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Exploring the factors driving AI adoption in production: a systematic literature review and future research agenda

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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 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 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 Introduction

The technological change resulting from deep digitisation and the increasing use of digital technologies has reached and transformed many sectors [1]. In manufacturing, the development of a new industrial age, characterized by extensive automation and digitisation of processes [2], is changing the sector's 'technological reality' [3] by integrating a wide range of information and communication technologies (such as Industry 4.0-related technologies) into production processes [4].

Although the evolution of AI traces back to the year 1956 (as part of the Dartmouth Conference) [5], its development has progressed rapidly, especially since the 2010s [6]. 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 [7], there is an increasing number of AI applications available for implementation today [8]. The integration of AI into production processes promises to boost the productivity, efficiency as well as automation of processes [9], but is currently still in its infancy [10] 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 [11, 12].

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 [8, 13], which are often applied in combination with other AI technologies, such as natural language recognition. While promising areas for AI

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application already exist in various domains such as marketing [14], procurement [15], supply chain management [16] or innovation management [17], the integration of AI into production processes also provides significant performance potentials, particularly in the areas of maintenance [18], quality control [19] and production planning and management [20]. However, AI adoption requires important technological foundations, such as the provision of data and the necessary infrastructure, which must be ensured [11, 12, 21]. 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 [22]. 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 [23] and impacts work [24], which thus creates managerial challenges in organizations [25, 26]. 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, Osborne [27]. Another issue associated to the fear of machines replacing humans is the lack of acceptance resulting from the mistrust of technologies [28, 29]. This can also be linked to the various ethical challenges involved in working with AI [22]. This perspective, which focuses on the interplay between AI and humans [30], 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 [31, 32], leadership [33], implications on the organizational culture [34] as well as the need for digital capabilities and special organizational skills [33]. Although some studies on the general adoption of AI without a sectoral focus have already been conducted (such as by Chen, Tajdini [35] or Kinkel, Baumgartner, Cherubini [36]) 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 [37, 38]. 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.

2 Methodology

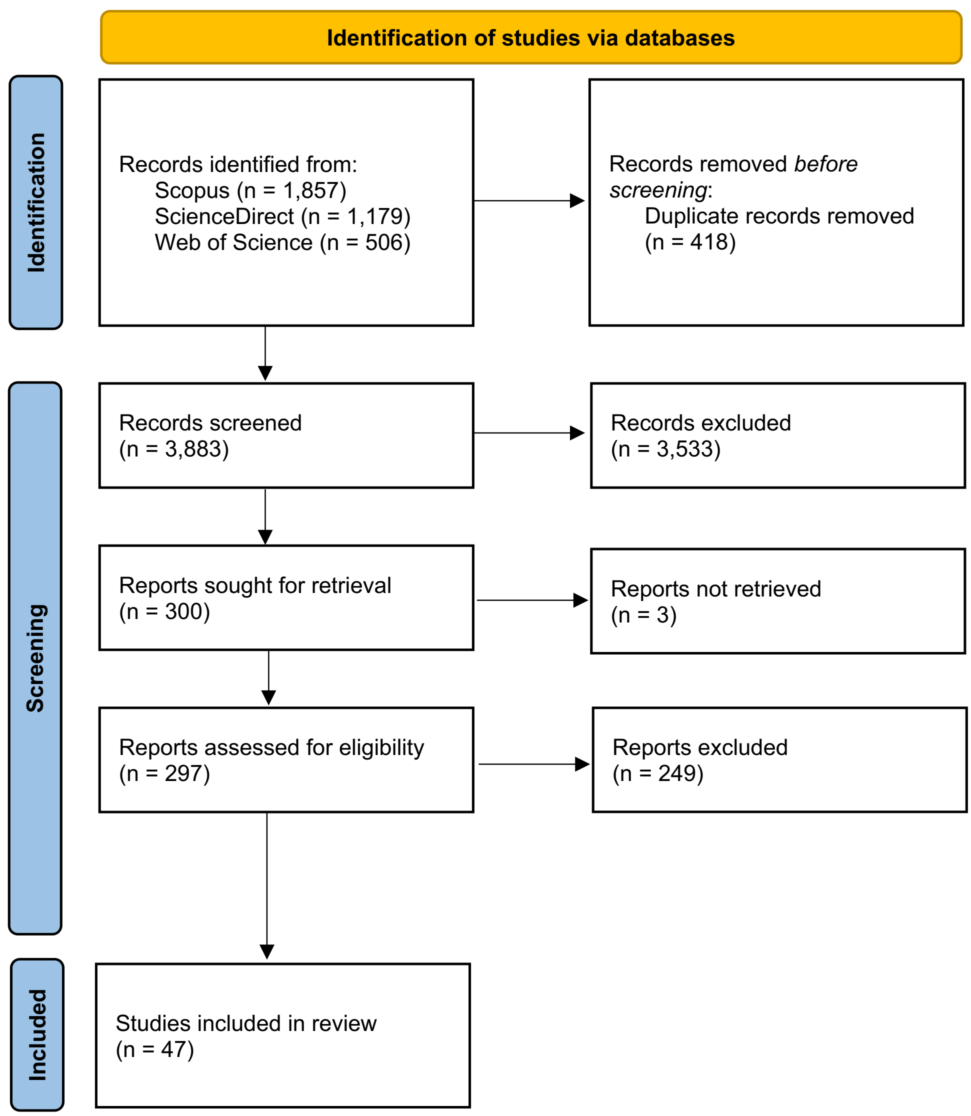
In order to create a sound information base for both policy makers and practitioners on the topic of AI adoption in production, this paper follows the systematic approach of a SLR. For many fields, including management research, a SLR is an important tool to capture the diversity of existing knowledge on a specific topic for a scientific investigation [39]. 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 [39] or identifying key research topics [40].

Our SLR aims to select, analyze, and synthesize findings from the existing literature on AI adoption in production over the past 24 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) [41]. 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 1 graphically summarizes the methodological approach that guides the content of the following sub-chapters.

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 contain international scientific articles and provide a broad overview of the interdisciplinary research field and its findings. To align the search with the RQs [42], 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 [42]. 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, Falster, Riis, Svendsen [43] 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.

Fig. 1 Methodical procedure of our SLR following PRISMA [41]



AI research has been credited with a resurgence since 2010 [6], 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.

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' [42]. 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.

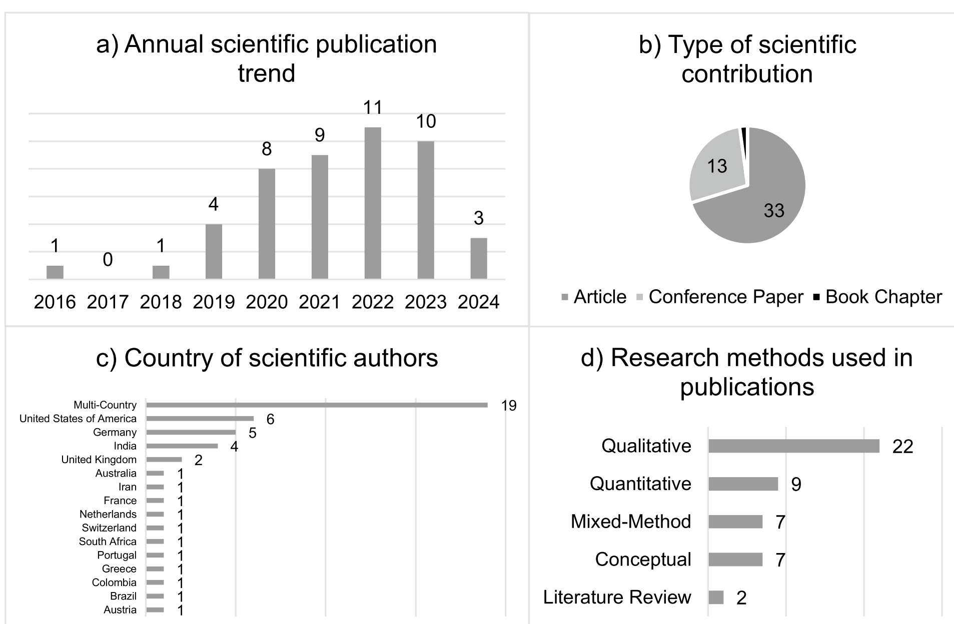
To ensure the paper's focus on all three topics regarded in our research (AI, production, and adoption), we followed clearly defined rules of inclusion and exclusion that all reviewers had to follow in the review process. As a first requirement for inclusion, AI must be the technology in focus that is 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 Fig. 1).

2.3 Descriptive analysis

Figure 2 summarises the results of the descriptive analysis on the selected literature regarding AI adoption in production that we analyse in our SLR. From Fig. 2a), which illustrates annual publication trends (2010–2024), the increase in publications on AI adoption in production over the past 5 years is evident, yet slightly declining after a peak in 2022.

Fig. 2 Descriptive analyses of the selected articles addressing AI adoption in production



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 Fig. 2b)).

The identified contributions reveal some additional characteristics in terms of the authors country base (Fig. 2c)) and research methods used (Fig. 2d)). 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 Fig. 2c), with qualitative methods (n = 22) being the most frequently used.

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 [44, 45]. To do this, we first read the entire text to gain an understanding of the content and then derive codes [46] that seem to capture key ideas [45]. 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 [44].

Various factors at different levels are of significance to AI and influence technology adoption [47, 48]. 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 1 visualizes each factor in the respective contributions sorted by the frequency of occurrence.

The presence of skills is considered a particularly important factor in AI adoption in the studies analyzed (n = 35). The availability of data (n = 25) as well as the need for ethical guidelines (n = 24) are also seen as key drivers of AI adoption, as data is seen as the basis for the implementation of AI and ethical issues must be addressed in handling such an advanced technology. As such, these three 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 managerial support (n = 22), as well as performance measures and IT infrastructure (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, Baumgartner, Cherubini [36].

3 Factors influencing AI adoption

The 35 factors presented characteristically in Sect. 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 Fig. 3). The factors that were mentioned most frequently (occurrence in at least half of the papers analyzed) are marked accordingly (*) in Fig. 3.

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.

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 [49, 54, 74, 79, 91]. Assessing possible risks [77] as well as the monetary

Table 1 Factors influencing AI adoption in production, resource, and count

Factor	Reference	Sum
Skilled workforce	[36, 49–83]	36
Data availability	[50, 52, 56–59, 61–63, 68–72, 76–78, 80, 81, 84–89]	25
Ethical guidelines	[49, 50, 52–54, 58–60, 62, 70–73, 75–79, 81, 82, 89–92]	24
Managerial support	[50–53, 55, 56, 59, 60, 62, 63, 66, 67, 71, 75, 78, 81–83, 86, 91, 93, 94]	22
Performance measures	[49, 53, 54, 57, 58, 60–63, 65, 67, 71, 73–75, 77–79, 91, 93]	20
IT Infrastructure	[51, 53, 54, 56, 57, 60, 62, 63, 66–72, 75, 78, 83, 84, 91]	20
Investment	[50, 51, 53, 56, 57, 59, 61–63, 66–68, 74, 79, 80, 82, 84, 92, 94]	19
Data analytics	[49, 54, 55, 58, 59, 65, 67, 69, 71, 72, 75–77, 80, 81, 86–88, 93]	19
Change management	[50–54, 56, 57, 61, 62, 65, 66, 71, 73, 78, 80, 83, 92, 93]	18
Privacy	[49, 58–61, 69, 70, 72, 76–79, 82, 88, 89, 91, 94]	17
Cooperation	[36, 52, 53, 57, 58, 63, 66, 67, 72, 75, 80, 82, 86, 91, 93, 94]	16
Education and training	[49–51, 54, 56, 59, 61, 64, 69, 71, 74, 75, 78, 80, 81, 92]	16
Strategic orientation	[50, 53, 54, 56, 59, 62, 66, 71, 75–77, 81, 87, 91, 93, 94]	16
Mindset and culture	[50, 51, 54, 56, 59, 65–67, 71, 75, 78, 80, 83, 91, 92]	16
System compatibility	[50, 53, 54, 56, 59, 60, 72, 78, 80, 82–84, 91, 93, 94]	15
Trust	[50, 52, 54, 60, 67, 68, 71, 75, 76, 78–80, 88, 90, 91]	15
Environmental dynamism	[36, 52, 53, 57, 58, 63, 66, 67, 72, 75, 82, 83, 86, 91, 93]	15
Laws and regulation	[49, 51, 52, 59, 61, 65, 67, 72, 76–78, 81, 82, 91]	14
Security	[49–52, 56, 68, 72, 76, 78, 79, 82, 88, 89, 94]	14
Innovation culture	[50–52, 54, 63, 66, 71, 72, 75, 81, 84, 86, 93, 94]	14
Data storage	[50, 54, 59, 68, 71, 72, 74, 78, 84, 87–89]	12
Safety	[49, 51, 54, 59, 60, 69, 71–73, 75, 78, 91]	12
Data processing	[58, 65, 76–79, 84, 86, 87, 89, 93]	11
Data governance	[50, 56, 59, 67, 68, 71, 78, 88, 89]	9
Data interoperability	[50, 53, 56, 59, 72, 84, 87, 89, 93]	9
User-friendliness	[50, 53, 67, 68, 72, 76, 84, 90]	8
Company size	[36, 53, 68, 69, 84, 93]	6
Strategic promoter	[54, 56, 62, 66, 74, 80]	6
Data consistency	[50, 62, 76, 77, 84]	5
Country	[36, 78]	2
Government support	[60]	1
Industrial sector	[36]	1
Product complexity	[36]	1
Batch size	[36]	1
R&D intensity	[36]	1

expected benefits for AI (e.g. Return on Investment (ROI)) in production plays an important role for adoption decisions in market-oriented companies [57, 58, 63, 65, 78]. Due to financial constraints, managers behave cautiously in their investments [78], so they need to evaluate AI adoption as financially viable to want to make the investment [61, 63, 93] and also drive acceptance [60]. AI systems can significantly improve cost–benefit structures in manufacturing, thereby increasing the profitability of production systems [73] and making companies more resilient [75]. However, in most cases, the adoption of AI requires high investments and the allocation of resources (s.a. personnel or financial) for this purpose [50, 51, 57, 80, 94]. Consequently, a lack of budgets and high expected transition costs often hinder the implementation of smart concepts [56, 62, 67, 82, 84, 92]. It is up to management to provide necessary funding for AI adoption [53, 59, 79], which is required, for example, for skill development of employees [59, 61, 63], IT adaptation [62, 66], AI development [74] or hardware deployment [68]. In their empirical study, Kinkel, Baumgartner, Cherubini [36] 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 [53] as they have less difficulties in comparison to small firms regarding the availability of resources [69], such as know-how, budget [68, 84] and general data organization [68]. Others argue that small companies tend to be more open to change and are characterized by faster

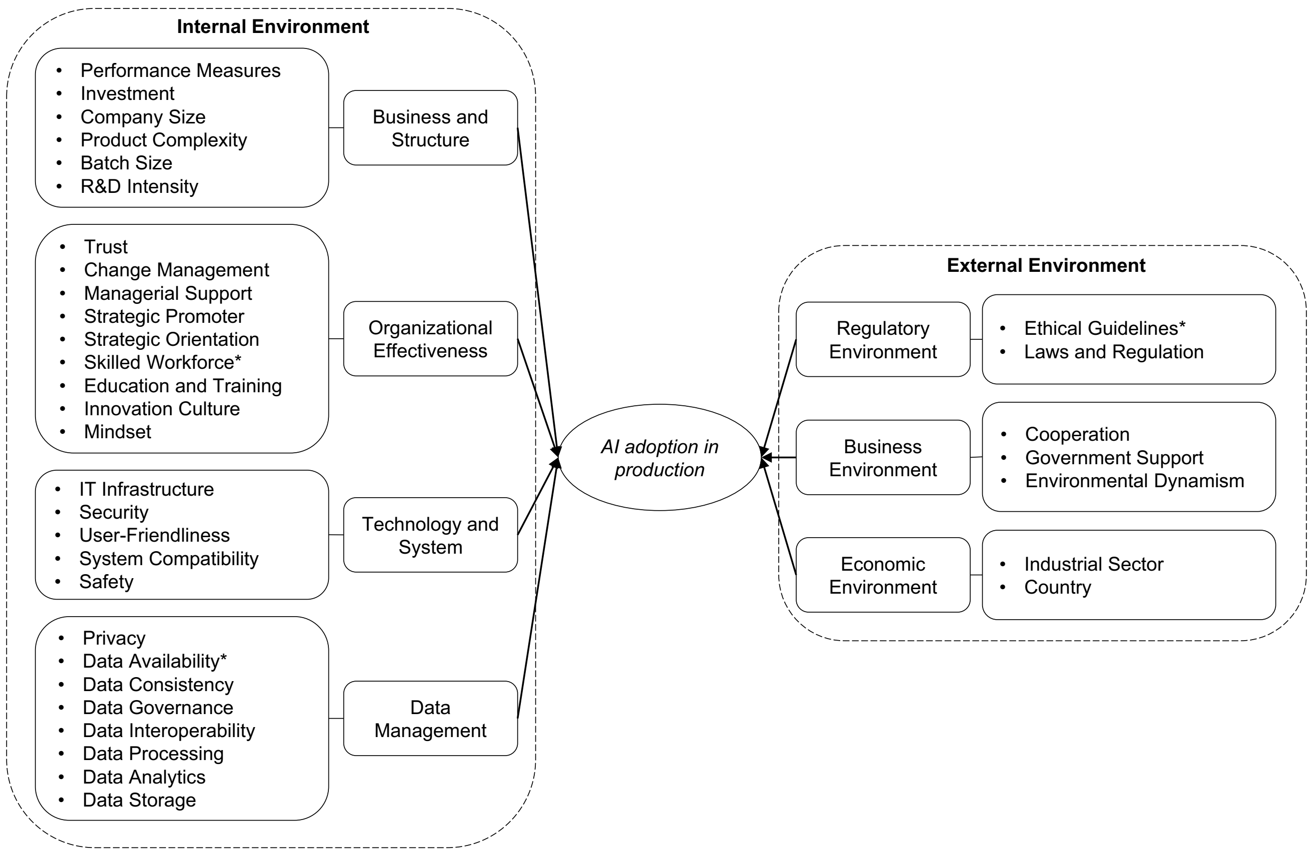


Fig. 3 Framework of factors influencing AI adoption in production

decision-making processes [68, 93]. 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 [36]. 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 [36]. 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 new innovations. This in turn speaks for existing competencies, know how and structures [36].

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 [52, 68, 78, 79, 88, 90]. From the users´ perspective, AI often exhibits the characteristics of a black box because its inherent processes are not fully understood [50, 90] which can lead individuals to develop a fear towards the unknown [71]. Because of this lack of understanding, successful interaction between humans and AI is not guaranteed [90], as trust is a foundation for decisions that machines are intended to make autonomously [52, 91]. To strengthen faith in AI systems [76, 80], AI users can be involved in AI design processes in order to understand appropriate tools [54, 90]. In this context, trust is also discussed in close connection with transparency and regulation [79]. User resistance is considered a barrier to implementing new information technologies, as adoption requires change [53, 62, 92]. Ignorance, as a kind of resistance to change, is a main obstacle to successful digital transformation [51, 56, 65]. Some employees may resist the change brought about by AI because they fear losing their jobs [52] or have other concerns [78]. Overcoming resistance to technology adoption requires organizational change and is critical for the success of adoption [50, 51, 62, 67, 71, 80]. Therefore, change management is important to create awareness of the importance of AI adoption and increase acceptance of the workforce [66, 68, 74, 83]. Management commitment is seen as a significant driver of technology adoption [53, 59, 81, 82, 86] and a lack of commitment can negatively impact user adoption and workforce trust and lead to skepticism towards technology [86]. The top management's understanding and support for the benefits of the adopted technology [53, 56, 67, 78, 93, 94] enhances AI adoption, can prioritize its implementation and also affects the performance of the AI-enabled application [55, 60, 83]. Preparing, enabling, and thus empowering the workforce, are considered the management's responsibility in the adoption of digital technologies [59, 75]. This requires intelligent leadership [52] as decision makers need to integrate their workforce into decision-making processes [75]. Guidelines can support managers by providing access to best practices that help in the adoption of AI [50]. 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 [54, 62]. 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 [62, 74, 80]. 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 [66, 80]. The development of strategies as well as roadmaps is considered another enabling and necessary factor for the adoption of AI in production [50, 53, 54, 62, 71, 93]. While many major AI strategies already exist at country level to further promote research and development of AI [87], strategy development is also important at the firm level [76, 77, 81]. In this context, strategies should not be delegated top-down, but be developed in a collaborative manner, i.e. by engaging the workforce [75] and be in alignment with clear visions [91, 94]. Roadmaps are used to improve planning, support implementation, facilitate the adoption of smart technologies in manufacturing [93] and should be integrated into both business and IT strategy [62, 66]. In practice, clear adoption roadmaps that provide approaches on how to effectively integrate AI into existing strategies and businesses are often lacking [56, 87]. The need for AI-related skills in organizations is a widely discussed topic in AI adoption analyses [79]. In this context, the literature points both at the need for specific skills in the development and design of AI applications [57, 71–73, 76, 93] as well as the skills in using the technology [53, 65, 73–75, 84, 93] which availability in the firm is not always given [49]. AI requires new digital skills [36, 50, 52, 55, 56, 59, 61, 63, 66, 78, 80], where e.g. advanced analytics [64, 75, 81], programming skills [68] and cybersecurity skills [78, 93] 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 [51, 54, 56, 60, 62, 67, 69, 70, 82, 93]. This lack of a necessary skillset hinders the adoption of AI tools in production systems [58, 77]. Closely related to skills is the need for new training concepts, which organizations need to consider when integrating digital technologies [49–51, 56, 59, 63, 71, 74, 75]. Firms must invest in qualification in order to create necessary competences [73, 78, 80, 81, 92]. Additionally, education must target and further develop the skills required for effectively integrating intelligent technologies into manufacturing processes [54, 61, 62, 83]. Regarding this issue, academic institutions must develop fitting curricula for data driven manufacturing engineering [64]. 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 [83, 91, 93]. These firms often invest in more expensive and advanced smart technologies as the pressure and resulting competition forces them to innovate [93]. 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 [52].The entrepreneurial orientation of a firm is characterized in particular by innovativeness [66], productivity [63], risk-taking [86] as well as continuous improvement [50]. Such characteristics of an innovating culture are considered essential for companies to recognise dynamic changes in the market and make adoption decisions [51, 71, 81, 84, 86, 94]. The prevalence of a digital mindset in companies is important for technology adoption, as digital transformation affects the entire organizational culture and behavior [59, 80, 92] and a lack of a digital culture [50, 65] as well as a 'passive mindset' [78] can hinder the digital transformation of firms. Organizations need to develop a corresponding culture [66, 67, 71], also referred to as 'AI-ready-culture' [54], that promotes development and encourages people and data through the incorporation of technology [71, 75]. 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 [75, 83].

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 [51, 60, 67, 69, 83]. A lack of appropriate IT infrastructure [68, 71, 78, 91] or small maturity of Internet of Things (IoT) technologies [70]) hinders the efficient use of data in production firms [56] which is why firms must update their foundational information systems for successful AI adoption [53, 54, 62, 66, 72, 75]. IT and data security are fundamental for AI adoption and must be provided [50, 51, 68, 82]. This requires necessary developments that can ensure security during AI implementation while complying with legal requirements [52, 72, 78]. Generally, security concerns are common when implementing AI innovations [72, 79, 91, 94]. This fear of a lack of security can also prevent the release of (e.g. customer) data in a production environment [56]. Additionally, as industrial production systems are vulnerable to failures as well as cyberattacks, companies need to address security and cybersecurity measures [49, 76, 88, 89]. 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 [50, 72, 84]. When developing user-friendly solutions which satisfy user needs [76], it is particularly important to understand and integrate the user perspective in the development process [90]. If employees find technical solutions easy to use, they are more confident in its use and perceived usefulness increases [53, 67, 68]. The compatibility of AI with a firm and its existing systems, i.e., the extent to which AI matches existing processes, structures, and infrastructures [53, 54, 56, 60, 78, 80, 82, 83, 93, 94], is considered an important requirement for the adoption of AI in IT systems [91]. Along with compatibility also comes connectivity, which is intended to ensure the links within the overall network and avoid silo thinking [59]. 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 [50, 72, 89]. The design of modular AI solutions can increase system compatibility [84]. Firms deciding for AI adoption must address safety issues [51, 54, 59, 72, 73, 78]. This includes both safety in the use and operation of AI [60, 69]. In order to address safety concerns of integrating AI solutions in industrial systems [49], systems must secure high reliability [71]. 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 [75].

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 [49, 58–60, 72, 76, 78, 79, 82, 88, 89, 91, 94] as '[M]anufacturing industries generate large volumes of unstructured and sensitive data during their daily operations' [89]. Closely related to this is the need for anonymization and confidentiality of data [61, 69, 70, 78]. The availability of large, heterogeneous data sets is essential for the digital transformation of organizations [52, 59, 78, 80, 88, 89] and is considered one of the key drivers of AI innovation [62, 68, 72, 86]. In production systems, lack of data availability is often a barrier to AI adoption [58, 70, 77]. In order to enable AI to establish relationships between data, the availability of large input data that is critical [62, 76, 81]. New AI models are trained with this data and can adapt as well as improve as they receive new data [59, 62]. Big data can thus significantly improve the quality of AI applications [59, 71]. As more and more data is generated in manufacturing [85], AI opens up new opportunities for companies to make use of it [62]. However, operational data are often unstructured, as they come from different sources and exist in diverse formats [85, 87]. This challenges data processing, as data quality and origin are key factors in the management of data [78–80, 88, 89, 91]. To make production data valuable and usable for AI, consistency of data and thus data integrity is required across manufacturing systems [50, 62, 77, 84]. Another key prerequisites for AI adoption is data governance [56, 59, 67, 68, 71, 78, 88] which is an important asset to make use of data in production [50] and ensure the complex management of heterogenous data sets [89]. 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 [53, 56, 84, 93], 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 [87]. Data processing refers to techniques used to preparing data for analysis which is essential to obtain consistent results from data analytics in production [58, 72, 80, 81, 84]. In this process, the numerous, heterogeneous data from different sensors are processed in such a way that they can be used for further analyses [87]. The capability of production firms to process data and information is thus important to enable AI adoption [77, 86, 93]. With the increasing data generation in the smart and connected factory, the strategic relevance of data analytics is gaining importance [55, 69, 78], as it is essential for AI systems in performing advanced data analyses [49, 67, 72, 86, 88]. Using analytics, valuable insights can be gained from the production data obtained using AI systems [58, 77, 87]. In order to enable the processing of big data, a profound data infrastructure is necessary [65, 75, 87]. Facilities must be equipped with sensors, that collect data and model information, which requires investments from firms [72]. In addition, production firms must build the necessary skills, culture and capabilities for data analytics [54, 75, 87, 93]. Data storage, one of the foundations and prerequisites for smart manufacturing [54, 68, 71, 74], must be ensured in order to manage the larg amounts of data and thus realize the adoption of intelligent technologies in production [50, 59, 72, 78, 84, 87–89].

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.

3.2.1 Regulatory environment

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 [70, 72, 79]. AI applications must be compliant with the requirements of organizational ethical standards and laws [49, 50, 59, 60, 62, 75] which is why certain issues must be examined in AI adoption and AI design [62, 73, 82, 91] so that fairness and justice are guaranteed [78, 79, 92]. Social rights, cultural values and norms must not be violated in the process [49, 52, 53, 81]. In this context, the explainability and transparency of AI decisions also plays an important role [50, 54, 58, 70, 78, 89] and can address the characteristic of AI of a black box [90]. In addition, AI applications must be compliant with legal and regulatory requirements [51, 52, 59, 77, 81, 82, 91] and be developed accordingly [49, 76] in order to make organization processes using AI clear and effective [65]. At present, policies and regulation of AI are still in its infancy [49] and missing federal regulatory guidelines, standards as well as incentives hinder the adoption of AI [67] which should be expanded simultaneously to the expansion of AI technology [60]. This also includes regulations on the handling of data (e.g. anonymization of data) [61, 72].

3.2.2 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 [52, 53, 59, 72], which is why partnerships are important for adoption [53, 59] and can positively influence its future success [52, 67]. Both intraorganizational and interorganizational knowledge sharing can positively influence AI adoption [49]. In collaborations, companies can use a shared knowledge base where data and process sharing [51, 59, 94] as well as social support systems strengthen feedback loops between departments [79, 80]. 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 [82, 93]. Without external IT support, companies can rarely integrate AI into their production processes [66], which is why thorough support from vendors can significantly facilitate the integration of AI into existing manufacturing processes [80, 91]. Public–private collaborations can also add value and governments can target AI dissemination [60, 74]. 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 [60]. Production companies are constantly exposed to changing conditions, which is why the dynamics of the environment is another factor influencing the adoption of AI [52, 63, 72, 86]. Environmental dynamics influence the operational performance of firms and can favor an entrepreneurial orientation of firms [86]. In order to respond to dynamics, companies need to develop certain capabilities and resources (i.e. dynamic capabilities) [86]. 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 [75]. A firm's environment (e.g. governments, partners or customers) can also pressure companies to adopt digital technologies [53, 67, 82, 91]. 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 [36, 66, 82, 93].

3.2.3 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 [36]. 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 [36]. From another perspective, 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 [78].

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, Baumgartner, Cherubini [36], 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 2. We developed the questions based on the literature review and identified research gaps for every factor that was most frequently mentioned. 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.

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

Table 2 Future research agenda for AI adoption in a production context

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?

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.

4 Conclusions

The use of AI technologies in production continues to gain momentum as managers hope to increase efficiency, productivity and reduce costs [9, 13, 20]. Although the benefits of AI adoption speak for themselves, implementing AI is a complex decision that requires a lot of knowledge, capital and change [95] 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 [96, 97], 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 [98, 99]. 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.

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 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 systematization 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 environment’ (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 2 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 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.

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 Fig. 2, 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 [39]. 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 [47] 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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