption in Production on Product Innovation

The following is a summary of the findings of the paper entitled ‘The Innovation Payoff of AI in Production: Evidence from German Manufacturing’, which is written by Djerdj Horvat, Heidi Heimberger, Angela Jäger, and Christian M. Lerch, and submitted to a scientific journal in December 2025.

4.4.1 Motivation and Methodology

In an increasingly dynamic and competitive market, manufacturing companies are under considerable pressure to innovate. There is a particular need for action in the areas of digital and environmentally-oriented product innovations, which are central elements of the so-called 'twin transition'. Increasing digitalization and the integration of new technologies are creating new opportunities to boost competitiveness by developing smart, connected products that can be tailored more precisely to customer requirements. At the same time, promoting environmentally friendly innovation is crucial to meeting regulatory requirements and realizing both ecological and economic benefits for a better future. In this context, AI has become a key technology that not only increases the efficiency of production processes, but can also boost innovation within the twin transition. AI can generate significant added value and improve existing processes through its ability to learn from large amounts of data, recognize patterns, and automate decision-making processes. Study D aims to explore the extent to which the adoption of AI in production, and thus AI-enabled processes, influence the introduction of product innovations, thereby contributing to the research objective derived in Section 3.3.

To address this, we draw on a representative sample of 1,334 manufacturing companies obtained from the 2022 wave of the GMS. In addition to descriptive analyses, we use logistic regressions to analyze the relationship between AI adoption in production processes and the likelihood of companies bringing product innovations to market. We use four regression models to differentiate between different types of innovation. We test the influence of AI adoption (as a binary variable) on the likelihood of new product launches and integrate traditional innovation determinants, including R&D intensity, the workforce qualification level, and human centricity measures into our models. In addition, we consider various structural variables to integrate further explanatory specifics.

4.4.2 Results

Our results show that 45% of German manufacturers have introduced new products in 2022, with 13% implementing digital and environmentally-oriented innovations, respectively. Large companies (500+ employees) are particularly active as product innovators, with 75% of large companies introducing new products, compared to only one-third of small companies. Twenty-two percent of companies in the manufacturing sector introduced market innovations. Looking at the firm-level innovation determinants in the German manufacturing sector shows that only 37% of companies carry out their own or outsourced R&D activities, which indicates a possible reluctance to pursue an innovation strategy. Nevertheless, 54% of companies enter partnerships with other firms or research institutions. In terms of workforce qualifications, an average of 22% of employees are highly skilled. Human-centricity also plays a role, as 46% of companies have implemented employee participation measures, however, only 18% offer targeted training to promote cross-functionality, creativity, and innovation. The connection between product innovation and AI adoption shows that AI adopters have higher innovation rates than non-adopters: 52% introduced new products that were new to the company, compared to 43% of non-adopters. The differences are particularly pronounced in digital and environmentally-oriented innovations, suggesting that AI improves companies' ability to innovate. However, no significant differences were found for market innovators.

Table 4 shows the results of the four regression analyses, including the odds ratios (ORs) and significance levels for the individual variables regarding the four types of product innovations:

A – product innovation (new for company)

B – digital-oriented product innovation

C – eco-oriented product innovation

D – product innovation (new for entire market)

Models A, B, and C reveal that the adoption of AI in production adds to the likelihood of product innovation. In model A, the adoption of AI has a significant positive impact on the likelihood that companies will implement product innovations that are new to the company, but only at a significance level of 10%. R&D activities are more decisive here, as direct R&D activities and collaborations significantly increase the probability of innovation. Human-centricity, in particular cross-functional and creativity trainings, also plays an important role. Model B shows that AI adoption in production significantly increases the likelihood of introducing digital products. The share of highly qualified employees and special training courses are also relevant, but only at a 10% significance level, while R&D activities have no influence on the type of innovation. Model C indicates that AI adoption also has a positive effect on eco-oriented product innovations, but only at a 10% significance level. Human centricity and specifically cross-functional and creativity trainings are particularly important role here, while R&D activities are less decisive. In model D, R&D and human-centricity are key for the development of market innovations, while AI adoption has no influence. Companies that engage in direct R&D activities and offer creative and interdisciplinary training are more likely to develop market innovations. In summary, R&D activities are crucial for the introduction of product innovations that are new the company and the market, while factors such as AI adoption and human-centricity influence the type of innovation (digital or eco). Industry-specific conditions also play a significant role in incremental innovation dynamics.

Table 4: Estimated ORs of the innovation drivers for product innovations in the four logistic models

	Models							
	A		**B**		**C**		**D**	
Innovation drivers	OR	Sig.	OR	Sig.	OR	Sig.	OR	Sig.
AI adoption		*		**		*		
AI adoption in production [(1)]	1.438	*	2.372	**	1.791	*	1.052	n.s.
Qualification		*						
Share of highly-qualified personnel (z-centered)	1.156	*	1.232	*	0.952	n.s.	1.090	n.s.
Human centricity		**		*		***		**
Employee involvement in innovation and improvement [(2)]	1.271	n.s.	1.239	n.s.	1.785	**	1.510	*
Cross-functional and/or creativity training for production employees		**		n.s.		**		*
Some training, but not both [(3)]	1.830	**	4.479	*	3.925	*	0.808	n.s.
Cross-functional and creativity training [(3)]	2.000	**	4.398	*	8.066	**	1.490	n.s.
R&D activities		***						**
R&D activity (internal/external) [(4)]	2.159	***	1.145	n.s.	1.369	n.s.	1.677	**
R&D cooperation(s) [(5)]	1.745	***	1.122	n.s.	1.411	n.s.	1.379	n.s.

Notes: Logistic regression models.
Model A included all manufacturers, models B, C and D only firms who were product innovators.
All models included also indicators for sector, firm size, product complexity and batch size.
Significance level: *** p< 0.001, ** p< 0.05, * p<0.1, n.s. not significant.
Reference groups: (1) no AI adoption in production, (2) no organisational concept implemented to involve production employees in improvement and innovation processes, (3) no training offer for production employees, (4) no R&D performed, (5) no R&D cooperation with another firm or research institution.

Source: Table to be published in Horvat et al. (forthcoming)

4.4.3 Discussion and Limitations

This study makes a significant contribution to understanding the role of AI-enabled processes in product innovation. The results indicate that AI has a moderate positive influence on product innovations that are new to the company, which can be attributed to improved information flows within the production system that reveal opportunities for product improvements. Specifically, AI facilitates digital product innovations and also demonstrates a moderate positive impact on eco-oriented product innovations. The results suggest that AI can function not only as a technological solution but also a strategic tool to enhance innovation. In contrast, the analysis shows that AI has no significant impact on market innovation. This implies that more radical market-related innovations are influenced by other factors, including R&D activities. The findings suggest that the flow of information from production systems alone is insufficient to address the complex demands of market innovation.

Despite the significant findings, the study has limitations that could inspire future research directions. First, the analysis focuses solely on physical product innovations, excluding non-physical innovations such as product-related services or business model innovations. Future studies should broaden the scope to explore how AI can have transformative effects in these contexts as well. Second, the analysis is based on industry-specific data and does not consider the interactions between companies within innovation ecosystems. Future research should investigate the interplay between AI adoption and external innovation networks to provide a more comprehensive understanding of AI's role in networked innovation. Third, the findings are confined to the German manufacturing industry, limiting their applicability to other countries. Therefore, conducting similar analyses in different countries would be valuable to determine whether the results vary between different countries. Such cross-country comparative studies could provide valuable insights into the influence of national and regional contexts on AI-driven innovation.

5 Implications

In this dissertation, the adoption of AI in a production context is examined comprehensively and from different perspectives. The findings are based on a well-founded synthesis of the current state of research and on diverse empirical data sets. The work comprises four journal articles that together address the three central RQs of this dissertation (as presented in section 1.2):

RQ1: What influences AI adoption in production?

RQ2: Are manufacturing firms ready to implement AI?

RQ3: What are effects of adopting AI in production?

The following section summarizes the implications of the three RQs and summarizes the findings from the individual journal articles.

5.1 AI in a Production Context

This work represents a comprehensive study on AI adoption in the specific context of production in manufacturing firms. In Germany, industry plays a central role, but the current market situation is tense, highlighting the need for change and new principles.

The results from studies B and D show that the current adoption of AI in production is not yet very advanced. In particular, certain industries (especially the automotive industry), large firms, and producers of complex products currently seem to offer the potential for AI use. According to our studies, the level of AI adoption in production in 2022 was only around 16 percent in Germany, which is in line with other empirical studies (e.g. Rammer et al. (2022)).

The results of study A illustrate that a variety of factors at different levels (both internal and external to the organization) influence the use of AI in a production context. A total of 35 different factors were identified that influence companies both internally and externally when it comes to adopting AI in production, thereby answering RQ1. The manufacturing industry has specific characteristics that must be taken into account. A key feature is the heterogeneous machine parks, which includes both old and new machines. This diversity poses challenges for the integration of AI technologies, as data collection in this industry is complex but a prerequisite for successful AI integration. Many machines need to be retrofitted and existing systems may not interact seamlessly with each other. In this era of digital transformation, companies must increasingly build up new skills.

The results also show that the potential bias of those involved poses a further challenge, as the attitudes and prejudices of various interest groups can influence the introduction of AI technologies. Here, managers should promote internal communication to break down prejudices and increase acceptance of AI technologies. By creating an open and supportive corporate culture, they can effectively drive the adoption of AI and thus ensure the competitiveness of their companies in the digital age.

It is crucial for those responsible for AI projects to thoroughly analyze the initial situation in order to identify the individual requirements for AI implementation in the manufacturing industry. The findings from the analyses in Study A on AI adoption in production make it clear that the implementation of AI entails different requirements depending on the specific area of application. Therefore, the respective situation should be carefully examined to gain a comprehensive understanding of the individual circumstances and the various influencing factors.

5.2 Influences on AI Readiness and AI Adoption

To address RQ2, studies B and C are particularly relevant, as they specifically address AI readiness in the manufacturing industry. Our comprehensive analyses in study B show that AI readiness and actual AI adoption are closely linked. The influencing factors identified in Study A also illustrate that various factors at different levels must be taken into account when it comes to AI adoption.

Our studies on AI readiness (Study B and Study C) focus on internal factors that can be determined by the companies themselves. These factors are an important prerequisite for the introduction of AI. The results of Study B show that successful AI adoption requires not only technical prerequisites, but especially organizational preparation. This finding is crucial because it indicates that the success of AI initiatives depends not only on the availability of technical resources, but also on internal organization and the framework conditions provided.

Although AI is highly technical in nature, organizational preparation involves a variety of ‘soft’ factors. These include skills development, targeted training programs, the promotion of a culture of innovation, and the creation of cooperation structures. These elements are essential for promoting the acceptance and integration of AI technologies and should be actively considered by managers.

In addition to these findings, the framework developed in Study B expands the existing literature by not only conceptually establishing the connection between AI readiness and AI adoption, but also measuring it empirically. This enables well-founded statements about the situation in the manufacturing industry in Germany. The results highlight the opportunities that can be achieved through the use of AI, but also point out that fundamental prerequisites must be created. In particular, companies must develop both organizational and technological resources to promote comprehensive readiness, which is crucial for the actual use of AI.

For managers, this means that before introducing AI, they must develop essential resources to create the necessary conditions for successful AI integration. This includes not only creating a solid IT and data base as a foundation for AI applications, but also, in particular, ensuring the necessary organizational structures and competencies are in place.

5.3 Effects of Adopting AI

In studies C and D, different effects of AI readiness and AI adoption for manufacturing companies were systematically examined, thereby addressing RQ3. The results contribute valuable insights to the existing literature by expanding common research areas such as productivity, efficiency, and waste reduction to include the effects of AI use on production system resilience and product innovation. This research addresses issues that are particularly relevant in today's world due to the numerous challenges the manufacturing industry faces.

Study C demonstrates that a high level of AI readiness can contribute to making production systems more resilient. To analyze this, insights from the COVID-19 pandemic were utilized, as it posed significant challenges for manufacturing companies. The results indicate that firms with technologically advanced systems and thus a high level of AI readiness were able to demonstrate greater resilience in their production systems in the developed index. These companies exhibited improved organizational and technology-driven responsiveness and were able to recover more quickly after restrictions.

Furthermore, the results from Study D indicate that the adoption of AI in production provides companies the opportunity to enhance their processes, supporting them to develop product innovations. This is particularly evident for digital product innovations, which can be implemented more effectively through AI-supported production processes. In addition, the results reveal that innovations that are new to the company and involve more incremental changes to products, as well as eco-innovations, also benefit from the capabilities offered by AI-enabled processes in production. These findings underscore the role of AI adoption in production for the development of new products and thus represent a significant opportunity to increase the competitiveness of manufacturing companies.

For managers, this indicates that a high level of AI readiness and proactive AI adoption can yield promising results. Companies can enhance their agility and adaptability, thereby boosting their innovative capacity. Consequently, integrating AI into production can significantly contribute to increasing the competitiveness of German industrial firms. By recognizing and leveraging the strategic advantages of AI, managers can effectively position their companies to meet future challenges and seize opportunities.

6 Conclusions

6.1 Summary

AI adoption in production is a promising opportunity for companies to advance their digitalization, improve processes, and thus optimize them in a data-driven manner. Currently, research in this area is still emerging, and this dissertation aims to contribute to its development and shed light on the specific application of AI in the context of production.

The results of this work show that a number of factors are important in this regard, which have different influences on companies and must be taken into account when introducing AI. These influences can occur both internally and externally to the organization and affect companies in different ways. At the internal level, organizational influences are of great importance in addition to necessary technological foundations that impact AI adoption in production.

In addition, the analyses of AI readiness show that companies should develop a certain level of AI readiness in order to lay the important foundations for driving successful AI adoption. In addition to analyzing the current situation in the manufacturing sector, which, according to empirical analyses, has already established a solid basis for AI, it turned out that actual AI adoption is rather weak in contrast. This empirical investigation reveals a gap between AI readiness and AI adoption in the manufacturing context in Germany. With regard to more in-depth analyses of the influence of AI readiness on AI adoption, it became evident that organizational resources in particular make a significant contribution to AI adoption and that companies should not neglect to establish these foundations. Consequently, the importance of a dual perspective on AI is emphasized: while technological foundations are important, organizational foundations are crucial for promoting AI users and require targeted development.

Furthermore, this dissertation shows that AI can have a range of effects. High AI readiness, and therefore a solid foundation for possible AI integration, is positively correlated with increased production system resilience. These findings illustrate that companies with a high level of AI readiness may be better able to respond to unpredictable events and their effects and also recover better from these fluctuations. This finding confirms the role of strong digitalization and preparation for AI in improving production system resilience.

In addition to the effect of resilience, the results show that AI adoption in production as a process innovation has a positive influence on the likelihood of companies developing different types of incremental product innovations. This finding is of great value to companies and managers and shows that AI can have an impact on the innovative capacity and can increase the competitiveness of manufacturing companies.

6.2 Critical Reflection and Future Research Opportunities

This work forms the basis for a comprehensive analysis of the adoption of AI in a production context and can serve as a starting point for future research. This section critically reflects on the limitations of this dissertation in terms of the data used, the methods employed, and the context analyzed. It also outlines possible approaches for further research.

6.2.1 Data Limitations

The investigation of AI adoption is based on various data sources. The results of the SLR in Study A are based on scientific literature from 2010 to early 2024. Although this time restriction is necessary, it limits the relevance of the results, as knowledge and technologies in the field of AI are constantly evolving. In the meantime, new and exciting findings have certainly emerged that could be relevant to the analysis. In addition, the content of the analysis was limited to three specific scientific databases, which could restrict the range of information. Future studies could therefore include additional databases or publication types or consider alternative data extraction methods such as web scraping to obtain a more comprehensive picture of the current state of research.

In addition, three of the four journal articles (Studies B, C, and D) are based on the empirical results of the GMS surveys. Studies B and D are based on the GMS 2022, which involved active preparation, including the development and integration of a series of questions on the topic of AI in production. The analysis in Study C is based on the GMS 2018 and a special COVID-19 survey from 2021. Both GMS surveys provide a thorough picture of the entire manufacturing sector in Germany and enable detailed analyses of the modernity and performance of companies. The additional COVID-19 survey also add interesting information on the specific circumstances and constraints that companies faced during the pandemic.

However, it is important to consider the structural characteristics and limitations of the surveys used when evaluating the results. The results of studies B, C, and D are specific to the manufacturing sector in Germany, which is internationally known for its traditional industry and large number of small and medium-sized enterprises. The findings are therefore country-specific and reflect the situation in Germany. Future extensions of the analyses to other countries would be of great interest in order to enable cross-country comparisons of AI readiness, AI adoption, and the impact of AI in different nations.

Another interesting aspect of the GMS data is that these surveys are conducted every three to four years, which allows for temporal comparisons. However, since the AI survey items were only integrated in the last survey round (GMS 2022), no findings can be derived from a temporal progression in this dissertation. It remains to be seen how AI adoption will develop in the next survey, which is expected in 2026, and whether the trends from the consumer sector will also become visible in industry. The longitudinal comparison of AI adoption development forms an interesting basis for future research.

6.2.2 Methodological Limitations

The choice of methods in the underlying studies of this work must also be critically reflected upon. The decision to use logistic regression analyses in the three empirical studies (Studies B, C, D) is based on several reasons. First, logistic regression enables effective analysis of binary dependent variables, which are well suited to the contexts under investigation. Since the relationships examined in the RQs model the probability of AI adoption or the probability of various effects caused by AI adoption (e.g., resilience of the production system or introduction of product innovations), logistic regression is particularly suitable for quantifying the relationship between various influencing factors and the outcome.

Second, logistic regression offers the possibility of considering the effects of several independent variables simultaneously. This is particularly important in complex research fields such as manufacturing, where numerous factors such as company size, industry, and production characteristics interact and can influence the results. Although various factors were included in the empirical analyses, a selection had to be made, and additional variables could be of interest in order to shed light on potentially interesting effects in the context of AI.

While logistic regression offers a robust, flexible, and interpretable method for analyzing the complex relationships regarding AI adoption in production, the integration of additional empirical methods in future analyses could open up new perspectives and help to more comprehensively capture and analyze the complexity of AI integration in the production environment. An interesting possibility for alternative methods would be the application of structural equation modeling, which allows complex relationships between multiple dependent and independent variables to be modeled. This method could provide valuable insights into the causal relationships between various factors of AI adoption and analyze their impact on innovation.

In addition, qualitative methods, such as case studies or interviews with representatives of the manufacturing industry, could provide valuable contextual information that complements the quantitative results. An in-depth analysis of individual AI adoption cases (both successful and unsuccessful) could provide incentives for future studies that take a more case study-based approach. This would allow for a broader view of adoption and consider it more as a process.

6.2.3 Context Limitations

The application context of AI in this dissertation is very specifically limited to production and is therefore context-dependent. Production is an important and value-adding field for the manufacturing industry with promising areas of application for AI. However, future studies could also examine the extent to which AI can influence other areas of the manufacturing industry, such as marketing, logistics, sales, or finance.

In this paper, AI is considered as a group of self-learning applications that can be integrated into the production context. Further specifications of the possible AI disciplines are not employed in the studies; instead, the focus is on the organizational implications of AI. A detailed examination of the various AI concepts, distinguishing between different AI disciplines such as machine learning or deep learning, could also provide interesting insights into which specific AI technologies are particularly promising for production.

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II
Conducted Studies

The following part of the dissertation contains the four journal articles on which the work is based.

Table 5: Overview of related publications

Study	**Title**	**Authors**	**Journal**	**Publication status**
A	Exploring the factors driving AI adoption in production - A systematic literature review and future research agenda	Heidi Heimberger, Djerdj Horvat, Frank Schultmann	Information Technology and Management	Published
B	Exploring AI adoption in manufacturing: An empirical study on effects of AI readiness	Heidi Heimberger, Djerdj Horvat, Angela Jäger, Frank Schultmann	International Journal of Production Economics	Published
C	AI-readiness and production resilience: Empirical evidence from German manufacturing in times of the Covid-19 pandemic	Christian Lerch, Heidi Heimberger, Angela Jäger, Djerdj Horvat, Frank Schultmann	International Journal of Production Research	Published
D	The Innovation Payoff of AI in Production: Evidence from Ger-man Manufacturing	Djerdj Horvat, Heidi Heimberger, Angela Jäger, Christian M. Lerch	Production Planning & Control	Submitted

A Exploring the Factors Driving AI Adoption in Production - A Systematic Literature Review and Future Research Agenda[1]

Abstract:

Our paper analyzes the current state of research on Artificial Intelligence (AI) adoption from a production perspective. We represent a holistic view on the topic which is necessary to get a first understanding of AI in a production-context and to build a comprehensive view on the different dimensions as well as factors influencing its adoption. We review the scientific literature published between 2010 and May 2024 to analyze the current state of research on the use of AI in production. Following a systematic approach to select relevant studies, our literature review is based on a sample of articles that contribute to production-specific AI adoption. Our results reveal that the topic has been emerging within the last five years and that AI adoption research in production is to date still in an early stage. We are able to systematize and explain 35 factors with a significant role for AI adoption in production and classify the results in a framework. Based on the factor analysis, we establish a future research agenda that serves as a basis for future research and addresses open questions. Our paper provides an overview of the current state of the research on the adoption of AI in a production-specific context, which forms a basis for further studies as well as a starting point for a better understanding of the implementation of AI in practice.

Keywords: Artificial intelligence; technology adoption; AI adoption; production; adoption factors; systematic literature review

[1] This chapter includes the Accepted Manuscript of an article published by Springer Nature in *Information Technology and Management* on August 23rd 2024, available online: https://link.springer.com/article/10.1007/s10799-024-00436-z.

A.1 Introduction

The technological change resulting from deep digitisation and the increasing use of digital technologies has reached and transformed many sectors (Benner and Waldfogel 2020). In manufacturing, the development of a new industrial age, characterized by extensive automation and digitisation of processes (Roblek et al. 2016), is changing the sector's ‘technological reality’ (Oliveira et al. 2020) by integrating a wide range of information and communication technologies (such as Industry 4.0-related technologies) into production processes (Li et al. 2017).

Although the evolution of AI traces back to the year 1956 (as part of the Dartmouth Conference) (Dhamija and Bag 2020), its development has progressed rapidly, especially since the 2010s (Collins et al. 2021). Driven by improvements, such as the fast and low-cost development of smart hardware, the enhancement of algorithms as well as the capability to manage big data (Chien et al. 2020), there is an increasing number of AI applications available for implementation today (Chen 2019). The integration of AI into production processes promises to boost the productivity, efficiency as well as automation of processes (Sanchez et al. 2020), but is currently still in its infancy (Lee et al. 2018) and manufacturing firms seem to still be hesitant to adopt AI in a production-context. This appears to be driven by the high complexity of AI combined with the lack of practical knowledge about its implementation in production and several other influencing factors (Heimberger et al. 2023; Horvat and Heimberger 2023).

In the literature, many contributions analyze AI from a technological perspective, mainly addressing underlying models, algorithms, and developments of AI tools. Various authors characterise both machine learning and deep learning as key technologies of AI (Chen 2019; Wang et al. 2018), which are often applied in combination with other AI technologies, such as natural language recognition. While promising areas for AI application already exist in various domains such as marketing (Davenport et al. 2020), procurement (Cui et al. 2022), supply chain management (Pournader et al. 2021) or innovation management (Su et al. 2024), the integration of AI into production processes also provides significant performance potentials, particularly in the areas of maintenance (Venkatesh et al. 2024), quality control (Senoner et al. 2022) and production planning and management (Fosso Wamba et al. 2024). However, AI adoption requires important technological foundations, such as the provision of data and the necessary infrastructure, which must be ensured (Heimberger et al. 2023; Horvat and Heimberger 2023; Uren and Edwards 2023). Although the state of the art literature provides important insights into possible fields of application of AI in production, the question remains: To what extent are these versatile applications already in use and what is required for their successful adoption?

Besides the technology perspective of AI, a more human-oriented field of discussion is debated in scientific literature (Berente et al. 2021). While new technologies play an essential role in driving business growth in the digital transformation of the production industry, the increasing interaction between humans and intelligent machines (also referred to as 'augmentation') creates stress challenges (Scafà et al. 2019) and impacts work (Wang and Qiu 2023), which thus creates managerial challenges in organizations (Baskerville et al. 2020; Lindebaum et al. 2020). One of the widely discussed topics in this context is the fear of AI threatening jobs (including production jobs), which was triggered by e.g. a study of Frey and Osborne (2017). Another issue associated to the fear of machines replacing humans is the lack of acceptance resulting from the mistrust of technologies (Fügener et al. 2021; Jarrahi 2018). This can also be linked to the various ethical challenges involved in working with AI (Berente et al. 2021). This perspective, which focuses on the interplay between AI and humans (Klumpp 2018), reveals the tension triggered by AI. Although this is discussed from different angles, the question remains how these aspects influence the adoption of AI in production.

Another thematic stream of current literature can be observed in a series of contributions on the organizational aspects of the technology. In comparison to the two research areas discussed above, the number of publications in this area seems to be smaller. This perspective focuses on issues to implement AI, such as the importance of a profound management structure (Li et al. 2021; Schrettenbrunnner 2020), leadership (Brock and Wangenheim 2019), implications on the organizational culture (Lee et al. 2019) as well as the need for digital capabilities and special organizational skills (Brock and Wangenheim 2019). Although some studies on the general adoption of AI without a sectoral focus have already been conducted (such as by Chen and Tajdini (2024) or Kinkel et al. (2022)) and hence, some initial factors influencing the adoption of AI can be derived, the contributions from this perspective are still scarce, are usually not specifically analyzed in the context of production or lack a comprehensive view on the organization in AI adoption.

While non-industry specific AI issues have been researched in recent years, the current literature misses a production-specific analysis of AI adoption, providing an understanding of the possibilities and issues related to integrating AI into the production context. Moreover, the existing literature tells us little about relevant mechanisms and factors underlying the adoption of AI in production processes, which include both technical, human-centered as well as organizational issues. As organizational understanding of AI in a business context is currently still in its early stages, it is difficult to find an aggregate view on the factors that can support companies in implementing AI initiatives in production (McElheran et al. 2024; Mikalef and Gupta 2021). Addressing this gap, we aim to systematise the current scientific knowledge on AI adoption, with a focus on production. By drawing on a systematic literature review (SLR), we examine existing studies on AI adoption in production and explore the main issues regarding adoption that are covered in the analyzed articles. Building on these findings, we conduct a comprehensive analysis of the existing studies with the aim of systematically investigating the key factors influencing the adoption of AI in production. This systematic approach paves the way for the formulation of a future research agenda.

Our SLR addresses three research questions (RQs). RQ1: What are the statistical characteristics of existing research on AI adoption in production? To answer this RQ, we conduct descriptive statistics of the analyzed studies and provide information on time trends, methods used in the research, and country specifications. RQ2: What factors influence the adoption of AI in production? RQ2 specifies the adoption factors and forms the core component of our analysis. By adoption factors, we mean the factors that influence the use of AI in production (both positively and negatively) and that must therefore be analyzed and taken into account. RQ3: What research topics are of importance to advance the research field of AI adoption in production? We address this RQ by using the analyzed literature as well as the key factors of AI adoption as a starting point to derive RQs that are not addressed and thus provide an outlook on the topic.

A.2 Methodology

In order to create a sound information base for both policy makers and practitioners on the topic of AI adoption in production, this paper follows the systematic approach of a SLR. For many fields, including management research, a SLR is an important tool to capture the diversity of existing knowledge on a specific topic for a scientific investigation (Tranfield et al. 2003). The investigator often pursues multiple goals, such as capturing and assessing the existing environment and advancing the existing body of knowledge with a proprietary RQ (Tranfield et al. 2003) or identifying key research topics (Cooper et al. 2009).

Our SLR aims to select, analyze, and synthesize findings from the existing literature on AI adoption in production over the past twenty years. In order to identify relevant data for our literature synthesis, we follow the systematic approach of the Preferred Reporting Items for Systematic reviews (PRISMA) (Page et al. 2021). In evaluating the findings, we draw on a mixed-methods approach, combining some quantitative analyses, especially on the descriptive aspects of the selected publications, as well as qualitative analyses aimed at evaluating and comparing the contents of the papers. Figure 4 graphically summarizes the methodological approach that guides the content of the following sub-chapters.

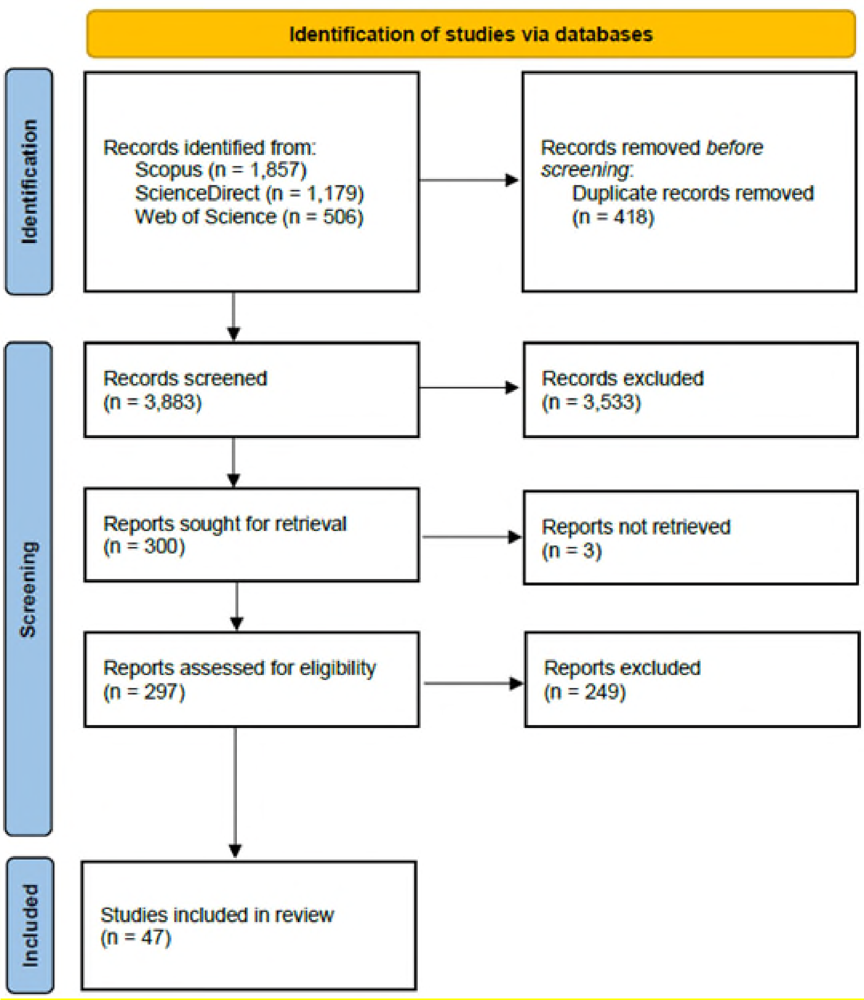


Figure 4: Methodical procedure of our SLR following PRISMA (Page et al. 2021)

A.2.1 Data Identification

Following the development of the specific RQs, we searched for suitable publications. To locate relevant studies, we chose to conduct a publication analysis in the databases Scopus, Web of Science and ScienceDirect as these databases primarily contains international scientific articles and provide a broad overview of the interdisciplinary research field and its findings. To align the search with the RQs (Denyer and Tranfield 2011), we applied predefined key words to search the titles, abstracts, and keywords of Scopus, Web of Science and ScienceDirect articles. Our research team conducted several pre-tests to determine the final search commands for which the test results were on target and increased the efficiency of the search (Denyer and Tranfield 2011). Using the combination of Boolean operators, we covered the three topics of AI, production, and adoption by searching combinations of 'Artificial Intelligence' AND ‘production or manufacturing’ AND ‘adopt*’ in the three scientific databases. Although ‘manufacturing’ tends to stand for the whole sector and ‘production’ refers to the process, the two terms are often used to describe the same context. We also follow the view of Burbidge et al. (1987) and use the terms synonymously in this paper and therefore also include both terms as keywords in the study location as well as in the analysis.

AI research has been credited with a resurgence since 2010 (Collins et al. 2021), which is the reason for our choice of time horizon. Due to the increase in publications within the last years, we selected articles published online from 2010 to May 8, 2024 for our analysis. As document types, we included conference papers, articles, reviews, book chapters, conference reviews as well as books, focusing exclusively on contributions in English in the final publication stage. The result of the study location is a list of 3,833 documents whose titles, abstracts, and keywords meet the search criteria and are therefore included in the next step of the analysis.

A.2.2 Data Analysis

For these 3,833 documents, we then conducted an abstract analysis, ‘us[ing] a set of explicit selection criteria to assess the relevance of each study found to see if it actually does address the research question’ (Denyer and Tranfield 2011). For this step, we again conducted double-blind screenings (including a minimum of two reviewers) as pilot searches so that all reviewers have the same understanding of the decision rules and make equal decisions regarding their inclusion for further analysis.

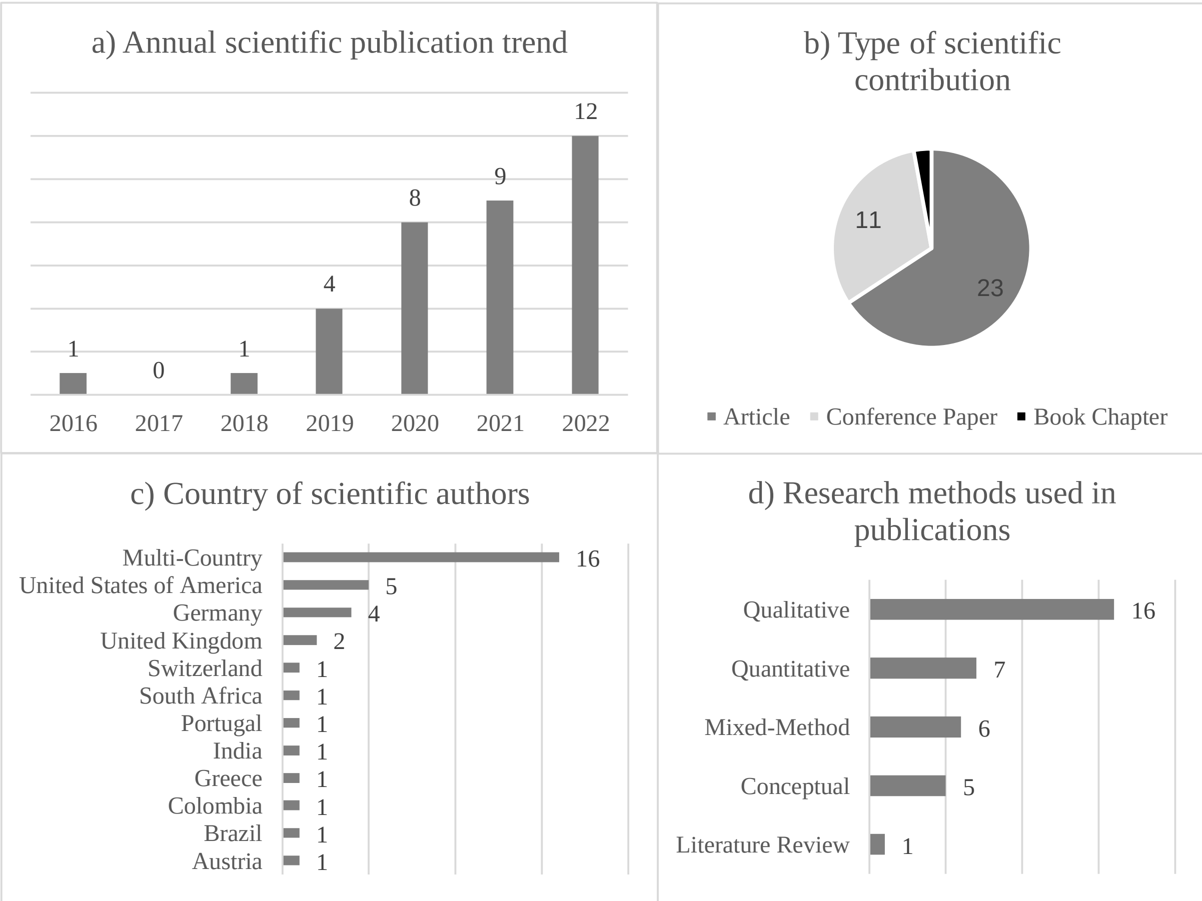
To ensure the paper's focus on all three topics regarded in our research (AI, production, and adoption), we followed clearly defined rules of inclusion and exclusion that all reviewers had to follow in the review process. As a first requirement for inclusion, AI must be the technology in focus that is analysed in the publication. If AI was only mentioned and not further specified, we excluded the publication. With a second requirement, we checked the papers for the context of analysis, which in our case must be production. If the core focus is beyond production, the publication was also excluded from further analysis. The third prerequisite for further consideration of the publication is the analysis of the adoption of a technology in the paper. If technology adoption is not addressed or adoption factors are not considered, we excluded the paper. An article was only selected for full-text analysis if, after analyzing the titles, abstracts, and keywords, a clear focus on all three research areas was visible and the inclusion criteria were met for all three contexts.

By using this tripartite inclusion analysis, we were able to analyse the publications in a structured way and to reduce the 3,833 selected documents in our double-blind approach to 300 articles that were chosen for the full-text analysis. In the process of finding full versions of these publications, we had to exclude three papers as we could not access them. For the rest of the 297 articles we obtained full access and thus included them for further analysis. After a thorough examination of the full texts, we again had to exclude 249 publications because they did not meet our content-related inclusion criteria mentioned above, although the abstract analysis gave indications that they did. As a result, we finally obtained 47 selected papers on which we base the literature analysis and synthesis (see Figure 4).

A.2.3 Descriptive Analysis

Figure 5 summarises the results of the descriptive analysis on the selected literature regarding AI adoption in production that we analyse in our SLR. From Figure 5a), which illustrates annual publication trends (2010-2024), the increase in publications on AI adoption in production over the past five years is evident, yet slightly declining after a peak in 2022. After a steady increase until 2022, in which 11 articles are included in the final analysis, 2023 features ten articles, followed by three articles for 2024 until the cut-off date in May 2024. Of the 47 papers identified through our search, the majority (n=33) are peer-reviewed journal articles and the remaining thirteen contributions conference proceedings and one book chapter (see Figure 5b)).

Figure 5: Descriptive analyses of the selected articles addressing AI adoption in production



The identified contributions reveal some additional characteristics in terms of the authors country base (Figure 5c)) and research methods used (Figure 5d)). Almost four out of ten of the publications were written in collaboration with authors from several countries (n=19). Six of the papers were published by authors from the United States, five from Germany and four from India. In terms of the applied research methods used by the researchers, a wide range of methods is used (see Figure 5c), with qualitative methods (n=22) being the most frequently used.

A.2.4 Factor Analysis

In order to derive a comprehensive list of factors that influence the use of AI in production at different levels, we follow a qualitative content analysis. It is based on inductive category development, avoiding prefabricated categories in order to allow new categories to emerge based on the content at hand (Hsieh and Shannon 2005; Mayring 2000). To do this, we first read the entire text to gain an understanding of the content and then derive codes (Miles and Huberman 2009) that seem to capture key ideas (Hsieh and Shannon 2005). The codes are subsequently sorted into distinct categories, each of which is clearly defined and establishes meaningful connections between different codes. Based on an iterative process with feedback loops, the assigned categories are continuously reviewed and updated as revisions are made (Mayring 2000).

Various factors at different levels are of significance to AI and influence technology adoption (Alsheibani et al. 2018; Tornatzky and Fleischer 1990). To identify the specific factors that are of importance for AI adoption in production, we analyze the selected contributions in terms of the factors considered, compare them with each other and consequently obtain a list of factors through a bottom-up approach. While some of the factors are based on empirical findings, others are expected factors that result from the research findings of the respective studies. Through our analysis, a list of 35 factors emerges that influence AI adoption in production which occur with varying frequency in the studies analyzed by our SLR. Table 6 visualizes each factor in the respective contributions sorted by the frequency of occurrence.

Factor	**Reference**	**Sum**
Skilled Workforce	(Akinsolu 2023; Bettoni et al. 2021; Boavida and Candeias 2021; Botha 2019; Chatterjee et al. 2021; Chiang et al. 2022; Chouchene et al. 2020; Corti et al. 2021; Demlehner et al. 2021; Dohale et al. 2022; Drobot 2020; Ghani et al. 2022; Hammer and Karmakar 2021; Hartley and Sawaya 2019; Jan et al. 2023; Javaid et al. 2023; Kinkel et al. 2022; Kyvik Nordås and Klügl 2021; Mubarok and Arriaga 2020; Muriel-Pera et al. 2018; Olsowski et al. 2022; Pazhayattil and Konyu-Fogel 2023; Rath et al. 2024; Rathore et al. 2023; Rodríguez-Espíndola et al. 2022; Ronaghi 2023; Schkarin and Dobhan 2022; Sharma et al. 2022; Siaterlis et al. 2022; Stohr et al. 2024; Tariq et al. 2021; Trakadas et al. 2020; Vernim et al. 2022; Waschull and Emmanouilidis 2023; Williams et al. 2022; Wuest et al. 2020)	35
Data Availability	(Agostinho et al. 2023; Bettoni et al. 2021; Bonnard et al. 2021; Botha 2019; Confalonieri et al. 2015; Corti et al. 2021; Demlehner et al. 2021; Dohale et al. 2022; Drobot 2020; Dubey et al. 2020; Hammer and Karmakar 2021; Hartley and Sawaya 2019; Jan et al. 2023; Javaid et al. 2023; Kyvik Nordås and Klügl 2021; Lee et al. 2020; Pazhayattil and Konyu-Fogel 2023; Rathore et al. 2023; Schkarin and Dobhan 2022; Sharma et al. 2022; Siaterlis et al. 2022; Stohr et al. 2024; Tariq et al. 2021; Trakadas et al. 2020; Turner et al. 2019)	25
Ethical Guidelines	(Agostinho et al. 2023; Akinsolu 2023; Bettoni et al. 2021; Botha 2019; Chatterjee et al. 2021; Chiang et al. 2022; Csiszar et al. 2020; Demlehner and Laumer 2024; Dohale et al. 2022; Drobot 2020; Ghani et al. 2022; Hartley and Sawaya 2019; Jan et al. 2023; Javaid et al. 2023; Merhi and Harfouche 2023; Pazhayattil and Konyu-Fogel 2023; Ronaghi 2023;	22

	Siaterlis et al. 2022; Trakadas et al. 2020; Vernim et al. 2022; Waschull and Emmanouilidis 2023; Wuest et al. 2020)	
Managerial Support	(Bettoni et al. 2021; Binsaeed et al. 2023; Boavida and Candeias 2021; Botha 2019; Chatterjee et al. 2021; Chouchene et al. 2020; Corti et al. 2021; Drobot 2020; Dubey et al. 2020; Ghani et al. 2022; Ghobakhloo and Ching 2019; Hartley and Sawaya 2019; Jan et al. 2023; Kyvik Nordås and Klügl 2021; Merhi and Harfouche 2023; Olsowski et al. 2022; Pazhayattil and Konyu-Fogel 2023; Rath et al. 2024; Rodríguez-Espíndola et al. 2022; Ronaghi 2023; Tariq et al. 2021; Wuest et al. 2020)	21
Performance Measures	(Akinsolu 2023; Chatterjee et al. 2021; Chiang et al. 2022; Demlehner et al. 2021; Dohale et al. 2022; Ghani et al. 2022; Ghobakhloo and Ching 2019; Hammer and Karmakar 2021; Hartley and Sawaya 2019; Jan et al. 2023; Kyvik Nordås and Klügl 2021; Merhi and Harfouche 2023; Muriel-Pera et al. 2018; Rathore et al. 2023; Rodríguez-Espíndola et al. 2022; Tariq et al. 2021; Vernim et al. 2022; Waschull and Emmanouilidis 2023; Williams et al. 2022; Wuest et al. 2020)	20
Investment	(Bettoni et al. 2021; Binsaeed et al. 2023; Boavida and Candeias 2021; Bonnard et al. 2021; Chatterjee et al. 2021; Corti et al. 2021; Demlehner et al. 2021; Demlehner and Laumer 2024; Drobot 2020; Hammer and Karmakar 2021; Hartley and Sawaya 2019; Kyvik Nordås and Klügl 2021; Olsowski et al. 2022; Rodríguez-Espíndola et al. 2022; Ronaghi 2023; Schkarin and Dobhan 2022; Stohr et al. 2024; Waschull and Emmanouilidis 2023; Williams et al. 2022)	19
Data Analytics	(Akinsolu 2023; Chiang et al. 2022; Chouchene et al. 2020; Dohale et al. 2022; Drobot 2020; Dubey et al. 2020; Ghobakhloo and Ching 2019; Javaid et al. 2023; Lee et al. 2020; Muriel-Pera et al. 2018; Pazhayattil and Konyu-Fogel 2023; Rathore et al. 2023; Rodríguez-Espíndola et al. 2022; Sharma et al. 2022; Stohr et al. 2024; Tariq et al. 2021; Trakadas et al. 2020; Turner et al. 2019; Wuest et al. 2020)	19
Change Management	(Bettoni et al. 2021; Boavida and Candeias 2021; Botha 2019; Chatterjee et al. 2021; Chiang et al. 2022; Corti et al. 2021; Demlehner et al. 2021; Demlehner and Laumer 2024; Ghobakhloo and Ching 2019; Hammer and Karmakar 2021; Hartley and Sawaya 2019; Jan et al. 2023; Muriel-Pera et al. 2018; Olsowski et al. 2022; Rath et al. 2024; Stohr et al. 2024; Tariq et al. 2021; Vernim et al. 2022)	18
Cooperation	(Binsaeed et al. 2023; Botha 2019; Chatterjee et al. 2021; Demlehner et al. 2021; Dohale et al. 2022; Dubey et al. 2020; Ghobakhloo and Ching 2019; Kinkel et al. 2022; Kyvik Nordås and Klügl 2021; Merhi and Harfouche 2023; Olsowski et al. 2022; Rodríguez-Espíndola et al. 2022; Ronaghi 2023; Stohr et al. 2024; Trakadas et al. 2020; Wuest et al. 2020)	18

IT Infrastructure	(Boavida and Candeias 2021; Bonnard et al. 2021; Chatterjee et al. 2021; Chiang et al. 2022; Corti et al. 2021; Demlehner et al. 2021; Ghani et al. 2022; Hartley and Sawaya 2019; Jan et al. 2023; Kyvik Nordås and Klügl 2021; Merhi and Harfouche 2023; Olsowski et al. 2022; Rath et al. 2024; Rodríguez-Espíndola et al. 2022; Schkarin and Dobhan 2022; Sharma et al. 2022; Siaterlis et al. 2022; Tariq et al. 2021; Trakadas et al. 2020; Wuest et al. 2020)	17
Education and Training	(Akinsolu 2023; Bettoni et al. 2021; Boavida and Candeias 2021; Chiang et al. 2022; Corti et al. 2021; Demlehner and Laumer 2024; Drobot 2020; Hammer and Karmakar 2021; Jan et al. 2023; Mubarok and Arriaga 2020; Pazhayattil and Konyu-Fogel 2023; Sharma et al. 2022; Stohr et al. 2024; Tariq et al. 2021; Williams et al. 2022; Wuest et al. 2020)	16
Strategic Orientation	(Bettoni et al. 2021; Binsaeed et al. 2023; Chatterjee et al. 2021; Chiang et al. 2022; Corti et al. 2021; Drobot 2020; Ghobakhloo and Ching 2019; Hartley and Sawaya 2019; Javaid et al. 2023; Lee et al. 2020; Merhi and Harfouche 2023; Olsowski et al. 2022; Pazhayattil and Konyu-Fogel 2023; Rathore et al. 2023; Tariq et al. 2021; Wuest et al. 2020)	16
Mindset and Culture	(Bettoni et al. 2021; Boavida and Candeias 2021; Chiang et al. 2022; Corti et al. 2021; Demlehner and Laumer 2024; Drobot 2020; Jan et al. 2023; Merhi and Harfouche 2023; Muriel-Pera et al. 2018; Olsowski et al. 2022; Rath et al. 2024; Rodríguez-Espíndola et al. 2022; Stohr et al. 2024; Tariq et al. 2021; Wuest et al. 2020)	16
Privacy	(Agostinho et al. 2023; Akinsolu 2023; Binsaeed et al. 2023; Dohale et al. 2022; Drobot 2020; Ghani et al. 2022; Hammer and Karmakar 2021; Jan et al. 2023; Javaid et al. 2023; Merhi and Harfouche 2023; Ronaghi 2023; Sharma et al. 2022; Siaterlis et al. 2022; Trakadas et al. 2020; Turner et al. 2019; Waschull and Emmanouilidis 2023)	16
System Compatibility	(Bettoni et al. 2021; Binsaeed et al. 2023; Bonnard et al. 2021; Chatterjee et al. 2021; Chiang et al. 2022; Corti et al. 2021; Drobot 2020; Ghani et al. 2022; Ghobakhloo and Ching 2019; Jan et al. 2023; Merhi and Harfouche 2023; Rath et al. 2024; Ronaghi 2023; Stohr et al. 2024; Trakadas et al. 2020)	15
Trust	(Bettoni et al. 2021; Botha 2019; Chiang et al. 2022; Csiszar et al. 2020; Ghani et al. 2022; Jan et al. 2023; Javaid et al. 2023; Merhi and Harfouche 2023; Rodríguez-Espíndola et al. 2022; Schkarin and Dobhan 2022; Stohr et al. 2024; Tariq et al. 2021; Turner et al. 2019; Waschull and Emmanouilidis 2023; Wuest et al. 2020)	15
Environmental Dynamism	(Botha 2019; Chatterjee et al. 2021; Demlehner et al. 2021; Dohale et al. 2022; Dubey et al. 2020; Ghobakhloo and Ching 2019; Kinkel et al. 2022; Kyvik Nordås and Klügl 2021; Merhi and Harfouche 2023; Olsowski et al. 2022; Rath et al.	15

	2024; Rodríguez-Espíndola et al. 2022; Ronaghi 2023; Trakadas et al. 2020; Wuest et al. 2020)	
Laws and Regulation	(Akinsolu 2023; Boavida and Candeias 2021; Botha 2019; Drobot 2020; Hammer and Karmakar 2021; Jan et al. 2023; Javaid et al. 2023; Merhi and Harfouche 2023; Muriel-Pera et al. 2018; Pazhayattil and Konyu-Fogel 2023; Rathore et al. 2023; Rodríguez-Espíndola et al. 2022; Ronaghi 2023; Trakadas et al. 2020)	14
Security	(Agostinho et al. 2023; Akinsolu 2023; Bettoni et al. 2021; Binsaeed et al. 2023; Boavida and Candeias 2021; Botha 2019; Corti et al. 2021; Jan et al. 2023; Javaid et al. 2023; Ronaghi 2023; Schkarin and Dobhan 2022; Trakadas et al. 2020; Turner et al. 2019; Waschull and Emmanouilidis 2023)	14
Innovation Culture	(Bettoni et al. 2021; Binsaeed et al. 2023; Boavida and Candeias 2021; Bonnard et al. 2021; Botha 2019; Chiang et al. 2022; Dubey et al. 2020; Ghobakhloo and Ching 2019; Kyvik Nordås and Klügl 2021; Olsowski et al. 2022; Pazhayattil and Konyu-Fogel 2023; Tariq et al. 2021; Trakadas et al. 2020; Wuest et al. 2020)	12
Data Storage	(Agostinho et al. 2023; Bettoni et al. 2021; Bonnard et al. 2021; Chiang et al. 2022; Drobot 2020; Jan et al. 2023; Lee et al. 2020; Schkarin and Dobhan 2022; Tariq et al. 2021; Trakadas et al. 2020; Turner et al. 2019; Williams et al. 2022)	12
Safety	(Akinsolu 2023; Boavida and Candeias 2021; Chiang et al. 2022; Drobot 2020; Ghani et al. 2022; Jan et al. 2023; Merhi and Harfouche 2023; Sharma et al. 2022; Tariq et al. 2021; Trakadas et al. 2020; Vernim et al. 2022; Wuest et al. 2020)	12
Data Processing	(Agostinho et al. 2023; Bonnard et al. 2021; Dohale et al. 2022; Dubey et al. 2020; Ghobakhloo and Ching 2019; Jan et al. 2023; Javaid et al. 2023; Lee et al. 2020; Muriel-Pera et al. 2018; Rathore et al. 2023; Waschull and Emmanouilidis 2023)	11
Data Governance	(Agostinho et al. 2023; Bettoni et al. 2021; Corti et al. 2021; Drobot 2020; Jan et al. 2023; Rodríguez-Espíndola et al. 2022; Schkarin and Dobhan 2022; Tariq et al. 2021; Turner et al. 2019)	10
Data Interoperability	(Agostinho et al. 2023; Bettoni et al. 2021; Bonnard et al. 2021; Chatterjee et al. 2021; Corti et al. 2021; Drobot 2020; Ghobakhloo and Ching 2019; Lee et al. 2020; Trakadas et al. 2020)	9
User-Friendliness	(Bettoni et al. 2021; Bonnard et al. 2021; Chatterjee et al. 2021; Csiszar et al. 2020; Javaid et al. 2023; Rodríguez-Espíndola et al. 2022; Schkarin and Dobhan 2022; Trakadas et al. 2020)	8

Company Size	(Bonnard et al. 2021; Chatterjee et al. 2021; Ghobakhloo and Ching 2019; Kinkel et al. 2022; Schkarin and Dobhan 2022; Sharma et al. 2022)	6
Strategic Promoter	(Chiang et al. 2022; Corti et al. 2021; Hartley and Sawaya 2019; Olsowski et al. 2022; Stohr et al. 2024; Williams et al. 2022)	6
Data Consistency	(Bettoni et al. 2021; Bonnard et al. 2021; Hartley and Sawaya 2019; Javaid et al. 2023; Rathore et al. 2023)	5
Country	(Jan et al. 2023; Kinkel et al. 2022)	2
Government Support	(Ghani et al. 2022)	1
Industrial Sector	(Kinkel et al. 2022)	1
Product Complexity	(Kinkel et al. 2022)	1
Batch Size	(Kinkel et al. 2022)	1
R&D Intensity	(Kinkel et al. 2022)	1

Table 6: Factors influencing AI adoption in production, resource, and count

The presence of skills is considered a particularly important factor in AI adoption in the studies analyzed (n=35). The availability of data is also seen as a key driver of AI adoption (n=25), as data is seen as the basis for the implementation of AI. As such, these two factors make up the accelerants of AI adoption in production that are most frequently cited in the studies analyzed.

Also of importance are issues of ethical guidlines (n=22), managerial support (n=21), as well as performance measures (n=20). Some factors were also mentioned, but only addressed by one study at a time: government support, industrial sector, product complexity, batch size, and R&D Intensity. These factors are often used as quantitatively measurable adoption factors, especially in empirical surveys, such the study by Kinkel et al. (2022).

A.3 Factors Influencing AI Adoption

The 35 factors presented characteristically in Section A.2.4 serve as the basis for our in-depth analysis and for developing a framework of influences on AI adoption in production which are grouped into supercategories. A supercategory describes a cluster of topics to which various factors of AI adoption in production can be assigned. We were able to define seven categories that influence AI adoption in production: the internal influences of ‘Business and Structure’, ‘Organizational Effectiveness’, ‘Technology and System’, ‘Data Management’ as well as the external influences of the ‘Regulatory Environment’, ‘Business Environment’ and ‘Economic

Environment' (see Figure 6). The factors that were mentioned most frequently (occurrence in at least half of the papers analyzed) are marked accordingly (*) in Figure 6.

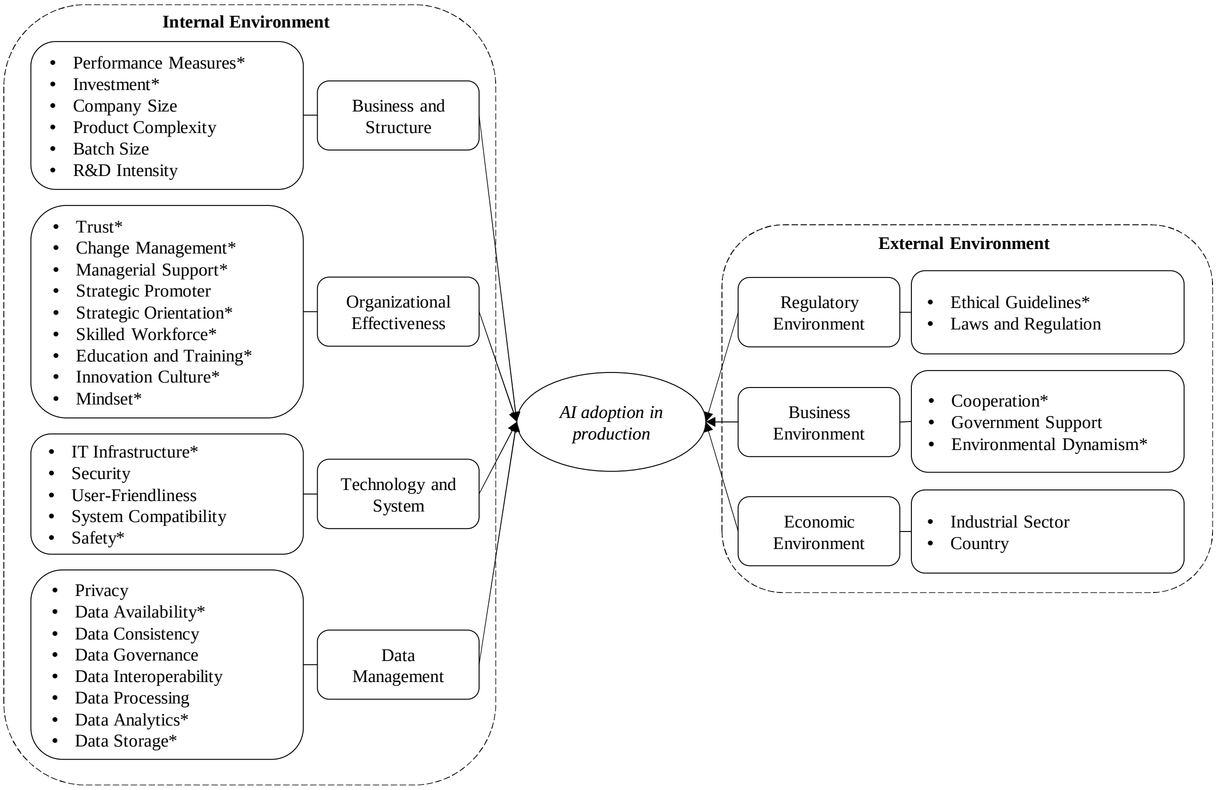


Figure 6: Framework of factors influencing AI adoption in production

A.3.1 Internal Environment

The internal influences on AI adoption in production refer to factors that an organization carries internally and that thus also influence adoption from within. Such factors can usually be influenced and clearly controlled by the organization itself.

A.3.1.1 Business and Structure

The supercategory 'Business and Structure' includes the various factors and characteristics that impact a company's performance, operations, and strategic decision-making. By considering and analyzing these business variables when implementing AI in production processes, companies can develop effective strategies to optimize their performance, increase their competitiveness, and adapt to changes in the business environment.

To understand and grasp the benefits in the use of AI, quantitative performance measures for the current and potential use of AI in industrial production systems help to clarify the value and potential benefits of AI use (Akinsolu 2023; Chiang et al. 2022; Merhi and Harfouche 2023; Waschull and Emmanouilidis 2023; Williams et al. 2022). Assessing possible risks (Rathore et al. 2023) as well as the monetary expected benefits for AI (e.g. Return on Investment (ROI)) in production plays an important role for adoption decisions in market-oriented companies (Demlehner et al. 2021; Dohale et al. 2022; Jan et al. 2023; Kyvik Nordås and Klügl 2021; Muriel-Pera et al. 2018). Due to financial constraints, managers behave cautiously in their investments (Jan et al. 2023), so they need to evaluate AI adoption as financially viable to want to make the investment (Ghobakhloo and Ching 2019; Hammer and Karmakar 2021; Kyvik Nordås and Klügl 2021) and also drive acceptance (Ghani et al. 2022). AI systems can significantly improve cost-benefit structures in manufacturing, thereby increasing the profitability of production systems (Vernim et al. 2022) and making companies more resilient (Wuest et al. 2020). However, in most cases, the adoption of AI requires high investments and the allocation of resources (s.a. personnel or financial) for this purpose (Bettoni et al. 2021; Binsaeed et al. 2023; Boavida and Candeias 2021; Demlehner et al. 2021; Stohr et al. 2024). Consequently, a lack of budgets and high expected transition costs often hinder the implementation of smart concepts (Bonnard et al. 2021; Corti et al. 2021; Demlehner and Laumer 2024; Hartley and Sawaya 2019; Rodríguez-Espíndola et al. 2022; Ronaghi 2023). It is up to management to provide necessary funding for AI adoption (Chatterjee et al. 2021; Drobot 2020; Waschull and Emmanouilidis 2023), which is required, for example, for skill development of employees (Drobot 2020; Hammer and Karmakar 2021; Kyvik Nordås and Klügl 2021), IT adaptation (Hartley and Sawaya 2019; Olsowski et al. 2022), AI development (Williams et al. 2022) or hardware deployment (Schkarin and Dobhan 2022). In their empirical study, Kinkel et al. (2022) confirm a positive correlation between company size and the intensity in the use of AI technologies. Large companies generally stand out with a higher propensity to adopt (Chatterjee et al. 2021) as they have less difficulties in comparison to small firms regarding the availability of resources (Sharma et al. 2022), such as know-how, budget (Bonnard et al. 2021; Schkarin and Dobhan 2022) and general data organization (Schkarin and Dobhan 2022). Others argue that small companies tend to be more open to change and are characterized by faster decision-making processes (Ghobakhloo and Ching 2019; Schkarin and Dobhan 2022). Product complexity also influences a company's propensity for AI. Companies that produce rather simple products are more likely to digitize, which in turn offers good starting points for AI adoption. On the other hand, complex product manufacturers (often characterized by small batch sizes) are often less able to standardize and automate (Kinkel et al. 2022). The company's produced batch size has a similar influence on AI adoption. Small and medium batch sizes in particular hinder the integration of intelligent technologies, as less automation often prevails here as well. Nevertheless, even small and medium lot sizes can benefit economically from AI (Kinkel et al. 2022). Since a high R&D intensity indicates a high innovation capability of a company, it is assumed to have a positive influence on AI adoption, as companies with a high R&D intensity already invest heavily in and use innovations. This in turn speaks for existing competencies, know how and structures (Kinkel et al. 2022).

A.3.1.2 Organizational Effectiveness

This supercategory focuses on the broader aspects that contribute to the effectiveness, development, and success of an organization when implementing AI in a production context. As the factors are interconnected and influence each other, decision makers should consider them carefully.

Users´ trust in AI is an essential factor to enable successful AI adoption and use in production (Botha 2019; Csiszar et al. 2020; Jan et al. 2023; Schkarin and Dobhan 2022; Turner et al. 2019; Waschull and Emmanouilidis 2023). From the users´ perspective, AI often exhibits the characteristics of a black box because its inherent processes are not fully understood (Bettoni et al. 2021; Csiszar et al. 2020) which can lead individuals to develop a fear towards the unknown (Tariq et al. 2021). Because of this lack of understanding, successful interaction between humans and AI is not guaranteed (Csiszar et al. 2020), as trust is a foundation for decisions that machines are intended to make autonomously (Botha 2019; Merhi and Harfouche 2023). To strengthen faith in AI systems (Javaid et al. 2023; Stohr et al. 2024), AI users should be involved in AI design processes in order to understand appropriate tools (Chiang et al. 2022; Csiszar et al. 2020). In this context, trust is also discussed in close connection with transparency and regulation (Waschull and Emmanouilidis 2023). User resistance is considered a barrier to implementing new information technologies, as adoption requires change (Chatterjee et al. 2021; Demlehner and Laumer 2024; Hartley and Sawaya 2019). Ignorance, as a kind of resistance to change, is a main obstacle to successful digital transformation (Boavida and Candeias 2021; Corti et al. 2021; Muriel-Pera et al. 2018). Some employees may resist the change brought about by AI because they fear losing their jobs (Botha 2019) or have other concerns (Jan et al. 2023). Overcoming resistance to technology adoption requires organizational change and is critical for the success of adoption (Bettoni et al. 2021; Boavida and Candeias 2021; Hartley and Sawaya 2019; Rodríguez-Espíndola et al. 2022; Stohr et al. 2024; Tariq et al. 2021). Therefore, change management is important to create awareness of the importance of AI adoption and increase acceptance of the workforce (Olsowski et al. 2022; Rath et al. 2024; Schkarin and Dobhan 2022; Williams et al. 2022). Management commitment is seen as a significant driver of technology adoption (Chatterjee et al. 2021; Drobot 2020; Dubey et al. 2020; Pazhayattil and

Konyu-Fogel 2023; Ronaghi 2023) and a lack of commitment can negatively impact user adoption and workforce trust and lead to skepticism towards technology (Dubey et al. 2020). The top management's understanding and support for the benefits of the adopted technology (Binsaeed et al. 2023; Chatterjee et al. 2021; Corti et al. 2021; Ghobakhloo and Ching 2019; Jan et al. 2023; Rodríguez-Espíndola et al. 2022) enhances AI adoption, can prioritize its implementation and also affects the performance of the AI-enabled application (Chouchene et al. 2020; Ghani et al. 2022; Rath et al. 2024). Preparing, enabling, and thus empowering the workforce, are considered the management's responsibility in the adoption of digital technologies (Drobot 2020; Wuest et al. 2020). This requires intelligent leadership (Botha 2019) as decision makers need to integrate their workforce into decision-making processes (Wuest et al. 2020). Guidelines can support managers by providing access to best practices that help in the adoption of AI (Bettoni et al. 2021). Critical measures to manage organizational change include the empowerment of visionaries or appointed AI champions leading the change and the collaborative development of digital roadmaps (Chiang et al. 2022; Hartley and Sawaya 2019). To demonstrate management commitment, managers can create such a dedicated role, consisting of an individual or a small group that is actively and enthusiastically committed to AI adoption in production. This body is considered the adoption manager, point of contact and internal driver of adoption (Hartley and Sawaya 2019; Stohr et al. 2024; Williams et al. 2022). AI initiatives in production do not necessarily have to be initiated by management. Although management support is essential for successful AI adoption, employees can also actively drive integration initially and thus realize pilot projects or initial trials (Olsowski et al. 2022; Stohr et al. 2024). The development of strategies as well as roadmaps is considered another enabling and necessary factor for the adoption of AI in production (Bettoni et al. 2021; Chatterjee et al. 2021; Chiang et al. 2022; Ghobakhloo and Ching 2019; Hartley and Sawaya 2019; Tariq et al. 2021). While many major AI strategies already exist at country level to further promote research and development of AI (Lee et al. 2020), strategy development is also important at the firm level (Javaid et al. 2023; Pazhayattil and Konyu-Fogel 2023; Rathore et al. 2023). In this context, strategies should not be delegated top-down, but be developed in a collaborative manner, i.e. by engaging the workforce (Wuest et al. 2020) and be in alignment with clear visions (Binsaeed et al. 2023; Merhi and Harfouche 2023). Roadmaps are used to improve planning, support implementation, facilitate the adoption of smart technologies in manufacturing (Ghobakhloo and Ching 2019) and should be integrated into both business and IT strategy (Hartley and Sawaya 2019; Olsowski et al. 2022). In practice, clear adoption roadmaps that provide approaches on how to effectively integrate AI into existing strategies and businesses are often lacking (Corti et al. 2021; Lee et al. 2020). The need for AI-related skills in organizations is a widely discussed topic in AI adoption analyses (Waschull and Emmanouilidis 2023). In this context, the literature points both at the need for specific skills in the development and design of AI applications (Demlehner et al. 2021; Ghobakhloo and Ching 2019; Javaid et al. 2023; Tariq et al. 2021; Trakadas et al. 2020; Vernim et al. 2022) as well as the skills in using the technology (Bonnard et al. 2021; Chatterjee et al. 2021; Ghobakhloo and Ching 2019; Muriel-Pera et al. 2018; Vernim et al. 2022; Williams et al. 2022; Wuest et al. 2020) which availability in the firm is not always given (Akinsolu 2023). AI requires new digital skills (Bettoni et al. 2021; Botha 2019; Chouchene et al. 2020; Corti et al. 2021; Drobot 2020; Hammer and Karmakar 2021; Jan et al. 2023; Kinkel et al. 2022; Kyvik Nordås and Klügl 2021; Olsowski et al. 2022; Stohr et al. 2024), where e.g. advanced analytics (Mubarok and Arriaga 2020; Pazhayattil and Konyu-Fogel 2023; Wuest et al. 2020), programming skills (Schkarin and Dobhan 2022) and cybersecurity skills (Ghobakhloo and Ching 2019; Jan et al. 2023) gain importance. The lack of skills required for AI is seen as a major challenge of digital transformation, as a skilled workforce is considered a key resource for companies (Boavida and Candeias 2021; Chiang et al. 2022; Corti et al. 2021; Ghani et al. 2022; Ghobakhloo and Ching 2019; Hartley and Sawaya 2019; Rodríguez-Espíndola et al. 2022; Ronaghi 2023; Sharma et al. 2022; Siaterlis et al. 2022). This lack of a necessary skillset hinders the adoption of AI tools in production systems (Dohale et al. 2022; Rathore et al. 2023). Closely related to skills is the need for new training concepts, which organizations need to consider when integrating digital technologies (Akinsolu 2023; Bettoni et al. 2021; Boavida and Candeias 2021; Corti et al. 2021; Drobot 2020; Kyvik Nordås and Klügl 2021; Tariq et al. 2021; Williams et al. 2022; Wuest et al. 2020). Firms must invest in qualification in order to create necessary competences (Demlehner and Laumer 2024; Jan et al. 2023; Pazhayattil and Konyu-Fogel 2023; Stohr et al. 2024; Vernim et al. 2022). Additionally, education must target and further develop the skills required for effectively integrating intelligent technologies into manufacturing processes (Chiang et al. 2022; Hammer and Karmakar 2021; Hartley and Sawaya 2019; Rath et al. 2024). Regarding this issue, academic institutions must develop fitting curricula for data driven manufacturing engineering (Mubarok and Arriaga 2020). Another driving factor of AI adoption is the innovation culture of an organization, which is influenced by various drivers. For example, companies that operate in an environment with high innovation rates, facing intense competitive pressures are considered more likely to see smart technologies as a tool for strategic change (Ghobakhloo and Ching 2019; Merhi and Harfouche 2023; Rath et al. 2024). These firms often invest in more expensive and advanced smart technologies as the pressure and resulting competition forces them to innovate

(Ghobakhloo and Ching 2019). Another way of approach this is that innovation capability can also be supported and complemented by AI, for example by intelligent systems supporting humans in innovation or even innovating on their own (Botha 2019).The entrepreneurial orientation of a firm is characterized in particular by innovativeness (Olsowski et al. 2022), productivity (Kyvik Nordås and Klügl 2021), risk-taking (Dubey et al. 2020) as well as continuous improvement (Bettoni et al. 2021). Such characteristics of an innovating culture are considered essential for companies to recognise dynamic changes in the market and make adoption decisions (Binsaeed et al. 2023; Boavida and Candeias 2021; Bonnard et al. 2021; Dubey et al. 2020; Pazhayattil and Konyu-Fogel 2023; Tariq et al. 2021). The prevalence of a digital mindset in companies is important for technology adoption, as digital transformation affects the entire organizational culture and behavior (Demlehner and Laumer 2024; Drobot 2020; Stohr et al. 2024) and a lack of a digital culture (Bettoni et al. 2021; Muriel-Pera et al. 2018) as well as a 'passive mindset' (Jan et al. 2023) can hinder the digital transformation of firms. Organizations need to develop a corresponding culture (Olsowski et al. 2022; Rodríguez-Espíndola et al. 2022; Tariq et al. 2021), also referred to as 'AI-ready-culture' (Chiang et al. 2022), that promotes development and encourages people and data through the incorporation of technology (Tariq et al. 2021; Wuest et al. 2020). With the increasing adoption of smart technologies, a 'new digital normal' is emerging, characterized by hybrid work models, more human-machine interactions and an increased use of digital technologies (Rath et al. 2024; Wuest et al. 2020).

A.3.1.3 Technology and System

The 'Technology and System' supercategory focuses on the broader issues related to the technology and infrastructure that support organizational operations and provide the technical foundation for AI deployment.

By IT infrastructure we refer to issues regarding the foundational systems and IT needed for AI adoption in production. Industrial firms and their IT systems must achieve a mature technological readiness in order to enable successful AI adoption (Boavida and Candeias 2021; Ghani et al. 2022; Rath et al. 2024; Rodríguez-Espíndola et al. 2022; Sharma et al. 2022). A lack of appropriate IT infrastructure (Jan et al. 2023; Merhi and Harfouche 2023; Schkarin and Dobhan 2022; Tariq et al. 2021) or small maturity of Internet of Things (IoT) technologies (Siaterlis et al. 2022)) hinders the efficient use of data in production firms (Corti et al. 2021) which is why firms must update their foundational information systems for successful AI adoption (Chatterjee et al. 2021; Chiang et al. 2022; Hartley and Sawaya 2019; Olsowski et al. 2022; Trakadas et al. 2020; Wuest et al. 2020). IT and data security are fundamental for AI adoption and must be provided (Bettoni et al. 2021; Boavida and Candeias 2021; Ronaghi 2023; Schkarin and Dobhan 2022). This requires necessary developments that can ensure security during AI implementation while complying with legal requirements (Botha 2019; Jan et al. 2023; Trakadas et al. 2020). Generally, security concerns are common when implementing AI-innovations (Binsaeed et al. 2023; Merhi and Harfouche 2023; Trakadas et al. 2020; Waschull and Emmanouilidis 2023). This fear of a lack of security can also prevent the release of (e.g. customer) data in a production environment (Corti et al. 2021). Additionally, as industrial production systems are vulnerable to failures as well as cyberattacks, companies need to address security and cybersecurity measures (Agostinho et al. 2023; Akinsolu 2023; Javaid et al. 2023; Turner et al. 2019). Developing user-friendly AI solutions can facilitate the adoption of smart solutions by increasing user understanding and making systems easy to use by employees as well as quick to integrate (Bettoni et al. 2021; Bonnard et al. 2021; Trakadas et al. 2020). When developing user-friendly solutions which satisfy user needs (Javaid et al. 2023), it is particularly important to understand and integrate the user perspective in the development process (Csiszar et al. 2020). If employees find technical solutions easy to use, they are more confident in its use and perceived usefulness increases (Chatterjee et al. 2021; Rodríguez-Espíndola et al. 2022; Schkarin and Dobhan 2022). The compatibility of AI with a firm and its existing systems, i.e., the extent to which AI matches existing processes, structures, and infrastructures (Binsaeed et al. 2023; Chatterjee et al. 2021; Chiang et al. 2022; Corti et al. 2021; Ghani et al. 2022; Ghobakhloo and Ching 2019; Jan et al. 2023; Rath et al. 2024; Ronaghi 2023; Stohr et al. 2024), is considered an important requirement for the adoption of AI in IT systems (Merhi and Harfouche 2023). Along with compatibility also comes connectivity, which is intended to ensure the links within the overall network and avoid silo thinking (Drobot 2020). Connectivity and interoperability of AI-based processes within the company's IT manufacturing systems must be ensured at different system levels and are considered key factors in the development of AI applications for production (Agostinho et al. 2023; Bettoni et al. 2021; Trakadas et al. 2020). The design of modular AI solutions can increase system compatibility (Bonnard et al. 2021). Firms deciding for AI adoption must address safety issues (Boavida and Candeias 2021; Chiang et al. 2022; Drobot 2020; Jan et al. 2023; Trakadas et al. 2020; Vernim et al. 2022). This includes both safety in the use and operation of AI (Ghani et al. 2022; Sharma et al. 2022). In order to address safety concerns of integrating AI solutions in industrial systems (Akinsolu 2023), systems must secure high reliability (Tariq et al. 2021). AI can also be integrated as a safety enabler, for example, by providing technologies to monitor health and safety in the workplace to prevent fatigue and injury (Wuest et al. 2020).

A.3.1.4 Data Management

Since AI adoption in the organization is strongly data-driven, the 'Data Management' supercategory is dedicated to the comprehensive aspects related to the effective and responsible management of data within the organization.

Data privacy must be guaranteed when creating AI applications based on industrial production data (Agostinho et al. 2023; Akinsolu 2023; Binsaeed et al. 2023; Dohale et al. 2022; Drobot 2020; Ghani et al. 2022; Jan et al. 2023; Javaid et al. 2023; Merhi and Harfouche 2023; Ronaghi 2023; Trakadas et al. 2020; Turner et al. 2019; Waschull and Emmanouilidis 2023) as '[M]anufacturing industries generate large volumes of unstructured and sensitive data during their daily operations' (Agostinho et al. 2023). Closely related to this is the need for anonymization and confidentiality of data (Hammer and Karmakar 2021; Jan et al. 2023; Sharma et al. 2022; Siaterlis et al. 2022). The availability of large, heterogeneous data sets is essential for the digital transformation of organizations (Agostinho et al. 2023; Botha 2019; Drobot 2020; Jan et al. 2023; Stohr et al. 2024; Turner et al. 2019) and is considered one of the key drivers of AI innovation (Dubey et al. 2020; Hartley and Sawaya 2019; Schkarin and Dobhan 2022; Trakadas et al. 2020). In production systems, lack of data availability is often a barrier to AI adoption (Dohale et al. 2022; Rathore et al. 2023; Siaterlis et al. 2022). In order to enable AI to establish relationships between data, the availability of large input data that is critical (Hartley and Sawaya 2019; Javaid et al. 2023; Pazhayattil and Konyu-Fogel 2023). New AI models are trained with this data and can adapt as well as improve as they receive new data (Drobot 2020; Hartley and Sawaya 2019). Big data can thus significantly improve the quality of AI applications (Drobot 2020; Tariq et al. 2021). As more and more data is generated in manufacturing (Confalonieri et al. 2015), AI opens up new opportunities for companies to make use of it (Hartley and Sawaya 2019). However, operational data are often unstructured, as they come from different sources and exist in diverse formats (Confalonieri et al. 2015; Lee et al. 2020). This challenges data processing, as data quality and origin are key factors in the management of data (Agostinho et al. 2023; Jan et al. 2023; Merhi and Harfouche 2023; Stohr et al. 2024; Turner et al. 2019; Waschull and Emmanouilidis 2023). To make production data valuable and usable for AI, consistency of data and thus data integrity is required across manufacturing systems (Bettoni et al. 2021; Bonnard et al. 2021; Hartley and Sawaya 2019; Rathore et al. 2023). Another key prerequisites for AI adoption is data governance (Corti et al. 2021; Drobot 2020; Jan et al. 2023; Rodríguez-Espíndola et al. 2022; Schkarin and Dobhan 2022; Tariq et al. 2021; Turner et al. 2019) which is an important asset to make use of data in production (Bettoni et al. 2021) and ensure the complex management of heterogenous data sets (Agostinho et al. 2023). The interoperability of data and thus the foundation for the compatibility of AI with existing systems, i.e., the extent to which AI matches existing processes, structures, and infrastructures (Bonnard et al. 2021; Chatterjee et al. 2021; Corti et al. 2021; Ghobakhloo and Ching 2019), is considered another important requirement for the adoption of AI in IT systems. Data interoperability in production systems can be hindered by missing data standards as different machines use different formats (Lee et al. 2020). Data processing refers to techniques used to preparing data for analysis which is essential to obtain consistent results from data analytics in production (Bonnard et al. 2021; Dohale et al. 2022; Pazhayattil and Konyu-Fogel 2023; Stohr et al. 2024; Trakadas et al. 2020). In this process, the numerous, heterogeneous data from different sensors are processed in such a way that they can be used for further analyses (Lee et al. 2020). The capability of production firms to process data and information is thus important to enable AI adoption (Dubey et al. 2020; Ghobakhloo and Ching 2019; Rathore et al. 2023). With the increasing data generation in the smart and connected factory, the strategic relevance of data analytics is gaining importance (Chouchene et al. 2020; Jan et al. 2023; Sharma et al. 2022), as it is essential for AI systems in performing advanced data analyses (Akinsolu 2023; Dubey et al. 2020; Rodríguez-Espíndola et al. 2022; Trakadas et al. 2020; Turner et al. 2019). Using analytics, valuable insights can be gained from the production data obtained using AI systems (Dohale et al. 2022; Lee et al. 2020; Rathore et al. 2023). In order to enable the processing of big data, a profound data infrastructure is necessary (Lee et al. 2020; Muriel-Pera et al. 2018; Wuest et al. 2020). Facilities must be equipped with sensors, that collect data and model information, which requires investments from firms (Trakadas et al. 2020). In addition, production firms must build the necessary skills, culture and capabilities for data analytics (Chiang et al. 2022; Ghobakhloo and Ching 2019; Lee et al. 2020; Wuest et al. 2020). Data storage, one of the foundations and prerequisites for smart manufacturing (Chiang et al. 2022; Schkarin and Dobhan 2022; Tariq et al. 2021; Williams et al. 2022), must be ensured in order to manage the larg amounts of data and thus realize the adoption of intelligent technologies in production (Agostinho et al. 2023; Bettoni et al. 2021; Bonnard et al. 2021; Drobot 2020; Jan et al. 2023; Lee et al. 2020; Trakadas et al. 2020; Turner et al. 2019).

A.3.2 External Environment

The external drivers of AI adoption in production influence the organization through conditions and events from outside the firm and are therefore difficult to control by the organization itself. This supercategory captures the broader concept of establishing rules, standards, and frameworks that guide the behavior, actions, and operations of individuals, organizations, and societies when implementing AI.

AI adoption in production faces many ethical challenges (Siaterlis et al. 2022; Trakadas et al. 2020; Waschull and Emmanouilidis 2023). AI applications must be compliant with the requirements of organizational ethical standards and laws (Akinsolu 2023; Bettoni et al. 2021; Drobot 2020; Ghani et al. 2022; Hartley and Sawaya 2019; Wuest et al. 2020) which is why certain issues must be examined in AI adoption and AI design (Hartley and Sawaya 2019; Merhi and Harfouche 2023; Ronaghi 2023; Vernim et al. 2022) so that fairness and justice are guaranteed (Demlehner and Laumer 2024; Jan et al. 2023; Waschull and Emmanouilidis 2023). Social rights, cultural values and norms must not be violated in the process (Akinsolu 2023; Botha 2019; Chatterjee et al. 2021; Pazhayattil and Konyu-Fogel 2023). In this context, the explainability and transparency of AI decisions also plays an important role (Agostinho et al. 2023; Bettoni et al. 2021; Chiang et al. 2022; Dohale et al. 2022; Jan et al. 2023; Siaterlis et al. 2022) and can address the characteristic of AI of a black box (Csiszar et al. 2020). In addition, AI applications must be compliant with legal and regulatory requirements (Boavida and Candeias 2021; Botha 2019; Drobot 2020; Merhi and Harfouche 2023; Pazhayattil and Konyu-Fogel 2023; Rathore et al. 2023; Ronaghi 2023) and be developed accordingly (Akinsolu 2023; Javaid et al. 2023) in order to make organization processes using AI clear and effective (Muriel-Pera et al. 2018). At present, policies and regulation of AI are still in its infancy (Akinsolu 2023) and missing federal regulatory guidelines, standards as well as incentives hinder the adoption of AI (Rodríguez-Espíndola et al. 2022) which should be expanded simultaneously to the expansion of AI technology (Ghani et al. 2022). This also includes regulations on the handling of data (e.g. anonymization of data) (Hammer and Karmakar 2021; Trakadas et al. 2020).

A.3.2.1 Business Environment

The factors in the ‘Business Environment’ supercategory refer to the external conditions and influences that affect the operations, decision making, and performance of the company seeking to implement AI in a production context.

Cooperation and collaboration can influence the success of digital technology adoption (Botha 2019; Chatterjee et al. 2021; Drobot 2020; Trakadas et al. 2020), which is why partnerships are important for adoption (Chatterjee et al. 2021; Drobot 2020) and can positively influence its future success (Botha 2019; Rodríguez-Espíndola et al. 2022). Both intraorganizational and interorganizational knowledge sharing can positively influence AI adoption (Akinsolu 2023).

In collaborations, companies can use a shared knowledge base where data and process sharing (Binsaeed et al. 2023; Boavida and Candeias 2021; Drobot 2020) as well as social support systems strengthen feedback loops between departments (Stohr et al. 2024; Waschull and Emmanouilidis 2023). With regard to AI adoption in firms, vendors as well as service providers need to collaborate closely to improve the compatibility and operational capability of smart technologies across different industries (Ghobakhloo and Ching 2019; Ronaghi 2023). Without external IT support, companies can rarely integrate AI into their production processes (Olsowski et al. 2022) , which is why thorough support from vendors can significantly facilitate the integration of AI into existing manufacturing processes (Merhi and Harfouche 2023; Stohr et al. 2024). Public-private collaborations can also add value and governments can target AI dissemination (Ghani et al. 2022; Williams et al. 2022). The support of the government also positively influences AI adoption. This includes investing in research projects and policies, building a regulatory setting as well as creating a collaborative environment (Ghani et al. 2022). Production companies are constantly exposed to changing conditions, which is why the dynamics of the environment is another factor influencing the adoption of AI (Botha 2019; Dubey et al. 2020; Kyvik Nordås and Klügl 2021; Trakadas et al. 2020). Environmental dynamics influence the operational performance of firms and can favor an entrepreneurial orientation of firms (Dubey et al. 2020). In order to respond to dynamics, companies need to develop certain capabilities and resources (i.e. dynamic capabilities) (Dubey et al. 2020). This requires the development of transparency, agility, as well as resilience to unpredictable changes, which was important in the case of the COVID-19 pandemic, for example, where companies had to adapt quickly to changing environments (Wuest et al. 2020). A firm’s environment (e.g. governments, partners or customers) can also pressure companies to adopt digital technologies (Chatterjee et al. 2021; Merhi and Harfouche 2023; Rodríguez-Espíndola et al. 2022; Ronaghi 2023). Companies facing intense competition are considered more likely to invest in smart technologies, as rivalry pushes them to innovate and they hope to gain competitive advantages from adoption (Ghobakhloo and Ching 2019; Kinkel et al. 2022; Olsowski et al. 2022; Ronaghi 2023).

A.3.2.2 Economic Environment

By considering both the industrial sector and country within the subcategory ‘Economic Environment’, production firms can analyze the interplay between the two and understand how drivers can influence the AI adoption process in their industrial sector's performance within a particular country.

The industrial sector of a firm influences AI adoption in production from a structural perspective, as it indicates variations in product characteristics, governmental support, the general digitalization status, the production environment as well as the use of AI technologies within the sector (Kinkel et al. 2022). Another factor that influences AI adoption is the country in which a company is located. This influences not only cultural aspects, the availability of know-how and technology orientation, but also regulations, laws, standards and subsidies (Kinkel et al. 2022). On the other hand, AI can also contribute to the wider socio-economic growth of economies by making new opportunities easily available and thus equipping e.g. more rural areas with advanced capabilities (Jan et al. 2023).

A.3.3 Future Research Directions

The analysis of AI adoption in production requires a comprehensive analysis of the various factors that influence the introduction of the innovation. As discussed by Kinkel et al. (2022), our research also concludes that organizational factors have a particularly important role to play. After evaluating the individual drivers of AI adoption in production in detail in this qualitative synthesis, we draw a conclusion from the results and derive a research agenda from the analysis to serve as a basis for future research. The RQs emerged from the analyzed factors and are presented in Table 7. We developed the questions based on the literature review and identified research gaps for every factor that was most frequently mentioned (in ten or more papers). From the factors analyzed and RQs developed, the internal environment has a strong influence on AI adoption in production, and organizational factors play a major role here.

	Topic	Research Questions
Internal Environment	Business and Structure	What financial measurements can help managers evaluate the complex cost-benefit structures for integrating AI into production?
		How can the financial impact of AI adoption on the complex internal organizational change journey be best determined?
	Organizational Effectiveness	What methods can be used to prepare employees for AI implementation to ensure trust in the technology?
		What change management processes are required to guide AI adoption throughout the process?
		What measures can managers use to continuously ensure and communicate their understanding and support for the use of AI?
		Which roadmaps for AI adoption can help firms strategically implementing AI?
		How can workforce know-how and skills at different levels (handling AI, developing AI, etc.) be ensured for the adoption of AI?
		Which training measures can be applied to develop the necessary skillforce?
		How can firms create a positive innovative culture that pushes AI adoption?
		How can a positive workforce mindset be developed for AI, which will help the adoption process?
	Technology and System	What IT infrastructure is necessary to create a basic starting position for the introduction of AI?
		What measures are needed to ensure safety when working with AI?
	Data Management	How can production firms get support in building a profound data basis for integrating AI?
		How can the challenge of supplying data be overcome, which forms the technical basis for AI?
		What data analytics capabilities do production firms need to successfully use AI?
		Which options exist to ensure safe storage of the large amount of data in production firms?
External Environment	Regulatory Environment	Who is responsible for developing ethical standards for the use of AI and how can these be ensured?
	Business Environment	How can manufacturing companies be helped to build valuable collaborations that support them in AI adoption?
		How can companies make decisions when implementing AI under constant competitive pressure and environmental changes?

Table 7 Future research agenda for AI adoption in a production context

Looking at the supercategory 'Business and Environment', performance indicators and investments are considered drivers of AI adoption in production. Indicators to measure the performance of AI innovations are necessary here so that managers can perform cost-benefit analyses and make the right decision for their company. There is a need for research here to support possible calculations and show managers a comprehensive view of the costs and benefits of technology in production. In terms of budget, it should be noted that AI adoption involves a considerable financial outlay that must be carefully weighed and some capital must be available to carry out the necessary implementation efforts (e.g., staffing costs, machine retrofits, change management, and external IT service costs). Since AI adoption is a complex process and turnkey solutions can seldom be implemented easily and quickly, but require many changes (not only technologically but also on an organizational level), it is currently difficult to estimate the necessary budgets and thus make them available. Especially the factors of the supercategory 'Organizational Effectiveness' drive AI adoption in production. Trust of the workforce is considered an important driver, which must be created in order to successfully implement AI. This requires measures that can support management in building trust. Closely related to this are the necessary change management processes that must be initiated to accompany the changes in a targeted manner. Management itself must also play a clear role in the introduction of AI and communicate its support, as this also influences the adoption. The development of clear processes and measures can help here. Developing roadmaps for AI adoption can facilitate the adoption process and promote strategic integration with existing IT and business strategy. Here, best practice roadmaps and necessary action steps can be helpful for companies. Skills are considered the most important driver for AI adoption in manufacturing. Here, there is a lack of clear approaches that support companies in identifying the range of necessary skills and, associated with this, also opportunities to further develop these skills in the existing workforce. Also, building a culture of innovation requires closer research that can help companies foster a conducive environment for AI adoption and the integration of other smart technologies. Steps for developing a positive mindset require further research that can provide approaches for necessary action steps and measures in creating a positive digital culture. With regard to 'Technology and System', the factors of IT infrastructure and security in particular are driving AI adoption in production. Existing IT systems must reach a certain maturity to enable AI adoption on a technical level. This calls for clear requirements that visualize for companies which systems and standards are in place and where developments are needed. Security must be continuously ensured, for which certain standards and action catalogs must be developed. With regard to the supercategory 'Data Management', the availability of data is considered the basis for successful

AI adoption, as no AI can be successfully deployed without data. In the production context in particular, this requires developments that support companies in the provision of data, which usually arises from very heterogeneous sources and forms. Data analytics must also be closely examined, and production companies usually need external support in doing so. The multitude of data also requires big data storage capabilities. Here, groundwork is needed to show companies options about the possibilities of different storage options (e.g., on premis vs. cloud-based).

In the 'Regulatory Environment', ethics in particular is considered a driver of AI adoption in production. Here, fundamental ethical factors and frameworks need to be developed that companies can use as a guideline to ensure ethical standards throughout the process. Cooperations and environmental dynamism drive the supercategory 'Business Environment'. Collaborations are necessary to successfully implement AI adoption and action is needed to create the necessary contact facilitation bodies. In a competitive environment, companies have to make quick decisions under strong pressure, which also affects AI adoption. Here, guidelines and also best practice approaches can help to simplify decisions and quickly demonstrate the advantage of the solutions. There is a need for research in this context.

A.4 Conclusions

The use of AI technologies in production continues to gain momentum as managers hope to increase efficiency, productivity and reduce costs (Fosso Wamba et al. 2024; Sanchez et al. 2020; Wang et al. 2018). Although the benefits of AI adoption speak for themselves, implementing AI is a complex decision that requires a lot of knowledge, capital and change (Papadopoulos et al. 2022) and is influenced by various internal and external factors. Therefore, managers are still cautious about implementing the technology in a production context. Our SLR seeks to examine the emergent phenomenon of AI in production with the precise aim of understanding the factors influencing AI adoption and the key topics discussed in the literature when analyzing AI in a production context. For this purpose, we use the current state of research and examine the existing studies based on the methodology of a systematic literature analysis and respond to three RQs.

We answer RQ1 by closely analyzing the literature selected in our SLR to identify trends in current research on AI adoption in production. In this process, it becomes clear that the topic is gaining importance and that research has increased over the last few years. In the field of production, AI is being examined from various angles and current research addresses aspects from a business, human and technical perspective. In our response to RQ2 we synthesized the existing literature to derive 35 factors that influence AI adoption in production at different levels from inside or outside the organization. In doing so, we find that AI adoption in production poses particularly significant challenges to organizational effectiveness compared to other digital technologies and that the relevance of data management takes on a new dimension. Production companies often operate more traditionally and are sometimes rigid when it comes to change (Chirumalla 2021; Fragapane et al. 2022), which can pose organizational challenges when adopting AI. In addition, the existing machines and systems are typically rather heterogeneous and are subject to different digitalization standards, which in turn can hinder the availability of the necessary data for AI implementation (Javaid et al. 2021; Shahbazi and Byun 2021). We address RQ3 by deriving a research agenda, which lays a foundation for further scientific research and deepening the understanding of AI adoption in production. The results of our analysis can further help managers to better understand AI adoption and to pay attention to the different factors that influence the adoption of this complex technology.

A.4.1 Contributions

Our paper takes the first step towards analysing the current state of the research on AI adoption from a production perspective. We represent a rather holistic view on the topic, which is necessary to get a better understanding of AI in a production-context and build a comprehensive view on the different dimensions as well as factors influencing its adoption. To the best of our knowledge, this is the first contribution that systematises research about the adoption of AI in production. As such, it makes an important contribution to current AI and production research, which is threefold:

First, we highlight the characteristics of studies conducted in recent years on the topic of AI adoption in production, from which several features and developments can be deduced. Our results confirm the topicality of the issue and the increasing relevance of research in the field.

Having laid the foundations for understanding AI in production, we focused our research on the identification and systematisation of the most relevant factors influencing AI adoption in production at different levels. This brings us to the second contribution, our comprehensive factor analysis of AI adoption in production provides a framework for further research as well as a potential basis for managers to draw upon when adopting AI. By systematizing the relevant factors influencing AI adoption in production, we derived a set of 35 researched factors associated with AI adoption in production. These factors can be clustered in two areas of analysis and seven respective supercategories. The internal environment area includes four levels of analysis: ‘Business and Structure’ (focusing on financial aspects and firm characteristics), ‘Organizational Effectiveness’ (focusing on human-centred factors), ‘Technology and System’ (based on the IT infrastructure and systems) as well as ‘Data Management’ (including all data related factors). Three categories are assigned to the external environment: the ‘Regulatory Envirionment’ (such as ethics and the regulatory forms), the ‘Business Environment’ (focused on cooperation activities and dynamics in the firm environment) and the ‘Economic Environment’ (related to sectoral and country specifics).

Third, the developed research plan as outlined in Table 7 serves as an additional outcome of the SLR, identifying key RQs in the analyzed areas that can serve as a foundation for researchers to expand the research area of AI adoption in production. These RQs are related to the mostly cited factors analyzed in our SLR and aim to broaden the understanding on the emerging topic.

The resulting insights can serve as the basis for strategic decisions by production companies looking to integrate AI into their processes. Our findings on the as factors influencing AI adoption as well as the developed research agenda enhance the practical understanding of a production-specific adoption. Hence, they can serve as the basis for strategic decisions for companies on the path to an effective AI adoption. Managers can, for example, analyse the individual factors in light of their company as well as take necessary steps to develop further aspects in a targeted manner. Researchers, on the other hand, can use the future research agenda in order to assess open RQs and can expand the state of research on AI adoption in production.

A.4.2 Limitations

Since a literature review must be restricted in its scope in order to make the analyses feasible, our study provides a starting point for further research. Hence, there is a need for further qualitative and quantitative empirical research on the heterogeneous nature of how firms configure their AI adoption process. Along these lines, the following aspects would be of particular interest for future research to improve and further validate the analytical power of the proposed framework.

First, the lack of research on AI adoption in production leads to a limited number of papers included in this SLR. As visualized in Figure 5, the number of publications related to the adoption of AI in production has been increasing since 2018 but is, to date, still at an early stage. For this reason, only 47 papers published until May 2024 addressing the production-specific adoption of AI were identified and therefore included in our analysis for in-depth investigation. This rather small number of papers included in the full-text analysis gives a limited view on AI adoption in production but allows a more detailed analysis. As the number of publications in this research field increases, there seems to be a lot of research happening in this field which is why new findings might be constantly added and developed as relevant in the future (Tranfield et al. 2003). Moreover, in order to research AI adoption from a more practical perspective and thus to build up a broader, continuously updated view on AI adoption in production, future literature analyses could include other publication formats, e.g. study reports of research institutions and companies, as well discussion papers.

Second, the scope of the application areas of AI in production has been increasing rapidly. Even though our overview of the three main areas covered in the recent literature serves as a good basis for identifying the most dominant fields for AI adoption in production, a more detailed analysis could provide a better overview of possibilities for manufacturing companies. Hence, a further systematisation as well as evaluation of application areas for AI in production can provide managers with the information needed to decide where AI applications might be of interest for the specific company needs.

Third, the systematisation of the 35 factors influencing AI adoption in production serve as a good ground for identifying relevant areas influenced by and in turn influencing the adoption of AI. Further analyses should be conducted in order to extend this view and extend the framework. For example, our review could be combined with explorative research methods (such as case studies in production firms) in order to add the practical insights from firms adopting AI. This integration of practical experiences can also help exploit and monitor more AI-specific factors by observing AI adoption processes. In enriching the factors through in-depth analyses, the results of the identified AI adoption factors could also be examined in light of theoretical contributions like the technology-organization-environment (TOE) framework (Tornatzky and Fleischer 1990) and other adoption theories.

Fourth, in order to examine the special relevance of identified factors for AI adoption process and thus to distinguish it from the common factors influencing the adoption of more general digital technologies, there is a further need for more in-depth (ethnographic) research into their impacts on the adoption processes, particularly in the production context. Similarly, further research could use the framework introduced in this paper as a basis to develop new indicators and measurement concepts as well as to examine their impacts on production performance using quantitative methods.

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B Exploring AI Adoption in Manufacturing: An Empirical Study on Effects of AI Readiness[2]

Abstract:

Despite the promising potential of Artificial Intelligence (AI) in manufacturing, many companies remain hesitant to fully embrace this transformative technology, casting doubt on their preparedness for AI integration. While previous research has initiated the exploration of the relationship between AI readiness and AI adoption, empirical analyses in this domain are still scarce. To bridge this gap, we investigate how firms technological and organisational AI readiness, individually and in combination, influence the adoption of AI in manufacturing companies. Leveraging extensive empirical data from the *German Manufacturing Survey*, encompassing 1,334 firms, we employ both descriptive and multivariate analysis. Our findings demonstrate that companies need to cultivate a robust AI readiness across both technological and organisational dimensions to facilitate successful AI adoption. Nevertheless, our approach unveils a gap between AI readiness and actual AI adoption: while manufacturing companies appear to have considerable levels of AI readiness, they are still reluctant to successfully implement AI in production processes. The results also show that companies are pursuing different strategies in the development of AI capabilities. Moreover, our analysis uncovers significant disparities among firms, highlighting the crucial role of certain firm-specific characteristics for AI adoption. Particularly interesting is our result about the u-shaped relationship between the company size and AI adoption as well as the relevance of the product complexity.

Keywords: AI adoption, AI readiness, manufacturing, production, quantitative study

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B.1 Introduction

The digital transformation of manufacturing is characterised by an increasing digitalisation of processes, automation as well as the integration of versatile digital technologies (Benner and Waldfogel 2020; Li et al. 2017; Oliveira et al. 2020; Roblek et al. 2016). Advanced digital technologies are designed to help reduce the time and cost of production as well as generate new products and services (Verganti et al. 2020). AI, as one of these technologies, has gained attention across many sectors over the past few years promising significant potential for performance improvements (Mikalef et al. 2019). We understand AI as the ability of systems to recognise patterns or irregularities and, accordingly, to propose or independently make decisions (Lerch et al. 2022a; Merhi and Harfouche 2023; Russell and Norvig 2010; Toorajipour et al. 2021). In the narrow sense, we see AI as an innovation drawing on a range of technologies (such as machine learning or natural language processing (Collins et al. 2021)) that enable intelligent capabilities within an organisation. For manufacturing, the integration of AI solutions into production processes promises to improve productivity, flexibility, efficiency as well as enhanced automation of processes (Sanchez et al. 2020b) in production areas such as process management, quality control or maintenance. However, although the promising potential of AI integration (Bokrantz et al. 2023; Peretz-Andersson et al. 2024; Rammer et al. 2022b), its practical application in the production environment is at an early stage (Dohale et al. 2022) and manufacturing companies are currently still reluctant to utilise AI solutions (Holmstrom 2021; Kinkel et al. 2022; Lee et al. 2018). This raises questions about the actual structural readiness of these organisations as well as their functional readiness to support the changes associated with the introduction of AI (Stevens 2013).

A greater part of the literature acknowledges that the readiness of firms to adopt AI, and thus according to Rogers (2003) to actual use AI, can be analysed through the lenses of resources enabling a certain set of abilities (AI capabilities) (Mikalef and Gupta 2021b; Peretz-Andersson et al. 2024). Beyond the fundamental tangible resources i.e. technical prerequisites for AI adoption, such as the necessary data foundation and infrastructure, it is crucial to establish an organisational foundation and human resources to improve AI readiness (Dohale et al. 2022; Jöhnk et al. 2021; Pumplun et al. 2019). This, in turn, lays the groundwork for the development of AI capabilities. Therefore, literature highlights the significance of various intangible resources, including, for example, preparing the workforce and honing the necessary skills (Drobot 2020; Ghobakhloo and Ching 2019; Jöhnk et al. 2021), cultivating an open culture for new ideas (Dubey et al. 2020; Jöhnk et al. 2021), and leveraging collaboration to develop and implement suitable systems (Ghobakhloo and Ching 2019; Jöhnk et al. 2021). By addressing these aspects, companies can enhance their readiness for AI integration in various contexts, laying the foundation for successful adoption and performance improvement.

Recent qualitative studies shed light on the process of resource orchestration through which manufacturing companies implement AI solutions (Horvat et al. 2023; Horvat and Heimberger 2023; Peretz-Andersson et al. 2024). Additionally, numerous studies have analysed AI adoption in various corporate settings, providing valuable insights into the dynamics and factors of AI integration within companies (e.g. Kinkel et al. (2022) , Chatterjee et al. (2021) or Pillai et al. (2022)). Furthermore, existing literature highlights the correlation between AI capabilities and firms' performance (Mikalef and Gupta 2021b; Rialti et al. 2019) as well as business model innovation (Sjödin et al. 2021). However, what remains less explored in recent literature is the intermediate step between AI readiness and AI capabilities (Dwivedi et al. 2021; Steininger et al. 2022). In other words, recent research has yet to fully clarify the connection between the availability of resources necessary for AI readiness and the actual adoption of AI solutions in companies, despite some initial efforts by Jöhnk et al. (2021) and Alsheibani et al. (2019). Furthermore, recent studies often lack explicit reference to the production context, leaving a gap in understanding the distinctive characteristics of this relatively traditional industry (Dwivedi et al. 2021). To address this research gap, this paper aims to answer the following research question:

How does the readiness of a firm for AI influence the likelihood of AI adoption in production processes of manufacturing firms?

Building upon the shared theoretical foundations of AI adoption (Chatterjee et al. 2021; Ghani et al. 2022; Kinkel et al. 2022) and AI readiness (Alsheibani et al. 2019; Heimberger et al. 2023; Horvat et al. 2023; Horvat and Heimberger 2023; Jöhnk et al. 2021), we have constructed a conceptual framework to contextualise our study within current AI research. Within this framework, we have developed three measurement models to examine the impact of both technical and organisational AI readiness, as well as combined AI readiness, on the likelihood of a manufacturing company adopting an AI solution. The present study is conducted in the context of German manufacturing. Empirically, we use a representative large-scale survey conducted in 2022, which includes firm-level factual data reported by managers from 1,334 manufacturing firms in Germany. Based on this comprehensive and robust empirical analysis; our primary focus lies in empirically testing the link between AI readiness and AI adoption, thus making an important contribution to current AI research in manufacturing and providing valuable insights for practitioners.

In a first step, we research into the degree to which manufacturing firms are primed to use AI into their production. Our descriptive findings underscore the importance of not only assessing AI readiness as a unified score but also delving into its components as distinct dimensions of readiness. By doing so, we contribute to the existing literature by empirically exploring the relevance of AI readiness as a combination of relevant technological and organisational resources, individually and in combination, for the actual adoption of AI solutions in production. Our descriptive analysis reveals that, despite a relatively high level of readiness for implementing this advanced digital technology, AI is not yet widely used in production processes. Therefore, employing robust logistic regression analysis, we delineate the varying significance of technological, organisational, and combined AI readiness in explaining the likelihood of AI adoption in production processes. In this multivariate analysis, we highlight that the adoption of AI is heavily influenced by the complexity of the manufactured products. We also show, while AI readiness emerges as a pertinent predictor for AI adoption among smaller firms, larger firms' adoption is predominantly shaped by factors such as firm size and the industry context, with AI readiness playing a rather limited role.

B.2 Conceptual Background

B.2.1 AI Adoption

The adoption of technological innovations has been analysed and applied in various disciplines for many decades. Research has focused on organisational processes (Hameed et al. 2012; Klein and Sorra 1996; Pierce and Delbecq 1977; Rogers 1983) and factors (Rogers 1995; Tornatzky and Fleischer 1990) that describe or influence the adoption of innovations, as well as questions that analyse why some firms are more likely to adopt innovations than others (Damanpour and Schneider 2006). Technology adoption has been examined across multiple contexts and analyses at the individual level and the organisational level have become particularly established (Oliveira and Marins 2011; Pichlak 2016). For example, models such as the Technology Acceptance Model (Davis 1989), the Theory of Reasoned Action (Fishbein and Ajzen 1975), the Theory of Planned Behavior (Ajzen 1991), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003) are applied to analyse technology adoption at the individual level. In contrast, the Diffusion of Innovations (Rogers 1983) and the Technology, Organisation, Environment (TOE) (Tornatzky and Fleischer 1990) frameworks have been notably successful for analysing the organisation at firm level in order to study technology adoption (Oliveira et al. 2020).

Adoption analyses focus on a variety of technologies, such as e-business (Lin and Lin 2008; Wu et al. 2003), cloud computing (Al-Hujran et al. 2018; Oliveira et al. 2014), and more recently, AI (Alsheibani et al. 2019; Bettoni et al. 2021; Rammer et al. 2022b). The factors that enter and influence adoption frameworks and analyses vary depending on the specific context of each study (Oliveira and Marins 2011). The emerging technology of AI is considered an innovation that organisations can choose to implement and hence require far-reaching adoption analyses. Within the realm of IT innovation adoption, the TOE model often serves as a basis for the classification of various factors into a framework in connection with AI adoption analyses (Chatterjee et al. 2021; Ghani et al. 2022; Kinkel et al. 2022; Merhi and Harfouche 2023). Apart from that, there are other classifications of factors that influence organisations on their path to AI adoption, such as factors within the socio-technical system of people, processes and technology (Uren and Edwards 2023).

While existing studies have delved into the analysis of specific AI adoption factors (Chatterjee et al. 2021; Ghani et al. 2022; Kinkel et al. 2022; Pillai et al. 2022), a gap persists in comprehensive empirical analyses that capture the current landscape of AI adoption within the manufacturing industry, particularly in the context of AI applications in production. Although some in-depth production related AI adoption papers already exist, such as Pillai et al. (2022), their analysis focuses exclusively on the automotive industry, limiting cross-sector comparisons within manufacturing. There is a lack of studies that analyse different areas for potential AI application in the production processes of manufacturing companies and thus provide information on the current degree of dissemination and relevant fields of application. Furthermore, there is a lack of research that not only includes traditional adoption factors but also additional theoretical concepts such as the readiness of firms for AI, thus introducing further dimensions into the analysis of AI adoption.

B.2.2 AI Readiness

A phenomenon closely related to analyses of technology adoption is an organisation's readiness for change, which is widely discussed at individual and organisational levels (Jones et al. 2005; Rafferty et al. 2013; Rusly et al. 2012; Weiner 2009). Readiness for change refers to a shared psychological and practical state within an organisation in which members are both motivated to support change and confident in their collective ability to implement it. It is shaped by internal capacities and individual perceptions, which are influenced by how well the organisation communicates, involves its employees and promotes a sense of purpose and willingness (Jones et al. 2005; Lokuge et al. 2019). The theory of organisational readiness for change (e.g. Lokugea et al., 2019) is rooted in change management and provides the theoretical basis for our analysis of an organisation's readiness for AI (Hussain and Papastathopoulos 2022). Literature confirms that a higher readiness of organisations for change favours the adoption of innovations (Antony et al. 2023; Kelly et al. 2017; Weiner 2009). A strong readiness for change within a firm gives organisations the flexibility to reconfigure their resources (Hussain and Papastathopoulos 2022). This is why we turn to the theoretical foundations of the Resource Based View (RBV) including the organisational capabilities framework in the field of strategic management literature (Amit and Schoemaker 1993; Barney 1991; Bharadwaj 2000; Grant 1991; McGrath et al. 1995). This theoretical perspective offers valuable insights into how companies cultivate and orchestrate the distinct resources and capabilities essential for gaining a competitive edge in the AI era (Mikalef and Gupta 2021b; Peretz-Andersson et al. 2024; Schryen 2013).

The core tenet of the RBV revolves around the strategic importance of firm-level resources (Barney 1991). According to the RBV, competitive advantage arises from effectively harnessing unique resources, providing a nuanced understanding of these assets (Priem and Butler 2001). Grant's framework (1991) discerns various types of resources, categorizing them into tangible, intangible, and personnel-based categories. In addition to resources, the RBV introduces organisational capabilities as a combination and orchestration of resources, resulting in a company's ability to seamlessly integrate and deploy other resources to attain a competitive advantage (Amit and Schoemaker 1993). These functional capabilities can be amalgamated to form cross-functional capabilities, further enhancing a firm's competitive positioning (McGrath et al. 1995).

Recent literature in the information systems field extends the RBV framework to elucidate how information technology (IT)-related resources can be harnessed to create IT capabilities, which, in turn, impacts competitive performance (Schryen 2013). IT capabilities manifest themselves in various forms, including social media capabilities, business analytics, and big data capabilities (Gupta and George 2016). Recent research underscores the pivotal role of AI capabilities in driving performance improvements through AI-powered solutions, which Mikalef and Gupta (2021b) define as '[…] the ability of a company to select, orchestrate, and leverage its AI-specific resources'. To maximise the benefits of AI, organisations need to cultivate a unique combination of tangible, intangible, and human AI-specific resources (Horvat et al. 2023; Mikalef and Gupta 2021b).

Incorporating the RBV logic allows us to comprehend the fundamental principles of resource-based readiness for AI technology. Within this framework, AI-specific tangible and intangible resources assume central roles in developing AI capabilities and shaping the success of AI adoption (Horvat et al. 2023). Tangible resources encompass the requisite IT infrastructure for AI applications, including e.g. hardware for data storage and processing and software for intricate data processing (Gupta and George 2016; Mikalef and Gupta 2021b). The importance of data in AI, with its diverse types and voluminous nature, underscores its pivotal role as one of the most challenging aspects of AI implementation. In contrast, intangible resources are marked by their uniqueness and heterogeneity, stemming from organisational history, personnel, processes, and contextual factors (Grant 1991; Sirmon et al. 2011). Research on AI readiness underscores the paramount importance of intangible resources in both the adoption and performance enhancement (Alsheibani et al. 2019; Horvat and Heimberger 2023; Jöhnk et al. 2021). Finally, human resources, encompassing the collective knowledge and skills of employees, are vital components of AI readiness (Alsheibani et al. 2018; Horvat and Heimberger 2023). These resources entail technical IT skills essential for introducing and applying IT solutions, as well as managerial IT skills that involve conceptualising, creating, and utilising IT applications to enhance various aspects of a business. These skills are cultivated over time and are often specific to each organisation (Heimberger et al. 2023).

Understanding the interplay of tangible and intangible resources, along with the critical role of human resources, is paramount for AI readiness (Heimberger et al. 2023; Horvat and Heimberger 2023). We assume that companies can achieve individual levels of readiness, which in turn provides information about the current state (regarding AI readiness) of the organisation (Hussain and Papastathopoulos 2022).The development of resources along each of these resource based readiness levels form the basis for the successful adoption of AI.

B.2.3 Integrated Research Framework and Hypothesis

While some articles have begun to examine the links between AI readiness and AI adoption, research in this area is still rare (Alsheibani et al. 2019; Issa et al. 2022; Jöhnk et al. 2021; Uren and Edwards 2023). Analyses consider different factors and dimensions and lack broad empirical validation of the relationship between readiness and adoption. However, research agrees on a complex interplay between adoption and readiness, with readiness being an important prerequisite for successful AI adoption throughout the entire adoption process (Jöhnk et al. 2021; Uren and Edwards 2023).

In line with these perspectives, we build on the theoretical foundations of organisational readiness for change and the foundations of technology adoption. Regarding AI readiness, we consider an organisation's internal AI-specific resources that provide information about a company's AI readiness. We categorise these resources into technological and organisational AI readiness. We then link the construct of AI readiness to AI adoption and assume a direct and significant influence of AI readiness on successful AI adoption. We thus assume that there is a relationship between different dimensions of AI readiness, defined by critical AI-specific resources that an organisation can develop and configure, and the actual introduction of AI in the production system (see Figure 7).

Readiness observations usually include specific factors based on adoption theories or processes (e.g., by Jöhnk et al. (2021) or Aboelmaged (2014)). Analyses of readiness for AI typically involve the analysis of specific factors within dimensions, such as an organisational dimension (Jöhnk et al. 2021), a technical dimension (Heimberger et al. 2023; Lerch et al. 2022a), or a combined view of several fields (Heimberger et al. 2024b; Uren and Edwards 2023). Within those dimensions, readiness approaches are recognised as an important component when considering innovation, as they can uncover factors that prevent companies from adopting AI or influence them positively (Uren and Edwards 2023). A large number of factors influence the adoption of AI in the production processes of manufacturing firms (Heimberger et al. 2024b), however, we need to limit the factors considered in our analysis. It is our intention to consider all high impact factors influencing AI adoption while keeping the readiness model manageable to be able to enable group comparisons and provide decision makers with suggestions for action. We searched the literature analysing AI readiness and AI adoption (Heimberger et al. 2023, 2024b; Horvat and Heimberger 2023; Jöhnk et al. 2021; Lerch et al. 2021; Uren and Edwards 2023) for the most important factors following the RBV in the realm of tangible resources, human resources and intangible resources. After collecting and structuring the factors derived from the literature, we were able to identify seven factors that appear to be of particular importance for AI in a production context. We then categorised the factors derived into two dimensions forming our AI readiness model. Each factor can be categorised into different levels of readiness, allowing the current status of the company to be assessed based on the intensity of deployment.

Building on the principles of RBV and following key adoption analyses based on the TOE framework, we assess a company's AI readiness based on two dimensions: technological AI readiness (comprising tangible resources) and organisational AI readiness (including intangible as well as human resources). The resource-based factors of each dimension focus on the internal factors of the organisation. We refrain from including external factors (e.g. laws, regulations or the economic situation) in our AI readiness analysis in order to focus clearly on the internal readiness of an organisation, which it can influence and develop itself. In each dimension, several factors exert influence on the company's AI readiness, comprising three factors in the technological dimension and four in the organisational dimension. Drawing on recent studies, we include data availability and IT infrastructure as fundamental technical prerequisites for AI implementation on the technological side, alongside the need to ensure security within the production context. On the organisational side, we analyse the prevailing skills and training initiatives in order to successfully implement AI. In addition, we analyse the culture of the workforce as well as the willingness to cooperate (both within and outside of companies), which also influence the introduction of AI (Heimberger et al. 2024b). We describe all factors in detail in the following section.

Companies have the opportunity to shape their resource based AI readiness by implementing relevant measures and fostering them internally, which emphasises the importance of including these two dimensions in the readiness analysis. We stress that technological and organisational AI readiness separately, as analysed by Heimberger et al. (2023), Lerch et al. (2022a), or Jöhnk et al. (2021), as well as the combined AI readiness of both dimensions influence whether a company adopts AI in the production context. We assume that companies can only successfully adopt AI if they have established AI-related resources and thus a fundamental AI readiness. These considerations lead to three hypotheses, which are derived in the following sections and the conceptual framework visualised in Figure 7.

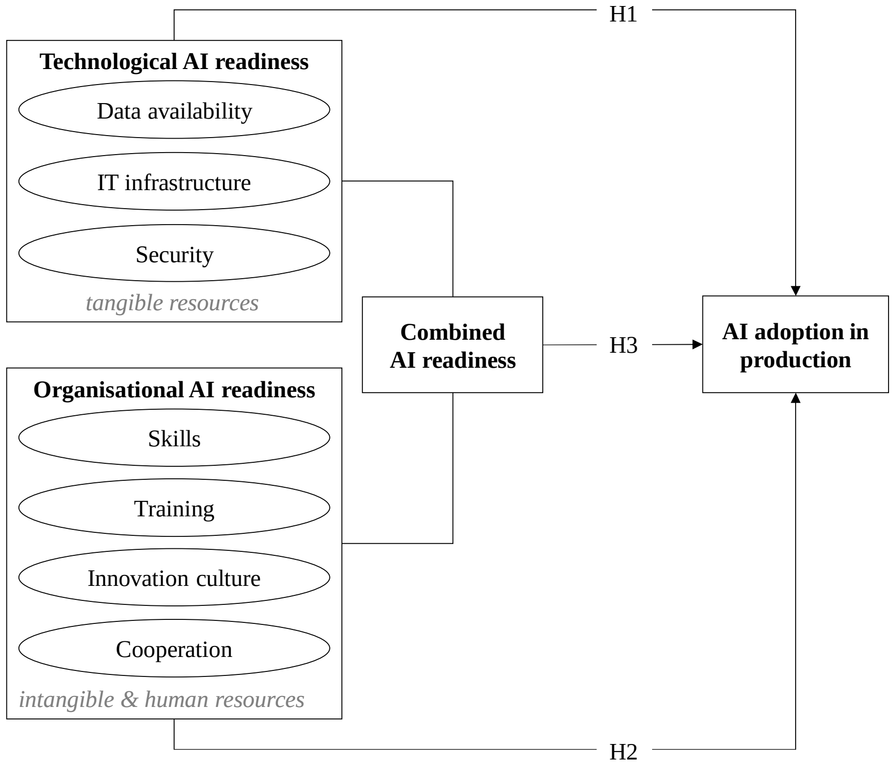


Figure 7: Conceptual framework of AI readiness and AI adoption analysis in production

B.2.3.1 Effects of Technological AI Readiness

The foundation of digital transformation is data, which is generated by a multitude of sensors in a smart and digitised factory (Oliveira et al. 2020; Roblek et al. 2016). Since input data is a prerequisite for AI for self-improvement and learning, companies that want to use AI efficiently must ensure the availability of data (Dubey et al. 2020; Hartley and Sawaya 2019). When integrating AI into existing systems, processes and programs are often supported with algorithms designed to improve their performance (Mantravadi et al. 2019). Consequently, existing systems play a crucial role in digitizing workflows, generating data and potential AI integration.

Building a robust AI infrastructure for both present and future systems requires the availability of IT resources (Chiang et al. 2022). This includes investments in the infrastructure as well as capabilities necessary for data analytics (Wuest et al. 2020). In production organisations, IT departments are responsible for providing the necessary infrastructure into which intelligent technologies can be integrated and which form the basis for the generation of numerous data in the sense of the Internet of Things. The foundation of IT capability (Awamleh and Bustami 2022; Garrison et al. 2015) is seen as a key driver in addressing complex challenges and enabling the IT department to implement AI technology swiftly and efficiently (Ghani et al. 2022).

Due to production facilities, which are often data-driven, production companies and their IT systems are vulnerable to failures as well as cyberattacks, which can reduce their competitiveness (Azambuja et al. 2023; Turner et al. 2019). Next to general data protection issues, safety risks are the subject of discussion in connection with AI (McCauley 2007; Trakadas et al. 2020). These conditions indicate that companies must implement measures to ensure the security of operational data, teach employees and thus create a fundamental basis for secure systems in production (Akinsolu 2023; Trakadas et al. 2020).

In view of the necessity of IT infrastructure and the availability and security of data for the successful adoption of AI, we assume that these technological AI resources within the organisation form an important basis for the adoption of AI in a production context. The availability of these resources together forms a specific technological AI readiness of a firm. Therefore, we assume:

H1: A higher level of technological AI readiness in manufacturing companies is positively associated with an increased likelihood of AI adoption in production processes.

B.2.3.2 Effects of organisational AI readiness

In order to exploit the potential of AI, the workforce within the manufacturing firm must possess a variety of digital skills , which include technical, cognitive as well as social skills (Drobot 2020; Kinkel et al. 2022; Trakadas et al. 2020). Although production companies may choose not to develop smart algorithms themselves, they must ensure basic technical skills and competencies in the use of the technology, such as the general digital affinity and process understanding of production employees in order to enable digital transformation (Ghobakhloo and Ching 2019; Huin et al. 2003; Hartley and Sawaya 2019).

To ensure a profound skillset amongst the production workforce, organisations must prepare their employees in a variety of areas to adapt to new technologies, improve their skills, and create a deeper understanding and, consequently, gain greater acceptance of these advances (Drobot 2020; Mubarok and Arriaga 2020; Sharma et al. 2022). Addressing this need for appropriate training requires resources and investments to improve workforce capabilities (Boavida and Candeias 2021; Ghobakhloo and Ching 2019; Kyvik Nordås and Klügl 2021; Vernim et al. 2022).

Innovative corporate cultures are characterised by continuous improvement (Bettoni et al. 2021), productivity (Kyvik Nordås and Klügl 2021), innovativeness (Olsowski et al. 2022) as well as risk-taking (Dubey et al. 2020), which increases companies` ability to adapt to ever-changing market conditions and make appropriate decisions (Boavida and Candeias 2021; Bonnard et al. 2021; Dubey et al. 2020; Tariq et al. 2021). An 'AI-ready culture' (Chiang et al. 2022), characterised by digital readiness, data integration, continuous development, and awareness of integrating smart technologies, can be supportive in the adoption of AI. Organisations that develop an environment for openness and new perspectives enable more opportunities for awareness and innovative approaches can emerge (Zmud 1982).

AI adoption can also be positively influenced by collaborations (both internal and external to the organisation) (Akinsolu 2023; Drobot 2020; Trakadas et al. 2020) as knowledge sharing and exchange can facilitate adoption (Boavida and Candeias 2021; Drobot 2020). External IT expertise is usually required to integrate AI into existing production processes, including, for example, implementation processes and organisational restructuring (Olsowski et al. 2022). Firms may benefit from public-private collaborations, e.g. with universities, and may gain access to government funding. In such research collaborations, ideas can be easily developed, tested and implemented in a collaborative environment among different actors (Ghani et al. 2022; Williams et al. 2022).

The development of organisational AI resources within the company, including skills, training, a culture of innovation and cooperation, forms an important foundation for a company's organisational readiness for AI in production. We therefore assume that:

H2: A higher level of organisational AI readiness in manufacturing companies is positively associated with an increased likelihood of AI adoption in production processes.

B.2.3.3 Effects of Combined AI Readiness

Having isolated the technological and organisational dimensions of AI readiness, our analysis takes a significant step forward by incorporating a synthesis of both aspects in our third hypothesis. Based on insights from the RBV-based AI literature(Horvat et al. 2023; Mikalef and Gupta 2021b), companies take different paths to prepare for AI integration, with a choice between a focus on organisational (intangible) measures or on technological (tangible) advances. Some companies initially focus on strengthening their organisational resources, thus creating a solid structural foundation, while others prioritise technological capabilities and gradually build tangible resources (Horvat et al. 2023). Despite these different paths, each of them can culminate in the adoption of AI in a production context and lead to complex resource combinations. In recognition of the distinct but equally critical role that both dimensions play in driving successful AI adoption, we introduce a unified AI readiness concept into our research framework.

This approach combines factors from both dimensions and summarises them in a consolidated index. Our integrated model is based on the principles of relative value theory and assumes that it is important to build both technological and organisational AI-related resources in order to implement AI. We hypothesise:

H3: A higher level of combined AI readiness in manufacturing companies is positively associated with an increased likelihood of AI adoption in production processes. This influence on AI adoption is stronger than in the assumed relationships in H1 or H2.

B.3 Data and Methodology

The empirical data used in this study were drawn from the *German Manufacturing Survey* (GMS) 2022. This survey was first launched in 1993 (Lay and Maloca 2004) to systematically observe production companies regarding their product, process, service and organisational innovations, it is currently conducted every three years, and has been part of the *European Manufacturing Survey* since 2001 (Fraunhofer Institute for Systems and Innovation Research ISI 2024). The data from this broad multi-topic survey were used in several firm-level studies (e.g. Bikfalvi et al. (2013), Bikfalvi et al. (2014), Dachs and Zahradnik (2022), Kinkel et al. (2011), Kirner et al. (2015)). The authors belong to the scientific team responsible for its operationalisation and questionnaire development for Germany.

We chose the German manufacturing sector for our analysis because Germany was an early lead market for the digitalisation of industrial production (Kagermann 2015) and is a large economy whose industrial applications are highly competitive and considered a role model for other industries worldwide (Audretsch et al. 2018; European Commission 2024). Furthermore, the year 2022 is a very interesting point in time to analyse the dissemination of AI applications in manufacturing, as it captures the diffusion of industrial applications based on speech recognition, image processing or computer vision after 2012 (Escobar et al. 2020; Fahle et al. 2020) and the boost by COVID-19 (Kapoor et al. 2021).

B.3.1 Data base and Sample Description

GMS addresses manufacturing firms with 20 or more employees from all manufacturing sectors (NACE Rev. 2, 10-33) in Germany. The questionnaires are sent to firms with at least 20 employees from all areas of manufacturing (NACE Rev. 2, 10-33) and are completed by production managers, chief technology officers, or general managers of the production facilities. The data for this study is based on the most recent survey, GMS 2022, which has been conducted as a push-to-web survey between fall 2021 and spring 2022 (Jäger and Maloca 2022a). This survey addressed a random gross sample of 15,299 manufacturing firms with at least 20 employees in Germany, which was drawn from a firm database as a proportionally stratified random sample in line with the distribution in the population. However, 2,047 selected cases turned out to not be part of the target population, or to be not active anymore. The processing of the random sample was carried out according to a strict protocol.

A total of 1,334 companies returned usable responses that met the quality criteria of more than 75 % of answered questions. This corresponds to a response rate of 10 % in relation to the net sample for the GMS 2022. Moreover, the realised data is a representative image of the manufacturing industry in Germany as the regional distribution, size classes and industry structure are in line with the distribution in the data from the Federal Statistical Office (Jäger and Maloca 2022a).

GMS 2022 provides a large set of data, including information on innovative production technologies and digitalisation, organisational practices and the implementation of training measures as well as performance indicators and general company data. Questions essentially comprise verifiable facts and figures, hardly any personal assessments are captured. The items on the use of AI in production processes were specifically developed for the 2022 survey to cover the production specific use of AI in linkage to their production context by a cross-country team including the authors. These data enable us to examine the relationship between AI readiness and AI adoption in manufacturing firms.

For the following descriptive statistics, bivariate group comparisons and multiple logistic regression analyses on the interlinkage between AI readiness and AI adoption, we use an extract of the GMS 2022 data from 1,130 firms. This extract includes all cases for which the necessary information regarding AI readiness, AI adoption and firm and production characteristics was provided. The comparison between the analysed data set and the excluded cases shows that the assumption of a systematic bias in the characteristics used can be rejected. Table 10 in the appendix summarises information on the main characteristics of the analysed data and provides the comparative data of the population regarding firm size and sector as provided by the Federal Statistical Office.

B.3.2 Measures

B.3.2.1 Dependent Variables: AI Adoption

The measure of AI adoption in production used in the following analyses captures the fact of the use AI in manufacturing processes and thus focuses on successful implementation of AI. It is based on companies' responses regarding their use of software solutions in specific production areas. Firms were asked to indicate in which production area a specific software is used. In a follow-up question, respondents were further asked whether these software solutions incorporate self-learning functionalities, explained in the questionnaire as algorithms capable of automatically improving their performance by recognizing patterns or irregularities without being explicitly programmed for each case (Lerch et al. 2022a; Merhi and Harfouche 2023; Toorajipour et al. 2021). We intentionally refrain from differentiating between specific AI technologies (e.g., machine learning, deep learning, or expert systems) and instead focus on the general presence of AI functionalities within production-related applications. This approach accounts for the fact that the respondents, typically not IT specialists but managers with operational responsibilities, may lack the technical expertise to accurately identify the underlying AI methods employed. Accordingly, the survey did not inquire about the specific types of AI technologies or models used. Rather, our focus lies in identifying whether self-learning functionalities, as a defining feature of AI, are present in the software systems used in production contexts, independent of their technical implementation.

Within this research, we consider four application areas commonly associated with AI-driven production processes (Fahle et al. 2020; Javaid et al. 2021): (1) AI-based software solutions for managing production processes (e.g., process monitoring), (2) for quality control (e.g., defect detection), (3) for maintaining machinery and equipment (e.g., condition monitoring), and (4) for managing internal logistics (e.g., warehouse management, transportation). These domains were chosen to reflect the integration of learning-based AI technologies in the production context. Thereby, the aim of operationalisation was to determine whether companies are using AI at all in these areas, rather than to what extent. Therefore, GMS asked a yes/no question about AI implementation for each of these areas of application.

In the here presented analyses, we focus on firms that use AI for production processes. The indicator therefore distinguishes between firms that already use an AI application in at least one of the four areas of their production (AI adopter) and those that do not yet use any software with self-learning functionality in one of these four AI applications applied (non-AI adopter). As done in previous studies of AI adoption, we thus treat our dependent indicator of AI adoption as a dichotomous variable (Dahlke et al. 2024; Zhan et al. 2024).

B.3.2.2 Independent Variables: AI Readiness Indices

Our conceptual framework considers both the technological and organisational perspectives of AI readiness, as these are the two dimensions that encompass the tangibles and intangibles of a company, which can be influenced by the organisation itself. In our analyses, we use separate indices for both dimensions as well as a combined index to capture the interaction between the two individual AI readiness dimensions. Each readiness dimension of the indices consists of different factors, which are measure by different survey responses and which, in their various configurations, lead to varying readiness assessments for each dimension. The combined AI readiness index, in turn, connects the two dimensions. In the following paragraphes, the indices are explained in more detail and the operationalisation is outlined; the constitutive factors are additionally listed in Table 8 as well as the measures they are based on. Moreover, in the appendix, the distributions of the constitutive factors for the three constructs in German manufacturing are displayed (see Table 11 in the appendix).

While many of the factors in these indices may primarily reflect broader aspects of digitalisation rather than AI-specific technologies, we assume that these fundamentals are necessary for the successful implementation of AI and therefore reflect a readiness for AI. Technological AI includes important foundations of data availability, IT infrastructure, and security, while organisational AI readiness addresses the importance of skills, training, innovation culture, and cooperation. These components are essential for the successful adoption of AI, as a sufficient digital infrastructure and organisational capacity are prerequisites for effective AI implementation (Jöhnk et al. 2021; Uren and Edwards 2023). Thus, while the indices do not measure existing AI algorithms or specific AI-related technologies, they capture critical AI-related resources and measure enablers for a successful AI integration in production contexts.

	Factor	Measurements	Measurement level
Technological AI readiness	Data availability	*Use of data-based technologies in production*	
		use of software systems for production planning and control (e.g. ERP system)	yes/no dummy
		digital data exchange with suppliers or customers (EDI)	yes/no dummy
		use of product lifecycle or product process data management systems	yes/no dummy
		use of near real-time production control systems	yes/no dummy
	IT infrastructure	*Professional specialisation*	
		share of operating personnel in IT infrastructure (hardware and software)	share of total employees
	Data security	*Implementation of data security measures*	
		measures raising the data security awareness of employees	yes/no dummy
		use of special software solutions (e.g. controlled data use, access, etc.)	yes/no dummy
		use of special hardware solutions (e.g. Network separation etc.)	yes/no dummy
		implementation of special organisational data security measures (e.g. access restrictions)	yes/no dummy
Organisational AI readiness	Skills	*Use of digital communication technologies*	
		use of mobile/wireless devices for programming and operating plants and machines	yes/no dummy
		use of digital solutions for work plans/instructions or drawings at the workers' workplace	yes/no dummy
	Training	*Offers for continuing education and skills development for production employees*	
		focused on a specific task (e.g. machine maintenance, workstation instructions)	yes/no dummy
		to support the introduction and use of digital production technologies or digital assistance systems	yes/no dummy
		focused on data security and data compliance	yes/no dummy
	Innovation culture	*Measures to motivate and involve production employees in innovation processes*	
		planning, controlling or monitoring functions for workers (task integration)	yes/no dummy
		involvement of workers in product or process development	yes/no dummy
		rewards for outstanding performance in the production or innovation area	yes/no dummy
	Cooperation	*Research & Development cooperation*	
		with suppliers or customers	yes/no dummy
		with other companies (not suppliers or customers)	yes/no dummy
		with research institutions/universities	yes/no dummy

Table 8: Operationalisation of AI readiness dimensions

On the one hand, the *technological AI readiness index* is operationalised as an index based on the measurement of the three factors presented above (Figure 7) using seven indicators. Each factor is measured on an ordinal scale ranging from zero to two, the distribution in the manufacturing sector is shown in Table 11 in the appendix. Zero points are achieved if none of the production systems are in use, no employees are assigned to IT and no measures are implemented to safeguard operational data. One point, meaning basic technological AI readiness is achieved if one or two of the production systems are in use, <5% of the employees are assigned to IT, and one or two of the security measures are implemented. The maximum score (two points) is achieved when at least three of the production systems are in use (data availability), a minimum of 5% of the employees at the site are engaged in IT, and if at least three of the four operational data security measures have been implemented.

With the additive combination of these three factors, a maximum score of six points can be achieved. To measure technological AI readiness, this score was standardised to a range from zero to two and then transformed into an ordinal indicator with four levels: no tech AI readiness (0 points), low technological AI readiness ((0<x<=2/3) points), medium technological AI readiness (2/3<x<=4/3), and high technological AI readiness (4/3<x<=2).

On the other hand, *organisational AI readiness* is operationalised as an index based on the measurement of four factors presented above (see Figure 7) using 11 indicators (see Table 8). As with the technological index, each factor is measured as an ordinal indicator with values zero, one or two; the distribution in the manufacturing sector is shown in the Table 11 in the appendix. Zero points are awarded to companies that have no digital skills, do not use any training measures, do not implement any of the three open innovation culture measures and do not engage in collaborations. One point is scored if one of the two digital communication tools is used, one of the three continuing education measures is offered to production employees, if one of the three innovation culture measures is utilised, and if collaboration is already underway. Two points are assigned if both digital communication tools are used and digital skills are therefore considered standard requirements in production if at least two of the three trainings are offered, if at least two of the three organisational measures are applied, and an integrative culture of innovation therefore is structurally supported and can thus provide impulses for innovation and new knowledge in the companies.

To measure organisational AI readiness, this score was standardised to a range from zero to two and then transformed into an ordinal indicator with four levels according to the same classification criteria: no organisational AI readiness (0 points), low organisational AI readiness

(0<x<=2/3), medium organisational AI readiness (2/3<x<=4/3), high organisational AI readiness (4/3<x<=2).

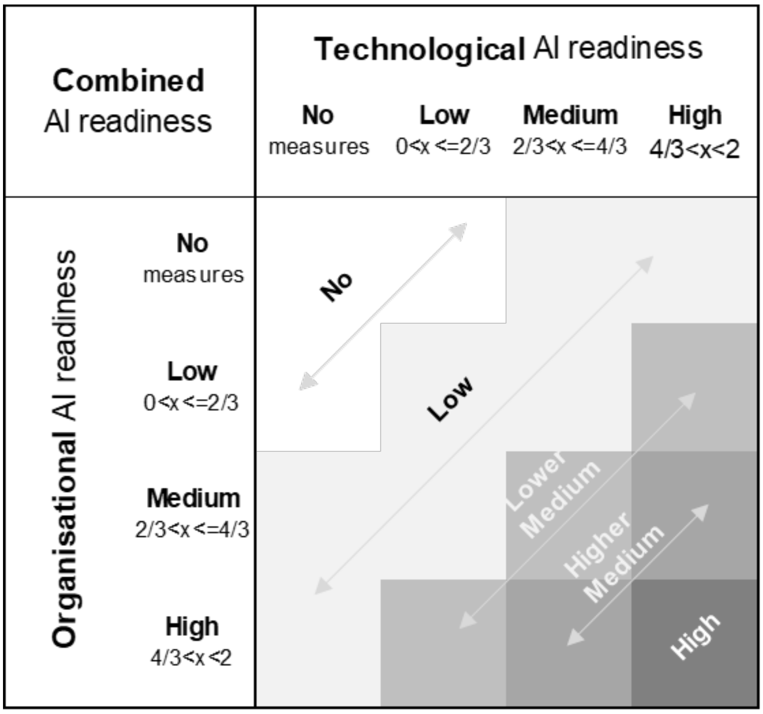


Figure 8: Group assignment combined AI readiness

Finally, we create the combined AI readiness index based on these two indices of technological AI readiness and organisational AI readiness, intending to reduce complexity and decrease measurement errors compared to using the two separate indicators (e.g. Kromrey et al. (2016)). Since the correlation between the two dimensions is of interest, the combined AI readiness index is an additive index, as shown in Figure 8. Thus, both the technological and organisational dimensions contribute equally to the combined AI readiness index. This was ensured by standardising both AI readiness dimensions and suggests that both dimensions complement and compensate to some extent. However, an interaction that would justify a multiplicative index is not assumed.

For constructing the index of combined AI readiness, the values on both dimensions are added up. No further weighting is applied. At the end, the resulting score is transformed into an ordinal indicator with five levels: no combined AI readiness, low combined AI readiness, lower medium combined AI readiness, higher medium combined AI readiness and high combined AI readiness. The group of firms assigned to *no combined AI readiness* includes those companies that either lack AI readiness in both dimensions or achieve no AI readiness in one of the two and only low readiness in the other, and are therefore still at the very beginning. The *low* *combined AI readiness* group consists of the firms that rather focus on one dimension and mostly or completely ignore the other dimension. *Lower* m*edium combined AI readiness* represents companies that are either at a medium readiness level in both dimensions or combine a high readiness in one with a low readiness on the other dimension. The group of *higher medium combined AI readiness* includes only those firms that combine a high readiness at one level with a medium readiness on the other one. Finally, the group of *high combined AI readiness* includes only those firms that have a high readiness rating for both technological AI readiness and organisational AI readiness. The group assignment is visualised in Figure 8.

B.3.2.3 Control Variables

In order to estimate the effect of AI readiness on AI adoption, structural characteristics of the firms and production characteristics are also taken into account in our analyses. As highlighted in previous research (DeStefano et al. 2022; Kinkel et al. 2022), we also assume that larger companies have more experience with the introduction of advanced production technologies and more opportunities and higher economies of scale to use AI systems efficiently in production. We also take into account the evidence from the literature that agile start-ups and small companies are among the pioneers in the AI adoption. Therefore, we take into account the firm size, measured as the number of employees, as a polynomial in the regression models (Armbruster et al. 2008; Bikfalvi et al. 2013; Broedner et al. 2009; Dachs et al. 2014; Kinkel et al. 2007). As a natural logarithm, the diminishing marginal utility of the number of employees is taken into account. With the simultaneous introduction of the quadratic term of this influence, we can also model a u-shaped relationship.

Considering the heterogeneity of manufacturing industries in terms of market and production-specific characteristics (e.g. automation, profit margin, digital environment) and the industrial differences with respect to AI adoption, we additionally control for the sector of a firm as adopted by other researchers analysing certain effects within the manufacturing industry (Armbruster et al. 2008; Bikfalvi et al. 2013; Broedner et al. 2009; Dachs et al. 2014; Rammer et al. 2022b; Wang and Qiu 2023). Based on open text information about the main product and perceived sector, firms are classified according to the sector classification NACE rev. 2 and grouped into eight classes afterwards.

As adopted in other studies (Kinkel et al. 2022; Kinkel et al. 2023), additional control variables such as product complexity (simple products, medium complexity products, complex products), batch size (single lot, small/medium lot, big lot) and the value chain position (manufacturer of final products, supplier, contract manufacturer) of the companies are suitable and have been interesting control variables in structural analyses of the manufacturing industry in regression analyses. We control for the batch size of the main production as we assume that companies with production processes in large batch sizes are more suitable for using AI solutions than companies with smaller batches or single unit production processes. Economies of scale are easier to realise under the frame conditions of large batch size production, enabling productivity growth through rationalising repetitive tasks (Bikfalvi et al. 2013; Broedner et al. 2009; Dachs et al. 2014; Lay et al. 2010). Product complexity is considered too as we assume that companies which produce simple products (in large volumes) have a higher need and more potential to automate their production processes than companies producing medium-complex or complex products (Broedner et al. 2009; Dachs et al. 2014). Finally, the value chain position is considered differentiating between manufacturers of final products for consumers or for industrial clients, system or parts suppliers, and contract manufacturers (Armbruster et al. 2008).

B.3.3 Model Description and Data Analysis

To test our three hypotheses, we first conduct bivariate group comparisons to find out to which extent differences in AI adoption can be detected between the AI readiness levels of the three AI readiness indices. We apply Mann-Whitney U tests (Mann and Whitney 1947) to compare two independent groups and the Kruskal-Wallis test (Kruskal and Wallis 1952) for multi-group comparisons to check whether the differences between the respective AI readiness levels in H1, H2 and H3 can be due to chance or can be assumed statistically significant. The null hypothesis in each case is that there are no differences in the share of AI adopters between the different AI readiness levels.

As a second step, we conduct multiple regression analyses to test our hypotheses. Since the dependent variable in our three hypotheses is a dichotomous variable (0: no AI adoption; 1: at least one of the four AI applications in use), we estimate logistic regression models that allow us to control for other company characteristics in addition to AI readiness. The firm and production characteristics are included in the models as presented above. Initially, only the influences of these indicators are estimated for each hypothesis. The models are then expanded to include the respective AI readiness index (technological, organisational or combined AI readiness). We estimate the regression parameter, visualise the statistical significance for each model and report the model fit for the entire model.

In order to ensure the robustness of the estimates, *firstly* the collinearity of the independent influencing factors was tested. In advance, no higher correlations were found in the bivariate relationship; Spearman's rho did not exceed the value of 0.3 between the ordinal factors. Pearson's r2 is mostly also in this order of magnitude. Only the information on company size (logarithmised number of employees) and the AI readiness are correlated with r=.434 for the combined indicator and .334/.379 for organisational and technological AI readiness. In conclusion, besides firm size no relevant bivariate correlation was found. We will use split data analyses to examine possible differences in the estimates for different company size groups. *Secondly*, approximate VIF inflation factors were calculated for all regressions; with values mainly below 3 and all below 4, these were all below a critical limit. *Finally*, standardised residuals of the regression estimations below 3 did not indicate specific outliers, nor did the analyses of the cook's distance with values below 0.36 reveal concerns on this behalf. Thus, additionally considering the specific model fit parameters, reliable logistic regression estimates can be assumed.

B.4 Results

B.4.1 AI Readiness in Manufacturing Companies

Firstly, there are intriguing findings concerning AI readiness in the manufacturing industry (refer to Figure 9). On one hand, in terms of resources related to technological AI readiness, the majority of analysed companies fall into the category of medium (49%) or high (40%) readiness. This suggests that a solid technological foundation for integrating AI applications into production contexts has been established in the manufacturing industry, irrespective of actual AI usage. On the other hand, in contrast to technological readiness, a high level of organisational readiness for AI is less frequently achieved (28%). Interestingly, one in four manufacturers exhibit no (5% of all companies) or only low (20%) level of resources related to organisational AI readiness. Overall, when analysing these two dimensions of AI readiness separately, it becomes apparent that manufacturing companies are more prepared in terms of technological readiness than in organisational readiness.

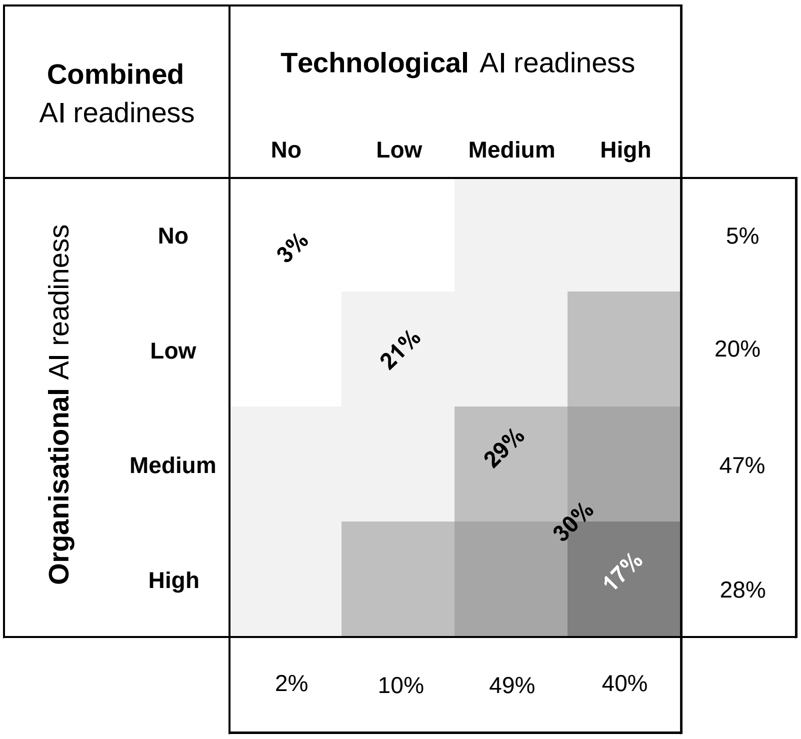
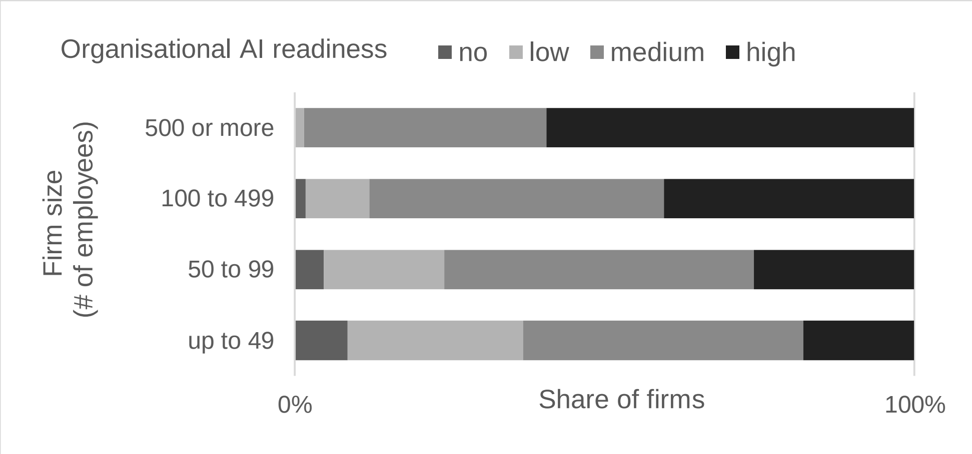


Figure 9: Distribution of technological, organisational, and combined AI readiness

When considering both AI readiness dimensions together, the findings reveal notable distinctions (see Figure 9). Roughly a quarter of all firms either show no readiness (3%) or are at a low level (21%) in terms of combined AI readiness. Medium combined AI readiness is prevalent among manufacturers, with approximately 60% of companies falling into this category. Only about one-sixth of firms (17%) demonstrate high combined AI readiness. It is interesting to note that the proportion of firms with high AI readiness is significantly lower when considering combined AI readiness compared to the separate dimensions. These results underscore the significance of not only considering AI readiness as a combined score but also opening it as a ‘black box’ and examining its two dimensions as distinct groups of related resources.

Further examinations highlight significant differences between firms of different size classes (see Figure 10). While the vast majority of large companies with more than 500 employees have a high level of technological AI readiness, less than 60% of these companies exhibit a high level of organisational AI readiness. In small companies, just under a quarter achieve the highest level of technological readiness, and less than a fifth are organisationally prepared at the highest level.



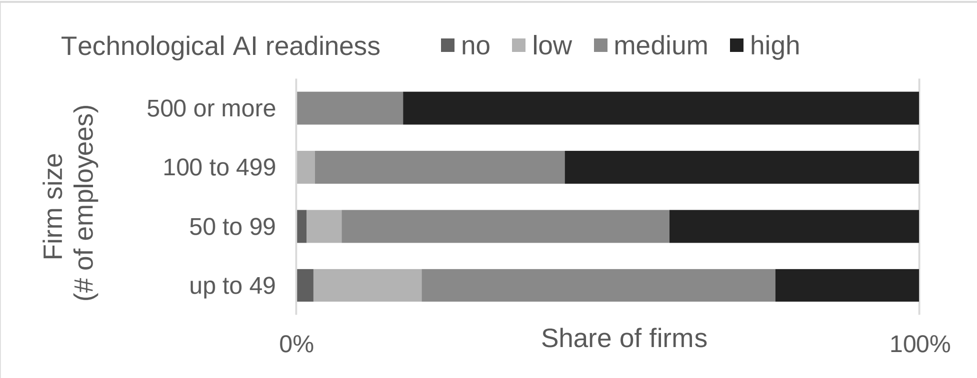


Figure 10: Technological and organisational AI readiness for different firm size groups

Not surprisingly, large companies also have a clear lead in terms of combined AI readiness (see Table 12 in the appendix). However, the reality is different already for medium-sized companies. Only a quarter achieve the highest level of combined AI readiness. Among small companies with fewer than 50 employees, this figure drops to 6%. It's noteworthy that among companies with fewer than 100 employees, still a quarter to a third exhibit either no readiness or only low AI readiness, a share significantly lower than the less than 10% among larger companies. Moreover, bivariate analyses reveal significant variance in combined AI readiness depending on industry affiliation as well as production characteristics. Manufacturers producing complex products and produce in larger series tend to have a higher combined AI readiness, as do system and parts suppliers.

B.4.2 AI Adoption in Production

Secondly, the data is also highly informative regarding the implementation of AI solutions in production (see Figure 11). While 8% of manufacturing firms in Germany use AI in software tools for production management, 7% leverage AI for quality control and 6% for both internal logistics management and machine maintenance. Overall, 14% of German manufacturing companies implement AI in at least one of the four production-specific application areas examined. Thus, we can conclude that the adoption of AI in production is not yet widespread. As of 2022, AI had not become a standard application in manufacturing in Germany. Moreover, the selected application areas appear to be quite specific, with none of the four areas of AI support standing out prominently. Furthermore, companies that do employ AI often utilise it in only one or, at most, two application areas.

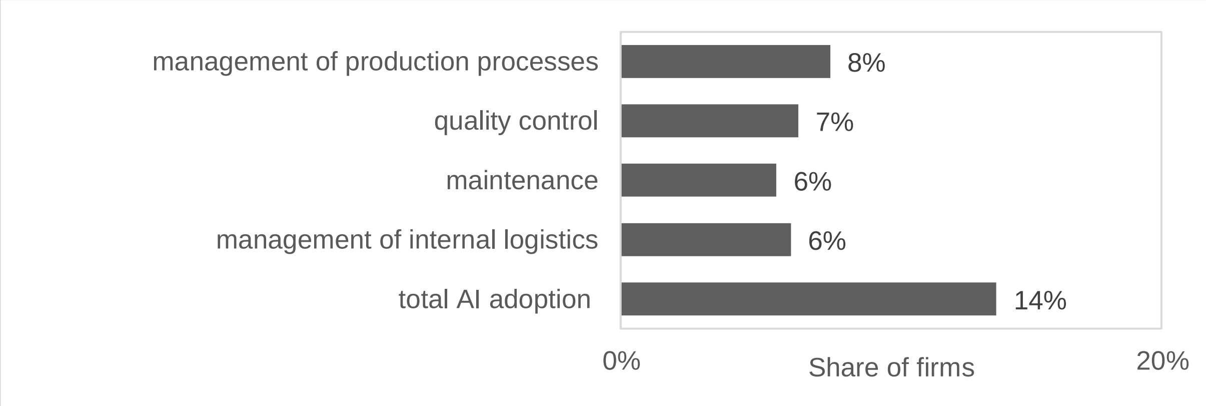


Figure 11: AI adoption per application area in production

There are clear structural differences in the spread of AI (see Table 12 in the appendix). As expected, large companies with more than 500 employees use AI in production much more frequently than companies with fewer employees. In terms of sector, the automotive industry stands out by far. In this sector, almost a third of companies use an AI application in production. The adoption rate of the other sectors differs significantly less, with the exception of the very low rate in the chemical and pharmaceutical industry. There are also clear differences regarding product complexity. 20% of manufacturers of complex products use AI in production compared to 8% of manufacturers of simple products. The differences are smaller regarding batch size and no clear trend can be observed in terms of position in the value chain.

B.4.3 Linking AI Readiness and AI Adoption

To analyse the relationship between AI readiness and adoption in manufacturing companies, we conducted regression analyses.

Table 9 presents the results of three regression model estimations, each for the impact of technological AI readiness, organisational AI readiness and combined AI readiness on the odds of a company being an AI adopter. The three estimated models are statistically significant. The highest explanatory power is reached using the combined AI readiness according to the lowest Log-Likelihood measure.

Looking at the estimation for H1 on the connection between the level of resources related to technological AI readiness and AI adoption, the results of our model, firstly, reveal the significant role of some structural characteristics of the companies that influence the odds of AI adoption and which thus emerge as key drivers of AI adoption. The results underline the role of the industry ($p<0.05$) and the product complexity ($p<0.01$) as decisive factors in the adoption of AI. AI adoption is more likely for medium (factor 1.75) and particularly for high product complexity (factor 3.37) than for companies with simple products. In comparison to the machinery sector, AI adoption is among rubber and plastics producers 2.5 times more likely resp. in the automotive industry the odds are 3 times higher. Batch size and the position of the companies in the value chain seem to not contribute to the model. Finally, for the relation to the firm size a u-shaped relationship is supported as both indicators reveal a statistically significant role and contribute together to the model.

However, when considering the overall impact of the level of resources related to technological AI readiness on AI adoption, the results do not show a statistically significant contribution; the estimation only reveals a contribution at a 10% significance level. Therefore, we must reject H1. However, the estimated odds ratios confirm the expected relationship of an increasing likelihood of AI adoption with higher technological AI readiness.

Table 9: Results of the logistic regression model estimations on AI adoption in production

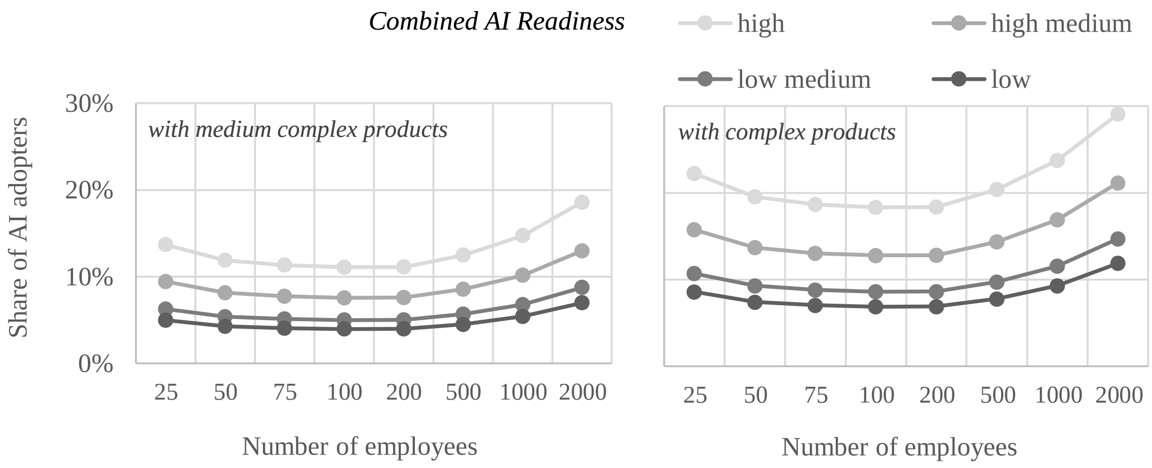
Variables	Model H1 Technological AI readiness		Model H2 Organisational AI readiness		Model H3 Combined AI readiness	
Firm/production characteristics	OR	Sig	OR	Sig	OR	Sig
Firm size		**		**		**
# of employees (Log value)	0,45	**	0,48	*	0,43	**
Squared log value	1,09	**	1,08	**	1,09	**
Sector (Reference: Machinery)		**		**		**
Metal industry	1,76	*	1,82	*	1,82	*
Food and beverage industry	1,95	*	2,20	*	2,17	*
Chemical and pharmaceutical	0,68		0,65		0,66	
Rubber and plastics industry	2,55	***	2,44	***	2,48	***
Electrical/electronics industry	0,96		0,93		0,93	
Automotive industry	3,19	***	2,98	***	3,02	***
Others	1,67		1,67		1,64	
Product complexity (Reference: simple)		***		***		***
Medium complex	1,75	**	1,71	*	1,69	*
High complex	3,37	***	3,20	***	3,04	***
Batch size (Reference: single lot)						
small/medium lot	1,30		1,30		1,24	
big lot	1,77	*	1,82	*	1,69	
Value chain position						
Supplier (system-, part-)	1,20		1,21		1,20	
AI readiness						
Technological AI readiness (Ref. low)		*				
no	0,60					
medium	1,22					
high	1,99	*				
Organisational AI readiness (Ref. low)				**		
no			0,98			
medium			1,33			
high			2,11	**		
Combined AI readiness (Ref. low)						***
no					1,65	
low medium					1,28	
high medium					1,99	**
high					3,04	***
Constant	0,139	*	0,12	**	0,16	*
Model fit						
Log Likelihood/sig.	840,73	***	840,05	***	834,25	***
Cox & Snell R^2	0,06		0,06		0,07	
Nagelkerke R^2	0,11		0,11		0,12	
Explanatory contribution of the AI construct (delta Log Likelihood)	7,81	*	8,49	**	14,29	***

The results for H2 on the link between the level of resources related to organisational AI readiness and AI adoption also support the significance of some structural conditions of the firms.

Again, a statistically significant impact of the industry affiliation, the firm size and the product complexity on AI adoption is estimated. Moreover, the findings demonstrate a statistically significant correlation between the level of resources related to organisational AI readiness of a firm and AI adoption in production ($p<0.05$), even with these structural factors controlled for. Thus, the results support the expected positive link between organisational AI readiness and AI adoption. AI adoption is two times more likely with a high organisational AI readiness than with a low organisational AI readiness. The estimation also still shows a positive influence for the mean level of organisational AI readiness with a factor of 1.13 resp. revealed a negative factor for no organisational AI readiness, even though these estimates are not statistically significant in itself. Due to the statistical significant impact of the construct for the model and the estimated factors, we can uphold H2.

The results of the third regression model estimations (H3) also support the statistically significant correlation between various structural characteristics of the companies and AI adoption. Here too, firm size, sector affiliation and product complexity make a statistically significant explanatory contribution to the model. Again, the batch size and the position in the value chain have no statistically significant contribution to the model. The addition of combined AI readiness clearly improves the estimated model ($p < 0.01$). AI adoption is three times more likely for firms with a high combined AI readiness than for firms with low combined AI readiness. Firms with a higher medium combined AI readiness still have a significant advantage. The odds for having implemented an AI solution in production is two times higher than for firms with a low combined AI readiness. Based on these results, we can uphold H3.

Besides this central finding, we highlight some further details in our empirical analysis. The estimated results already show that, in terms of AI readiness, the differentiation between high AI readiness and high medium readiness is of importance. In contrast, the differentiation of the lower levels does not provide any insights with regard to AI adoption. Figure 12 displays the calculated probabilities of AI adoption for a typical case of a mechanical engineering firm with a single unit production for producing a finished product. The distance for the lines of the various AI readiness levels visualise this central finding. Moreover, Figure 12 also illustrates the u-shaped relationship between firm size and AI adoption. When controlling for sector affiliation, batch size, product complexity and AI readiness, the probability of using AI for larger firms is much higher than for medium sized firms, whereas very small firms also seem to have a higher probability than medium sized firms. This relation becomes especially relevant for producers of complex products. With medium complex production smaller firms seem not positively differ from medium sized firms.



Note: Estimated probabilities of AI adoption by average producers of machinery with single unit production producing finished products showing different levels of AI readiness and product complexity.

Figure 12: The estimated share of AI adoption among firms of the machinery sector depending of the product complexity and firm size

However, as firm size and AI readiness are quite correlated, the regression analyses were repeated separately for small firms with less than 50 employees, for smaller firms with less than 100 employees, and for larger firms with at least 100 employees. The estimated results reveal a quite different picture for smaller firms (see Table 14 in appendix) in contrast to larger firms (see Table 15 in appendix). The tables in the appendix summarize the estimated results at construct level. It is shown whether a construct contributes statistically significantly to the estimation. According to these results, the odds for an AI adoption by smaller firms is affected by the complexity of the produced product as well as the organisational or combined AI readiness level. However, neither the sector affiliation nor the firm size have a relevant impact. The overall explanatory power of these models is rather low. In contrast, the models estimated for larger firms only reveal quite the contrary. The chance of AI adoption is strongly influenced by firm size and sector affiliation. Additionally, the product complexity contributes to the estimation as well. However, the AI readiness level does not affect the estimation. The overall explanatory power of these models is quite high in comparison. To verify these new insights, we also tried to model an interaction between firm size and AI readiness. However, we could not find a fitting relationship. Further research needs to be conducted on this behalf.

B.5 Discussion

Recent studies have shed light on AI adoption from different perspectives (Steininger et al. 2022). Today, we see AI readiness as a combination of various resources companies must have to be able to implement an AI solution (Alsheibani et al. 2018; Heimberger et al. 2023; Horvat and Heimberger 2023; Jöhnk et al. 2021). We also know how companies deal with the orchestration of these resources from a process perspective (Peretz-Andersson et al. 2024). Moreover, we know about the main factors important for the adoption of AI solutions in manufacturing companies (Heimberger et al. 2024b; Kinkel et al. 2022). What remains under-explored in the recent literature is the relationship between AI readiness, understood as the achieved combination of relevant resources, and the actual adoption of AI solutions in manufacturing companies (Dwivedi et al. 2021; Steininger et al. 2022). It is therefore still unclear which specific types of resources and their combinations are most important for the successful introduction of AI solutions and how manufacturing firms can prepare themselves for the introduction of AI in terms of available resources. This paper addresses this research gap by empirically examining how AI-specific resources, which constitute firms' AI readiness, influence the likelihood of AI adoption in manufacturing companies.

Based on organisational readiness for change (Weiner 2009), we structure AI readiness according to the RBV (Barney 1991; Bharadwaj 2000; Grant 1991) into two dimensions that represent the different resources required for AI adoption: technological AI readiness, which includes tangible assets, and organisational AI readiness, which includes both intangible and human resources. We further use this framework to empirically analyse the readiness of German manufacturing companies for AI adoption in production processes.

Through descriptive analysis, three notable findings emerge. First, regarding the readiness of manufacturing companies, the majority of manufacturers achieve a medium AI readiness level. Our results are similar to the analyses of AI readiness by Lerch et al. (2022a), but in comparison they show a general increase in AI readiness in the manufacturing sector (with the exception of high readiness). This might be due to the fact that Lerch et al. (2022a) use older data and that firms in the manufacturing sector are preparing for AI to a greater extent and taking appropriate measures. However, it should also be noted that the two AI readiness models draw on different factors, which makes a direct comparison more difficult. Second, our results show that AI readiness is strongly influenced by structural conditions in the manufacturing firms, which is consistent with the findings of recent studies (Chatterjee et al. 2021). Our results suggest that the company size significantly influences AI readiness (Chatterjee et al. 2021; Mikalef et al. 2019), with small manufacturers prioritising organisational preparedness, whereas larger companies demonstrate greater technological readiness. This difference may stem from various resource constraints, such as financial limitations and a shortage of specialised personnel, coupled with uncertainties regarding the return on investment of technology (Jöhnk et al. 2021). Third, despite relatively high AI readiness levels, we show empirically that actual AI adoption in manufacturing remains limited. We measure an adoption rate of around 14 per cent for AI in the production context in Germany. This result on AI adoption is consistent with empirical data from recent studies. According to Rammer et al. (2022b) , AI use in the electronics industry in Germany is 11 per cent, with similar adoption rates visible in international comparisons, such as reported by McElheran et al. (2024), who measure AI adoption of 12 per cent among manufacturing companies in the United States.

The gap between AI readiness and AI adoption suggests some apprehension towards AI implementation, possibly caused by concerns such as uncertainty about how AI works and hesitancy, as highlighted in AI readiness framework studies (Alsheibani et al. 2018; Heimberger et al. 2023; Jöhnk et al. 2021). Additionally, AI's novelty in the traditional manufacturing industry aligns with Rogers' innovation diffusion curve (1983), indicating an early-stage adoption akin to innovators or early adopters. We summarise our finding derived from the outcomes of the empirical analysis:

Finding 1: Despite a relatively high level of readiness for AI among manufacturing companies in Germany, actual adoption of AI in production is still low in practice. It seems that many companies are hesitant to use AI despite having strong AI-related resources that are relevant for the technical and organisational readiness to implement and work with AI.

To delve deeper into this phenomenon, we conducted multiple regression analyses. Our results unveil the varying significance of technological, organisational, and combined AI readiness in exploring the likelihood of AI adoption in manufacturing. Initially, while technological AI readiness is considered a fundamental prerequisite for firms to adopt AI solutions, our analysis does not reveal significant differences between various levels of technological AI readiness in explaining the odds of AI adoption. Nonetheless, the estimated odds ratios affirm the anticipated relationship, indicating a higher likelihood of AI adoption with increased technological AI readiness. In contrast, organisational AI readiness emerges as a pivotal factor, with companies exhibiting high organisational readiness being twice as likely to adopt AI compared to those with low organisational readiness. This result contradicts the study by Merhi and Harfouche (2023), which finds that the technological side is more vital for AI adoption than organisational factors. Despite this finding, Merhi and Harfouche (2023) also emphasise the importance of organisational factors, which is consistent with our finding about combined AI readiness. When considering Germany's manufacturing industry as a whole, our models consistently demonstrate that combined AI readiness significantly contributes to explaining AI adoption. This finding aligns with recent literature, underscoring AI's dual nature, which encompasses both technological complexity and organisational challenges, rather than thinking one-dimensionally (Merhi and Harfouche 2023; Mikalef et al. 2019; Mikalef et al. 2019; Mikalef et al. 2020; Mikalef and Gupta 2021b; Steininger et al. 2022). These findings underscore the multifaceted nature of AI adoption in manufacturing, emphasizing the intertwined roles of resources relevant to technological and organisational preparedness. It is therefore important for firms to strengthen both technological and organisational resources in order to be better prepared for AI adoption and to avoid a siloed perspective. They provide valuable insights for policymakers and practitioners aiming to facilitate AI integration within manufacturing firms. In summary, we summarise the following finding:

Finding 2: Manufacturing companies that consider both technological and organisational aspects and create holistic AI readiness are more likely to implement AI in a production context.

In our regression analysis, we researched into additional structural characteristics that play a significant role in the uptake of AI solutions in production (McElheran et al. 2024; Rammer et al. 2022b). Notably, the features of manufactured products emerge as pivotal factors influencing the decision to integrate AI into production processes (McElheran et al. 2024). Specifically, for manufacturers dealing with highly complex products, the adoption of AI proves notably compelling, aligning with findings by Kinkel et al. (2022). This trend is especially pronounced in complex production processes often associated with high-tech products in smaller batch sizes (Hobday 1998). This pattern is particularly reflected in the sector analysis, where the automotive industry, identified as a complex and cost-intensive sector (Demlehner et al. 2021), notably stands out in AI adoption for production processes. In contrast, our results indicate that batch size and the position of a firm in the value chain, do not significantly contribute to the explanatory power of our analysis. Therefore, we summarise:

Finding 3: The adoption of AI in the manufacturing industry is significantly influenced by the structural characteristics of the companies operating in this sector. Certain factors exert pressure and promote the introduction of AI, while other factors impose distinctive constraints. In particular, companies that manufacture complex products, especially in highly specialised industries such as automotive, are more attuned to AI adoption.

Finally, our analysis underscores the critical importance of differentiating between high and medium levels of AI readiness. Conversely, distinguishing between lower levels of factors relevant for readiness seems not to yield meaningful insights regarding AI adoption. In this regard, our study additionally emphasises the significant role that firm size plays (Collins et al. 2021; McElheran et al. 2024; Rammer et al. 2022b) and reveals a U-shaped relationship between firm size and AI adoption. Controlling for sector affiliation, batch size, product complexity, and AI readiness, larger firms demonstrate a significantly higher probability of using AI compared to medium-sized firms, while very small firms seems also to exhibit a higher probability. This correlation becomes particularly clear for manufacturers of complex products, the differences between companies with different levels of AI readiness are even more pronounced here.

Finding 4: The relationship between firm size and AI adoption follow a U-shape. Larger and very small manufacturing companies demonstrate a higher probability of AI adoption compared to medium-sized companies.

Additional multivariate analysis with respect to the significance of the firm size show that the introduction of AI at smaller companies is influenced to a relevant extent by AI readiness. Conversely, for larger companies, the adoption of AI is primarily influenced by structural factors such as company size and the specific industry they operate in, AI readiness does not provide any additional explanation.

B.6 Conclusions

This study makes several important contributions to the research field by examining how AI readiness affects the likelihood of AI adoption in the production processes of manufacturing firms. The implications of this research are far-reaching, making contributions to production research and enhancing theoretical discussions across multiple domains.

B.6.1 Theoretical Contributions

Building on the organisational readiness for change of companies, which we conceptualise based on the RBV, we propose a framework to analyse the role of various types of resources, and their combinations, in relation to technological and organisational readiness for the adoption of AI solutions in production companies. We distinguish between two interrelated dimensions of analysis: AI readiness and AI adoption: AI readiness serves as the foundation, representing a firm's technological and organisational readiness to adopt AI solutions (Alsheibani et al. 2019; Heimberger et al. 2023; Horvat et al. 2023; Horvat and Heimberger 2023; Jöhnk et al. 2021). The availability of these fundamental resources, on which AI readiness is built, increases the likelihood of successful AI implementation in the production context (Chatterjee et al. 2021; Ghani et al. 2022; Kinkel et al. 2023). The dimension of AI adoption provides a theoretical lens to explore the gap between technological and organisational readiness for AI and its actual implementation. This perspective underscores the critical role of deployment strategies in bridging this gap, offering valuable insights into the interplay between readiness and real-world AI adoption in production companies.

Our study introduces a novel approach to operationalising AI readiness by categorizing it into two dimensions: technological AI readiness and organisational AI readiness (see Figure 7). This dual perspective leads to a combined AI readiness score, structured as an ordinal indicator with five levels: no readiness, low readiness, lower medium readiness, higher medium readiness, and high readiness (see Figure 8). This operationalisation provides a more granular understanding of AI readiness, but is still simple enough for practical usage, and its implications for AI capability development in manufacturing companies, offering an approach that can be used in future research.

Empirically, we contribute to the literature by analysing unique data about German manufacturing firms from the 2022 GMS dataset. To the best of our knowledge, our study provides the first broad-based empirical research of the relationship between AI readiness and actual AI adoption. Our results empirically confirm that a combined AI readiness, which fosters both technological and organisational readiness, has a positive influence on AI adoption in a production context (Jöhnk et al. 2021; Uren and Edwards 2023). Manufacturing firms adopt different strategies when building their AI readiness and developing and coordinating the associated resources for AI implementation, a result that is consistent with current research (Horvat et al. 2023; Steininger et al. 2022). In particular, we identify the significant role of structural characteristics, such as firm size, in these strategies: smaller manufacturers tend to prioritise organisational preparedness, focusing on change management and workforce readiness, while larger companies exhibit higher levels of technological readiness, leveraging more advanced digital infrastructures. These results contribute to the existing literature (Horvat et al. 2023; Kinkel et al. 2022; McElheran et al. 2024; Steininger et al. 2022) by highlighting the diverse AI readiness development strategies firms employ based on their characteristics.

Furthermore, we explore the role of structural and organisational characteristics in AI adoption (Chatterjee et al. 2021; Dwivedi et al. 2021; Steininger et al. 2022). Our findings show that structural factors such as company size and product complexity significantly influence the relationship between AI readiness and adoption. For example, our study identifies a U-shaped relationship between company size and AI adoption rates, with both small and large companies showing higher adoption levels than medium-sized firms. Additionally, we find that product complexity amplifies the relevance of various levels of combined AI readiness for AI adoption. These structural factors suggest that even when resources are available, certain structural characteristics and organisational configurations may hinder the adoption process, offering new insights into the barriers manufacturers face when implementing AI technologies.

B.6.2 Practical Implications

The adoption of AI in production is a multidimensional challenge, requiring more than the availability of appropriate technology. Practitioners must promote readiness, which is important at both the organisational and technological levels, remain sensitive to industry- and company-specific dynamics, and implement targeted measures to promote AI readiness as companies move towards AI adoption. From a practical standpoint, our research offers valuable guidance for managers in manufacturing firms tasked with integrating AI solutions into their production operations.

First, our results reveal a persistent gap between AI readiness and actual AI adoption. Despite a large share of manufacturing firms exhibiting medium to high levels of AI readiness, adoption rates in production remain low. This indicates that while resource availability is important, it alone does not ensure implementation. Managers should use our readiness assessment tool to evaluate their condition (see Hussain and Papastathopoulos (2022)) and complement this by implementing targeted internal initiatives (Uren and Edwards 2023). Early steps such as awareness-building, employee engagement, and pilot projects can help reduce hesitancy and clarify the practical value of AI in production. This implication also extends to policymakers, who should foster investment in AI technologies and create incentives to accelerate AI uptake in manufacturing (Kinkel et al. 2023; Rammer et al. 2022b).

Second, our analysis shows that combined AI readiness, i.a. the integration of both technological and organisational resources, significantly increases the likelihood of AI adoption. While technological readiness remains a necessary foundation, organisational readiness exerts a greater influence on adoption. Managers should therefore prioritise the development of organisational capabilities, including intangible and human resources, before making substantial investments in technical infrastructure. An isolated focus on technology is insufficient (Jöhnk et al. 2021; Uren and Edwards 2023). Using our combined AI readiness framework, firms can take targeted steps to enhance both dimensions and improve their chances of successful AI adoption.

Third, we find that firms producing complex, high-tech products, especially in specialised sectors such as the automotive industry, are more likely to adopt AI (Kinkel et al. 2022). These firms face both greater pressure and more compelling opportunities for AI implementation (Demlehner et al. 2021). For this reason, adoption strategies must be aligned with structural characteristics. Managers should tailor their AI adoption strategies to reflect industry-specific and product-related factors. In particular, manufacturers of complex or customised products should prioritise AI use cases that enhance process efficiency, product quality, or innovation.

Fourth, our findings indicate that AI adoption follows a U-shaped pattern in relation to firm size. Small and large firms have distinct advantages or motivations for adopting AI, whereas medium-sized firms may face unique challenges (Kinkel et al. 2022; Sjödin et al. 2021; Zavodna et al. 2024). Smaller firms are highly dependent on their level of AI readiness, whereas adoption in larger firms is more strongly influenced by structural characteristics. Medium-sized firms may struggle with both limited agility and constrained resources, which can slow adoption (Kinkel et al. 2022). Based on this, we recommend that firms adapt their AI strategies to their specific size: Small firms should focus on strengthening their AI readiness and consider seeking external support. Medium-sized firms may benefit from additional resources, partnerships, or collaboration to overcome capacity limitations. Large firms should address internal structural barriers and ensure that AI initiatives are aligned with broader organisational objectives.

B.6.3 Limitations and Future Research

While our study provides valuable insights into AI adoption in the manufacturing industry, certain limitations pave the way for future research opportunities.

Firstly, while the AI readiness indices we developed (technological, organisational and combined AI readiness) capture key factors influencing adoption, the scope of our model remains focused on a selected set of relevant factors. We acknowledge that additional factors, both technical and organisational, may also play a crucial role in shaping AI readiness and adoption outcomes. In particular, our current model does not explicitly incorporate ethical and societal aspects, which are gaining increasing importance in both academic discourse and practical implementation of AI (Heimberger et al. 2024b). For instance, concerns about job replacement, as highlighted by Frey and Osborne (2017), can significantly influence employee attitudes and, consequently, organisational readiness. Similarly, data privacy concerns, especially in data-intensive production environments, can create barriers to AI adoption, both from a regulatory and workforce trust perspective (Wieringa et al. 2021). Although these factors were not within the primary scope of our study, we see them as important contextual factors that deserve deeper investigation. Future research could meaningfully expand on our readiness framework by integrating ethical and societal considerations alongside additional organisational and technological variables. This broader approach could provide a more nuanced understanding of AI readiness and adoption and support the development of holistic and context-sensitive implementation strategies.

Secondly, in our analysis we assume an additive relationship between the dimensions and do not analyse how technological and organisational AI readiness and their individual factors might influence each other. We see potential here for future research that analyses how different factors of technological and organisational readiness are linked and how they can mutually promote or hinder each other. Structural equation modelling approaches, which can also be used to analyse the relationships between the independent variables, are worth considering in future research on AI readiness factors, as they have already been applied to AI adoption (Baabdullah 2024). Another possibility would be to further examine the factors in terms of their weighting and thus identify particularly crucial factors, as proposed by Merhi and Harfouche (2023).

Third, we highlight that while firms may possess the necessary resources, the ability to effectively coordinate and deploy these resources is equally critical. This perspective aligns with the traditional capability-based view within the RBV framework (Amit and Schoemaker 1993; Teece et al. 1997), which posits that firms require company-specific, unique (dynamic) capabilities to align their resource base with actionable strategies, thereby achieving competitive advantages (Mikalef et al. 2019; Mikalef and Gupta 2021b; Peretz-Andersson et al. 2024; Steininger et al. 2022). Future research should delve deeper into identifying the specific capabilities that play a pivotal role and exploring how firms develop these capabilities.

Fourth, for the control of a firm's market context and further internal dynamics, we only include a selection of variables in our data analysis. It would be beneficial for future studies to incorporate additional factors, such as competitive strategy, management support, risk propensity or financial resources, to provide a more comprehensive understanding of the factors influencing

AI adoption in manufacturing. It would be important to specifically examine the different conditions for larger, medium and small companies in the analyses.

From a conceptual point of view, our study focuses on the fundamental analysis of the adoption of AI. We analyse those companies that actually use AI in their production process not going into detail of the extend of use or the contribution to the production. By doing that, our study covers four major AI applications within the production context. Future research could extend this view to include a broader range of production applications and explore the adoption of AI in additional areas of the production process such as shift allocation, or task assignment as well as in other areas of manufacturing companies, such as product development, procurement, or marketing. Since we consider AI adoption as a binary variable (Dahlke et al. 2024; Zhan et al. 2024), our analyses do not allow any conclusions to be drawn about the status and intensity of use (as proposed by Kinkel et al. (2022), Kinkel et al. (2023) or McElheran et al. (2024)). In future empirical studies, this would certainly be an interesting addition in order to better understand the state of adoption at the process level and to be able to make better statements about the depth of AI use in German manufacturing firms.

While our study focuses on analysing AI adopters in the German manufacturing industry, future research could shed light on non-AI adopters by exploring various cases such as failed adoption, discontinued adoption, unexpected outcomes, and the general relationship between AI adoption and expected firm performance. Despite a general willingness and increasing readiness to adopt AI, our results show that adoption remains limited. We do not address cases where companies, although AI-ready, ultimately decided against adoption, or where AI adoption efforts failed or did not deliver the expected outcomes (Sun 2013). Future studies could investigate these aspects to uncover barriers to adoption and better understand why some AI initiatives are unsuccessful or abandoned. Longitudinal case study research would be particularly suitable for in-depth analysis of individual implementation processes (Langley and Truax 1994). Additionally, examining the relationship between AI adoption and firm performance (Plewa et al. 2012) could help explore the economic rationale behind AI investments, identify conditions under which AI leads to performance improvements (see Baabdullah (2024)), and explain why some firms may choose not to implement AI despite having the readiness in place. Such research would provide a more nuanced understanding of the practical limitations of AI adoption and its broader impact on business strategy and competitive advantage.

Finally, our study focuses solely on the industry in Germany, limiting the generalisability of our findings to other countries and regions. Future studies could expand their scope to include multiple countries, allowing for comparisons to assess the influence of country-specific circumstances on AI adoption readiness. In addition, it would be of great interest to repeat the analyses in the near future, as the rapid development of the applications offered, the increasing usability of ready-made solutions and the development of the support structure for AI implementation will significantly change AI adoption. Thus, future AI adoption analyses based on GMS may be able to show further movement of companies in Germany along Rogers (1983) diffusion curve in terms of AI adoption.

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B.7 Appendix

Table 10: Sample characteristics of analysed data, N=1,130

		%
Firm size	< 50 employees	44%
	50 to 249 employees	42%
	> 250 employees	14%
Sector	Metal industry	22%
	Mechanical engineering	20%
	Rubber and plastics industry	15%
	Food and beverage industry	9%
	Electrical/electronics industry	8%
	Chemical and pharmaceutical	5%
	Vehicle construction	5%
	Others	15%
Product complexity	Simple complexity of products	21%
	Medium complexity of products	49%
	High complexity of products	30%
Batch size	Single lot manufacturing	26%
	Small/medium lot manufacturing	57%
	Big lot manufacturing	18%
N = 1,130		

Table 11: Distribution of the constitutive factors for technological and organisational AI readiness in German manufacturing

Technological AI readiness		
Data availability	No data availability (none of the systems used)	18%
	Basic data availability (1 or 2 systems used)	64%
	Large data availability (3 or 4 systems used)	18%
IT infrastructure	No employees assigned to IT infrastructure	31%
	< 5% IT employees	43%
	5% or more IT employees	26%
Data security	No security measures implemented	7%
	A few security measures (1 or 2 of 4 levels)	60%
	Various security (3 or 4 of 4 levels)	33%
Organisational AI readiness		
Skills	No digital skills required (no digital tools used)	47%
	Few digital skills required (at least 1 digital tool)	35%
	Digital skills required (more than 1 tool)	18%
Training	No training measures offered	18%
	Few training measures offered (1 of 3)	31%
	Several training measures offered (at least 2)	51%
Innovation culture	No innovation culture	26%
	Basic innovation culture (1 of 3)	29%
	Open innovation culture (at least 2)	44%
Cooperation	No cooperation	43%
	Basic R&D cooperation (1 of 3)	20%
	Broad R&D cooperation (at least 2)	37%

Table 12: AI readiness and AI adoption by manufacturers in Germany depending on structural and production features of the firms

	Combined AI readiness					
	no	low	low medium	high medium	high	AI adoption
*Firm size (# of employees) ***/****						
up to 49 employees	6%	31%	**34%**	22%	6%	12%
50 to 99 employees	3%	21%	29%	**32%**	15%	14%
100 to 499 employees	1%	9%	25%	**39%**	27%	14%
500 or more employees	0%	2%	9%	36%	**53%**	**28%**
*Sector groups (NACE rev. 2) ***/****						
metal products	3%	27%	27%	**29%**	14%	14%
machinery	7%	**32%**	30%	21%	10%	11%
rubber and plastics industry	2%	5%	**39%**	33%	21%	18%
food and beverage industry	5%	21%	29%	**32%**	14%	14%
chemical and pharmaceutical industry	1%	5%	31%	**41%**	21%	7%
electrical/electronic industry	1%	15%	**32%**	31%	22%	12%
automotive industry	2%	17%	17%	31%	**33%**	**31%**
other sectors	7%	**28%**	25%	26%	14%	12%
*Batch size ***/***						
single lot manufacturing	3%	27%	**31%**	27%	12%	11%
small/medium lot manufacturing	4%	20%	30%	**31%**	16%	13%
big lot manufacturing	2%	15%	23%	**31%**	29%	**20%**
*Product complexity ***/****						
simple products	7%	30%	**34%**	22%	8%	8%
medium complex products	3%	22%	30%	**31%**	15%	13%
complex products	2%	13%	24%	**34%**	27%	**20%**
Position in the value chain (multiple entries possible)						
producer of finished goods for consumers ***/n.s.	5%	26%	**29%**	26%	14%	12%
final products for industry n.s./*	3%	18%	28%	**33%**	18%	12%
supplier (system -, part -) ***/**	2%	18%	28%	**32%**	21%	**17%**
contract manufacturer **/n.s.	4%	27%	**30%**	28%	11%	10%
Total	3%	21%	**29%**	**30%**	17%	14%

Note: Group comparison using Kruskall-Wallis test.
Significance levels: *** p<0.01; ** p<0.05; * p<0.1. Modal values are marked in bold.

Table 13: Summary of estimated results of the logistic regression model estimations on AI adoption in production for smaller firms (less than 100 employees)

Construct	**Model H1 Technological AI readiness**		**Model H2 Organisational AI readiness**		**Model H3 Combined AI readiness**	
	Sig		Sig		Sig	
Firm and production characteristics						
Firm size		n.s.		n.s.		n.s.
Sector		n.s.		n.s.		n.s.
Product complexity		**		**		**
Batch size		n.s.		n.s.		n.s.
Value chain position		n.s.		n.s.		n.s.
AI readiness						
Technological AI readiness		*				
Organisational AI readiness				**		
Combined AI readiness						**
Model fit						
Log Likelihood/sig.	531,659	**	531,07	***	527,60	**
Cox & Snell R2	3,5%		3,6%		4,0%	
Nagelkerke R2	6,6%		6,8%		7,6%	
Explanatory contribution of the AI construct (delta Log Likelihood)	5,839	*	6,43	**	9,90	**
N= 734; firms with less than 100 employees Significance levels: *** p<0.01; ** p<0.05; * p<0.1						

Table 14: Summary of estimated results of the logistic regression model estimations on AI adoption in production for small firms (less than 50 employees)

Construct	**Model H1 Technological AI readiness**		**Model H2 Organisational AI readiness**		**Model H3 Combined AI readiness**	
	Sig		Sig		Sig	
Firm and production characteristics						
Firm size	n.s.		n.s.		n.s.	
Sector	n.s.		n.s.		*	
Product complexity	**		***		***	
Batch size	n.s.		n.s.		n.s.	
Value chain position	n.s.		n.s.		n.s.	
AI readiness						
Technological AI readiness	**					
Organisational AI readiness			**			
Combined AI readiness					***	
Model fit						
Log Likelihood/sig.	337,726	**	338,57	***	334,71	***
Cox & Snell R2	5,7%		5,6%		6,3%	
Nagelkerke R2	11,1%		10,8%		12,2%	
Explanatory contribution of the AI construct (delta Log Likelihood)	8,594	**	7,75	**	11,61	***
N=502; firms with less than 50 employees Significance levels: *** p<0.01; ** p<0.05; * p<0.1						

Table 15: Summary of estimated results of the logistic regression model estimations on AI adoption in production for larger firms (100 or more employees)

Construct	**Model H1 Technological AI readiness**		**Model H2 Organisational AI readiness**		**Model H3 Combined AI readiness**	
	Sig		Sig		Sig	
Firm and production characteristics						
Firm size	**		**		**	
Sector	*		*		*	
Product complexity	**		***		***	
Batch size	n.s.		n.s.		n.s.	
Value chain position	n.s.		n.s.		n.s.	
AI readiness						
Technological AI readiness	n.s.					
Organisational AI readiness			n.s.			
Combined AI readiness					n.s.	
Model fit						
Log Likelihood/sig.	299,790	***	300,82	***	298,56	***
Cox & Snell R2	12,0%		11,8%		12,3%	
Nagelkerke R2	20,4%		20,0%		20,9%	
Explanatory contribution of the AI construct (delta Log Likelihood)	2,663		1,63		3,90	
N= 396; firms with 100 and more employees Significance levels: *** p<0.01; ** p<0.05; * p<0.1						

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C AI-readiness and Production Resilience: Empirical Evidence From German Manufacturing in Times of the Covid-19 Pandemic[3]

Abstract:

The outbreak of the Covid-19 pandemic led to restrictions in production worldwide. Numerous firms were affected and unable to keep up production due to lockdowns. In disruptive events like this, the resilience of the production system is of central importance, as the survivability of the entire firm depends on it. In this context, the literature argues that cutting-edge technologies, such as Artificial Intelligence (AI), raise the proactive and reactive capabilities of firms, enabling them to better resist and recover from disruptive events and thus, show a higher resilience. This paper takes up this topic and observes the Covid-19 pandemic with the aim to analyse whether a firm's AI-readiness had an impact on its production resilience during the spring 2020 lockdown in Germany. For this purpose, we combine two large-scale surveys containing data from 237 manufacturers in Germany and test hypotheses based on quantitative analyses. Our results show that firms could indeed benefit from AI-enabled production during the lockdown. However, it is also clear that manufacturers have to exceed a certain AI threshold to significantly increase their resilient capabilities and realise positive effects. Our findings not only hold implications for research, but also provide recommendations for the resilience management of manufacturers.

Keywords: Artificial Intelligence, resilience, Covid-19 pandemic, industrial production, manufacturing

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C.1 Introduction

The digitisation of production currently represents one of the central challenges for manufacturers (Kagermann 2015). Their transformation is giving rise to new cutting-edge technologies that open up completely new potentials for industrial companies and can lead to significant efficiency gains (Drobot 2020; Koh et al. 2019). One of these cutting-edge technologies, which has increasingly become the focus of interest in recent years, is Artificial Intelligence (AI) (Chien et al. 2020; Drobot 2020; Ivanov et al. 2021). AI can be integrated with other innovative production technologies (Rodríguez-Espíndola et al. 2020; Sahu et al. 2021), which can result in the redesign or reconfiguration of a firm's entire production system (Queiroz et al. 2020b). The various AI applications using learning-based algorithms and big data are therefore leading to a completely new operations management paradigm (Dhamija and Bag 2020; Sahu et al. 2021).

In the case of unforeseen disruptive events, the organisation of the production system and operations management plays a crucial role (Queiroz et al. 2020a). Such events, for example, require companies to reorganise existing processes or to adopt certain technologies as an operational countermeasure to enable better responsiveness in new situations. Here, entire production systems may face new conditions and need to be able to react flexibly to fluctuations in demand. The survivability of the entire firm in the case of unforeseeable events thus depends to a large extent on the resilience of the production processes and their organization.

This fact became particularly clear during the global outbreak of the Covid-19 pandemic (Kumar et al. 2020). The rapid spread of the Coronavirus in the winter of 2019/20 led to lockdowns in many advanced industrialised economies (Kumar et al. 2020; UNIDO 2020). With the aim of limiting interpersonal contact as far as possible, large parts of industrial production were slowed down. Numerous companies were unable to uphold their production, some supply chains collapsed, and usual working hours were reduced (Kumar et al. 2020; Xu et al. 2020). Nevertheless, some firms were able to keep up production despite the lockdown and thus showed higher resilience to the production constraints than other firms.

In this context, recent literature argues that firms equipped with cutting-edge technologies in their production are more agile and robust to the onset of production constraints (Ivanov and Dolgui 2021; Javaid et al. 2020). In particular, AI applications that combine big data and learning-based algorithms are expected to be significantly more powerful than conventional production technologies in this regard (Belhadi et al. 2021b; Ivanov and Dolgui 2020). While big data provides the information base for real-time decision making (Javaid et al. 2020), learning-based algorithms raise the data analytics capabilities of firms. As a result, AI technologies and systems are able to increase the information processing capability of companies (Belhadi et al. 2021a; Dubey et al. 2021), allowing them to better resist and recover from unforeseeable disruptive events and hence, to increase their resilience (Heinicke 2014).

In production systems, AI technologies are often integrated with other cutting-edge technologies, such as robotics, cyber-physical production systems, 3D-printing, augmented reality-applications, or operations management tools (Javaid et al. 2020; Kumar et al. 2020; Rodríguez-Espíndola et al. 2020; Sahu et al. 2021). Since not all cutting-edge technologies that support the use of AI are used by all companies, the majority of product manufacturers is currently still on the path to AI-enabled production. The AI-readiness of each single manufacturer therefore varies greatly in practice (Jöhnk et al. 2021). In order to analyse how ready companies are to integrate AI technologies and systems into their production, readiness concepts are a suitable tool to create a structured measurement framework (e.g. Holmstrom (2021), Jöhnk et al. (2021), Heimberger et al. (2022)).

Given that AI-readiness can be measured in terms of the use of AI-enabling technologies, the question for managers is whether a manufacturer's level of AI-readiness is also related to its resilience to production constraints triggered by the Covid-19 pandemic. The pandemic is complex, it occurs in waves, whose peak phases have a particularly high incidence of infection and result in lockdowns of public life. This in turn affects the production system of manufacturers and hence, the operations management (Kumar et al. 2020). Thus, the question is not only whether firms with a higher AI-readiness are more robust against productions constraints and better able to recover from lockdown, but also whether they show a higher agility and therefore already undertake measures during the lockdown to counteract potential production constraints.

However, little is currently known whether AI technologies actually increase the production system resilience of companies or what impact they have on the operations management in the case of the Covid-19 pandemic (Dwivedi et al. 2021; Ivanov et al. 2021; Queiroz et al. 2020a). Therefore, the objective of our paper is to analyse the relationship between AI-enabled production and firms' production resilience during the Covid-19 pandemic. Based on the assumptions made so far, we formulate the following research question (RQ) for further investigation:

RQ: Do product manufacturers with a higher AI-readiness also show a higher production resilience to the restrictions of the Covid-19 pandemic?

To answer this research question, we use a large-scale special survey that was conducted in late summer of 2020 and contains firm-level data from 237 manufacturing companies located in Germany. This special survey is matched with a recurring survey of the German manufacturing sector (Jäger and Maloca 2019), which is conducted every three years and provides information from the same 237 firms on structural conditions and AI-enabling technologies used. Chapter 2 first lays out the theoretical background of this paper, while chapter 3 derives research hypotheses that focus on the interplay between AI-readiness and production resilience. In chapter 4, we develop a model to measure the manufacturers' AI-readiness as well as its resilient capabilities, before the research hypotheses are subsequently tested by quantitative analysis (chapter 5). We close with a discussion (chapter 6) as well as the implications for research and management, limitations and an outlook on future research (chapter 7).

C.2 Theoretical Background

C.2.1 Production Resilience

Rapidly changing environmental conditions in recent years have led to a need for manufacturing companies to become increasingly responsive. In addition to unforeseeable events another challenge for manufacturers are the globalized and highly dispersed supply chains that are influenced by the current turbulences on the market (Kapoor et al. 2021). Consequently, supply chain resilience and how manufacturers can strengthen it have been increasingly studied in recent years (Wamba et al. 2020; Wong et al. 2020). Under such harsh conditions, another crucial key success factor for a firm represents the resilience of its production processes and their organization and hence, its production resilience. In this context Mwangola (2018) defines resilience in manufacturing as "the extent to which manufacturing activities are able to withstand and/or quickly recover from disruptions that pose as a threat to manufacturing operations". This implies that the resilience of production processes includes two dimensions: robustness and agility (Heinicke 2014; Wieland and Wallenburg 2013). On the one hand, robustness characterises the proactive preparedness for unexpected events as well as the ability to withstand them. Anticipation, forecasting and prevention capabilities play a crucial role here. On the other hand, adapting reactively to new requirements, known as agility, includes the capability to respond appropriately to unexpected disruptions and to recover quickly from them (Mwangola 2018; Wieland and Wallenburg 2013).

Looking at a system's resilience, in our case a production system, three complementary resilience capacities are needed (Romero et al. 2021; Vugrin et al. 2010): (i) absorptive capacity, i.

e. the ability of a system to absorb a disruptive event; (ii) adaptive capacity, i. e. the ability to respond and adapt appropriately to an event; (iii) restorative capacity, i. e. the ability of the system to recover from an unforeseen event. While the first resilience capacity belongs to the dimension robustness, the other two capacities address the dimension agility. Consequently, "system resilience" covers both dimensions of resilience and can be increased by increasing one of the three complementary capacities.

C.2.2 Capabilities for Production Resilience

According to the organisational information processing theory (OIPT) (Galbraith 1974; Makkonen 2021), the information processing capability plays a central role in managing uncertainty, risk, and volatility as a result of internal and external turbulence. Strategically considered, it becomes essential for firms to develop such information processing capabilities to be able to sustain a certain performance level under changing environmental conditions. In this context, AI plays a decisive role, because AI collects and creates big data from external environment, analyses it by using learning-based algorithms, and then develops new approaches to respond to future environmental changes (Grover et al. 2022). In addition, big data supports companies in real-time decision making (Javaid et al. 2020) and strengthens their data analytics skills, which in turn support their information processing capabilities (Dubey et al. 2021). Moreover, AI is not only able to identify more information for developing creative ideas, thus strengthening resourcefulness, but also helping to overcome information processing constraints (Haefner et al. 2021). From this, literature concludes that AI is able to directly support and improve the information processing capability of companies.

There are also other theoretical strengths, in addition to OIPT, dealing with the relationship between the development of capabilities and the performance of firms. One of the most cited theories in this context is the dynamic capability view (DCV) of the strategic management literature (Chari et al. 2022; Gupta, S., Modgil, S., Gunasekaran, A. and Bag, S. 2020; Lin et al. 2020). According to the DCV there are two main types of capabilities, which are essential for gaining performance in companies. The first group are the so-called lower-order operative capabilities used for exploiting a firm's current resources through day-to-day operations (Winter 2003). The second group are higher-order dynamic capabilities required to alter a firm's resource base by integrating, building, and reconfiguring competences (Eisenhardt and Martin 2000; Teece et al. 1997). In this context, the DCV sees AI technologies and systems themselves as lower-order operative capabilities, but which form the basis for companies to develop higher-order dynamic capabilities (Belhadi et al. 2021a; Wamba et al. 2020). Mwangola (2018) again argues that resilience itself should be counted among the higher-order dynamic capabilities. Accordingly, AI technologies and systems as a lower-order capability are able to trigger the development of resilient capabilities, as a higher-order dynamic capability, in the firm. These higher-order dynamic capabilities are in turn not only necessary to create a better match between a company's resource configuration and its environmental conditions (Zahra et al. 2006), but also to be able to systematically reconfigure operational capabilities (Zott 2003).

In both theoretical perspectives, OIPT and DCV, AI technologies and systems, using big data and learning-based algorithms, can be seen as the basis for building the capabilities needed for firms to adapt to external conditions and unforeseen events. Considering manufacturers, establishing an AI-enabling production can be thus understood as an enabler for developing proactive and reactive capabilities, and hence for robustness and agility, the two dimensions of production resilience.

C.2.3 AI-Readiness and Production Resilience

The recent literature increasingly considers the role of AI technologies and systems for building capabilities for resilience in addition to classic information systems or other types of digital technologies. In a couple of papers both, the OIPT and DCV, have been actively used in the context of supply chain management (Belhadi et al. 2021a; Kamble et al. 2020; Wamba et al. 2020; Wong et al. 2020) aiming at explaining the role of information technologies for increasing supply chains resilience. While some papers exist which examine the interplay of AI and supply chain resilience (Belhadi et al. 2021a; Chien et al. 2020; Gupta et al. 2021), other works focus on the impact of the Covid-19 pandemic on supply chain disruptions (Belhadi et al. 2021b; Guan et al. 2020; Wuest et al. 2020; Xu et al. 2020). For example, Xu et al. (2020) analyse the impacts of Covid-19 on global supply chains, while Guan et al. (2020) calculate the effects of measures and restrictions as well as the length of Covid-19-driven lockdowns on supply chain losses. Wuest et al. (2020) on the other hand, use a conceptual approach to elaborate how AI can mitigate the losses caused by the Covid-19 pandemic and increase the resilience of future supply chain networks.

While the connections between the Covid-19 pandemic, AI and supply chain resilience have been studied in several papers, there are few comparable works that address production resilience. For example, there are publications that develop concepts for companies to help build resilient production systems and implement them in the firm. Corresponding frameworks are developed with the help of the concept of production control (Heinicke 2014), as well as in interaction with the development of product innovations by means of case studies (Romero et al. 2021). Mwangola (2018) also conceptualizes the resilience capabilities of product manufacturers along different activities of the firm including manufacturing activities. Moreover, the author works out the impact of resilience on the performance of firms using the dynamic capability view.

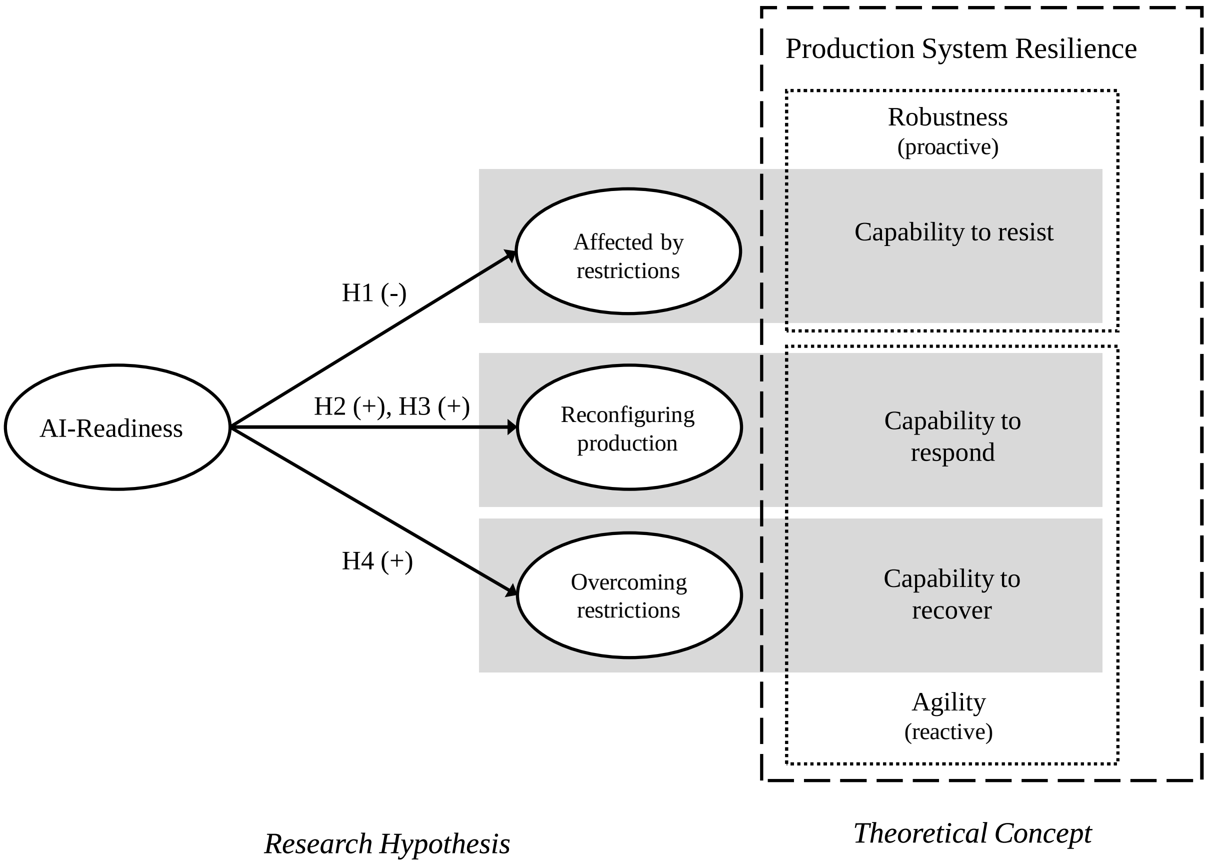
Overall, the previous literature on production resilience does not include the role of cutting-edge technologies such as AI in its considerations. Likewise, the works that exist to date pursue exclusively conceptual approaches or use case studies for analysis. Summing up, we conclude that the literature leaves two gaps: First, to date, only the relationship between AI technologies and supply chain resilience has been studied, while production resilience has been largely ignored. Second, previous work mostly examines the topic of production resilience on the basis of conceptual and theoretical considerations. Research that empirically analyses the relationship between AI technologies and production resilience using quantitative methods does not yet exist.

However, looking at the literature presented, we assume that AI-enabling technologies are generally able to build those capabilities that manufacturers need to increase the resilience of their production system. Regarding this assumption and following Romero et al. (2021) and Vugrin et al. (2010), we identify three types of capabilities with regard to the Covid-19 pandemic, allowing the relationship between AI-readiness and the resilience of the production system to be analysed: (1) The capability to resist the lockdown from the start, which is proactive in nature and can be categorized under the dimension of robustness. In this case, product manufacturers were not affected by the lockdown and could continue to produce as usual. The other two capabilities have a reactive nature and can be assigned to the agility dimension. This therefore only refers to companies that were unable to keep up production during the lockdown. This is the (2) capability to respond appropriately during the lockdown and introduce suitable countermeasures in production, as well as the (3) capability to recover from production breakdowns caused by the lockdown as quickly as possible. These three capabilities, along with the two dimensions of robustness and agility, span the theoretical concept for the rest of our investigation (compare right side of Figure 13).

C.3 Research Hypothesis

To elaborate our research hypotheses, we are guided by the theoretical concept of resilience of a manufacturer's production system. Hypothesis 1 addresses the robustness of firms and their ability to resist lockdown. Hypotheses 2 and 3 focus on the responsiveness of the companies, while hypothesis 4 addresses the capability to recover from the lockdown. Hypotheses 2 to 4 are thus related to the agility of firms. The research hypotheses and their relationship to the theoretical concept are presented in Figure 13 and derived in the following sections.

Figure 13: Theoretical concept (right side) and research hypotheses (left side) as well as their relationship.



Source: Own illustration

C.3.1 AI-Readiness and Affectedness of Covid-19 Restrictions

The Covid-19 pandemic disrupts the day-to-day business of many companies and has a major impact on the global industrialised world. Especially in the beginning of the pandemic, global value chains were affected by the large number of lockdowns and corresponding restrictions in countries, resulting in supply chain losses (Guan et al. 2020; Ivanov and Dolgui 2020). Depending on the type of supply network, some networks were more robust than others, yet all sectors were affected by the disruptions to varying degrees (Xu et al. 2020). To counter the widespread effects of the Covid-19 pandemic, some firms reduced the average number of hours worked (short-time work), which is considered a political strategy to support the labour market and in particular the maintenance of jobs (ECB 2020). In this case, the social unemployment insurance system compensates wage losses of employees that arise due to an involuntary reduction in working hours (Christl et al. 2021). During the lockdown, many countries evolved their short-time work schemes to expand eligibility and simplify access to funds. In April 2020, for example, 34% of all employees in France or 15% of all employees in Germany were on short-time work (ECB 2020).

Recent production research looks at managing unforeseen events, such as supply chain disruptions, and discusses the role of cutting-edge technologies, such as digital technologies and Industry 4.0, in addressing these issues (Dwivedi et al. 2021; Ivanov et al. 2019). Intelligent and learning-based information systems, using AI, promise to reduce supply chain disruptions by making decisions based on data patterns and modelling multiple response alternatives (e.g. Gupta et al. (2021), Modgil et al. (2021)). Following the OIPT, AI-based systems are expected to increase the information processing capability of companies, helping them to detect early signals and prepare in time (Belhadi et al. 2021a; Grover et al. 2022). AI thus enables to respond rapidly to disruptive environments, which in turn can reduce or even avoid the affectedness of firms (Gupta et al. 2021). AI-based systems also promise to quickly detect anomalies in unpredictable situations, allowing companies to adjust critical decisions early (Gupta et al. 2021; Modgil et al. 2021; Wuest et al. 2020) and thus even prevent disruption caused by unforeseen events (Heinicke 2014). This shows that AI-based systems enable manufacturers to anticipate and to prepare preventively for disruptive events and thus resist from the very beginning. Due to AI's capabilities to perceive possible disturbances of the environment at an early stage and to adapt necessary decisions in order to not be affected by disruptions, we expect hypothesis 1:

H1 The higher the AI-readiness level of a company, the less likely the company was affected by restrictions due to the Covid-19 lockdown.

C.3.2 AI-Readiness and Reconfiguration of Production During the Covid-19 Lockdown

As discussed above, the Covid-19 pandemic led to a strict lockdown in numerous industrialised countries in the spring of 2020. Although not all companies were affected by the consequences, many firms experienced impacts that required changes in operations. In order to meet the new requirements and respond to the effects of the lockdown, these firms had to restructure their business, implement updated health and safety requirements and redesign operations (Fana et al. 2020; Kumar et al. 2020; UNIDO 2020). Accordingly, operations management was faced with the challenge of reconfiguring production based on updated requirements, the flexibly increasing or decreasing production volume, depending on the demand for the manufactured product (Malik et al. 2021), as well as on supply chain disruptions (Xu et al. 2020).

The strategy of reorganising processes is considered an alternative to maintaining the original configuration triggered by difficult environmental conditions. The ability of an organisation to develop a reconfiguration that is better adapted to the new environmental context is also referred to as 'adaptive organisational resilience' (McCarthy et al. 2017). This adaptability of systems can be seen as a mechanism that prepares an organisation for unexpected environmental conditions (Bhamra et al. 2011). The challenges for operations management in times of uncertainty necessitate a flexible design of production processes and systems in order to react quickly and efficiently to market or product changes and to respond to system failures (Koren and Shpitalni 2010). Moreover, in the development and design of flexible manufacturing systems, the integration of AI methods has proven to be effective in enabling systems to be dynamic and robust (Renzi et al. 2014) as the application of AI methods in organisational systems promises to increase the flexibility of production systems (Arinez et al. 2020) and thus improve organisational resilience.

Following the DCV, Wamba et al. (2020) argue that AI as a lower-order capability builds the base for a company's dynamic capabilities. These in turn are able to maintain competitiveness by reconfiguring the intangible and tangible assets of an enterprise (Teece 2007). Accordingly, we assume that AI-enabled production enables manufacturers to undertake both organisational and technological countermeasures during a disruptive event, what can be considered in the context of capabilities as 'organisational-driven responsiveness' and 'technology-driven responsiveness'. Thus, the use of AI in production should increase the capability of manufacturers to make organisational reconfigurations within the production system. Based on this, we assume hypothesis 2:

H2 The higher the AI-readiness level of a company, the more likely the company is able to reorganise its production processes during the Covid-19 lockdown.

Considering the DCV, we also assume that AI enables manufacturers to introduce new technologies in production to respond to environmental changes. In this context, digitalisation as well as the integration of smart technologies are considered important drivers of industry restructuring (Isaksen et al. 2020; Rachinger et al. 2019; Spieske and Birkel 2021). As a reaction to unexpected environmental situations, the implementation of digital technologies, in addition to the reorganisation of production, promises to increase the resilience of companies (Zhang et al.

2021). However, an effective implementation of digital technologies requires a high level of technical competences and know-how that represent a challenge for many companies (Grant et al. 1991; Horvat et al. 2018; Horvat et al. 2019; Uzunca 2018).

Similarly, Syed et al. (2020) emphasise that companies need to reach a certain level of maturity in the use of digital technologies and innovation to pave the way to becoming a resilient organisation, prepared for unpredictable situations. Hence, highly digitally interconnected firms using a wide range of advanced digital technologies are considered more resilient to emergency situations (Syed et al. 2020; Zhang et al. 2021) and draw on a broad knowledge base in implementing digital technologies (Alsheibani et al. 2018; Grant et al. 1991; Jöhnk et al. 2021). That is why we expect that such manufacturers can more easily implement additional digital solutions into production during a disruptive event and hence, strengthen their technology-driven responding capabilities. As we assume that firms that use AI are more likely to undertake technological-driven reconfigurations in their production, the next hypothesis is as follows:

H3 The higher the AI-readiness level of a company, the more likely the company is able to implement additional digital solutions in its production during the Covid-19 lockdown.

C.3.3 AI-Readiness and Overcoming Restrictions After the Covid-19 Lockdown

The impact of the Covid-19 pandemic shows that companies are challenged throughout the ups and downs of new situations, especially during unforeseen environmental events. Increasing efficiency and continuous improvement of systems play an increasing role for the viability of companies (Dolgui et al. 2020). Not only did firms have to adapt to new conditions during the strict Covid-19 pandemic lockdown (Kumar et al. 2020; UNIDO 2020), they also faced the challenge of resuming production after the period of severe restrictions (Fana et al. 2020). Production systems are further on faced with the challenge of being agile, robust and flexible to new adjustments (Dolgui et al. 2020; Kumar et al. 2020; Malik et al. 2021), and to return to a normal state as quickly as possible after possible interruptions to operations (Wieland and Durach 2021). Holling (1996) refers to 'stability near a stable equilibrium state' as ‘engineering resilience’, which can be measured by the general resistance to disturbance and the speed of recovery to the equilibrium state.

In this context, AI promises to strengthen systems and to increase resilience, e.g. by integrating applications into information systems to support humans (Fragapane et al. 2022), their decisions

(Dwivedi et al. 2021; Gupta et al. 2021) or to provide precise suggestions to mitigate possible disruption risks (Gupta et al. 2021; Modgil et al. 2021). Based on the OIPT perspective, we assume that production systems are able to build information processing capabilities through AI. Therefore, information from various sources can be used and processed efficiently during lockdown, enabling companies to develop solutions and undertake measures to recover from a disruptive event as quickly as possible. In addition, AI helps overcome constraints on information processing (Belhadi et al. 2021a; Haefner et al. 2021), giving manufacturers with AI-enabled production further advantages to recover from lockdown. Based on the DCV, we further assume that manufacturers using AI systems develop dynamic capabilities (Wamba et al. 2020) and are thus able to adapt more quickly and perform better under turbulent conditions (Mwangola 2018). Accordingly, AI and its integration into production are considered to increase the capability of production system recovery that can support companies in returning to a given production state after turbulences in unforeseen events. Given this, we hypothesize:

H4 The higher the AI-readiness level of a company, the more likely the company is able to overcome the production restrictions after the Covid-19 lockdown.

C.4 Data and Methodology

C.4.1 Data

To test these hypotheses on the interlinkages of AI-readiness and production resilience during the first wave of the Covid-19 pandemic, we conducted empirical research based on data from the *German Manufacturing Survey* (GMS) of 2018 (Jäger and Maloca 2019) combined with an additional special survey on *Consequences of the Covid-19 pandemic in production* (COVMAN) of the same population conducted in autumn 2020.

The *German Manufacturing Survey* is a survey of manufacturing firms in Germany conducted by the Fraunhofer Institute for Systems and Innovation Research ISI that addresses a cross-section of manufacturing firms on product, process, service and organisational innovations. The objective of this regular, questionnaire-based postal survey is to systematically monitor manufacturing industries in Germany and their modernisation trends. The survey addresses firms with 20 or more employees from all manufacturing sectors (NACE Rev. 2, 10-33). Questionnaires are completed by high-level representatives at the manufacturing sites, i.e. production or general managers (CEOs). The GMS was first launched in 1993 and is currently conducted every three years.

In 2018, 17,305 manufacturing firms were asked to fill in the questionnaire, of which 1,256 returned useable responses (Jäger and Maloca 2019). The data set represents a cross-section of the manufacturing sector: machinery and equipment make up 17% of the total, metal products 20%, electronic and electrical products 12%, chemical, rubber and plastic products 11%, food industry 7%, and the remainder are firms in other sectors such as paper and publishing, wood and woodworking, textiles and transport equipment. Firm size and the regional distribution of the manufacturing industry in Germany are very well represented. Firms with fewer than 100 employees account for 71%, medium-sized enterprises for 27%, and large firms (with more than 1,000 employees) account for 3% of the sample.

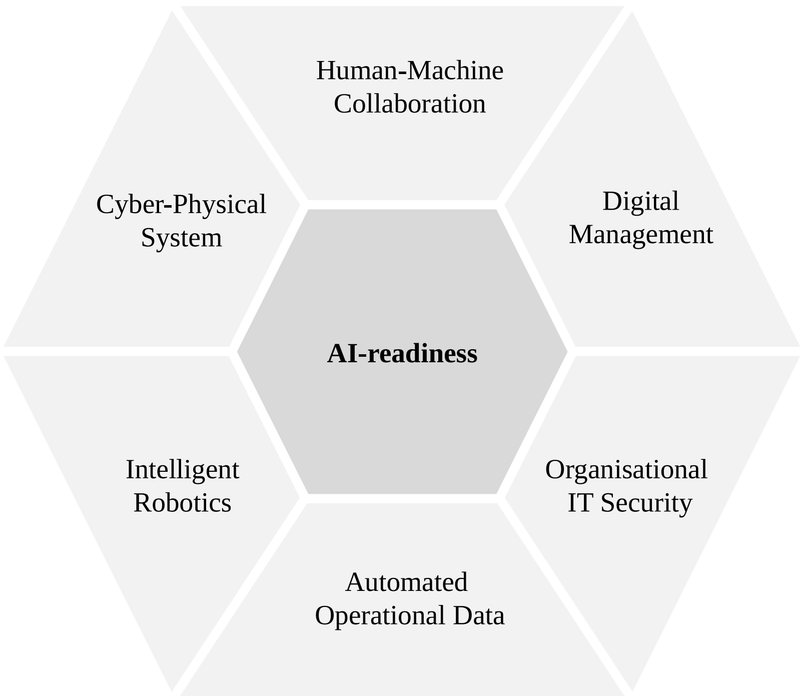
In addition to this recurring representative survey, the additional special survey COVMAN 2020 was conducted in September 2020, covering the period of the first lockdown in spring 2020 as well as the resurgence of the economy in late summer in Germany. For this purpose, the 1,256 manufacturing firms that had already participated in the GMS 2018 were contacted again and asked to provide feedback on seven questions related to the consequences of the Covid-19 pandemic. 237 firms took part in the special survey (response rate of 19%) and provided information on their situation during the lockdown in spring 2020 and on the situation at the time of the special survey after the lockdown. This sub-sample includes firms from all sectors and size groups. Very small firms and manufacturers of simple products responded a little more frequently. An overview of the distribution of the basic structural characteristics can be found in the appendix in Table 20. Subsequently, the responses of these 237 companies from the special survey COVMAN 2020 were merged with the information of the GMS 2018. Thus, for these companies, information on AI-readiness and firm structure is available from the 2018 GMS, as well as Covid-19-related information from the COVMAN 2020 special survey.

C.4.2 AI-Readiness Model: the Key Explanatory Indicator

Understanding AI as an advanced and sophisticated digital technology, its adaptation to manufacturing companies requires thorough technological preparation initially (Alsheibani et al. 2018). Hence, AI adoption as a gradual transformation process in companies, rather than technology leapfrogging, calls for effective digitisation as its precondition, i.e. the transformation of analogue processes into digitalised ones (Holmstrom 2021). In other words, manufacturing companies need to prepare the terrain with respect to digital technologies and processes to be able to implement AI effectively.

Following this logic, we limit the measurement of AI-readiness to the use of AI-enabling technologies considering them as a basis for further successful adoption of more sophisticated AI technologies in manufacturing companies. In the literature on digitalisation and AI-readiness, we looked for the most relevant AI-enabling processes associated with digital transformation in manufacturing. We then clustered them into six fields representing the dimensions of our AI-readiness model (see Figure 14).

Figure 14: Dimensions of the AI-readiness model



Source: Own illustration

To be able to analyse the AI-readiness along those six dimensions, representing the basis for further adoption of AI technologies, we only select the commonly used technologies and organisational measures with respect to AI in manufacturing companies. An overview of these indicators is provided in Table 16.

Hence, for enabling human-machine collaboration in manufacturing processes, companies first have to adopt the basic techniques for scheduling work instructions using digital solutions directly on the shop floor (Villalonga et al. 2021). Mobile devices like tablets are the prerequisite for this (Guhl et al. 2017; Morkos et al. 2012). If one considers manufacturing as a comprehensive system of various activities and processes, it is hard to imagine its effectiveness without an Enterprise Resource Planning (ERP) system combined with Product-Lifecycle-Management (PLM) and process data management (Erkayman 2019; Kakouris and Polychronopoulos 2005).

Moreover, smart manufacturing requires the further integration of cyber-physical systems enabling real-time control of all activities relevant to production and logistic/supply chain (inbound and out-bound) processes (Drobot 2020; Modgil et al. 2021; Villalonga et al. 2021; Wolf 2009). Also robotic systems including mobile, collaborating and autonomous robots play a significant role for smart manufacturing on the shop floor level and are included in our dimensions (Stanescu et al. 2008). Finally, the essential foundation for AI is represented in real-time data availability and a high IT security (Baryannis et al. 2019; Dogru and Keskin 2020; Jöhnk et al. 2021), creating our sixth dimension.

Table 16: Operationalisation of the six dimensions of the AI-readiness model

Dimensions	Operationalization of item	Measurement level
Human-Machine Collaboration	Digital solutions to provide drawings, work schedules or work instructions directly on the shop floor	yes/no dummy
	Mobile/wireless devices for programming and controlling facilities and machinery (e.g. tablets)	yes/no dummy
Digital Management	Product-Lifecycle-Management-Systems (PLM) or Product/Process Data Management	yes/no dummy
	Software for production planning and scheduling (e.g. ERP system)	yes/no dummy
Cyber-Physical System	Digital Exchange of product/process data with suppliers / customers (Electronic Data Interchange EDI)	yes/no dummy
	Near real-time production control systems (e.g. Systems of centralised operating and machine data acquisition, MES)	yes/no dummy
	Systems for automation and management of internal logistics (e.g. Warehouse management systems, RFID)	yes/no dummy
Intelligent Robotics	Mobile industrial robots Collaborating industrial robots (e.g. hand guided riveting robots) Autonomous industrial robots	Multiple choice question
Automated Operational Data	Machines or systems in production that automatically store operating data	yes/no dummy
Organisational IT Security	Activities raising employees‘ awareness on data security Use of organisational measures (specifically jamming radio and wifi reception, access restrictions, etc.) Use of specific software (data control, -access/use/volume/ transfer rates, etc.) Use of specific hardware solutions (separate web, subnetworks separated from the Internet DMZ, etc.)	Multiple choice question

Source: *German Manufacturing Survey* 2018

To analyse the AI-readiness of manufacturing companies, we develop a categorical index that summarizes the six dimensions of our AI-readiness model. Due to their equal significance for the adoption of AI technologies in manufacturing processes, we consider all six dimensions as equally weighted. To simplify the measurement and interpretation of the index, all six dimensions are included in the index as binary variables with a value of zero if the firm does not use either of the related technologies or organisational measures, or one if it uses at least one of the listed technologies or organisational measures of the dimension. In this vein, a total maximal score that a company can reach is six. The underlying logic is that the more AI-enabling dimensions a manufacturing company has mastered through technologies and organisational measures, the higher its AI-readiness. Based on this logic, we finally distinguish four groups of companies according to their AI-readiness: *No AI-readiness* with a score of 0, *low AI-readiness* with scores of 1 or 2, *moderate AI-readiness* with scores of 3 or 4 and *high AI-readiness* with scores of 5 or 6.

Table 21 in the appendix provides an overview of the distribution of AI-readiness scores and the six defining dimensions.

C.4.3 Dependent Indicators for the Consequences of the Covid-19 Pandemic in Production

To complement the structural information and the AI-readiness index, indicators concerning the Covid-19 pandemic based on the special survey COVMAN 2020 are used. These indicators refer to how firms were affected during the lockdown (H1), which countermeasures were implemented to keep production going (H2, H3), and what level of production volume the firms were able to realise after the lockdown ended (H4).

An overview of the variables taken from COVMAN 2020 is presented in Table 17. For the operationalisation of H1, two questions on the impact of the lockdown are used (regarding on the one hand, the use of state wage support, so-called short-time work, on the other hand, being affected by supplier problems). Based on this information, a firm is considered affected by the Covid-19 pandemic if at least one of the two restrictions is applicable. In order to analyse H2, we use the information whether a firm has reorganised production as a result of the lockdown restrictions. For H3, we analyse whether a company has expanded existing digital approaches or introduced new digital solutions in production to maintain production despite the restrictions. Regarding H4, we use the information given on the production volume (re-)reached in September 2020. Here we focus on those firms that have achieved a higher production volume after the first lockdown as opposed to firms with the same or lower production volume.

Table 22 in the appendix provides an overview of the distribution of the dependent indicators.

Table 17: Basis for operationalisation on the consequences of the Covid-19 pandemic in production

Dimensions	**Hypotheses**	**Survey question**	**Measurement level**
Restrictions on production during lockdown	(H1) Affectedness	Has short-time work been announced for the production at your site as a result of the Covid-19 pandemic?	yes/no dummy
		Have you been affected by delivery problems of your supplier(s)?	yes/no dummy
Measures during lockdown	(H2) Production reorganised	Have production processes at your site been restructured in order to maintain production despite the restrictions?	yes/no dummy
	(H3) Digital solutions	Have you introduced new digital solutions in production or expanded existing digital approaches in order to uphold the production despite restrictions?	yes/no dummy
Production volume after lockdown	(H4) Production ramp-up	Has the Covid-19 pandemic currently led to changed production volumes at your site? (no, increased, or reduced production volume)	categorical question

Source: Special survey *Consequences of the Covid-19 pandemic in production* 2020

At this point, it should be emphasised that for the analyses of H1, all firms are of interest. This makes it possible to analyse the affectedness by restrictions during the lockdown and hence, the capability of firms to resist. For H2, H3 and H4, however, only those firms that were affected by restrictions in production due to the lockdown are taken into account. This is necessary regarding the question of response and recovery, as firms that were not affected in their production by the lockdown never had to cope with changes or to resort to countermeasures; they never left their initial state before the lockdown with regard to production. In contrast, the affected companies had to cope with changes and were therefore unable to maintain their initial state. It is only when disruption occurs that the capability to respond and to recover can be analysed using our hypotheses H2, H3 as well as H4.

C.4.4 Model Description and Data Analysis

To test the four hypotheses, we performed bivariate analyses in a first step and multiple regression analyses in a second. The methodological approach is described in the following for both steps.

In the bivariate analyses, we carried out the appropriate bivariate group comparisons. This makes it possible to determine at a descriptive level to what extent differences can be observed depending on the AI-readiness levels. Therefore, three descriptive tests were performed for each hypothesis. Using the Mann-Whitney-U test, that compares two groups, we tested existing bivariate group differences between individual AI-readiness levels to determine whether these differences can be considered random or statistically validated. In this process, we first tested whether the firms differ statistically significantly depending on their AI-readiness level in contrast to the average of firms across all other AI-readiness levels. Second, we tested whether firms behaviour regarding the consequences on Covid-19 at the two upper levels differ on average from the ones of firms at the two lower levels. Third, we additionally run a Kruskal-Wallis test, which is similar to the Mann-Whitney-U test, but can be applied to compare more than two groups. This allowed us to simultaneously compare the variables for all four levels of the AI-readiness index.

To further test the differences regarding the observed reactions to Covid-19 restrictions, we carried out multiple regression analyses in a second step. All dependent variables regarding H1 to H4 are dichotomous variables. Therefore, we set up four logistic regression models. The aim of these analysis is to control further firms' characteristics and exclude them as a possible cause for the group differences. Given the number of cases in the analytical dataset, only a limited number of control variables can be considered at the same time. Thus, to be able to draw a clear picture and to present the study results in a compact way, we considered a uniform set of control variables in our models.

The multiple regression models control for firm size and sector affiliation, additionally to the impact of the explanatory AI-readiness indicator: *Firm size* is measured as the number of employees and helps differentiating between small and medium enterprises (SMEs) against larger firms. Thus, on the one hand, it is an indicator of the manufacturer's resources that can potentially be invested in digitalisation and the use of AI. On the other hand, it also reflects the complexity of the organisation and, to a certain extent, of production. *Sector affiliation* is measured as nominal information, differentiating between the NACE rev. 2 classes at 2-digit level. Four sector groups are differentiated: Firms with chemical, rubber, or plastic products (19%), mechanical engineering firms, automotive, and metal products (40%), firms of electronic and electrical products (8%), and finally firms producing food, textiles, wood products or others (33%). Finally, these models considered *AI-readiness* by distinguishing between companies with no or low AI-readiness and firms with moderate or high AI-readiness.

For the results, after presenting the bivariate analyses of H1 to H4, we demonstrate the four logistic regression models that were estimated including firm size and sector affiliation as explanatory indicators in addition to the AI-readiness indicator. In addition to statistical significance, odds ratios are reported so that a quick overview of the direction and extent of the effects is provided.

C.5 Research Results

C.5.1 Results from Descriptive and Bivariate Analyses

First, we distinguish between firms that were affected by production restrictions caused by Covid-19 and firms that were not affected, i.e. they neither applied short-time work nor did they encounter delivery difficulties. Overall, substantially more companies (n=185) were affected by the lockdown, compared to those not experiencing a considerable impact (n=49). This means a share of 79 percent of firms were affected by production restrictions caused by Covid-19.

Table 18: Distribution of companies according to their AI-readiness levels and to their affectedness by Covid-19 production restrictions

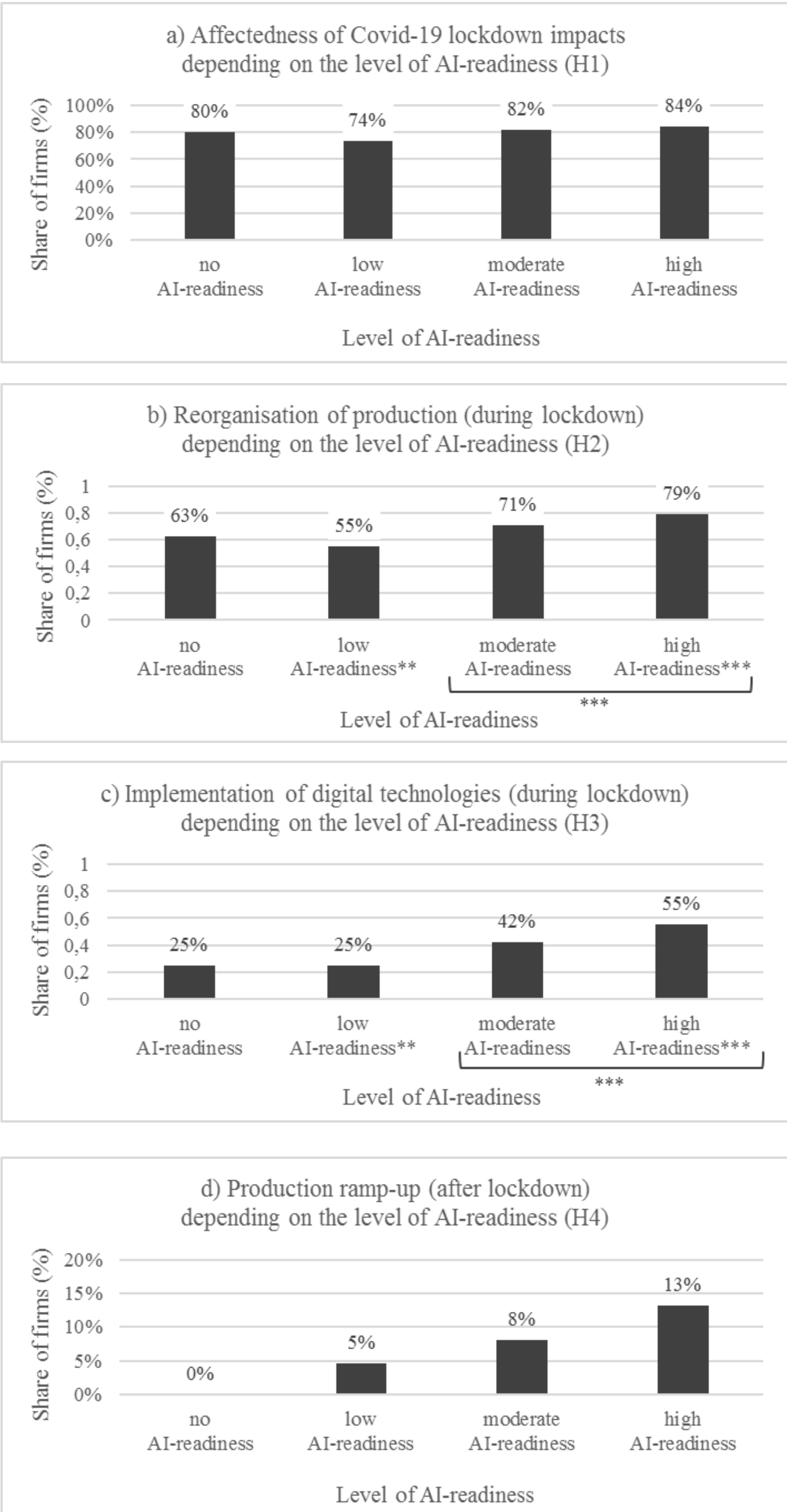
AI-readiness group	**Firms affected by Covid-19 production restrictions**		**Firms not affected by Covid-19 production restrictions**		**Total**	
	N	%	n	%	n	%
No AI-readiness	16	9%	4	8%	20	9%
Low AI-readiness	64	36%	23	48%	87	38%
Moderate AI-readiness	62	34%	14	29%	76	33%
High AI-readiness	38	21%	7	15%	45	20%
Total	**180**	**100%**	**48**	**100%**	**228**	**100%**

Note: Differences in AI-readiness levels statistically significant at ***p<0.01, **p<0.05 and *p<0.1 error probability (bivariate group comparison using Mann-Whitney U rank sum test)
Source: *German Manufacturing Survey* 2018 and special survey '*Consequences of the Covid-19 pandemic in production* 2020'

In Table 18, the information on the affectedness of the firms by the Covid-19 production restrictions is combined with their AI-readiness level. 228 manufacturing companies can be assigned to the four AI-readiness groups. The group with no AI-readiness includes 20 companies, while the group with low AI-readiness (score of 1 to 2) includes 87 manufacturers. Within the group with a moderate AI-readiness level are 76 firms. The group with the highest achievable AI-readiness level (5 or 6 points) holds 45 manufacturers. A comparison of non-affected and affected firms shows that affected firms have a slightly higher share of medium and high AI-readiness than non-affected firms. In contrast, the proportion of firms with low AI-readiness is higher among the non-affected firms. Even though a slight trend is noticeable, this difference does not stand up to a statistical test.

In the following, we examine the relationship between AI-readiness and production resilience. As explained in section C.4.2, the following analyses for H1 are based on all firms with information of the special survey and the AI-readiness status (n=228), while for the analyses for H2 to H4, only the firms affected by the lockdown are considered (n=180). Figure 15 visualises the shares of firms in each AI-readiness group that were a) affected by the restrictions of the Covid-19 lockdown (H1), b) reorganised their production processes during the lockdown (H2), c) introduced (additional) digital solutions in production (H3) and d) had an increased production output in autumn 2020 after the first lockdown period (H4). In addition to the descriptive figures, the results of the bivariate group comparisons are reported by indicating the statistical significance level in the respective figure.

Figure 15: Relationship between the AI-readiness level and the production resilience of firms related to the Covid-19 pandemic



Differences in AI-readiness levels statistically significant at ***p<0.01, **p<0.05 and *p<0.1 error probability (bivariate group comparison using Mann-Whitney U rank sum resp. Kruskal–Wallis test)
Source: *German Manufacturing Survey* 2018 and special survey *Consequences of the Covid-19 pandemic in production* 2020

As Figure 15a illustrates, the majority of firms was affected by the Covid-19 lockdown. Thereby, the shares of affected firms within the four AI-readiness levels are relatively similar and range from 74% of firms with low AI-readiness to 84% of the manufacturers with high AI-readiness. Using the Kruskal-Wallis test resp. the Mann-Whitney U test, no significant differences in the share of firms that were affected by production restrictions due to the Covid-19 lockdown can be identified depending on the different AI-readiness levels. Besides, Figure 15a also shows that there is no steady increase in affectedness. Firms without any AI-readiness do not have the highest proportion of affected firms.

Looking at the reorganisation of production processes during the lockdown (Figure 15b), it becomes clear that only just over half of the manufacturers with a low AI-readiness level undertook countermeasures. Compared to the other groups, this proportion is statistically significantly lower as indicated in the figure. In contrast, over 70% of the firms with moderate AI-readiness used reorganising measures. Among firms with a high level of AI-readiness, almost 80% reorganised their production. According to the bivariate statistical test, the differences in the proportion of firms that restructured their production processes is statistically significant. If the two upper AI-readiness levels are combined (moderate as well as high AI-readiness), the difference stands out clearly. Of firms with no or low AI-readiness, 56% reorganised their production, in contrast to 74% of the firms in the two upper AI-readiness levels (not displayed in the table). We can conclude that manufacturers with higher AI-readiness were more likely to reorganise their production in the lockdown than firms in the lower AI-readiness groups.

A quarter of the firms showing no AI-readiness or a low AI-readiness level implemented digital solutions in production during the lockdown (Figure 15c) as a measure to keep production running despite the restrictions. This share amounts to 42% for firms with moderate AI-readiness and 55% for firms with high AI-readiness. Looking at the separate levels, there are clear differences in both the companies with low AI-readiness and those with high AI-readiness. In this analysis, too, the difference becomes clearer when the two upper groups are combined. Manufacturers in the two upper AI-readiness levels implemented digital solutions to avoid lockdown restrictions significantly more often compared to firms in the lower AI-readiness levels.

Figure 15d visualises the relationship between the AI-readiness levels and the share of firms that could increase their production output after the lockdown. No firm with no AI-readiness was able to achieve an increased production volume after the lockdown. This share was 5% for low AI-readiness, 8% for medium AI-readiness and 13% for high AI-readiness. Even though the descriptive figures show a clear upward trend, these differences are not statistically validated. A reason for this is certainly also the average low share of firm with a higher production volume, which causes the standard errors to overshadow the differences. Only 14 firms (8%) reported a higher production volume in autumn 2020.

C.5.2 Results from Multiple Regression Analyses

In order to test the validity of the results of the descriptive analysis presented above, we conducted multiple logistic regression analyses, taking into account firm size and sector affiliation in addition to AI-readiness. The results of the four regression models are presented in Table 19.

With regard to our first hypothesis, we can conclude that the AI-readiness level has no impact on whether firms were affected by the lockdown or not. Even when controlling for the structural information such as industry and number of employees, firms with higher levels of AI-readiness were not less likely to be affected by the restrictions due to Covid-19 than firms with lower levels of AI-readiness. Additionally, we can state that the industry sector played a crucial role concerning the affectedness of a firm. Based on the consistent results of the bivariate and multiple regression analyses, we reject H1.

In our second hypothesis, we assumed that the increase of AI-readiness levels has a positive relationship with the probability that firms are reorganising their production processes. Through our multiple regression analyses, we find that firms in the two upper AI-readiness levels are statistically more likely to reorganise their production than firms in lower AI-readiness levels. However, as we also expected from the bivariate analyses, the assumed correlation of a steadily increasing probability of reorganising under control of the structural variables is not confirmed; the additional consideration of all four readiness levels in the model does not lead to an improvement of the model. Although there appears to be an increasing effect for the two upper levels, the lowest group without AI-readiness does not show a negative estimated regression coefficient. Considering that the correlation only exists when distinguishing between medium and high AI-readiness as opposed to low or no AI-readiness, and that the descriptive comparisons do not show a steady correlation either, we only accept H2 with constraints.

The bivariate analyses on the third hypothesis only partially support the hypothesis of a steadily increasing positive correlation between AI-readiness and the implementation of digital solutions during the Covid-19 lockdown. The result of the multiple logistic regression reinforces this assessment. Firms with a high or medium AI-readiness level were more likely to implement digital solutions during the lockdown. As expected, the model also suggests that SMEs are on average less likely to implement further digital solutions to overcome Covid-19 restrictions than larger firms. In contrast, industry affiliation had no significance for the model. However, in the extended model, taking into account all four AI-readiness levels, a steadily increasing chance could not be clearly determined. Again, the estimate does not confirm the expected relationship for the lower AI-readiness levels. Therefore, we also only accept H3 with constraints.

Table 19: Results of multiple regression analysis for the four hypothesis.

Dependent construct	**Model H1** No affectedness		**Model H2** Reorganisation of production		**Model H3** Implementation of digital solutions		**Model H4** Higher production volume	
	OR	Sig.	OR	Sig.	OR	Sig.	OR	Sig.
Sector		**						***
Food, textile, wood, others (1)	1.49		1.18		0.77		17.27	***
Chemical, rubber, plastics (1)	2.83	**	1.01		0.98		8.23	*
Firm size								
SME (2)	3.14		2.02		0.39	*	0.85	
AI-readiness level								
Medium or high level (3)	**0.61**		**2.32**	***	**2.57**	***	**3.30**	*
Constant	0.08	**	0.63		0.87		0.01	***
Model fit								
N	228		180		180		180	
-2 LL / sig.	223.70	**	222.44	*	224.778	**	78.16	***
Pseudo r^2 (Cox & Snell)	4.7%		4.4%		6.9%		8.1%	

Notes: Logistic regression models. Model 1: Not affected vs. affected firms. Model 2: Reorganisation of production vs. not reorganisation. Model 3: Implementation of digital solutions vs. not implementing it. Model 4: Higher production volume (than before lockdown) vs. equal or lower production volume. Reference categories: (1) Firms of mechanical engineering, electronics, or electrical products, (2) firms with more than 250 employees, (3) No or low AI-readiness level. OR - odds ratio, Sig. Significance level: ***p<0.01, **p<0.05 and *p<0.1.
Source: *German Manufacturing Survey* 2018 and special survey *Consequences of the Covid-19 pandemic in production* 2020

Even though the results of bivariate analysis did not indicate a positive correlation between the level of AI-readiness and an increased production output after the lockdown, the descriptive numbers on our fourth hypothesis still suggest a positive trend. Our multiple regression analysis then reveals that the two higher AI-readiness levels hold a significantly higher proportion of firms with increased production output than the two lower levels do. The industrial sector also has an impact on whether or not firms emerge from the lockdown stronger; compared to the other models considered, the industry sector has by far the greatest impact. Considering the multiple regression result on the one hand and the recognisable positive trend from the descriptive analyses across all four AI-readiness levels on the other, we accept H4.

C.6 Discussion

The Covid-19 pandemic has brought new attention to the issue of production resilience due to disruptive events, while also raising the question of the role of new cutting-edge technologies in this regard. Although literature on this topic is still scarce, there is consensus that the use of cutting-edge technologies, and AI in particular, increases both robustness and agility of firms, which in turn strengthens their production system resilience. Based on the current literature, we derived four research hypotheses related to the relationship between AI-readiness and production resilience during the spring 2020 lockdown in Germany. The first hypothesis addressed the capability of firms to resist lockdown, while hypotheses two to four focused on their responsiveness to and recovery from the lockdown. This allowed us to cover the two dimensions of resilience and ultimately determine which of the three complementary resilience capabilities firms can establish and strengthen with the help of AI (see Figure 13).

Using multiple regression analyses based on a linkage of two large-scale surveys, however, we find that the positive correlations assumed in the literature are only partially valid and cannot be fully confirmed. We rather find that the correlations between AI-readiness and production resilience are diverse and complex. Therefore, in this section, we discuss not only the outcome of the hypothesis testing, but in particular the identified correlations of AI-readiness and production resilience along the different resilience dimensions and capabilities. Due to the fact that our results cannot be transferred directly to other disruptive events beyond the Covid-19 pandemic, we derive propositions that can be used for future research. Therefore, in the light of our research question *'Do product manufacturers with a higher AI-readiness also show a higher production resilience to the restrictions of the Covid-19 pandemic?'*, we first reflect on the research hypothesis and afterwards derive propositions respectively.

At the beginning we examined our first hypothesis (H1) 'The higher the AI-readiness level of a company, the less likely the company was affected by restrictions due to the Covid-19 lockdown'. Here, the results show that the likelihood of a firm to be affected by restrictions in production was independent of its AI-readiness level. This means that the usage of AI-enabling technologies did not protect a firm from restrictions such as delivery problems or short-time work during the lockdown. Accordingly, we assume that AI-enabling production is not able to improve the capability of firms to resist the lockdown and hence, to strengthen their robustness and proactive capabilities. Moreover, we showed that whether a firm was affected by restrictions during the lockdown or not depended largely on its industry sector and size and thus on its structural conditions. In sum, our analysis cannot confirm the assumption made in the literature that AI-based systems and technologies strengthen the resisting capabilities and provide early signals about unforeseen events and thus enable proactive countermeasures (Gupta et al. 2021; Wuest et al. 2020; Xu et al. 2020). Consequently, we formulate our first proposition as follows:

Proposition 1. AI-enabled production does not affect a firm's capability to resist an unforeseen disruptive event. Rather, a firm's affectedness by such an event is determined by its structural conditions, such as industry sector and firm size.

Although all firms were equally affected by the restrictions of the Covid-19 lockdown, regardless of their AI-readiness, AI-enabling technologies played a crucial role for the responsiveness of affected firms. We addressed this issue with our second and third hypotheses, targeting the capability of a firm to respond to the lockdown in spring 2020 in Germany. The question is whether a higher AI-readiness enables firms to undertake appropriate countermeasures to keep up production despite restrictions. Organizational measures exist for firms to respond to an unforeseen disruptive event, as well as technological ones. Therefore, we subdivided the responding capabilities of firms into organisational-driven responsiveness (reorganisation of production, H2) and technology-driven responsiveness (introduction of digital solutions in production, H3).

In terms of H2 ‘The higher the AI-readiness level of a company, the more likely the company is able to reorganise its production processes during the Covid-19 lockdown’, firms with a low AI-readiness level reorganised their production less frequently and hence, showed the lowest capability to respond to the lockdown even compared to firms without AI-readiness. In contrast, firms with a moderate or high AI-readiness possessed the highest capabilities to reorganize their production and also clearly outperformed the responsiveness of firms without AI-readiness. Consequently, when entering AI-enabled production, the capability of firms to undertake the necessary organisational measures to keep up production first decreases for a low AI-readiness level, while it rises again at a moderate AI-readiness level and can be even increased at a high AI-readiness level. Therefore, we propose that the capability to respond by organisational measures to an unforeseen disruptive event is affected by an AI-enabling production. However, as argued in the literature (Arinez et al. 2020; Bhamra et al. 2011; Renzi et al. 2014), a positive correlation can only be confirmed in those groups that already use AI-enabled production (levels 1 to 3). Overall, we conclude that firms starting with AI-enabled production are initially in an AI implementation valley in terms of their organisational-driven responsiveness, which indicates an initial loss of organizational control and must be passed through before resilience gains can be achieved at higher AI-readiness levels. This leads to our second proposition:

Proposition 2. The AI-readiness level of a firm affects its capability to respond to an unforeseen disruptive event through organizational measures. When entering AI-enabled production, the organisational-driven responsiveness of a firm first decreases but can then increase steadily as AI-readiness rises. Firms entering AI-enabled production are therefore initially in an AI implementation valley before resilience gains can be achieved at higher AI-readiness levels.

In the case of H3, 'The higher the AI-readiness level of a company, the more likely the company is able to implement additional digital solutions in its production during the Covid-19 lockdown', both firms without AI-readiness and a low AI-readiness show the lowest capability to introduce digital solutions to keep production going during the lockdown. However, once firms are at one of the two higher AI-readiness levels, they implement digital solutions more frequently and thus show rising responding capabilities. Consequently, when entering AI-enabled production, firms initially stagnate at a low technology-driven response level, which only rises steadily once a certain AI threshold has been crossed, at which point there are late resilience gains. Therefore we assume, that an AI-enabled production only increases the responding capabilities of a firm, once a critical mass of AI-enabling technologies has been established in production. As with the previous hypothesis, we can therefore confirm the assumed positive correlation from the literature (Syed et al. 2020; Zhang et al. 2021) only for those groups that already use AI-enabled production (levels 1 to 3). Beyond AI-readiness, we can state that firm size also plays a role here. We state our third proposition as follows:

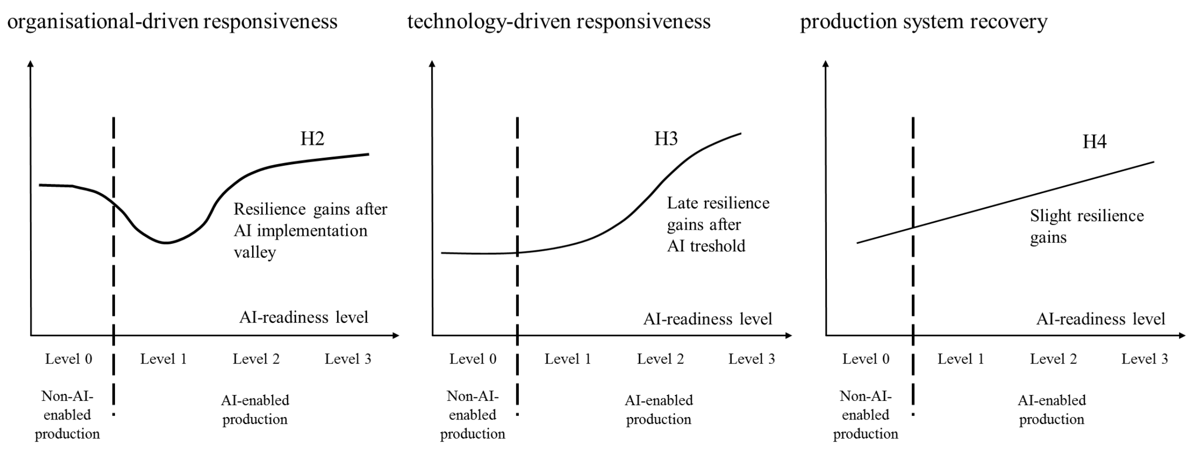
Proposition 3. The AI-readiness level of a firm affects its capability to respond to an unforeseen disruptive event by implementing new digital solutions. When entering AI-enabled production, firms initially stagnate at a low technology-driven responsiveness, which can then be boosted substantially the more AI readiness increases. Consequently, firms do not achieve late resilience gains until they exceed a certain AI threshold.

In order to draw conclusions on the recovery of the production system due to the lockdown, we analysed H4 'The higher the AI-readiness level of a company, the more likely the company is able to overcome the production restrictions after the Covid-19 lockdown'. We find that the higher the AI-readiness level, the higher the share of firms which generate a higher production output after the lockdown compared to their initial situation before the lockdown. Thus, we conclude, the higher the AI-readiness level of a firm, the higher its capability to recover from a disruptive event. As our regression analysis for this model only shows a significance level of ten percent, we propose that AI-enabled production supports a firm to slightly increase its capability to recover faster from a disruptive event. Therefore, for H4, we can confirm the assumptions of a positive relationship between AI-readiness and production resilience made in the literature (Dolgui et al. 2020; Fragapane et al. 2022; Wieland and Durach 2021) by our analyses. In addition to the AI-readiness of a firm, the industry sector also plays a crucial role for the production volume after the lockdown. We therefore formulate the fourth proposition as follows:

Proposition 4. The capability of a firm to recover from an unforeseen disruptive event slightly increases with rising AI-readiness. The higher the AI-readiness of a firm, the higher its probability to reach a higher production system state after the disruptive event than it showed before the event. Consequently, with rising AI-readiness, firms can achieve slight resilience gains from the start, but these are also determined by the industry sector.

We visualise our findings regarding hypotheses 2 to 4 using a graphical presentation in Figure 16 representing our findings on the relationships between AI-readiness and the production system resilience related to the Covid-19-driven lockdown in spring 2020 in Germany.

Figure 16: Proposed relationship of AI-readiness levels and production resilience of a company during the spring 2020 lockdown in Germany



Source: Own illustration

If we summarize our findings we conclude that when the Covid-19 lockdown began, an AI-enabled production in terms of the likelihood of being affected by restrictions did not matter to companies, but their structural conditions did. However, of the companies that were affected by restrictions during the lockdown, those that had already reached a medium or high level of AI-readiness showed higher production system resilience. Thus, as soon as a critical mass of AI-enabling technologies was used, going along with overcoming the AI threshold and AI implementation valley, the production system resilience of a firm could be increased, which is basically consistent with the assumptions of (Syed et al. 2020). Consequently, as our results show, differences between the two dimensions of production resilience do indeed exist. While AI-readiness is positively related to a firms´ agility, however, we cannot find a correlation with robustness. If we follow the theoretical discussion from the literature, this means that the use of AI-enabling technologies in production is linked to the development of different capabilities in the firm. While AI-enabling technologies in production seem to significantly improve reactive capabilities, they do not have a measurable impact on a company's proactive capabilities. Finally, we can summarise our findings by answering our research question, whether product manufacturers with higher AI-readiness also show higher production resilience, in a concluding proposition as follows:

Proposition 5. Once the AI threshold has been crossed, a higher AI-readiness level increases a manufacturer's production system resilience, but only strengthens its reactive capabilities, not its proactive ones. Thus, the AI-readiness level of a manufacturer increases its agility in the case of a disruptive event, but not its robustness. Consequently, an AI-enabled production does not protect a firm from being affected by disruptive events, but helps to respond more adequately and to recover faster.

C.7 Conclusions

While the hype around cutting-edge technologies, particularly AI-enabling technologies, and their effects on performances of manufacturers is rapidly growing in the literature, their relationship to production resilience remains rather unexplored in empirical research. This topic has been becoming increasingly relevant in the current Covid-19 pandemic due to its negative impacts in form of massive restrictions in production worldwide. In this study, we take up this issue and examine, based on a quantitative analysis and two large-scale surveys, whether AI-readiness had an impact on production resilience in the German manufacturing sector during the Covid-19 lockdown in spring 2020. In this context, our results not only add to the literature, but also provide implications for management and for future research needs.

C.7.1 Practical Implications

In general, we see that the use of AI-enabling technologies in production can certainly lead to an increase of the resilience of manufacturing companies. On the one hand, the resilience of the production system can be strengthened, which not only makes it easier to overcome unforeseen events, but also enables companies to emerge stronger from the crisis. On the other hand, AI-enabling technologies in production can also enable operations management to initiate necessary countermeasures in production during an unforeseen situation. Due to this fundamental effectiveness, the integration of AI-enabling technologies into companies' resilience management should certainly be considered and used in a targeted manner right from the start. Nevertheless, we see two fundamental restrictions from our analyses that limit the effectiveness of AI-enabling technologies on production resilience and should be taken into account by companies: first, AI-enabling technologies in production allow only reactive capabilities to be built up in the company, which increases the agility of companies but not their robustness against unforeseen events. Second, the identified AI threshold must be overcome by manufacturers in order to build resilient capabilities in the first place. Consequently, manufacturers with a low AI-readiness level are also unable to increase their agility in the face of external influences.

For practitioners, the developed AI-readiness model can be used as a framework to position themselves along the different AI-readiness levels and draw conclusions for resilience management. This can be derived via the number of dimensions of AI-readiness in production (see Figure 14). Basically, a distinction must be made as to whether a manufacturer is below (two or less dimensions), or above the AI treshold (three or more dimensions): Manufacturers which are below the AI threshold (two or less dimensions; level 0/1) are hardly in a position to develop resilient capabilities with the help of AI-enabling technologies. These firms should rely on flexibly designed production processes to increase their reactive capabilities. Companies that are at a low AI-readiness level are also in the AI implementation valley, which should be overcome by implementing additional cutting-edge technologies in production. Resilience management for these companies should therefore focus on flexible work and process design so that they can make short-term organizational adjustments in production in the case of unforeseen events. Manufacturers that are at a moderate or high AI-readiness level, and thus above the AI treshold (three to six dimensions; level 2/3), should specifically integrate their AI-enabling technologies in production into resilience management. At these levels, manufacturers are able to build up strong reactive capabilities and adapt their production to external events at short notice, even technically. However, the resilience management of these companies should be aware that establishing predictive capabilities must be done through other channels and sources.

C.7.2 Theoretical Implications

As the literature review shows, there is a lack of papers that examine the interplay of AI-enabled production and production resilience. Our paper addresses this research gap by empirically analysing the relationship derived from the literature using quantitative analysis. In particular, our paper provides several theoretical implications, consisting of a conceptual and an empirical contribution.

Conceptually, our paper delivers new perspectives on the AI-readiness of manufacturers as well as on production resilience. Thus we develop (i) a conceptual model to measure the AI-readiness of product manufacturers by combining different AI-enabling technologies from manufacturing. This AI-readiness model is able to analyse and demonstrate possible effects and impacts of AI-based production already in a very early phase of AI implementation in the manufacturing sector. Such AI-readiness models can therefore not only help practitioners but also be used for this type of research analysis in the future. Moreover, (ii) we create a new conceptual understanding on the term production resilience. By transferring the idea of system resilience described in the literature to the production system of a company, we succeed in providing an extended perspective on the resilient capabilities of manufacturers in case of disruptive events. Thus, our concept of production (system) resilience provides not only two dimensions of resilience, but also three different capabilities that help increase overall resilience. Consequently, the concept of production resilience consists of multiple levels that generate a novel perspective and can also be used for future research.

The empirical contribution provides two additional theoretical implications: with the help of our empirical analysis, it is possible (iii) to further substantiate the relationships assumed in theory that a new cutting-edge technology in the company also leads to the development of new capabilities. Thus, cutting-edge technologies are not only able to build higher-order capabilities such as resilience, but also to increase the information processing capabilities of firms. Thus, our empirical study also confirms assumptions of OIPT and DCV. With the hypotheses we have developed, we address (iv) both dimensions of resilience: robustness and agility. Through this, we are able to look much deeper into the interplay between AI-readiness and production resilience. Indeed, we can find that differences exist in the impact of AI-readiness on robustness as well as agility of manufacturers. While there is no relationship between AI-readiness and robustness, positive effects on agility can be shown. In addition, further differences can be identified with respect to the impacts on responsiveness and recovery. This indicates a high complexity and diversity of the interplay, which is why we derive propositions for future research.

C.7.3 Limitations and Future Research Needs

Finally, it should be mentioned that our study reveals limitations, which at the same time points to a need for research in future work.

With our hypotheses, we focus on the relationship between AI-readiness and production resilience, relying on two theoretical concepts, DCV and OIPT. These provide a theoretical explanation of how AI can help firms build the very capabilities they need to increase their production resilience. Nevertheless, we have not conducted a more in-depth analysis of how exactly the process of capability development based on AI-enabling technologies takes place and what the prerequisites are. Therefore, future research could investigate the link between AI technologies and capability development in detail and analyse, for example, how exactly this process takes place, what factors influence this process, or why reactive capabilities are built but not predictive ones. Qualitative case studies or long-term studies that examine capability development in companies over a longer period of time would be suitable for this purpose.

There are also limitations in measuring AI and resilience in manufacturing. For example, due to the low implementation rate of AI in practice, it is currently only possible to use AI-enabling technologies to measure the resulting effects. However, in a few year' time, when AI has become more widespread in manufacturing, various AI tools can be used to study its impact on resilience. To measure production resilience, we use the two dimensions of robustness and agility. For future analyses, however, other resilience capabilities could also be taken up, such as anticipation, preparedness, visibility, or speed (Heinicke 2014). Through new measurement methods, future research could gain deeper insights into the relationship between AI-technologies and production resilience.

In addition, our analyses are geographically and temporally limited. Our survey and analysis focus exclusively on the manufacturing sector in Germany and consider the consequences of the first lockdown caused by the Covid-19 pandemic in spring 2020. Future work could therefore not only look at the production resilience of the first lockdown, but also consider, for example, a longer period of time and consider multiple lockdowns. In particular, it would be interesting to investigate whether production resilience changes in the aftermath of multiple lockdowns and whether manufacturers build higher robustness in the presence of repeating events.

C.8 Appendix

Table 20: Data overview: Summary on structural information

Data structure		**n**	**%**	**participation rate in COVMAN**	
Firm size	up to 49 employees	127	54,3%	22%	***
	50 to 249 employees	91	38,9%	18%	
	more than 250 employees	16	6,8%	11%	
Sector	Food, beverages, textile, wooden products, others	77	32,9%	24%	**
	Chemical, rubber, plastic products	53	22,6%	22%	
	Machinery, metal industry, automotive	86	36,8%	16%	
	Electrical, electronic products	18	7,7%	12%	
Batch size	single lot manufacturing	61	27,1%	18%	n.s.
	small/medium lot manufacturing	137	60,9%	20%	
	big lot manufacturing	27	12,0%	16%	
Product complexity	simple complexity of products	49	21,7%	20%	**
	medium complexity of products	128	56,6%	21%	
	high complexity of products	49	21,7%	14%	

Notes: Number of cases and indicator shares. Participation rate as share of participating firms in COVMAN. Significance level: ***p<0.01, **p<0.05 and *p<0.1.
Source: *German Manufacturing Survey* 2018 and special survey *Consequences of the Covid-19 pandemic in production* 2020

Table 21: Data overview: Summary on data for AI readiness score

AI readiness score base		n	%	participation rate in COVMAN	
Human machine collaboration	none of the two technologies	113	48,9%	19%	n.s.
	at least one of the technologies	118	51,1%	19%	
Digital management	none of the two technologies	64	28,2%	20%	n.s.
	at least one of the technologies	163	71,8%	18%	
Cyper-Physical system	none of the two technologies	100	43,9%	19%	n.s.
	at least one of the technologies	128	56,1%	18%	
Intelligent robotics	none of the three features	204	88,3%	19%	n.s.
	at least one of the technologies	27	11,7%	18%	
Automated operational data	no	105	45,5%	18%	n.s.
	yes	126	54,5%	19%	
Organisational IT security	no or only one measuremente	145	62,2%	19%	n.s.
	at least two measurement	88	37,8%	17%	
AI readiness level	no AI-readiness	20	8,8%	20%	n.s.
	low AI-readiness	87	38,2%	20%	
	moderate AI-readiness	76	33,3%	17%	
	high AI-readiness	45	19,7%	18%	

Notes: Number of cases and indicator shares. Participation rate as share of participating firms in COVMAN. Significance level: ***p<0.01, **p<0.05 and *p<0.1.
Source: *German Manufacturing Survey* 2018 and special survey *Consequences of the Covid-19 pandemic in production* 2020

Table 22: Data overview: Summary on dependent constructs

Dependent constructs		n	%
Affectedness (State substitute for shorter work times, delivery problems)	not affected in these topics	49	20,9%
	affected in at least one of the topics	185	79,1%
State substitute for shorter work times	no	92	39,3%
	yes	142	60,7%
Delivery problems	no	134	57,3%
	yes	100	42,7%
Production reorganised	no	97	41,5%
	yes	137	58,5%
Newly introduced or expanded digital solutions	no	158	67,5%
	yes	76	32,5%
Production ramp-up	production volume unchanged	52	22,2%
	... less than pre-pandemic	160	68,4%
	... higher than pre-pandemic	22	9,4%

Notes: Number of cases and indicator shares.
Source: *German Manufacturing Survey* 2018 and special survey *Consequences of the Covid-19 pandemic in production* 2020

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D The Innovation Payoff of AI in Production: Evidence from German Manufacturing[4]

Abstract:

This paper explores the influence of AI adoption in production processes on product innovation outcomes in manufacturing companies, complementing traditional innovation factors including research and development (R&D) activities, workforce qualifications, and human-centricity. Utilizing unique data from 1,334 firms in the 2022 German Manufacturing Survey, our findings reveal that while R&D ais one of the primary drivers of product innovation, encompassing both new to the firm and the market, AI adoption and human-centric strategies significantly influence the nature of innovation by promoting product variation rather than merely increasing output. Notably, AI enhances manufacturers' digital capabilities, facilitating the development of digitally advanced products, whereas eco-innovations are more significantly affected by human-centered approaches. Moreover, firm size and industry affiliation play a substantial role in shaping product innovation outcomes in manufacturing companies, while product complexity and batch size do not appear to have a significant impact.

Keywords: AI in production, product innovation, digital product innovation, eco product innovation, manufacturing, German Manufacturing Survey.

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D.1 Introduction

Artificial intelligence (AI) is increasingly recognized as a foundational technology shaping operational and innovation performance, and thereby competitiveness of manufacturing companies. By enabling machines and systems to learn from large volumes of data, detect patterns, and support or autonomously execute decisions, AI enables process innovation and capabilities that extend beyond traditional automation (Gabsi 2024; Papadopoulos et al. 2022). When integrated into production environments through e.g. speech-, vision-, or sensor-based analytics, AI enables manufacturing systems with new forms of adaptive and predictive intelligence (Alam et al. 2023; Cheng et al. 2021; Duan et al. 2019). These capabilities open up opportunities to reconfigure production processes and enhance operational outcomes, particularly in terms of efficiency, productivity, and flexibility (Waltersmann et al. 2021; Sanchez et al. 2020; Wamba-Taguimdje et al. 2020). At the same time, the role of AI enabled process innovations extends beyond operational optimization. By processing and interpreting large-scale and heterogeneous data, AI increasingly contributes to innovation activities across critical stages of the innovation process, including opportunity identification, idea evaluation and selection, concept and solution development as well as commercialization (Bahoo et al. 2023; Broekhuizen et al. 2023; Füller et al. 2022; Verganti et al. 2020).

Within the literature, AI is increasingly understood as a transformative general-purpose technology that fundamentally enhances firms' ability to create, accumulate, and purposefully use knowledge (Broekhuizen et al. 2023; Paschen et al. 2019), as well as processes that are central to innovation (Füller et al. 2022). One of the central theoretical concepts in this term is the absorptive capacity of companies (Cohen and Levinthal 1990; Horvat et al. 2019a; Song et al. 2018; Zahra and George 2002). AI has the potential to strengthen all core dimensions of knowledge absorption by augmenting how organizations acquire, assimilate, transform, and exploit knowledge. By enabling the analysis of large, heterogeneous, and continuously growing datasets from multiple internal and external sources, AI substantially improves firms' capacity to assimilate new knowledge and to integrate it with existing the knowledge base (Broekhuizen et al. 2023; Rožanec et al. 2022; Wu et al. 2019). Moreover, by rapidly identifying relevant patterns, relationships, and emerging trends within complex data, AI accelerates the exploitation of knowledge for innovation-related purposes, such as problem solving, opportunity recognition, and solution development (Makarius et al. 2020). Recent advances in large language-based tools, including AI-powered chatbots and autonomous agents, further extend these effects by supporting knowledge sharing, interpretation, and recombination across organizational boundaries, thereby fostering organizational learning (Burton et al. 2024; Soller et al. 2023). Importantly, AI also reshapes the role of domain-specific and tacit expert knowledge. Rather than replacing human expertise, AI makes such knowledge more accessible, interpretable, and transferable within organizations (Choudhary et al. 2025). As a result, absorptive capacity evolves from a predominantly human-driven capability into a hybrid, human–machine-enabled capability that leverages synergies between expert knowledge and AI-generated insights from big data. Through this expansion and reconfiguration of absorptive capacity, AI can ultimately enhance the creativity and innovation capability of firms (Benbya et al. 2024).

However, AI alone does not guarantee product innovation. Its capacity to accelerate innovation is contingent on the availability, quality, and alignment of complementary firm-level resources and capabilities (Füller et al. 2022). In particular, sustained investments in research and development (R&D) activities are critical for building absorptive capacity (Griffith et al. 2003) and, in turn, for translating AI-generated insights into viable product innovations (Broekhuizen et al. 2023). Lee at al. (2022) provide evidence that benefits of AI adoption are greater at firms that also invest in internal R&D. Furthermore, because a firm's existing knowledge base constitutes the foundation of its absorptive capacity (Cohen and Levinthal 1990) investments in human resources, especially through continuous employee training, play a crucial role in fostering individual and organizational learning (Sung and Choi 2014) and, consequently, innovation (Demirkan et al. 2022). Accordingly, AI and traditional innovation drivers should be viewed as mutually reinforcing rather than substitutive. While AI expands the scope and speed of opportunity identification, further organizational resources, capabilities, and practices ultimately determine whether and how these opportunities are transformed into tangible product innovations (Füller et al. 2022).

Production research has extensively examined AI-driven process automation and operational efficiency in production, but its influence on innovation processes in manufacturing remains insufficiently understood (Bahoo et al. 2023). Furthermore, while existing studies in innovation management predominantly focus on traditional product innovation determinants, such as R&D investments, workforce competencies, and collaborations (Horvat et al. 2019b; Jesus Pacheco et al. 2017; Rammer et al. 2022a), evidence on how the implementation of AI solutions in production can shape product innovations is limited (Mariani et al. 2023; Rammer et al. 2022a). Empirical insights on how AI interacts with established firm-level innovation drivers also remain scarce (Baumgartner et al. 2024; Füller et al. 2022; Rammer et al. 2022a). To address these gaps, this paper investigates the following research question:

How does AI adoption in production influence the product innovation capability of manufacturing companies, while accounting for traditional firm-level innovation determinants including R&D activities, workforce qualifications and human centricity?

To investigate our research question, we draw on a representative sample of 1,334 firms from the 2022 wave of the *German Manufacturing Survey* (GMS). We employ logistic regressions to examine the relationship between AI adoption in production processes and the likelihood of firms introducing product innovations. In doing so, we distinguish between two types of innovation outcomes based on their degree of market novelty: (1) new-to-the-firm product innovations and (2) new-to-the-market product innovations. Furthermore, we assess whether AI adoption is associated not only with product innovation in general, but also with a systematic shift toward more specific digital and sustainability-oriented product innovations, compared to conventional product innovations lacking digital or environmental attributes. Hence, by explicitly differentiating innovation orientation, this study contributes to advancing empirical research on the context of the industrial twin transition (Rehman et al. 2023).

Acknowledging that AI adoption does not occur in isolation, we integrate established firm-level innovation drivers into our modelling framework, with particular emphasis on R&D activities and competence-related organizational practices. The latter include the qualification level of employees, as well as investment in training for production employees and the workforce involvement in innovation processes as key dimensions of the human-centricity of companies. This approach enables us to examine potential complementarities and interaction effects between AI adoption and traditional innovation determinants. To ensure robustness, we control structural firm characteristics, including firm size, sectoral affiliation, batch size, and product complexity.

Our results indicate that AI-enabled processes affect product innovation through multiple, partly distinct mechanisms. R&D activities remain among the primary drivers of overall product innovation, both for innovations that are new to the firm and those that are new to the market. In contrast, AI adoption and human-centric approaches in manufacturing firms mainly shape the *nature* of product innovation by influencing the direction of product innovation rather than increasing innovation output per se. Among all explanatory factors, AI adoption makes one of the strongest contributions to explaining digital product innovation, suggesting that the integration of AI into production processes facilitates digital innovation trajectories and supports the development of digitally enhanced products. In comparison, eco-oriented product innovation is predominantly driven by a human-centered focus, while AI adoption plays only a marginal explanatory role here. In addition, contextual factors such as industry affiliation and firm size influence firms' likelihood to engage in product innovation.

D.2 Theoretical Background and Hypotheses

Traditional research on the determinants of firm-level innovation has long emphasized internal R&D activities, employee qualifications, continuous training, and employee involvement as critical foundations of innovation capability (Raymond and St-Pierre 2010; Schmiedeberg 2008). These factors foster the development of organizational knowledge and routines required to generate new products. With advancing digitalization, however, technological factors, particularly advanced digital technologies, have become equally central drivers of innovativeness (Blichfeldt and Faullant 2021; Usai et al. 2021). They enable substantial process improvements that enhance operational efficiency, knowledge flows, and production flexibility, thereby facilitating innovation (Damanpour and Gopalakrishnan 2001; Koellinger 2008). Recent studies confirm this complementarity and provide evidence about their synergetic effect on product innovation. Horvat et al. (2025), for example, demonstrate the synergistic effects of emerging I5.0 relevant technologies and human-centric strategies of manufacturing companies, such as employee training and engagement, on product innovation.

According to the innovation management literature, the effects of advanced technologies on the innovativeness of companies are to be explained through the interdependence between process and product innovation. Process innovations are focused on identifying more effective operations and better output performance (Martínez-Ros and Labeaga 2009). They are internally oriented and focus on increasing efficiency. That is why they are often not as visible or central when it comes to communicating the success. By introducing digital technologies, companies can enable process innovations and optimize product development and marketing efficiency (Damanpour and Gopalakrishnan 2001; Utterback and Abernathy 1975). In contrast, product innovations are externally oriented and are often influenced by customer needs and market opportunities. Unlike process innovations, product innovations are more visible and are often considered more significant, as improvements are easier to quantify and, if successful, enjoy considerable attention within the network. To successfully implement product innovations, companies must accurately understand their customers' requirements and design, produce, and market appropriate products (Damanpour 1996; Damanpour and Gopalakrishnan 2001; Ettlie et al. 1984). Utterback and Abernathy (1975) show that the priority accorded to product or process innovation shifts over a product's life cycle: product innovation dominates early phases to explore market opportunities, whereas process innovation becomes more important in mature phases to enhance efficiency and reduce costs. Technological advances drive both forms of innovation and shape their dynamic interplay. Barras' (1986) reverse product cycle provides a complementary perspective, illustrating how, in service industries, process innovation often precedes product innovation after the introduction of a new technology. Efficiency-oriented process improvements subsequently create the foundation for new or enhanced products. Despite differences in sequencing across sectors, both theories emphasize the synergy between product and process innovation and the need for firms to continually adjust their innovation focus to remain competitive.

Within the broader landscape of advanced digital technologies, AI has emerged as a particularly transformative force in manufacturing. AI-driven applications continue to evolve, pushing the industry toward increasingly smart and autonomous production systems (Gao et al. 2024). Owing to its ability to learn from data, detect patterns, and support or automate decision-making, AI has the potential to substantially enhance manufacturing processes (Gabsi 2024; Papadopoulos and Spanaki 2017). AI-enabled process innovations span process control, quality assurance, predictive maintenance, and internal logistics, improving efficiency, stability, and responsiveness in production systems (Buchmeister et al. 2019; Plathottam et al. 2023). When integrated across different facets of production, AI contributes to higher levels of operational efficiency, adaptability, and innovation (Alzoubi et al. 2024; Rammer et al. 2022a), strengthening firms' competitiveness in a digitalized industrial environment (Heimberger et al. 2024a; Sanchez et al. 2020a). These advancements underscore the role of AI-enabled process innovation as a pivotal driver of firms' broader innovation capabilities.

The transformative power of AI has been seen in its role for creating and leveraging knowledge resources representing a fundamental factor of innovation. Implementation of AI systems support namely the assimilation and exploitation of knowledge through advanced analytics, automated data processing, pattern recognition, and generative design (Cockburn et al. 2018; Neirotti et al. 2021; Verganti et al. 2020). However, AI does not automatically translate into improved innovation performance; its impact depends on firms' ability to assimilate and integrate AI-generated knowledge. This aligns with absorptive capacity (AC) theory, which conceptualizes innovation as contingent upon a firm's capability to recognize valuable new (external) knowledge, assimilate it, transform it, and apply it for commercial ends (Cohen and Levinthal 1990; Weidner et al. 2023; Zahra and George 2002).

In the context of AC, AI can influences the ability to generate and absorb knowledge, as well as enhance learning capability, thereby playing a crucial role for innovation (Cohen and

Levinthal 1990; Liu et al. 2020; Weidner et al. 2023). Pedota (2024) provides one of the first studies to explore the relationship between AI and AC and highlights two important mechanisms enabling the synergy between AI-knowledge and human knowledge: cognitive ambidexterity and the virtualization of tacit knowledge. On the one hand, cognitive ambidexterity is defined as the ability to blend domain specific and AI-related knowledge, leveraging the strengths of both human intelligence and AI. This mechanism links the human- and AI-related components of AC and clarifies how employees jointly with AI can acquire and assimilate, as well as exploit new knowledge created by combining human and AI-generated knowledge (Mikalef and Gupta 2021a), for example for facilitating innovation processes. On the other hand, the virtualization of tacit knowledge refers to uncovering human tacit knowledge and utilizing it to carry out sophisticated tasks by functioning as a transmitter of knowledge. AI is able to shift individual tacit knowledge to the organizational level and make it available to everyone across the organization. This creates an opportunity for employees to learn something new and reveals tacit knowledge that even experts are unaware of (Pedota 2024).

Nonetheless, AI alone does not guarantee product innovation outcomes. Its innovation-accelerating value depends on complementary firm-level innovation resources. Continuous R&D activities expand the firm's absorptive capacity for translating AI-generated knowledge into new digital product architectures instead of analog product improvements (Cohen and Levinthal 1990). Workforce qualifications determine the firm's ability to technically develop and govern AI models. Human centricity approaches in companies, such as organizational training, support the diffusion of AI-derived design knowledge across functions, while structured employee involvement enables the identification of digital product innovation opportunities grounded in tacit operational knowledge. AI and traditional innovation drivers thus operate as complementary capability enablers: AI opens generative innovation opportunity spaces, while organizational resources and practices determine whether these opportunities result in product innovation. This leads us to our first hypothesis:

H1: The implementation of AI solutions in production, i.e. AI-enabled process innovation, alongside traditional firm-level innovation determinants including R&D activities, workforce qualifications and human centricity approaches, enhances the likelihood of ***product innovation in manufacturing firms****.*

In the contemporary digital economy, digital product innovation has become a central driver of value creation and a core component of business model development (Nambisan et al. 2017). Lyytinen et al. (2016) define digital product innovation as *'significantly new […] products or* *services that are either embodied in information and communication technologies or enabled by them'*. This understanding captures two key innovation pathways: the development of fundamentally new ICT-based products and services, and the digital enhancement of existing physical products through the integration of software, connectivity, sensors, or embedded intelligence. Digital product innovation therefore reflects not only technological novelty, but new forms of digital resource recombination in product innovation processes (Nambisan 2013; Nambisan et al. 2017).

A critical prerequisite for digital product innovation is the firm's ability to assemble, mobilize, and deploy digital resources across all stages of the innovation lifecycle (Chae et al. 2014; Nwankpa and Datta 2017; Wiesböck 2019). Digital technologies in manufacturing provide essential infrastructures for digital experimentation, real-time sensing, and data-driven problem solving, thereby facilitating innovation processes in manufacturing settings (Barrett et al. 2015). However, traditional automation technologies remain constrained to pre-programmed routines and improve performance only within predefined operational parameters, lacking interpretive flexibility or generative learning capability. In contrast, AI-enabled process innovation establishes organizational learning loops that connect production operations with product innovation functions (Cooper 2024). AI introduces learning-based adaptivity, enabling systems to autonomously interpret complex data, refine decision logic, and generate design-relevant knowledge for product innovation that extends beyond static programming boundaries (Grech et al. 2023). In other words, by converting operational data into reusable innovation knowledge, firms increasingly generate digital product ideas grounded in real system behavior and usage intelligence rather than relying exclusively on conventional R&D activities. AI allow firms not only to automate existing workflows but also to detect latent patterns, reconfigure processes, personalize product features or service offerings, and accelerate responses to dynamic market or environmental conditions, strengthening both efficiency-oriented and innovation-oriented performance outcomes (Agrawal et al. 2018; Paschen et al. 2020; Raisch and Krakowski 2021). Building on the same logic of technological uniqueness and organizational complementarity from the *H1*, we propose the following hypothesis with respect to digital product innovation:

H2a: The implementation of AI solutions in production, i.e. AI-enabled process innovation, alongside traditional firm-level innovation determinants including R&D activities, workforce qualifications and human centricity approaches, enhances the likelihood that the manufacturing company realizes ***digital-oriented product innovation instead of traditional non-digital product innovation****.*

Sustainability has emerged as a pivotal element in modern manufacturing, particularly within the framework of Industry 4.0, Industry 5.0 and the twin transition (Rehman et al. 2023). The integration of AI technologies into production processes not only improves operational efficiency but also plays a crucial role in fostering eco-oriented product innovation. First, AI in production generates valuable data relevant to sustainability issues such as optimizing resource efficiency, reducing waste, and promoting circular economy principles (Waltersmann et al. 2021). This data acquisition enhances the absorptive capacity of firms, enabling them to assimilate and implement sustainability-related insights effectively (Dzhengiz and Niesten 2020). As companies become more capable of leveraging this knowledge, their potential for eco-oriented product innovation increases. By integrating AI-driven analytics, manufacturers can identify and exploit energy-efficient production methods, optimize material utilization, and innovate product designs that minimize environmental impacts. Second, AI enhances the sustainability of production processes themselves (Waltersmann et al. 2021). Through continuous monitoring and optimization, manufacturers can improve their processes towards greater sustainability, thus enhancing their capabilities to innovate in eco-oriented ways (Dou and Gao 2023). Improvements in production methodologies not only contribute to sustainability goals but also bolster the firm's overall innovation capabilities. Combining these insights with traditional innovation-related factors, such as R&D activities, workforce qualifications, training, and employee involvement, creates a robust environment for fostering eco-oriented product innovation. The effective interplay between AI solutions and these traditional factors may significantly enhance the likelihood of a manufacturing company realizing eco-oriented innovations rather than merely focusing on traditional, non-eco-oriented products (Ying and Jin 2024). Based on this rationale, we propose the following hypothesis:

H2b: The implementation of AI solutions in production, i.e. AI-enabled process innovation, alongside traditional firm-level innovation determinants including R&D activities, workforce qualifications and human centricity approaches, enhances the likelihood that the manufacturing company ***realizes eco-oriented product innovation instead of traditional non-eco-oriented product innovation.***

When considering product innovation, it is essential to differentiate between new products that are new to the company and products that are new to market, i.e. 'do what we do better' vs. 'do something different' (Joe and John 2013). Innovations classified as new to the firm primarily involve incremental improvements, optimizing existing products, services, or processes to enhance specific features for a defined customer base. This type of innovation is often characterized by lower complexity and greater certainty, as both target markets and customer needs are well understood (Robertson et al. 2012). Established production processes typically use existing technology that does not significantly differ from current practices. As a result, companies can leverage their existing knowledge, minimizing the risks associated with innovation while improving efficiency, product quality, and reducing production costs without necessitating fundamental structural changes. Hence, the exploitation of existing knowledge plays a crucial role for this kind of innovation. This type of innovation is crucial for competitiveness, as it enables companies to respond flexibly to market changes and maintain their position in the market (Valle and Vázquez-Bustelo 2009).

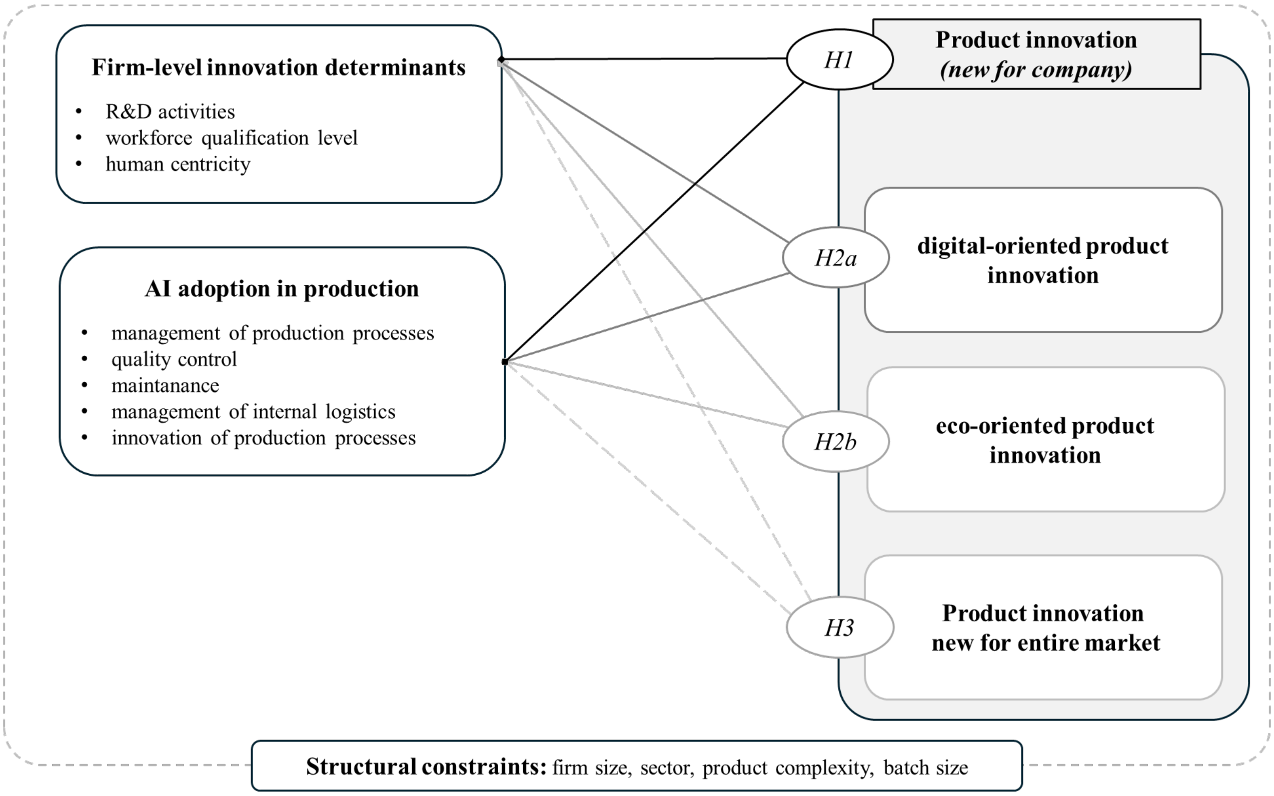
However, opening new markets by creating completely new products, services, or technologies that are revolutionary for both the company and the overall market, goes with various innovation process relevant challenges. This form of innovation is namely characterized by a high degree of uncertainty and complexity, as the technological requirements and customer needs are often still unclear and can change rapidly (Slater et al. 2014; Valle and Vázquez-Bustelo 2009). Companies pursuing this level of novelty must embrace significant risks and be adaptable to evolving conditions (Slater et al. 2014). These innovations have the potential to disrupt existing market structures by introducing new business models and value chains that outperform traditional offerings (Garcia and Calantone 2002). Consequently, their implementation demands a profound level of learning, flexibility, and adaptability. AI solutions in manufacturing can play a crucial role in fulfilling these tasks.

AI implemented in production environments enhances knowledge exploration and implementation in innovation processes. Rather than merely automating established tasks, AI facilitates knowledge exploration by enabling firms to uncover previously hidden data structures, recombine work routines, tailor solutions for specific applications, and respond more swiftly to shifting markets and technological conditions. This capability strengthens both operational performance and innovation outcomes. Moreover, AI-driven process innovation increases production adaptability and supports the development of intricate product system designs, expanding the solution space for viable product concepts. Consequently, this directly facilitates the creation and market introduction of novel product offerings. By amplifying firms' ability to generate, internalize, and deploy new knowledge through manufacturing operations, AI equips production companies with enhanced capabilities to transform process-level insights into successful market innovations. Thus, we hypothesize that:

H3: *The implementation of AI solutions in production, i.e. AI-enabled process innovation, alongside traditional firm-level innovation determinants including R&D activities, workforce qualifications and other human centricity approaches, enhances the likelihood that the manufacturing company realizes market-novel product innovation, i.e.* ***products that are not only new to the firm but also new to the entire market.***

Figure 17 summarizes our research concept and illustrates the four hypotheses (H1, H2a, H2b, and H3).

Figure 17: Concept of research



D.3 Methodology

This study draws on empirical data from the GMS, a well-established quantitative survey of industrial firms in Germany (Fraunhofer Institute for Systems and Innovation Research ISI 2025). The survey assesses innovation activities within the German manufacturing sector, focusing on various practices related to production processes, products, services, and organizational aspects. Initiated in 1993 (Lay and Maloca 2004), the GMS has been conducted every three to four years and represents Germany's contribution to the European Manufacturing Survey. The 2022 data provides comprehensive information for our analysis, including data on AI adoption in production, product innovations, organizational practices, performance indicators, and general company characteristics (Jäger and Maloca 2022b). The items for evaluating AI adoption were developed by our team (Heimberger et al. 2025) to explore its relationship with product innovations.

D.3.1 Data Base and Sample Description

For our analysis, we utilize the most recent dataset from the GMS 2022 round, conducted between fall 2021 and spring 2022 (Jäger and Maloca 2022b). A gross sample of 15,299 manufacturing sites in Germany (NACE rev. 2, 10–33) with at least 20 employees was randomly selected using a proportional stratified sampling procedure. A net sample of 14,045 firms was then contacted, with the survey being addressed to the production managers or chief technical officers of these firms. As a result, 1,334 fully usable questionnaires were received that met the criteria of 75% of questions being answered in full, yielding a 10% response rate. The realized dataset reflects the regional distribution, firm size, and industry composition of the German manufacturing sector aligning with data from the Federal Statistical Office. Thus, it can be regarded as representative in these aspects. Table 28 in the appendix summarizes the key characteristicsb of the analyzed sample and compares them with corresponding structural data of the population in the German manufacturing industry by company size and industry, based on Federal Statistical Office information (Jäger and Maloca 2022b).

D.3.2 Key Variables

Dependent variable: Product innovation types

To evaluate the innovative strength of manufacturing companies, we focus on four indicators on product innovation as our dependent variables (Horvat et al. 2025). First, we identify *product innovators* as firms that have introduced new products or significantly improved existing ones (e.g., through new materials or modified functions) in the last three years preceding the survey. Following prior research, we consider these innovations to provide new benefits, even if their changes and impacts are limited (Benner and Tushman 2003; Guisado-González et al. 2016; Varadarajan 2009). Second, we assess the digital dimension of product innovation by distinguishing between firms that have incorporated digital extensions or significant improvements to existing digital elements in their new products, i.e. *digital-oriented product innovators*, and those firms that have not. We assume these digital innovations have substantial potential for enhancing functionality (Lyytinen et al. 2016; Matt et al. 2015; Nylén and Holmström 2015; Pesch et al. 2021). Third, we analyze eco-oriented product innovations, differentiating between firms that have significantly improved the environmental impact of their new products during use or disposal and those product innovators with new products that showed no significant improvements in environmental dimensions retrofitting (Dangelico and Pujari 2010; Paparoidamis et al. 2019; Pujari 2006). The survey allowed six dimensions to be identified as ecological improvements in the new product: (a) a reduction in health risks during use, (b) lower energy consumption, (c) minimized emissions or environmental pollution during use of the product, (d) better recycling properties, (e) a longer product life, and (f) easy maintenance or retrofitting. Firms that achieved improvements in at least two of these sustainability aspects were classified as *eco-oriented product innovators*, whereas those with fewer or no such improvements were considered non-eco-oriented product innovators. Finally, we investigate whether the new products have led to market innovations. The firms reported whether their new products included any products that they had launched on the market for the first time. The indicator distinguishes between *market innovators* and firms whose new products did not include market innovations. We posit that these market innovations reflect greater innovative strength than those that are merely new to the company (Guisado-González et al. 2016; Kyriakopoulos et al. 2016; Mosey 2005).

Independent variables: Determinants of product innovation

We consider various constructs as influencing factors. In addition to the use of AI in production, these also include innovation determinants at the firm-level (as displayed in Figure 17).

<u>*AI adoption in production*</u>

In our study, we analyze *AI adoption in production* as a determinant for product innovation, focusing on five main application areas (Heimberger et al. 2025). Firms surveyed were asked if they use AI-based self-learning software solutions, defined as algorithms that recognize patterns and offer actionable recommendations. The indicator measures whether a manufacturing firm uses AI in at least one of five key production areas:

(1) management of production processes (e.g. process monitoring)

(2) quality control (e.g. defect detection)

(3) maintenance of machinery and equipment (e.g. condition monitoring)

(4) management of internal logistics (e.g. warehouse management and transport)

(5) improvement or innovation of product processes.

Based on this specific information, the indicator makes a binary distinction between AI adopters (firms that use AI in at least one possible production application area) and non AI-adopters (those firms that do not use AI in any of the five areas) (Heimberger et al. 2025).

Firm-level innovation determinants

In addition to the impact of AI adoption in production on product innovations, we include three additional firm-level innovation determinants in our analysis. Table 23 displays the indicators and measurement level of these three determinants. First, we consider the *R&D activities* of manufacturing firms, as these are known to positively influence product innovation (Becker and Dietz 2004; Bianchi et al. 2016; Un et al. 2010). To assess R&D activities, we examine on the one hand whether firms conduct R&D internally or outsource it. On the other hand, we also examine whether a firm collaborates with other companies, or research institutions on R&D topics. Both indicators are dichotomous variables and are considered independently of each other. In order to assess the significance of R&D activities as such, the influence of the two indicators for the construct are considered jointly. Secondly, we examine the *workforce qualification level* and assume that a certain degree of knowledge and specific skills among employees positively impacts the capabilities to realized product innovation (Herrmann and Peine 2011; Kach et al. 2015; Romano 1990). The indicator is based on the proportion of highly qualified employees, i.e. employees with an ISDEC level of at least 5 (including university graduates, technical college graduates, technicians, or master craftsmen) and is taken into account as a centered value in the regressions.

Third, we analyze firms' *human-centricity*, focusing on two dimensions: targeted employee training and production employees' involvement. Specific training initiatives can enhance employee skills and boost product innovation capabilities (Manresa et al. 2018; Romano 1990), while the dedicated involvement of production employees is recognized as another key driver of product innovation (Abu El-Ella et al. 2013; Rangus and Slavec 2017). In order to assess the training opportunities available to production employees, we use an ordinal indicator to distinguish between firms that do not offer any training at all, firms that offer cross-functional training as well as a creativity-focused training for production employees, and firms that offer training for their production employees but not both specific training. For involving employees in innovation, we distinguish between firms that actively involve employees in innovation and product development by applying organizational concepts, such as dedicated working time or formalized sessions for idea generation, and those firms that do not apply such concepts.

Table 23: Operationalization of firm-level innovation determinants

Firm-level innovation determinants	**Indicators**	**Measurement level**
R&D activities	- Performed R&D or awarded R&D contracts to external partners in 2021 - Cooperated in R&D with another firm or a research institution	Yes-no dummy Yes-no dummy
Workforce qualification level	- Share of highly qualified employees (ISDEC level >=5) on the all employees	Centered value of the share

Human centricity	- Involvement of production employees in the development of products or processes
	- Cross-functional and creativity training for production employees
	  - No training offered for production employees
	  - Other training offered for production employees, but not these two specific offers
	  - Training offered for production employees at least on both topics: creativity and innovation (e.g., problem solving, idea generation, brainstorming techniques) and with interdisciplinary focus (e.g., project management, team leadership, language courses)
		Yes-no dummy
		Ordinal variable
		(3 groups)

Context variables: structural constraints

In our analysis, we also consider other variables reflecting structural characteristics and production specifics. A key contextual variable is firm size, measured by the total employee count. For regression models, this indicator is logarithmically transformed to adjust for decreasing marginal costs. In descriptive analyses the metric information is classified into distinct groups. As noted in previous studies, larger firms typically have more resources and often implement innovation-enabling measures (s.a. R&D) to drive product innovation (Ettlie 1987; Shefer and Frenkel 2005). However, small businesses can also excel due to their dynamism and agility (Ettlie 1987; Romano 1990; Stock et al. 2002). In addition to firm size, we take into account the industry affiliation, which reveals specific characteristics such as automation or competitive pressure that influence innovation activity. This indicator is of crucial importance since manufacturing sub-sectors vary in technological intensity (e.g. high tech vs. low tech) and innovative capacity (Romano 1990; Vega-Jurado et al. 2008). We categorize industries into eleven groups based on the NACE Rev. 2 classifications (cp. Table 28). We also take into account the batch size of the company's main product, as firms with smaller batch sizes often drive product innovation more than companies with larger series (Hobday 1998). We distinguish between single-item production, small- to medium-series production, and large-batch production. Furthermore, we consider the product complexity, as companies with highly complex products typically involve more intricate innovation processes and require enhanced collaboration (Caniato and Größler 2015; Hobday 1998). The assumption is that firms with highly complex products face greater pressure to innovate than those with simpler products. The indicator differentiates production of simple products, of products with medium complexity and of complex products.

D.4 Results

D.4.1 Innovation Determinants

In order to measure the influence of different innovation determinants on the introduction of new product innovations, we examine some descriptive results on their prevalence in the manufacturing sector in Germany. To do this, we first look at the three firm-level innovation determinants. As shown in Table 24, this descriptive analysis reveals interesting insights into the current innovation landscape in German manufacturing. In terms of R&D, only 37% of companies appear to conduct in-house R&D or outsource R&D to external contractors. This suggests that the majority of German manufacturers (63%) did not invest in R&D in 2021, which could indicate a reluctance to pursue an innovation strategy. However, when looking at R&D collaborations with other companies, or with research institutions, it can be seen that a large proportion of companies (54%) actively enter into partnerships that go beyond pure business contracts in order to strengthen their innovative capabilities. In detail, 45% of manufacturers cooperate with research institutions, 39% cooperate on R&D topics with customers or suppliers, and 27% of manufacturers cooperate on these topcis with other companies.

With regard to the second factor, the qualification level of the workforce, the analysis shows that, on average, 22% of the personnel in the manufacturing firms in Germany (median = 18%) are considered highly skilled with an educational background at least at a level of 5 at the ISDEC scale, i.e. employees which graduated from a university or technical college, or who holds a technician or master craftsmen certificate. The third innovation factor, human-centricity, is also important for strengthening the innovative capacity of manufacturing firms. As shown in Table 24, 46% of manufacturers have organizational concepts implemented to involve their employees in innovation processes When it comes to training measures to promote creativity and innovation or boost cross-functional skills, the results show that only 18% of manufacturers in Germany offer specific training for both these areas to their production employees. While another two-thirds of companies (63%) offer training for their production employees, these training offers do not cover these cross-cutting topics. In addition, 16% of manufacturers in Germany do not offer their production employees any further training opportunities. To be specific, only 26% of firms offer training to promote creativity and innovation, e.g. on problem solving, idea generation or brainstorming techniques. This could be an obstacle to the development of innovative ideas. In contrast, training with cross-functional focus as project management, team management, or language courses is somewhat more widespread, with 43% of firms offering such programs and thus promoting the integration of different disciplines into the innovation process.

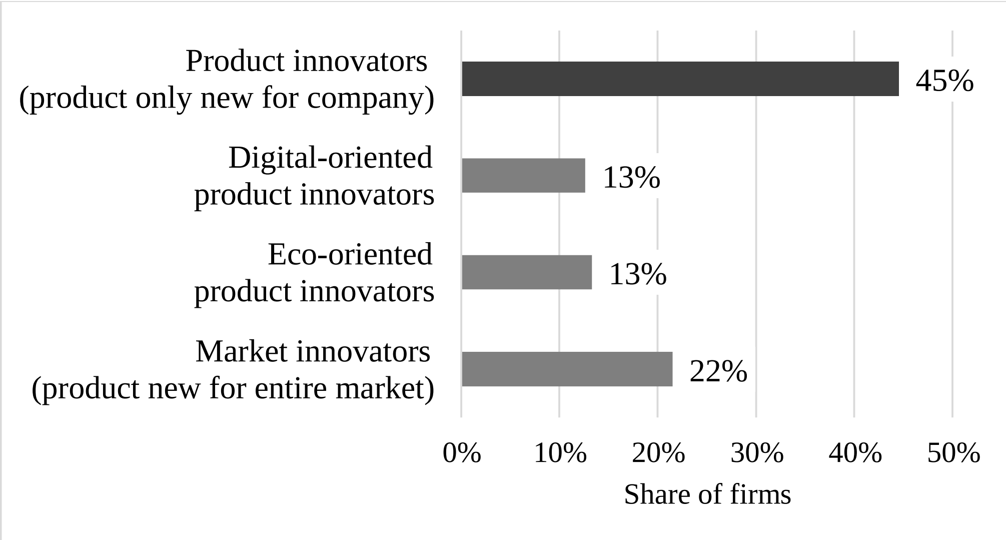
Table 24: Utilization of firm-level innovation determinants across manufacturing firms in Germany

Firm-level innovation determinants	**Indicators**	**% of yes**	**mean %**
R&D activities	R&D performed internally or outsourced	37%	-
	R&D cooperations with another firm or a research institution	54%	-
Workforce qualification level	Share of highly qualified personnel	-	22%
Human centricity	Measures for employee involvement	46%	-
	Training in creativity and innovation and with cross-functional focus:		-
	- No training offers	16%	
	- Some training offers but not those both specific ones	66%	-
	- training with cross-functional focus and training for creativity and innovation	18%	

Sources: Own calculation.

Figure 18 shows the share of product innovators within the German manufacturing industry, differentiated by the types of product innovation: 45% of manufacturers in Germany had introduced a new product that were not previously available in the company. More than a quarter of them launched new products that were (also) based on a digital product extension or a major improvement of existing digital product elements. With regard to the whole population, this represents 13% of all manufacturers. Comparably, also 13% of all manufacturers introduced eco-oriented product innovations. Furthermore, nearly half of all product innovators claimed to have introduced product innovations that were new to the entire market which means 22% of all manufacturers are considered as market innovators. These results illustrate the willingness of manufacturers in Germany to invest in various types of product innovations, with a surprisingly high share of market innovation.

Figure 18: Share of product innovators in German manufacturing



Sources: Own calculation.

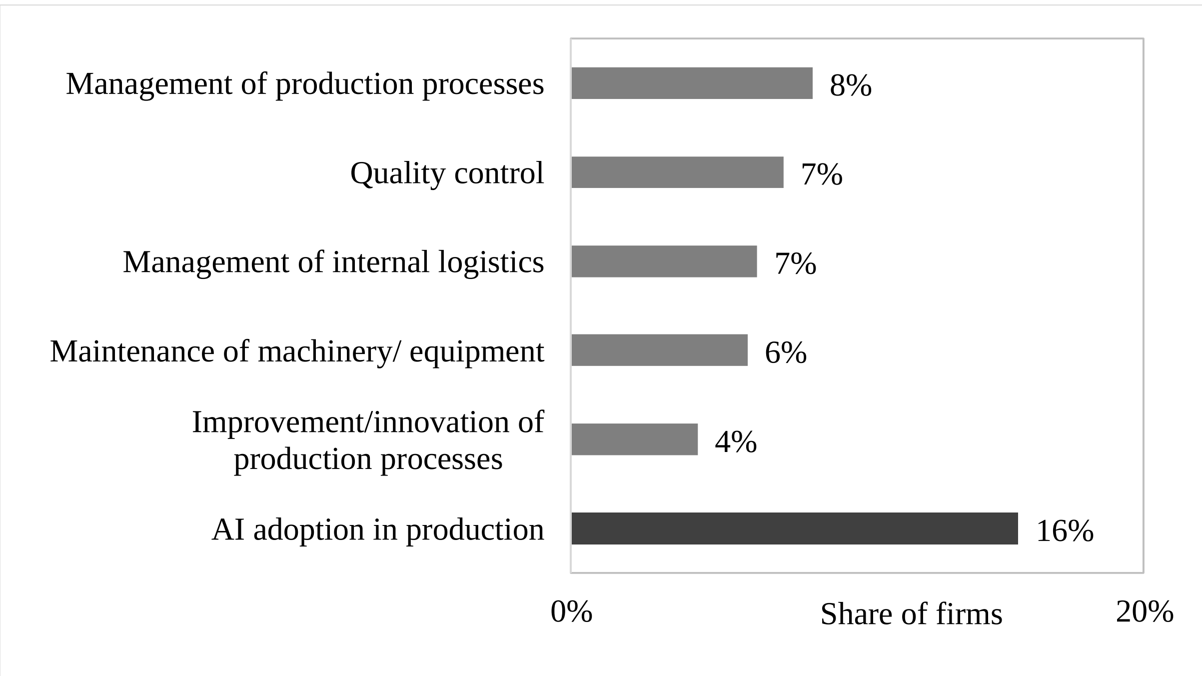
As visualized in Table 29 in the appendix, the bivariate analyses of the various types of product innovators also reveal some interesting structural features: When examining firms size, it is noticeable that large manufacturers (with 500 or more employees) are predominantly product innovators. Three-quarters of large firms (75%) introduced new products in the three years prior to 2022. In contrast, only a third of small firms with less than 50 employees introduced new products. In addition, 39% of large product innovators focused on digital-oriented product innovation, among the small product innovators this share was 31%. Moreover, many large product innovators realized eco-oriented product innovation (43%). Only a quarter of the small product innovators (25%) launched such products. However, when looking at the share of market innovators, no statistically significant differences between the firm size groups could be identified.

In addition, there are striking differences between the various sector groups and between the product complexity classes, while the different batch size groups did not show any statistically significant differences. Regarding sectoral differences, some sectors stand out as particularly active product innovators, with strong differences depending on the type of product innovation. For digital-oriented product innovations, the electronics industry stands out with 63% of product innovators who have developed digital-oriented new products, followed by the machinery sector with 42%. In contrast, eco-oriented product innovations were particularly evident among product innovators from the wood and paper industry (48%). With regard to product complexity, it becomes clear that manufacturers of complex products in particular are more focused on product innovation across all types of product innovations compared to the manufacturing firms that offer simple or medium complex products.

D.4.2 AI Adoption and Product Innovation

Our data also provides insightful findings on AI adoption in the German manufacturing landscape. To this end, Figure 19 visualizes the AI adoption rate in the five analyzed areas of application in production for the manufacturing industry in Germany and the overall AI adoption rate which considers AI use in at least one of these five application areas. In 2022, 8% of the companies used AI for managing their production processes, while 7% used it for quality control and another 7% for internal logistics. In addition, 6% of companies used AI for machine and equipment maintenance, and 4% for improving or innovating production processes. Overall, only 16% of the manufacturing firms in Germany used AI in at least one of the five application areas in 2022. This adoption rate may appear relatively low, but it reflects the state of AI adoption in 2022.

Figure 19: AI adoption in production by application area



Sources: Own calculation.

To further test the relationship between AI adoption and product innovation, Table 25 shows the shares of product innovators for the four types of product innovations analyzed, depending on AI adoption in production. The comparison between the proportions of product innovators among AI adopters and non-adopters provides some interesting insights. Across all four types of product innovations, firms that adopt AI in a production context have a higher rate of product innovators. Between 2019 and 2022, 52% of all AI adopters introduced new products that were new to the company, while only 43% of non-adopters did so. The differences are particularly striking in the case of digital-oriented and eco-oriented product innovations. Here, 42% of AI adopters who had implemented product innovations were able to introduce digital-oriented new products, while this figure was only 25% among non-AI users who implemented new products. A similar pattern can be seen in eco-oriented product innovations: 48% of AI adopters with new products developped eco-oriented product innovations, compared to only 26% among non-AI adopters who implemented new products. This suggests that the new capabilities enabled by the adoption of AI within production made organizations better able to deliver innovation. Only when looking at market innovations no statistically significant differences were identified. Roughly half of the product innovators introduced market innovations, regardless of whether AI was adopted in production or not.

Table 25: Correlation between the adoption of AI and product innovations in manufacturing firms

Type of product innovation	**AI adopters**	**non-AI adopters**
Product innovators (products new for company) [among all manufacturers] **	52%	43%
Digital-oriented product innovators [among product innovators] ***	42%	25%
Eco-oriented product innovators [among product innovators] ***	48%	26%
Market innovators (products new for entire market) [among product innovators] n.s.	52%	48%

Note: Statistical significance level of group comparison: *** p< 0,001, ** p< 0,05, * p<0,1, n.s. not statistically significant with p>=0.1.
Sources: Own calculation.

D.4.3 Linking Innovation Determinants and Product Innovation

In order to further investigate the influence of the various innovation determinants on the realization of product innovations, we also tested our hypotheses using estimation of various logistic regressions. Table 26 summarizes the results of the four models in terms of the explanatory contribution of the factors analyzed. For each model, the model improvement achieved by including the indicators for the factor is shown by the change in the log-likelihood statistic between the baseline model without the indicator(s) and the model with the indicator(s). Taking into account the necessary degrees of freedom, this allows an assessment of the independent explanatory contribution for each explanatory factor. In addition, Table 27 lists the estimated odds ratios (OR) and the results of the statistical significance tests for the individual indicators of the various constructs of innovation factors. This makes the influence of the various innovation factors transparent.

Table 26: Explanatory power of the impact factors in the estimated logistic models for models A-D

	Models			
Population	All manufacturers	All product innovators		
Dependent construct	Product innovator	Digital-oriented product innovator	Eco-oriented product innovator	Market innovator (product new to the market)
	(vs. non-product innovator)	(vs non-digital-oriented product innovator)	(vs. non- eco-oriented product innovator)	(vs. non-market innovator)
Factors	A (H1)	B (H2a)	C (H2b)	D (H3)
Firm size	-10.61 (1) **	n.s.	n.s.	n.s.
Industry affiliation	-32.14 (10) ***	-31.49 (10) **	-23.24 (10) ***	n.s.
Batch size	n.s.	n.s.	n.s.	n.s.
Product complexity	n.s.	n.s.	-5.38 (2) *	n.s.
AI adoption in production	-2.89 (1) *	-7.40 (1) **	-3.64 (1) *	n.s.
R&D activities	-47.01 (2) ***	n.s.	n.s.	-8.44 (2) **
Workforce qualification level	-2.88 (1) *	n.s.	n.s.	n.s.
Human centricity	-12.16 (3) **	6.58 (3) *	-20.02 (3) ***	-10.64 (3) **
N	968	429	427	429
-2-LL / Sig.	1123.915 ***	417.023 ***	438.240 ***	555.253 **

Notes: Logistic regression models. Model A included all manufacturers, models B, C and D only firms who were product innovators. For each construct the realized difference in the -2LL due to the indicators is displayed as well as the degree of freedom in brackets and the significance level for the model modification.
Parameter of model fit: -2LL = -2 Log-Likelihood, N = number of cases.
All models are statistically significant (Models A, B, C $p< 0.001$; Model D $p< 0.05$).
Significance level: *** $p< 0.001$, ** $p< 0.05$, * $p<0.1$, n.s. not statistically significant with $p>=0.1$.
The authors are happy to provide more detailed information on all models upon request.
Sources: Own calculation

A comparison of the estimation models presented shows that they make a relevant contribution to explaining the probability of product innovations per se and the type of product innovation. Table 26 shows that in three of the four models, the consideration of the adoption of AI in production, in addition to structural and traditional, primarily organizational innovation factors, makes an additional explanatory contribution to a certain extent. It also becomes clear that, in addition to the diverse R&D activities, human centricity plays an important role in predicting product innovation activities. Furthermore, industry-specific conditions continue to be a decisive factor in a manufacturer's product innovation activities.

As summarized in Table 27, our estimated results for Model A show in detail that the adoption of AI in production processes has a positive effect on the probability that product innovations are realized at all (OR=1.4), even when important drivers for product innovations and structural characteristics are controlled for. However, this effect is only statistically significant at the 10 percent level. R&D related activities are more decisive for becoming a product innovator with new products for the firm. Both the firms own direct R&D activities (OR=2.2) and the R&D cooperation with external innovation partners (OR=1.7) increase the likelihood that a firm is a product innovator. These results suggest that the integration of R&D efforts plays a more important role in whether a company can introduce a new product than the adoption of AI in production processes. In addition, indicators for a human centricity make a relevant contribution. Firms that offer trainings for production employees are more likely to be product innovators than firms without such training offers (OR = 1.8). Moreover, firms that offer their production employees a training with a cross-functional focus and a creativity-related training demonstrate even greater innovative strength (OR=2.0). However, organizational efforts to involve production employees in innovation processes do not provide any additional explanatory contribution to the model. In addition, firms with a larger share of highly qualified employees are more likely to be product innovators (OR=1.2). Finally, from a structural perspective, the size of the company and the industry are also relevant explanatory factors. In contrast, the production characteristics do not play a relevant role whether a firm can introduce new products successfully.

Table 27: Estimated ORs for the indicators of innovation drivers in the estimated models A-D

	Models							
	A (H1)		**B (H2a)**		**C (H2b)**		**D (H3)**	
Innovation drivers	OR	Sig.	OR	Sig.	OR	Sig.	OR	Sig.
AI adoption		*		**		*		
AI adoption in production (1)	1.438	*	2.372	**	1.791	*	1.052	n.s.
Qualification		*						
Share of highly-qualified personnel (z-centered)	1.156	*	1.232	*	0.952	n.s.	1.090	n.s.
Human centricity		**		*		***		**
Employee involvement in innovation and improvement (2)	1.271	n.s.	1.239	n.s.	1.785	**	1.510	*
Cross-functional and creativity training for production employees		**		n.s.		**		*
Some training, but not both (3)	1.830	**	4.479	*	3.925	*	0.808	n.s.
Cross-functional as well as creativity training (3)	2.000	**	4.398	*	8.066	**	1.490	n.s.
R&D activities		***						**
R&D activity (internal/external) (4)	2.159	***	1.145	n.s.	1.369	n.s.	1.677	**
R&D cooperation(s) (5)	1.745	***	1.122	n.s.	1.411	n.s.	1.379	n.s.

Notes: Logistic regression models. Model A included all manufacturers, models B, C and D only firms who were product innovators. All models included also indicators for sector, firm size, product complexity and batch size.
Significance level: *** p< 0.001, ** p< 0.05, * p<0.1, n.s. not statistically significant with p>=0.1..
Reference groups: (1) no AI adoption in production, (2) no organisational concept implemented to involve production employees in improvement and innovation processes, (3) no training offer for production employees, (4) no R&D performed, (5) no R&D cooperation with another firm or research institution.
The authors are happy to provide more detailed information on all models upon request.
Sources: Own calculation.

Next, we examined what determines that product innovators are more likely to launch digital-oriented products than traditional, non-digital product innovations. The reference group consists of companies that have introduced traditional product innovations, i.e., those that have entered the market with analog improvements (model B). Our results indicate that the adoption of AI in production processes increases the likelihood that a company will introduce digital-oriented product innovations instead of traditional, non-digital new products (OR=2.4). Compared to the other influencing factors, the consideration of AI adoption makes one of the largest contributions to the model. This suggests that AI adoption in production promotes digital innovation processes and supports companies in the development of digitally enhanced products. A higher share of qualified employees also increases the likelihood (OR=1.2) that a company will be a digital product innovator rather than a traditional product innovator; however, this effect is only significant at the 10 percent level. The human centricity also contributes at the 10-percent significance level, especially the training offer is affecting whether a company focuses on digital product innovation. In contrast, the indicator for the involvement of production employees in innovation processes does not provide additional explanatory power for this distinction. R&D activities as such also do not contribute to this distinction, which means that although R&D is relevant for the development of new products and the organizational changes required for this, it has no influence on the type of new product introduced. From a structural perspective, the manufacturers industry affiliation, which refers to the different possibilities for digitization and digitalization of the product in the various manufacturing industries, is an influencing factor. However, other company and production characteristics are not relevant to this model.

In Model C, we examined the factors that influence the likelihood of a company to introduce eco-oriented product innovations instead of non-eco-oriented ones. Our results show that the adoption of AI in production processes has a positive effect on the likelihood of a company implementing eco-innovations (OR=1.8); however, this effect is only significant at a 10% significance level. Here, human centricity plays a more important role in promoting eco-product innovations. Training measures to promote the innovative ability and cross-functional skills of production employees strongly increase the likelihood (OR=8.1) of eco-oriented product innovation, but also other training offers increase the odds (OR=3.9). Additionally, the involvement of production employees in innovation processes (OR=1.8) also increase the chance that a company will introduce eco-oriented product innovations. In contrast, the qualification level of employees does not contribute to the model of eco-oriented product innovation. R&D activities do not play a significant role in determining whether a firm introduces eco-oriented product innovations or not. Structural firm information and production characteristics as such are also of lesser importance; only the sector in which the firm operates is a decisive criterion for predicting whether a company will introduce eco-oriented product innovations.

Finally, using Model D, we examined the factors that influence whether or not a company was able to launch a product that was new to the market instead of introducing a new product which was only new for the firm. First, it becomes clear that the development of market innovations is determined less by structural factors and more by R&D activities and human centricity. Moreover, we see that the adoption of AI in production has no influence here. In detail, it can be seen that manufacturers who engage in direct R&D activities (OR=1.7) are more likely to develop market innovations. Collaboration with other companies or research institutions in R&D, on the other hand, plays no role. Furthermore, the results show that companies that offer cross-functional as well as creativity-related training for production employees (OR=1.5) are more likely to be market innovators than firms that offer no training or other trainings to their production employees. Moreover, firms that involve their production employees in innovation processes (OR=1.5) are also more likely to be able to develop market innovations. However, both effects are only significant at the 10 percent significance level.

A comparison of the four models yields some interesting insights: While R&D activities and research partnerships are essential for the development of product innovations, the specific type of innovation (digital, or eco-oriented) is not determined by them. This is where factors such as AI adoption in production and, in the case of eco-innovations, human centricity come into play. Furthermore, our findings underscore the importance of structural factors for a company's overall innovation activity and specific innovation paths. Larger companies generally engage in product innovation significantly more often. However, company size does not play a decisive role in whether a company pursues digital or eco-oriented product innovations. This suggests that while larger companies benefit from greater resources and capabilities for general product innovation, the type of innovation pursued is more influenced by strategic and technological decisions than by company size. Finally, industry affiliation is consistently relevant for explaining innovation trends across all types of innovation. Different industries show varying propensities for traditional, digital, or green product innovations, likely due to industry-specific regulations, technological advances, and market demand dynamics.

D.5 Discussion

AI-enabled processes as a driver for variety and new types of product innovation

Regarding H1, AI adoption in production shows a moderate positive effect on product innovations that are new for the company (OR=1.438). This relationship can be explained by enhanced information flows within the production system of a firm (Lerch et al. 2022b), which also reveals potential for product improvement. Recent research (Frank et al. 2019) argues that smart manufacturing, once it reaches a certain level of maturity, enables greater flexibility and the use of additive manufacturing, which in turn increases the variety and complexity of product design, thereby fostering product innovation. We therefore assume that AI-enabled production processes will mainly contribute to incremental product innovations such as product modifications, customizations and improvements, which will then be supplemented by ongoing R&D activities (OR=2.159), that have the strongest impact on generic product innovations. The incremental aspect is also supported by H3, as AI-enabled processes have no impact on market innovations (OR=1.052), which tend to be rather radical in nature.

Furthermore, with reference to H2, we can determine that AI-enabled processes not only promote product innovation in general but also foster variety and new types of product innovations. In this context (H2a), we can state that manufacturers using AI in their production are significantly more likely to introduce digital-oriented product innovations (OR=2.372) than firms without AI-enabled processes. In our analysis, the adoption of AI in production proves to be the most significant influencing factor. Human-centricity, especially the offer of cross-functional and creative training, shows a strong effect on the development of digital product innovations (OR=4.398) as well, but only reaches a significance level of 10%. This can be attributed to the fact that manufacturers developing or expanding digital capabilities tend to use them across the firm due to individual and organizational learning effects (Lenka et al. 2017; Lerch et al. 2026). Furthermore, firms assemble, mobilize, and deploy their digital resources across all stages of the innovation lifecycle (Chae et al. 2014; Nwankpa and Datta 2017; Wiesböck 2019). Since digital technologies in production often serve as a foundation for AI adoption (Heimberger et al. 2025), it is reasonable to assume that firms possessing both digital and AI capabilities apply them not only within production processes but also in the development of their products (Frank et al. 2019). Over time, this dual application fosters the emergence of both smart product innovations and smart production systems.

Regarding H2b, our results show that manufacturers adopting AI in production are slightly more likely to implement eco-oriented product innovations (OR=1.791). Here, employee involvement (OR=1.785) and especially cross-functional training (OR=8.066) play a much more significant role than the use of AI in production though. However, the observed effect may be linked to the broader dynamics of the twin transition, combining digitalization and sustainability efforts (Montresor and Vezzani 2023). Manufacturers are increasingly prioritizing the development of environmentally friendly products with reduced ecological impact (Rehman et al. 2023). In this context, it is conceivable that manufacturers could specifically use the information from their AI-enabled production processes to increase the resource efficiency of their products, reduce waste, and improve the recyclability of the products (Waltersmann et al. 2021). By providing better information, AI-enabled processes can therefore be able to promote the sustainability of products.

Market innovation – another story?

In contrast to product innovations that are new for the company, our analysis shows no impact of AI-enabled processes on product innovations that are new to the entire market (H3). Therefore, our findings confirm that market innovations, which are more radical in nature, generally appear to be subject to other mechanisms. These innovations are characterized by greater uncertainty and complexity, as customer needs and technological requirements are usually unclear (Sheng and Chien 2016; Slater et al. 2014). We therefore assume that AI-enabled production processes primarily provide information from the production system of already produced products, while they cannot provide information on customer expectations and technological requirements of completely new products that are not yet manufactured.

However, we can state that both R&D activities (OR=1.677) and human centricity (OR=1.510; OR=1.490) have a moderate effect on market innovations. We therefore assume that employees' knowledge of customer needs is a key aspect of market innovation. This knowledge can then be fed into the company through employee involvement and result in target-oriented R&D activities. This mechanism allows information about customer needs and corresponding technological requirements to be linked in the innovation process. Consequently, manufacturers that can ensure this flow of information are also more likely to produce market innovations.

As our descriptive analyses show, 22% of all manufacturers develop new products that are also innovations for the market. On the one hand, this means that market innovations they are more complex and difficult for companies to develop and require more effort. On the other hand, our findings show that their underlying mechanisms follow another story: firstly, market innovations require less process knowledge about production. Secondly, they seem to arise more unsystematically, as structural factors have no influence. Thirdly, the combination of human centricity and R&D activities plays a more central role than in product innovations that are new for the company only.

Innovation beyond R&D: the interplay of AI-enabled processes and human centricity

Regarding H1 and H3, our findings show that R&D is a key driver for generic product innovations as well as for market innovations. This result is going along with findings of earlier studies (Rammer et al. 2022a; Shefer and Frenkel 2005; Un et al. 2010). However, R&D efforts do not directly support either digital-oriented or eco-oriented product innovations (H2a/b). We therefore assume that most manufacturers' R&D activities are still focused on traditional, analog product innovations. Furthermore, our analyses show that AI-enabled production processes and human centricity primarily foster new types of product innovation and can trigger smart and sustainable products. Therefore, we assume that R&D activities serve as the central basis for generic product innovations, while AI-supported processes and human centricity increase the variety of product innovations and support new types of innovation, as they represent a source of supplementary information. In detail, AI-enabled processes tend to drive digital-oriented innovations, while human centricity is more important for eco-oriented innovations. Consequently, the organizational knowledge created by combining AI-supported processes and human experience is a key factor in driving modern types of product innovations among manufacturers.

Beyond the interplay of R&D, human centricity, and AI-enabled processes, several contextual factors of a manufacturer play a role in product innovation. Here, industry affiliation has a significant influence on generic product innovation, as well as on digital-oriented and eco-oriented innovation. Manufacturers from technology-intensive industrial sectors generate product innovations more frequently, which confirms findings from previous studies (Kirner et al. 2009). The share of highly qualified personnel also has a moderate positive influence on generic product innovations, as well as on digital-oriented innovations, which once again emphasizes the importance of human knowledge for innovation processes at manufacturers. Interestingly, however, firm size is irrelevant for digital-oriented and eco-oriented innovations, as well as for market innovations. Among the factors relating to manufacturers' production characteristics, there is only a positive correlation with complex products and eco-oriented product innovations. Overall, this leads to the conclusion that the technology intensity of the sector, the adoption of AI in production, and the integration of human knowledge are more important for generic, but especially for new types of product innovations, than a manufacturer's production structures and resources.

D.6 Conclusions

This study makes a substantial contribution to the understanding of how AI impacts innovation within production environments, enriching both production research and broader innovation management theories. By systematically examining the interplay between AI-enabled production processes and product innovation capabilities in manufacturing firms, we unveil critical insights into how AI functions as a transformative tool that complements traditional innovation determinants like R&D investments, a qualified workforce and human-centricity. Our findings not only highlight the practical applications of AI in driving innovation but also challenge existing paradigms, thereby paving the way for a more nuanced understanding of the mechanisms that underpin successful innovation in today’s rapidly evolving industrial landscape.

D.6.1 Implications

By investigating the relations between AI-driven processes and firms’ innovation outcomes, we provide empirical evidence that contributes to the explanation of how industrial AI enhances both assimilation and exploitation of new knowledge. This dual action of AI positions it as a pivotal enabler in firms' innovation strategies, enriching the absorptive capacity literature by demonstrating that AI in production not only aids in acquiring and assimilating new knowledge in production processes (Broekhuizen et al. 2023; Rožanec et al. 2022; Wu et al. 2019) but also enhances the capacity to utilize this knowledge effectively for innovation. The first effect can be explained through the complementary role of AI to traditional determinants of the innovation process including R&D activities and human centricity approaches in companies. The second one can be concluded by the significant role of AI for product innovation outcomes (Benbya et al. 2024).

Furthermore, our research delves into the varying impacts of AI on different types of product innovations. While we acknowledge R&D as a fundamental determinant of innovation across the board (Rammer et al. 2022a; Shefer and Frenkel 2005; Un et al. 2010), our findings highlight that AI's effect is primarily restricted to product innovations that are new within the company context rather than generating market novelties. This delineation contributes to the industrial innovation literature by clarifying the specific role AI plays in the innovation landscape, paralleling its contributions to internal process related product innovations which are new for the company rather than broad market innovation. In respect to the digital transition, our empirical results clarify that AI significantly influences innovation capabilities (Haefner et al. 2021; Verganti et al. 2020), particularly for products embedded with digital features. We elucidate that AI's transformative capacity not only enhances existing digital capabilities within manufacturing firms but also serves to increase the overall output of digital product innovations. Conversely, we observe that AI's impact on eco-product innovations is existing but limited; in these instances, other human-centric mechanisms appear to play a more crucial role. This finding underscores the multifaceted nature of innovation, suggesting that digital and sustainable innovations may require distinct, human and AI related approaches and mechanisms.

Finaly, our analysis into the role of structural factors relevant for production companies offers additional clarity on the variables that influence innovation outcomes. Although initial expectations suggested that batch size and product complexity would alter innovation dynamics (Caniato and Größler 2015; Hobday 1998), our findings indicate that these factors do not exert a substantial influence. However, company size and industry affiliation emerge as critical determinants, emphasizing the need for nuanced interpretations when assessing innovation capabilities across various manufacturing contexts.

Furthermore, our findings also hold implications for practitioners and innovation managers. As our results show, AI-enabled processes in production are well capable of providing valuable information for product development and product design. Therefore, AI should be viewed as a strategic lever for innovation rather than merely an operational tool. When embedded in a broader innovation strategy, AI adoption in production processes can facilitate both digital and sustainable product development. To unlock this potential, firms should strategically invest in collecting, storing and analyzing AI-generated data and learn how this information can be transferred into new product development.

Our study also highlights the importance of the interplay between R&D, human centricity, and AI-enabled production processes. According to our findings, it is not enough to rely solely on AI. For modern types of product innovation, it is crucial to combine human experience with AI-generated information, link this to new knowledge, and apply it in a targeted manner in R&D activities. Manufacturers who can master these factors and process them into a flow of information have a decisive advantage when it comes to product innovations and their various types. Interestingly, his is not only relevant for large firms, but particularly for small and medium-sized enterprises (SMEs), too. While company size typically has an impact on driving general product innovation (Ettlie 1987; Shefer and Frenkel 2005), these effects do not significantly apply to digital or eco-oriented product innovation. This suggests that resource constraints may be less of a barrier in these domains, opening up new innovation opportunities for SMEs.

Moreover, our study highlights ways in which manufacturers can be specifically encouraged to pursue digital or eco-oriented innovations (Rehman et al. 2023). For digital-oriented product innovation, companies can harness AI capabilities such as predictive analytics, real-time monitoring, and smart product development to create digitally enhanced offerings. Eco-oriented innovation, in turn, can benefit from AI-driven approaches to improving resource efficiency, reducing waste, and supporting circular economy principles (Ying and Jin 2024). These insights highlight the value of AI not only in enhancing innovation performance but also in aligning product strategies with broader sustainability and digitalization agendas.

D.6.2 Limitations and Future Research

Our study holds some limitations, which at the same time offer potential for future research. First, our analyses refer exclusively to physical product innovations and complementary, new types of product innovations that are gaining in importance in the context of global trends such as digitalization and sustainability. However, we cannot comment on non-physical innovations, such as product-related services or business model innovations in particular. Therefore, future studies should expand the analytical scope beyond product innovation to examine how AI enables broader forms of innovation, such as product-service systems or platform-based business models. This would deepen our understanding of the transformative potential of AI in production across various dimensions of industrial value creation.

Second, our analyses and the underlying assumptions refer exclusively to the production system and innovation outcome of a manufacturer itself. However, modern innovations, e.g. based on AI, often arise across companies and in ecosystems. For our quantitative analyses, we had to disregard the significance of interactions between companies. Therefore, future research should examine how AI adoption interacts with external innovation ecosystems, such as collaborations with startups, research institutions, and suppliers. Such analysis could provide a more comprehensive view of AI's role in networked innovation. Such research could illuminate how external partnerships amplify or shape the innovation potential of AI technologies of production processes.

Third, our results are based on a representative, large-scale survey with firm-level data and multiple regression analysis. Even though we can make reliable statements about the connections between AI-supported processes and product innovations, we have no information about the strategies of individual manufacturers and how they interact with product innovations. Therefore, our paper confirms the need for qualitative research designs, including case studies and ethnographic methods, that are well-suited to explore the organizational and contextual mechanisms that underline the impact of AI-enabled production on product innovation capabilities of manufacturers. These approaches could uncover how cultural, structural, and leadership factors mediate the relationship between AI implementation and innovation outcomes.

Finally, our findings relate exclusively to the manufacturing sector in Germany. Although we were able to use a representative data set for our analyses, our results should not be directly transferred to other countries. It would therefore be interesting to carry out similar analyses for other countries and determine whether the results vary, for example, between developed and emerging countries. Furthermore, cross-country comparative studies would provide valuable insights into how national and regional contexts influence AI-driven innovation. Differences in regulatory frameworks, industry structures, digital infrastructures, and workforce skills can have a significant impact on how manufacturing companies use and benefit from AI. Expanding the geographic and institutional scope of empirical research can improve the generalizability and relevance of findings.

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D.7 Appendix

Table 28: Basic descriptions for GMS 2022 and for the German manufacturing industry

# of firms	n=1.334 [(a)]	N=46.158 [(b)]
Firm size (# of employees)		
up to 49 employees	44,5%	51,0%
50 to 99 employees	21,1%	21,4%
100 to 499 employees	28.8%	23,6%
500 and more employees	5,7%	4,0%
Sector (Nace rev. 2)		
Metal industry (24-25)	21,8%	19,9%
Rubber and plastics; glass and stone products (22-23)	15,7%	14,3%
Machinery (28)	20,6%	13,7%
Food and beverages (10-12)	8,8%	13,4%
Products of wood, paper etc. (16-18)	6,1%	7,1%
Electrical products (27)	3,6%	4,9%
Chemicals and pharmaceuticals (20-21)	5,0%	4,5%
Electronic products (26)	4,6%	4,3%
Automotive and transport equipment (29-30)	4,3%	3,7%
Textile, leather, clothing industry (13-15)	3,1%	2,2%
Other sectors	6,4%	11,9%

Source: (a) *German Manufacturing Survey* 2022, (b) Federal Statistical Office (2022). Own calculation.

Table 29: Different types of product innovators depending on selected structural characteristics.

Structural features	**Product innovators (new for company)**		**Digital-oriented product innovators**		**Eco-oriented product innovators**		**Market innovators (new for market)**	
	[all firms]		*[Product innovators only]*					
	yes	**no**	**yes**	**no**	**yes**	**no**	**yes**	**no**
Firm size (# of employees)	***		*		*		n.s.	
up to 49 employees	34%	66%	31%	69%	25%	75%	45%	55%
50 to 99 employees	47%	53%	23%	77%	28%	72%	53%	47%
100 to 499 employees	52%	48%	26%	74%	32%	68%	48%	52%
500 or more employees	75%	25%	39%	61%	43%	57%	48%	52%
Sector groups (NACE rev. 2)	***		***		***		n.s.	
metal products	27%	73%	24%	76%	23%	77%	37%	63%
textile, clothing and leather industry	46%	54%	11%	89%	21%	79%	63%	37%
wood products, paper, cardboard industry	36%	64%	24%	76%	48%	52%	48%	52%
machinery	59%	41%	41%	59%	34%	66%	53%	47%
rubber and plastics industry	39%	61%	16%	84%	25%	75%	41%	59%
food and beverage industry	42%	58%	4%	96%	9%	91%	48%	52%
chemical and pharmaceutical industry	58%	42%	8%	92%	43%	57%	39%	61%
electronic industry	62%	38%	63%	37%	33%	67%	50%	50%
electrical equipment industry	58%	42%	32%	68%	41%	59%	68%	32%
automotive industry	53%	47%	29%	71%	35%	65%	47%	53%
other sectors	48%	52%	33%	67%	23%	78%	50%	50%
Batch size	n.s.		n.s.		n.s.		n.s.	
single lot	40%	60%	28%	72%	31%	69%	49%	51%
small/medium lot	45%	55%	29%	71%	28%	72%	49%	51%
big lot	47%	53%	21%	79%	33%	67%	41%	59%
Product complexity	***		***		***		**	
simple products	29%	71%	10%	90%	13%	87%	38%	62%
medium complex products	43%	57%	28%	72%	30%	70%	46%	54%
complex products	56%	44%	36%	64%	36%	64%	55%	45%

Note: Statistical significance level of group comparison: *** p< 0,001, ** p< 0,05, * p<0,1, n.s. not statistically significant with p>=0.1.

D.8 References

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Eidesstattliche Versicherung

gemäß § 13 Abs. 2 Ziff. 3 der Promotionsordnung des Karlsruher Instituts für Technologie für die KIT-Fakultät für Wirtschaftswissenschaften

1. Bei der eingereichten Dissertation zu dem Thema ‚Adoption of Artificial Intelligence Technologies in Production: Empirical Insights from the Manufacturing Industry' handelt es sich um meine eigenständig erbrachte Leistung.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.

3. Die Arbeit oder Teile davon habe ich wie folgt nicht an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt.

4. Die Richtigkeit der vorstehenden Erklärungen bestätige ich.

5. Die Bedeutung der eidesstattlichen Versicherung und die strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt. Ich versichere an Eides statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe.

Karlsruhe, den 13.01.2026

Heidi Heimberger