The Why and What of AI Deployment and Innovation in Companies – Results and Learnings from a Systematic Literature Research Enlightened by the Capability Theory

Abstract: Despite soaring interest in AI, only one-tenth of companies have reported tangible business results. We conducted a Systematic Literature Research on peer-reviewed reports to establish an updated status and baseline of AI deployment for research and companies. We analyzed selected peer-reviewed articles for deployment objectives, approaches, results, and learnings. This research confirms that AI is still at the early stages of deployment and innovation in companies. Deploying AI successfully represents a management – rather than a technology – challenge. It requires more cognizance, innovation, learning, and effort than generally thought. Through the results and a novel conceptual framework, this research increases the knowledge and emphasizes the importance of the pre-deployment from theoretical and practical viewpoints. The Sensing stage of the Dynamic Capability theory aligns well with the developed pre-deployment concept. We propose several research topics to increase the knowledge and theoretical understanding of deploying AI cognizably for business and stakeholder benefits.

Keywords: Artificial Intelligence, Strategy, Deployment, Innovation, Objectives, Results, Learnings

1 Introduction and the research purpose

Artificial Intelligence (AI) is said to be the most important general-purpose technology of our era (Brynjolfsson and Mcafee, 2017) and to fundamentally change our business environment (Iansiti and Lakhani, 2020). Several indicators from recent years concretize the growth of expectations for AI in companies. First, private investments have grown to USD 91.9 bn in 2022, eighteen times more than in 2013. Second, the number of patents has grown 30-fold between 2015 and 2021, with a compound annual growth rate of 76.9 percent. Third, research activity on AI continues at a high level, doubling from 162 000 publications in 2010 to 334 000 in 2021 (Maslej, 2023, 2024; Zhang, 2022). What have the companies achieved with the reported massive AI spending and efforts? Current academic research literature does not give answers either from a practical or theoretical point of view. In the following paragraphs, we look in more detail at what we know and do not know about the spending and the results and why it matters.

According to a comprehensive industry research report (Ransbotham et al., 2020), 70% of the participating companies said they understand how to generate business value with AI, 59% said they have an AI strategy, and 57% said they are piloting or deploying AI. However, only about 10 % of companies said they had obtained significant financial benefits through investments in AI. According to Zhang (2022), the average AI adoption rate was 56 percent in 2021, up 6 % from 2020. A third industry survey (McKinsey, 2022) finds that while the adoption of AI in companies is leveling off at about 50% in 2022, after peaking at 58% in 2019, companies believe their investments continue to increase in the coming three years. This survey also finds “more indications that AI leaders are expanding their competitive advantage than finding evidence that others are catching up." The proportion of respondents seeing significant bottom line (EBIT) impact has remained steady at about 8 % during the past three years (McKinsey, 2022, 2023).

The picture from recent years on financial and operational results is even more modest when looking at the peer-reviewed research reports. Brock and von Wangenheim (2019) state that there is "mixed evidence and paucity of empirical insights related to the successes and failures of AI implementation projects." They conclude that only 8 % of the companies studied are "digital transformation leaders" and are thus well-positioned to benefit from AI projects. Quite similarly, Caner and Bhatti (2020) maintain that AI studies focusing on business are relatively rare but call for a holistic conceptual framework to help "define AI business strategy." The study by Borges et al. (2021) raises both practical and strategic viewpoints, arguing that "there are still issues involved in practical use and lack of knowledge as regards using AI in a strategic way in order to create business value." Enholm et al., (2021) point out business value and lack of understanding, stating that "there is a lack of coherent understanding of how AI technologies can create business value and what type of value can be expected." Furthermore, Mikalef and Gupta (2021) discuss the importance of theoretical knowledge and capabilities, stating: "Despite the popular press, often written by technology consultants and vendors, there is little theoretically grounded knowledge about how to build AI capabilities to gain measurable results." In innovation management, several researchers conclude that the understanding of the influence of AI in innovation based on real-world examples is limited. We are still at the beginning of a transformation in innovation processes, and many fundamental questions related to AI in innovation are still open (Gama and Magistretti, 2023; Truong and Papagiannidis, 2022; Enholm et al., 2021; Verganti et al., 2020).

From a theoretical perspective, it is evident from the above that there is a need to develop theoretical frameworks for AI deployment because a) AI differs from other technologies through its cognizance features (Borges et al., 2021), and b) extant theories seem to be insufficient to explain what it takes to deploy AI successfully (Gama and Magistretti, 2023; Truong and Papagiannidis, 2022; Enholm et al., 2021). Technology in general, and IT/AI technology in particular, is, for many companies, a crucial way to improve growth and productivity. That is why searching, testing, and selecting technologies to invest in become a strategic issue for top management (Brynjolfsson, 1993, 2021; Yuhn and Park, 2010; Crafts et al., 2002; Brynjolfsson and Hitt, 2000; Prasad and Harker, 1997; Brynjolfsson and Lorin, 1993). The extant research recognizes that AI opportunities and challenges should be considered from leadership and management perspectives, not just as ordinary technology implementation or adoption projects. It has been demonstrated in the extant literature that AI calls both for a dynamic, innovative leadership approach, and provides new means for improving organizational dynamics and innovation (Gama and Magistretti, 2023; Enholm et al., 2021; Mikalef and Gupta, 2021; Verganti et al., 2020; Brock and von Wangenheim, 2019). Therefore, we selected Capability Theory as the framework for this study because it is recognized as the leading strategic framework for dynamic, competitive environments in which continuous development of capabilities is needed to survive and thrive (Peng, 2022, pp.60-70; Teece, 2019; Schilke, 2018; Teece, 2017; Pisano, 2017).

The AI field is developing fast and in many different areas and directions. Systematic literature research (SLR) is our preferred method for this study because a) an update is needed since many new research reports on AI are published annually, b) new AI technologies emerge continuously, c) no references to existing SLRs were found focusing on critical questions of business objectives and results of AI in companies, d) it is vital to create a shared understanding of the scarcely researched domain in order to direct the attention to relevant and interesting questions for future research.

Peer-reviewed research does not seem to have produced a deeper empirical or theoretical understanding of the results and benefits gained in companies so far. This study fills the research gap between company investments (The Why) and achieved business results (The What). We look for empirical and theoretical contributions by searching recently published research reports related to deployment. We expect this article to be attractive, particularly to innovation and IT scholars and management. Deployment of AI for business calls for an innovative approach from the company. It also provides forward-looking learning opportunities for all management disciplines (Gama and Magistretti, 2023; Borges et al., 2021; Brynjolfsson, 2021; Iansiti and Lakhani, 2020; Teece, 2019). We strive to improve understanding and produce new knowledge to develop approaches and capabilities for AI deployment. The outcome is a novel and detailed framework for critical stages of pre-deployment supported by analyzed and documented case briefings of 99 experimental AI articles. The framework and results can be used to develop models, and a detailed understanding of the actual deployment stages still missing today. The study connects to business strategy through the Capability Theory and opens practical understanding for research of AI deployment and AI in innovation. These are areas where a great majority of companies seem to be struggling today. Hence, this article is also interesting and valuable for other management disciplines.

We summarize the research logic describing the initial situation (the interest and the research gaps), the importance, and our research approach in Figure 1. The following Chapter will qualify, define, and anchor the context and research question. Chapter 3 describes the research methodology, and Chapter 4 the research findings. In Chapter 5, we discuss the findings, present a conceptual model for pre-deployment, and reflect on other literature. Conclusion, limitations, and future research needs are discussed in Chapter 6.

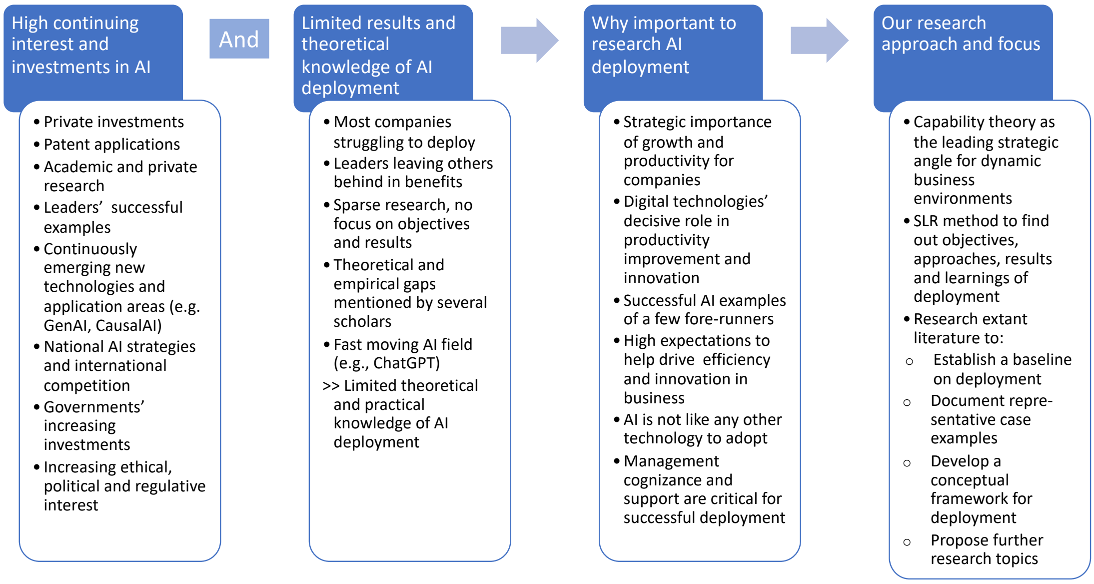


Figure 1. Summarizing the research logic with the current state, motivation, and our approach for the study.

2 Research context and the research question

As a starting point for the study, we examined several peer-reviewed AI articles that focus on questions relevant to the research purpose. We collected and summarized the foci, aims, and contributions of these exemplary articles in Table 1, and a brief conclusion of the analysis follows in the next paragraphs.

Table 1. Themes emerging from examples of recent research articles.

Article (year of publishing)	Borges, et. al. (2021)	Caner and Bhatti (2020)	Kitsios and Kamariotou (2021)	Mikalef and Gupta (2021)	Brock and von Wangen-heim (2019)	Burström et. al. (2021)	Gama and Magistretti (2023)	Barenkamp, et.al. (2020)	Altemeyer (2019)	Stone et. al. (2020)
Emerging theme	AI and strategy			AI and enablers				AI and outcomes		
Focus	AI and organi-zational strategy	AI business strategy	AI and corporate strategy	AI-resources and capabilities	AI and digital transforma-tion	AI and busi-ness model innovation	AI in innovation management	AI in classical software engineering	AI to assess, recruit and retain staff	AI in strategic marketing
Aim	Present conceptual framework on integrating AI to organi-zational strategy based on SLR*	Develop conceptual framework on defining firm AI business strategy through SLR	Develop a theoretical model on convergence of AI and cor-porate stra-tegy based on SLR*	Develop an instrument to capture AI capability of a firm, exam-ine AI-capa-bility and cre-ativity groun-ded on RBT*	Demystify AI by studying AI-implem-entation in connection with digital transforma-tion	Evolutionary model for strategic transition of incumbents in their firms and eco-systems	The aim of the SLR is to summarize the role of AI in influencing innovation capabilities and provide a taxonomy	Assess the developme-nt, future potentials and risks of AI in soft-ware engi-neering	Study and analyze two large scale HR cases	Review literature and identify research needs on AI in strategic marketing decisions
Contribu-tion/ model	Four sources of value crea-tion related to the con-ceptual framework on inter-play between AI and business strategy	Consolidati-ng technical and business views of AI into a six-factor frame-work and discusses major ele-ments of AI in business	Theoretical model and four sources of value creation and gaps in research	The capa-bility instru-ment, rela-tionship between AI capability and creativity and performance	Framework and guidance to implem-ent AI in the context of digital trans-formation, argues for "realistic AI"	Establish need for alignment of AI business model inno-vation and ecosystem innovation	Identifies innovation capabilities important for AI adoption and proposes a taxonomy of AI appli-cations	Major achie-vements and future pote-ntials are in automation and data analysis and neural net-works	AI helps in bias avoida-nce, time and resource savings, imp-ove cultural fit and diver-sity. Humans need to decide finally	Research is needed into applying AI to strategic marketing decision making

*SLR (Systematic Literature Rsearch), RBT (Resource Based Theory)

Several articles focus on AI and strategy, aiming to develop a conceptual framework or a theoretical model for integrating AI into organizational strategy (Borges et al., 2021), on defining AI business strategy (Caner and Bhatti, 2020) or on the convergence of AI and corporate strategy (Kitsios and Kamariotou, 2021). These articles are based on systematic literature reviews and cover the AI and strategy points of view.

Another emerging theme is related to AI and enablers from different angles. Mikalef and Gupta, (2021) developed a survey instrument for measuring the AI capability of organizations and demonstrated that firms could realize creativity and performance gains through fostering AI capability. Brock and von Wangenheim, (2019) focus on AI and digital transformation and develop a framework and guidance for implementing AI in digital transformation. Burström et al. (2021) discuss AI and business model innovation, concluding that a firm's AI business model innovation needs to be aligned with ecosystem innovation. The article by Gama and Magistretti (2023) discusses the role of AI in influencing innovation capabilities and finds it both to enable and enhance these capabilities.

The third theme is AI and its outcomes in different business contexts. The research by Barenkamp et al., (2020) aims to assess AI's development, future potentials, and risks in software engineering. The report states, that significant achievements and possibilities are in automation, data analysis, and neural networks. Altemeyer (2019) studies AI in human resource management (HRM) and, based on two case studies, concludes that AI can help in bias avoidance, time and resource savings, and improving cultural fit and diversity. Finally, Stone et al., (2020) focus on AI in strategic situations and marketing, concluding through a literature review the importance of further research in applying AI to strategic marketing decision-making.

While all these articles study important points for AI deployment, it seems that academic research has not focused on business objectives and results of AI deployment. Furthermore, the paucity of practical objectives and concrete understandings of issues related to using AI in a strategic way in innovation, to produce business value and results are expressed in several articles (e.g., Gama and Magistretti, 2023; Truong and Papagiannidis, 2022; Borges et al., 2021; Burström, 2021; Kitsios and Kamariotou, 2021; Mikalef and Gupta, 2021; Caner and Bhatti, 2020; Stone et al., 2020; Verganti et al., 2020; Brock and von Wangenheim, 2019). Before finalizing this section, we will clarify the critical terms of AI and AI deployment for the study.

There are many definitions for AI (e.g., Enholm et al., 2021; Mikalef and Gupta, 2021; Russell and Norvig, 2021), and they have significantly evolved over the years. The seminal book by Russell and Norvig (2021) defines AI using the so-called standard model by explaining that "in a nutshell, AI has focused on the study and construction of agents that do the right thing," defined by the objective provided to the agent (Ibid., p.4). Even though compelling, we prefer a definition slightly modified from Mikalef and Gupta (2021) for this research. Hence, we define AI as:

> *A system that observes its environment and takes actions to maximize its possibilities to reach the objectives set for it.*

The other definition we need to make is for deployment in this research context. Deployment as a term can be seen through various lenses, such as change and innovation management (Pool and Van de Ven, 2021; van Oorschot et al., 2018), technology diffusion and adoption (Raffaelli et al., 2019; Rad et al., 2018; Gangwar et al., 2014) and capability management (Schilke et al., 2018; Teece, 2017). Out of these lenses, we consider capability management and dynamic capabilities most suitable for the research as AI deployment is about many other things besides technology (Issa et al., 2022; Borges et al., 2021; Jöhnk et al., 2021). AI cannot be taken into effective use as short-term island solutions but calls for long-term commitment and organizational learning (Iansiti and Lakhani, 2020, pp. 215-229; Ransbotham et al., 2020; Brock and von Wangenheim, 2019; Castrounis, 2019, pp. 242-250). Hence, we clarified the term for AI deployment as another critical term for the research (Apple Inc., 2023):[1]

> *Deployment means bringing into effective use a solution (method, data, and application) intended for enduring use with objectives, metrics for results, support, and updates.*

For companies, deciding to invest in AI deployment is a lot easier when more information is available on goals, objectives, and business results achieved from those who started their journey earlier. For academic readers, this research presents a new model for pre-deployment. It produces new information and knowledge crucial for

[1]See also https://www.merriam-webster.com/dictionary/deployment#examples

complementing theoretical models and concepts to understand AI deployment in companies. We also aim to uncover potential learnings from deployment approaches, opportunities, challenges, and their connection to innovation management. We conclude this section by setting the research question as follows:

> *The Research Question (RQ): Why and how is AI being deployed in companies, and what are the reported results and lessons learned so far?*

The following Chapter outlines the research methodology and defines the sub-questions.

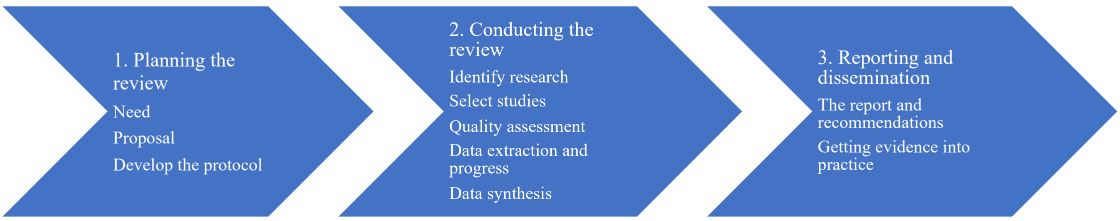
3 Research Methodology

The researchers' worldview[2] is best described as constructivist-pragmatist. It is constructivist in the sense that there seems to be very little empirical and theoretical information from earlier research on the objectives and results of AI deployment and AI and innovation. It is also pragmatist in the sense that SLR is a standard method to look for data from reported peer-reviewed literature. We found the Dynamic capability view as the most suitable basis and theoretical frame for analysis and synthesis in this research (Creswell and Creswell, 2020, pp.25-29).

Literature Review Protocol

We chose SLR as the research method because of 1) its suitability for this type of research situation (process, synthesis, evidence base, and quality (Rojon et al., 2021; Tranfield et al., 2003), and 2) AI deployment research from the RQ angle has not been found to have been carried out previously in peer-reviewed literature to the depth and concreteness of theoretical and practical interest. Also, the field of AI adoption is developing fast, and it is essential to find out if articles relevant to the RQ have been published since the ones mentioned in Chapter 2.

We chose to follow the approach combined from (Tranfield et al., 2003) and (Rojon et al., 2021) in the SLR process as their approach provides clarity, coverage, relevance, and quality for this research and topic. We describe the research process in Figure 2 and highlight corresponding sections in the text to aid readability.



- Introduction and the research purpose, Chapter 1
- Research context and research question, Chapter 2
- Literature Review Protocol, Chapter 3

- The Sub-questions, Chapter 3
- Search queries and sources of literature, Chapter 3
- Screening the articles for review, Chapter 3
- Data extraction and documentation, Chapter 3
- Quality assessment, Chapter 3
- Findings of the review, Chapter 4

- Discussion, Chapter 5
- Conclusion, limitations and further research, Chapter 6

[2] Other terms for worldview, such as paradigm, epistemology and ontology are also used, e.g., (Creswell and Creswell, 2020).

Figure 2. Structure of the SLR (Rojon et al., 2021; Tranfield et al., 2003) with the corresponding research report chapters.

The Sub-questions

We divided the main research question into sub-questions described and justified below.

- *Sub-question 1: What kind of goals and objectives have been set for AI deployment?*

It is common in companies to set goals, milestones, and objectives to keep abreast of whether the strategy and related investments are producing results. This sub-question is intended to provide a concrete answer to why companies deploy AI and help consider theoretical alternatives for decision-making.

- *Sub-question 2: What types of approaches, methods, and models have been used in AI deployment, and are some methods and models found to have produced better results than others?*

When goals and objectives have been set, there needs to be a way, a plan, or a method for a company to deploy and go after those goals and objectives. Finally, this would answer how AI is deployed in companies and potentially find ideas to develop these models further.

- *Sub-question 3: What kind of reported business and stakeholder results based on AI deployment can be found in the research material?*

We expected to find results such as revenue growth, improved earnings, and a better yield for invested capital. From a stakeholder perspective, environmental, social, and governance (ESG) footprints and fingerprints are also of great interest. If a connection between goals and objectives and measurable results is found, the connection would also provide new perspectives for possible theoretical considerations.

- *Sub-question 4: What kind of opportunities and challenges have been found and reported in AI deployments?*

With this sub-question, we aim to answer what, thus far, has been learned related to opportunities and challenges in the deployment projects. These learnings open insights and questions for theoretical considerations and will be of particular interest to companies early in their AI journey.

The main research question with the sub-questions defines the scope of our research and, thus, the themes (AI, Strategy, and Outcomes) for our search queries. The previously published articles by Borges et al., (2021); Kitsios and Kamariotou (2021; and Caner and Bhatti (2020) have covered both AI and Strategy themes. Therefore, we added a third theme, the Outcomes of AI and Strategy. The Outcomes theme should cover our goal of finding the objectives, approaches, results, and learnings of AI deployment.

Search Queries and Sources of Literature

We used the research questions to define the themes for our searches. Each consists of several keywords that could be used with the theme (see Table 2). We determined the first set of keywords based on our expertise on the topic and performed test searches, evaluated the results of the searches, and refined the keywords.

Table 2. Search themes and keywords used in preliminary searches.

Theme	*Keywords used in preliminary test searches*
AI	Artificial intelligence, Machine learning, Deep learning, Represent* learning
Strategy	Plan, Execution, Implementation, Corporate, Business, Digital, IT, IS, Cognitive, Competitive
Outcomes	Financial, Business, Economic, Revenue, Result, Profit, Cost, Value, Productivity, Transformation, Quality, Lead time

Based on the test searches, we added several new keywords in strategy (such as organizational strategy and emergent strategy) and in outcomes (such as productivity improvement and revenue growth) to increase coverage for capabilities and innovation. In addition to the themes, the search string shows the filters used in the searches, i.e., searches only in the business domain, publications including the years 2017 to 2023, and only in English. The final search string (in Scopus format) is presented in Table 3. We used the corresponding search string also for the WoS database.

Table 3. String example (Scopus database) for the final literature search.

TITLE-ABS-"EY (("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Represent* Learning") "AND ("strateg* plan" OR "emergent* strateg*" OR "strateg* execution" OR "strateg* implementation" OR "competitive strateg*" OR "competitive advantage*" OR "digital strateg*" OR "business strateg*" OR "corporate strategy" OR "organi*ational strategy" OR "information technology strateg*" OR "IT*strategy" OR "IS*Strategy" OR "cognitive strateg*" OR "strategic use" OR "strategic usage") AND (financial* OR business OR economic* OR "top line" OR revenue OR "revenue growth" OR turnover OR "bottom line" OR result* OR profit OR "profit growth" OR earning* OR cost* OR value OR transformation OR productivity OR "productivity improvement" OR quality OR "lead times")) AND (LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017)) AND (LIMIT-TO (LANGUAGE , "English"))

Table 4. The screening process and the number of articles in each phase.

Number of papers after each phase	*Initial search*	*Left after title review*	*Left after abstract review*	*Accepted for full iterative review*
Scopus	283	170	101	78
Web of Science	134	53	42	21
Total	417	223	143	99

We summarize the screening process and the criteria used as boundaries for the screening in Tables 4 and 5. Most papers are peer-reviewed journal articles, apart from a few conference papers. In addition, some book chapters and even one lecture note were included to provide a broader perspective to the research. We discussed and considered the screening criteria within the team and concluded that because the topic is sparsely researched, it is meaningful to avoid an overly restrictive approach (Rojon et al.,2021) to ensure adequate coverage of the material.

Table 5. Summary of inclusion and exclusion criteria for the screening of articles.

Inclusion	*Exclusion*
Papers in journals, conference publications, and book chapters on the intersection of AI, strategy, objectives, and results	Papers without any indication of deployment objectives or results in the abstract
We focused queries on titles, keywords, and abstracts	Papers with deep technical – not deployment – objectives and results
Papers in the English language	Papers not available as digital documents (Anitha and Dinesh, 2023), pdfs included if available digitally
Papers published (full text) between Jan2017 and Dec2023	Duplicates (8) on Scopus and WoS

Data Extraction and Documentation

As the outcome of the screening process, we selected 99 documents for the entire final review. First, we collected data from the research questions' points of view in spreadsheets. Data included the first writer, title, industry class[3], and company function for demographic orientation. In the next phase, we extracted the following information from the deployment perspective for answers and insights into the research questions:

1. Goals and objectives
2. Approaches, methods, and models (including model types)
3. Business and stakeholder results
4. Opportunities and challenges

As the inductive analysis progressed within the team, it turned out that none of the selected 99 articles contained business outcomes of deployment (see definition in Chapter 2). Hence, it did not provide answers to the research questions. This observation confirmed that peer-reviewed research on deployment continues to be very scarce. Therefore, we found it essential to go deeper into the details of the articles to shed light and understand how AI adoption had been studied and discussed in the papers. The key findings from the perspective of our research questions were added to the spreadsheets. The results were then analyzed and verified with the respective articles in an iterative manner. The resulting information accumulated from this process is available in online Appendices A, B, and C (https://doi.org/10.5281/zenodo.11091404). Appendices A and B include summaries for a quick review of the contents of the articles. They can be used as such in many ways when searching for information by industry and function from a multitude of cases and examples at stages earlier than the actual deployment. The findings of this analysis are presented in Chapter 4 and discussed in Chapter 5.

Quality Assessment

To ensure high quality in applying the methodology, we used Rojon et al., (2021) and Tranfield et al., (2003) as guidance described earlier in this Chapter. We emphasized scientific rigor, credibility, and relevance in individual work and team discussions. We aimed at rigor following the selected methodology and practices in conducting searches, screening, and extracting data in the inductive qualitative approach. We assessed the credibility of each article individually and collectively through feedback and discussions. Relevance for academic and practitioner audiences is based on the findings from the peer-reviewed literature and the personal experiences of researchers. As the outcome, this research brings new and desired information and sheds novel insights to academic and industry audiences, not forgetting governmental organizations active in the field.

Based on the discussion above, we summarize the critical research elements, sources, and search strategy in Figure 3.

3 (SIC-code; https://en.wikipedia.org/wiki/Standard_Industrial_Classification#Codes)

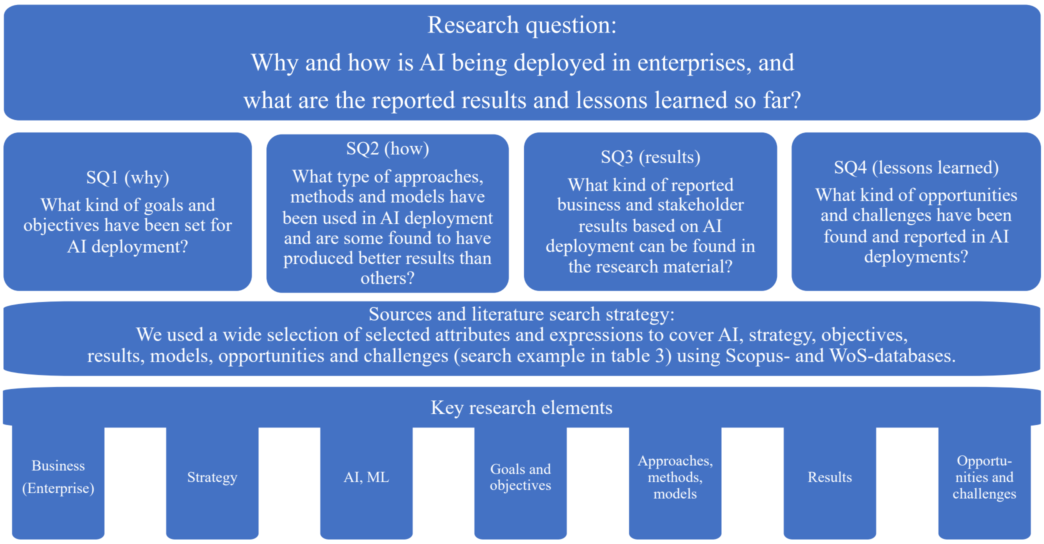


Figure 3. Summarizing the research questions, key research elements, the sources, and the search strategy.

4 Findings of the Review

In this Chapter, we present the findings of the SLR according to the structure that emerged during the inductive and iterative analysis and team discussions. We first present and discuss the distribution of the analyzed 99 articles by industry classes and business functions for background and demographic overview.

Articles by Industry Classes and company functions

Distributions of all (99) articles in industry classes and company functions are presented in Figure 4. The leading industry verticals are services (16%), followed by manufacturing (10%), finance, insurance, and real estate (9%), transportation (including utilities, 4%), and retail (3%), making up 42 % of the total.

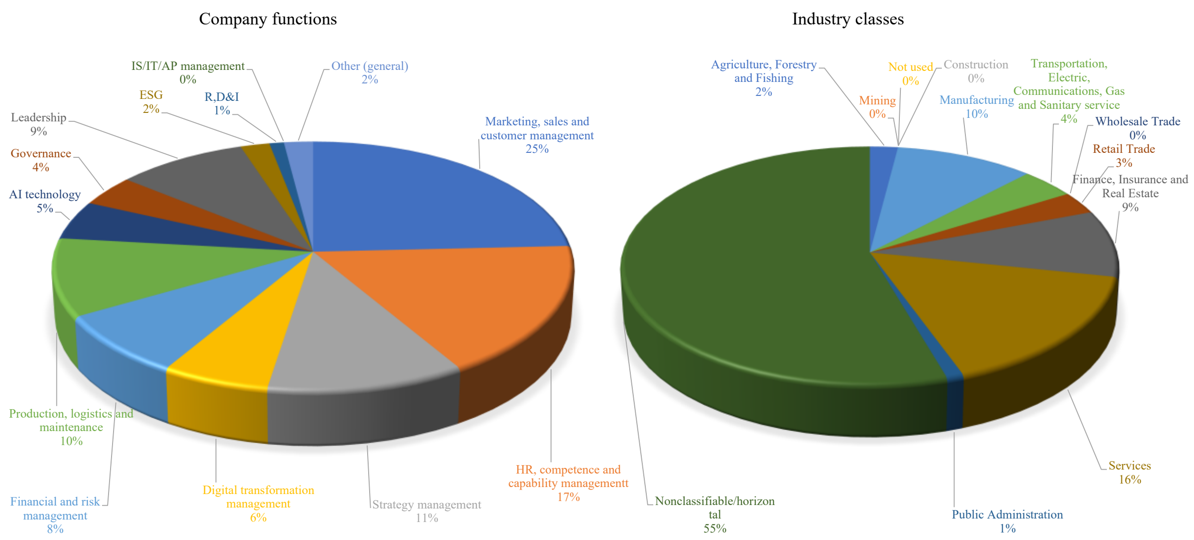


Figure 4. Distribution of the articles in industry classes (SIC codes) and in company functions (left-hand side).

The share of horizontal (i.e., not industry-specific, including some non-classifiable) is more than half (55%). In company functions, the focus has been on marketing, sales and customer management (25%), HR including competence and capability management (17%), strategy management (11%), production, logistics and maintenance (10%), and financial and risk management making (8%, altogether 71 %). These are all primarily horizontal functions, which explains the large share. The classification criteria of the functions we used differ slightly from typical. The reason is that classes like digital transformation, strategy management, information systems, information technology and applications (IS/IT/AP) management, ESG (environmental, social, governance), leadership, and governance are emerging but contextually interesting. It is not possible or even relevant in this context to get a detailed classification of all the articles. Figure 4 indicates the research interest and focus on AI adoption in the last seven years.

When summing up both sides of Figure 4, it seems that:

1. Services is the central area of interest in AI activities in industries, with manufacturing, finance and insurance, transportation, and communication following. The share of horizontal is more than half.
2. In company functions, the articles indicate interest in employees, customers, and management.

Articles by pre-deployment Stages in industries and functions

In this section, we present the distribution of the articles in industry and function classes at different stages of pre-deployment. We condense this in Figure 5, where the left-hand side describes the distribution of articles at the Explore (blue) and Validate (orange) stages by industry codes. Exploration is focused on horizontal areas, which is also true for Validate (69 and 29%, respectively). However, when considering specific industry classes, the focus is shifted to Validate (e.g., services, 25%). This indicates that exploration is horizontal, but validation is industry specific. The change of focus from horizontal to industry-specific seems to start quite early at the pre-deployment stage.

Even more remarkable change is found on the right-hand side of Figure 5, where customer-related activities (marketing, sales and customer management) are the most prominent segment, with 57 % at Validate stage, compared to only 9 % at Explore. The Validate stage also has a more significant share in financial and risk management and production, logistics, and maintenance, indicating sustained interest in those areas. Digital transformation management, governance, leadership, and ESG are lifting their heads at Explore but practically invisible at Validate. In HR (including competence and capability management) and strategy management, both stages are visible, with Explore leading clearly (21 vs. 7% and 18 vs. 7%, respectively). We have not included the Prototype stage in this Figure since only three articles (3%) are at that stage.

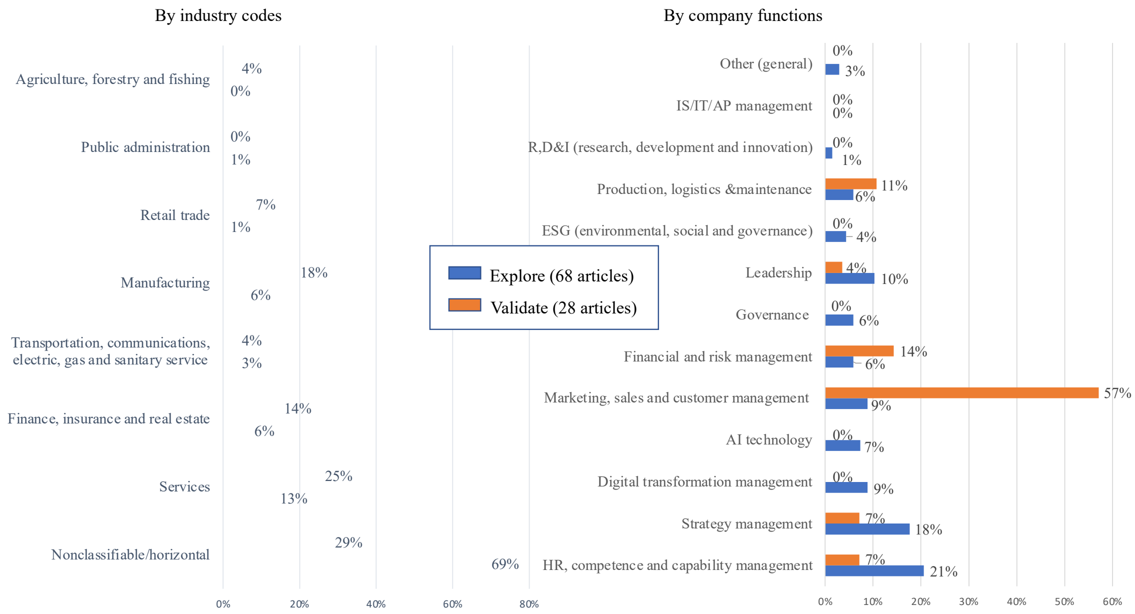


Figure 5. Distribution of articles at Explore and Validate stages by industry codes and company functions.

We summarize the key insights in Figure 5 as follows:

1. At the Explore stage, the interest is not industry-specific but horizontal. At the Validate stage, the interest is turning to industry-specific areas but still maintaining a significant share in horizontal.
2. Marketing, sales, and customer management is very clearly furthest with about a 6-fold share of Validate vs. Explore. Financial and risk management, production, logistics and maintenance are next, with the Validate shares bigger than Explore's. Finally, significant interest is also in HR (including competence and capability management) and strategy management, where the shares of Explore are still more prominent, but those of Validate are also visible.

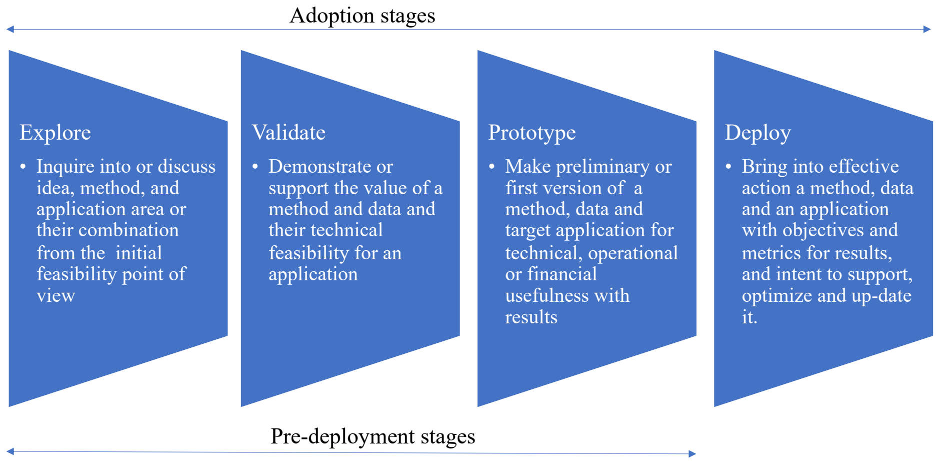
From a practical point of view, it is promising that there is much interest horizontally in marketing, sales, and customer management and likewise in manufacturing and services industries at Validate stage.

Defining Stages of Deployment

An important question emerges when analyzing the articles (as mentioned in Chapter 3): How far in the deployment process are the companies based on the studied articles? Our analysis, with the definition of deployment in Chapter 2 in mind, showed that none of the articles described the deployment stage or its concrete results.[4] Hence, we analyzed the pre-deployment deeply to understand the phenomena better. For this purpose, we found it necessary to define the pre-deployment stages as depicted in Figure 6. We call the first three phases in Figure 6 the stages of pre-deployment. Belonging to each stage has been determined based on the definitions in Figure 6, the information provided in each article, and our interpretation and analysis of each article.[5]

[4] Without going into details at this point, we can say that this conclusion is in alignment with the discussion on AI readiness, e.g., in (Russel, 2021; Ransbotham, et al., 2020; Castrounis, 2019; Ellefsen, et al., 2019).

[5] It is not possible, or even meaningful, to try and make precise borderlines for the stages.



Stage of evolution	Explore	Validate	Prototype	Deploy
Number and share of articles	68 (69%)	28 (28%)	3 (3%)	0 (0%)

Figure 6. The stages of adoption[6] and pre-deployment, and numbers and shares of articles (99in total) found at each stage.

After careful analysis, it turned out that 69 % of the articles were related to the Explore and 28% to Validate stage. Only 3% were classified to the Prototype stage, represented by three articles. We collected the details of the analyses in Appendices A and B. Due to their size, they are available online at (https://doi.org/10.5281/zenodo.11091404). These appendices provide valuable information for research and piloting ideas for companies in different industries.

Overall, it is encouraging to see (Figures 5 and 6) that quite a lot is happening in different industries and functions related to AI, even though the action seems to be at the pre-deployment stages.

Articles by Sub-Questions and Stages

The critical information of the article reviews from the research questions' point of view is presented in Appendices A (Prototype and Validate), B (Explore), and C (sub-question 1), available at (https://doi.org/10.5281/zenodo.11091404).

Sub-question 1, Goals and Objectives

To further analyze sub-question 1, we collected the key verbs and objects used in defining the goals and objectives of each of the articles. The idea was to better understand and compare the key themes and motivations described in the papers. The expressions to describe the goals and objectives are numerous and varied. Another observation is that there is no clear distinction between the Explore and Validate stages in expressing goals and objectives. Furthermore, the descriptions of goals and objectives are far from the coverage and precision of those used to define business goals and objectives in companies. Even at the Prototype stage, the key verbs are demonstrate, propose, and present, similar to expressions at Validate. However, the objects point to a more concrete direction at the Prototype stage, such as operative use.

We summarize the findings from this analysis as follows:

[6] Adoption is defined as in the dictionary (Apple Inc., 2023) as "the action or fact of choosing to take up, follow, or use something" as "adoption of agricultural technology". See also https://www.merriam-webster.com/dictionary/adoption

1. Numerical goals and objectives are typically not set for AI pre-deployment.
2. The goals and objectives set are abundant and varied.
3. There is minimal distinction between pre-deployment stages in terms of how goals and objectives are described.

Sub-question 2, Approaches, Methods, and Models

The purpose is to determine if a particular approach, method, or model was developed or used to reach the goals and objectives. For analysis purposes, the approaches, methods, and models were further grouped in the following way based on the descriptions in the articles:

- COM, Conceptual model, a high-level, principal model describing key elements and dependencies (for example, (Caner and Bhatti, 2020));
- AIM, AI model, such as machine learning, reinforcement learning, or support vector matrix model used for, e.g., tuning the model or comparing characteristics or suitability or efficiency between models (e.g., (Eletter, 2020);
- DOM, Domain model, used to describe the dependencies of different domain elements (like in maintenance management (Coetzee and Pretorius, 2020));
- DAM, Data model, describes the process of how data is used for an AI application (e.g., Ballestar et al., (2021));
- LEM, Leadership model, describing things like strategy, business, operative, or capability (like the one described in de Carlo et al., (2021);
- INM, the Integrated model, integrates domain-, data-, and AI models to enable a useful application (like the one described and further proposed by Xu et al., (2020));
- DEM, Deployment model, describes the continued, successful deployment of AI, not found in the target literature of this study.

The result of this classification is presented in Figure 7. It is remarkable that the share of combined Conceptual and No models represents more than half of all articles, and they are found chiefly at the Explore stage with a minor exception. Another interesting finding is that the share of combined AI and Domain models (AIM+DOM) increases from Explore to Validate. Noticeable, too, is that the percentage of Conceptual models is almost nonexistent at the Validate stage. These findings align very well with the early stages of deployment. Most surprising is the absence of data models (DAM) in the studied articles, reflecting the early stages of value- and benefit-driven deployment.

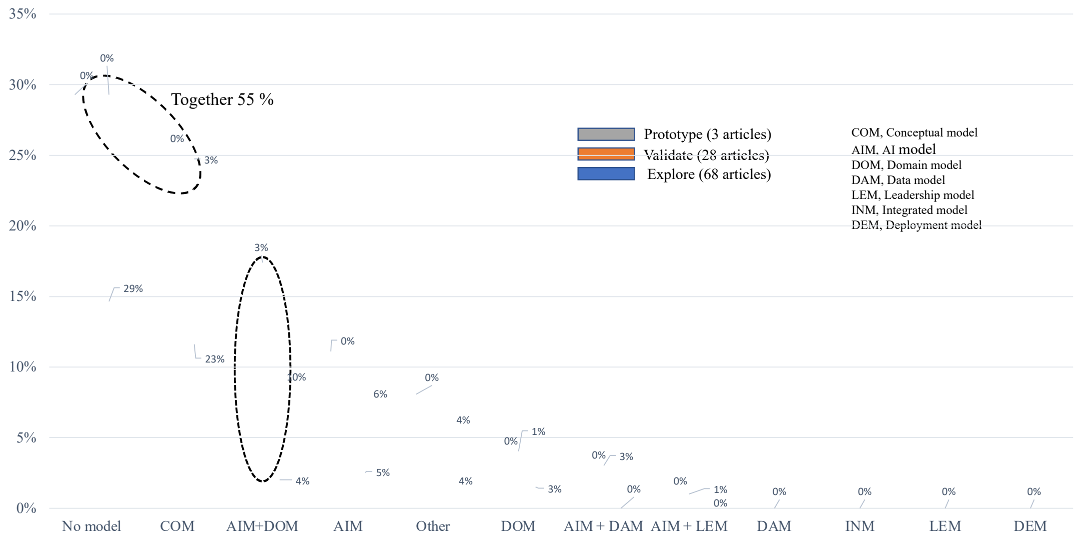


Figure 7. Distribution of all articles (99) in approach-method-model -classes by stages.

The findings on approaches, methods, and models are summarized as follows:

1. Most articles (Explore stage) had a conceptual model, or no models described.
2. At the Validate stage, AI models and AI + domain models (AIM + DOM) appear.
3. Data models (DAM), integrated models (INM), leadership models (LEM), and deployment models (DEM) are not found.

Sub-question 3, Business and Stake Holder Results

To get a better grasp of the results collected in the spreadsheets in the online Appendices A and B (https://doi.org/10.5281/zenodo.11091404), we grouped the articles into two categories by stage as follows:

A, results described in the articles using concrete-outcome-oriented expressions (like saved time and money, improved accuracy);

B, results described in the articles using qualitative or abstract-outcome-oriented expressions (like discussion and arguments for a concept of AI in management).

The first finding, as earlier with sub-question 1 (goals and objectives), is that numerically measured results are very scarce. The description of results is primarily verbal and versatile and not related to business or stakeholders, such as value, revenue, profit, or even productivity. This type of grouping and analysis is rough and somewhat exaggerating, but it aims to make an important distinction related to handling and discussing results in the deployment-related research.

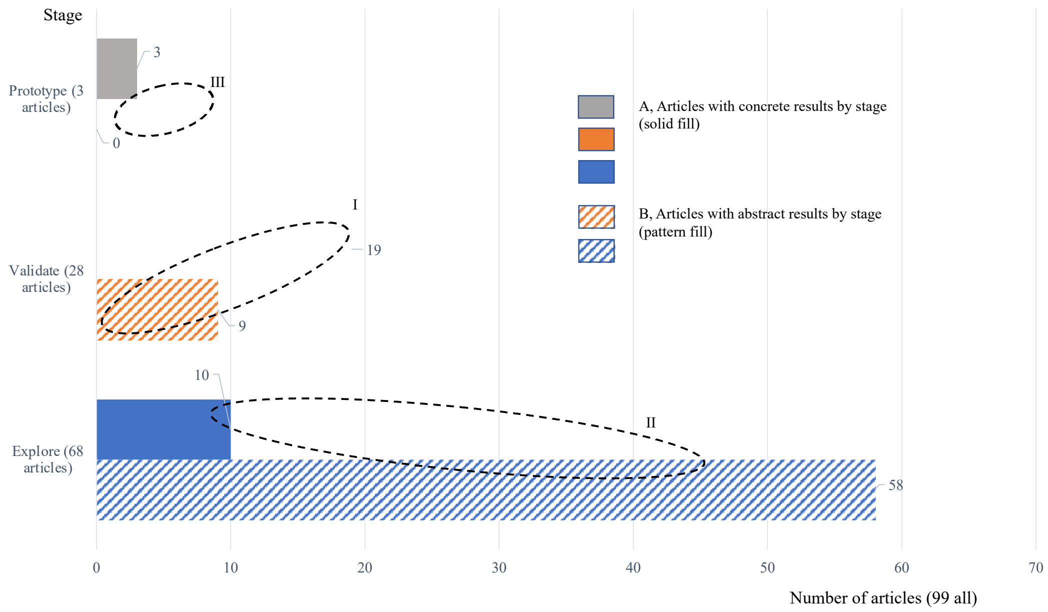


Figure 8. Distribution of results descriptions of all articles in result categories (concrete vs. abstract) by pre-deployment stages.

We present the outcome of this analysis in Figure 8. First, the number of concrete result expressions (A) is more than double (19 vs. 9) compared to abstract expressions (B) at the Validate stage (highlighted as I in Figure 8). Second, the number of concrete results expressions is about one-sixth (10 vs. 58) compared to abstract expressions at the Explore stage (highlighted as II). Third, at the Prototype stage, all the results expressions were found to be in category A (concrete expressions), highlighted as III. At the Explore stage, the concreteness is often related to AI algorithms, such as how good they are in a particular classification problem. At the Validate stage, the results usually concern using AI to resolve application problems. The level of concreteness of the results seems to increase when moving from Explore to Prototype. The analysis of results is summarized as follows:

1. Reporting results is primarily verbal and versatile.
2. The verbal descriptions at the Validate stage tend to be more concrete than at the Explore stage.
3. The descriptions of the results reflect the pre-deployment stages, not the deployment stage.

Sub-question 4, Opportunities and Challenges

There is a wide variety of descriptions of opportunities and challenges. For further insight, these attributes were categorized as follows, with explanations given in parentheses.

Opportunities
- Articles furthering research (when further research opportunities were emphasized)
- Articles furthering deployment (when deployment opportunities were emphasized)
- Articles describing general opportunities (when utilization, in general, was the emphasis)
- Not mentioned (when no opportunities were mentioned)

Challenges
- People/Organization related (e.g., organizational structure or resistance by the employees)
- Technology/methodology related (need for more work was seen as necessary for progress)
- Financial/leadership related (shortage of financing or leadership support were considered as challenges)
- General/Policy related (challenges related to AI usage overall, such as ethics and security)
- Not mentioned (when no challenges were mentioned)

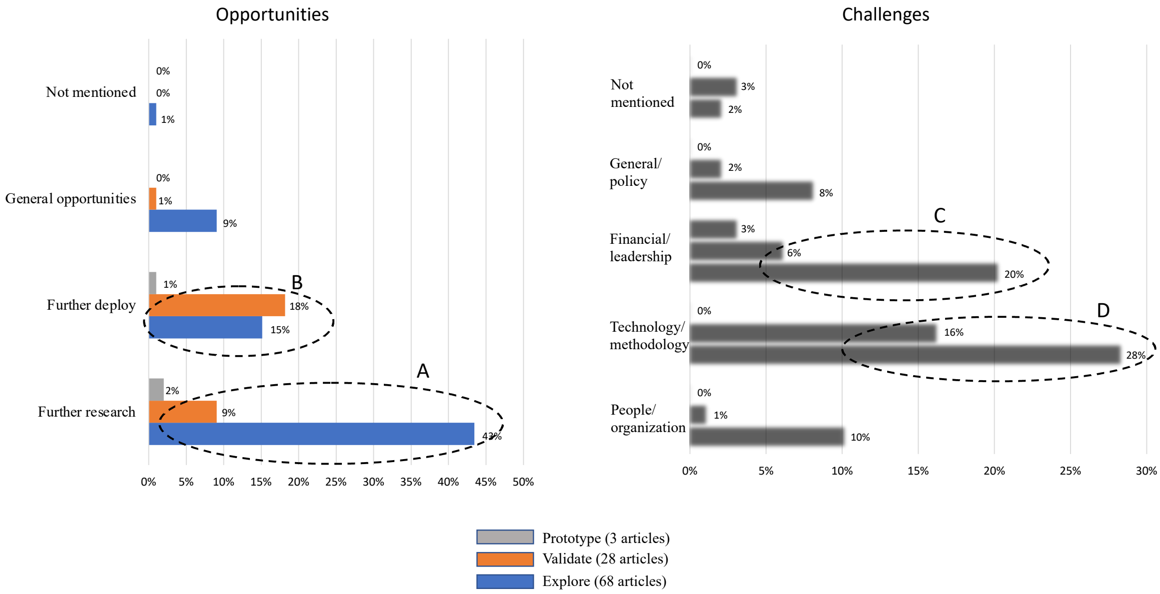


Figure 9. Distribution (as a percentage of 99 articles) of opportunity and challenge descriptions of articles in categories by stages.

We present the results of this analysis in Figure 9. The first observation (A in Figure 9) is that further research is four times (43 vs.9%) more common at the Explore stage than at the Validate stage. About one-fifth of all the articles at the Validate stage indicate further deployment compared to about 15 % at the Explore stage (B). These two observations align well with the findings from the analyses of the previous questions and figures. Most challenges are at the Explore stage in all categories (C and D). Almost one-third of the challenges are at the Validate stage. The opportunities and challenges findings are summarized as follows:

1. At the Explore stage, opportunities are seen mainly in further research, and at the Validate stage, opportunities are mainly seen in further deployment.
2. Challenges are seen in the Technology/Methodology and Financial/Leadership areas at both stages.
3. The high share of Technology/Methodology challenges can be interpreted as symptomatic of the early stage of technology adoption.

5 Discussion

In this section, we discuss the findings of this research and reflect on the other included research relevant to the topic. We collected the discussion points by sub-questions in the online Appendix D (https://doi.org/10.5281/zenodo.11091404) and, in the following, present the conclusionary discussion on the main research question. In the second section, we discuss the connections and implications of the research in the context of AI, dynamic capability theory, and innovation management.

The main research question: Why and how is AI being deployed in companies, and what are the reported results and lessons learned so far?

Based on the analysis and synthesis of the 99 peer-reviewed articles, the answer to the RQ is that AI deployment in companies is at the early stages. Hence, measurable objectives, results, deployment approaches, and learnings do not exist yet in the academic research literature. There is, however, a considerable amount of exploration and validation going on, raising future expectations of deployment topics becoming attractive for research and providing more understanding of these critical areas.

An explanation of the situation can be found in the following points:

1. Digital Maturity. Many companies still have a lot of work to do with infrastructure, data availability, and competence before embracing AI deployment. Building these things to a sufficient level in companies can take time. Companies are mainly at the Sensing stage of the Dynamic Capabilities model. Sensing and Seizing stages can prevail simultaneously since many new capabilities might be needed, depending on the case.
2. Cognizance Maturity. Artificial Intelligence deployment is not just a technology usage matter, but a comprehensive business issue. Many companies are unsure why they should become interested in AI. These companies are at the Sensing stage or not even there yet.
3. Deployment Difficulty. Even if companies have recognized the importance of AI for their success and survival, they have not yet found ways to go forward with deployment due to multi-faceted challenges related to, e.g., the needed capabilities.
4. Research Maturity. Academic research has approached the issue to some extent on a general level from strategic, capability, and transformation management viewpoints but more intensively from a technology and point solution perspective, not reaching enough for concrete deployment case research.
5. Transparency Maturity. We cannot confirm this directly from the studied articles. Our interpretation is that companies are unwilling to share information on their AI experiments and pilots if they have not gained the expected results, or because of confidentiality reasons.

Based on our analysis of the 99 articles, we developed a conceptual framework (Figure 10) to concretize and explain the findings on the pre-deployment. The critical elements in the model are the identified pre-deployment stages described in Chapter 4 and the explanation points (1 to 3) above. The model describes the steps companies face on their early deployment path. It is not surprising that companies face difficulties and are struggling to get forward from the early stages. Several projects need to be started, pivoted, and abandoned before enough learning accumulates. If the expectations are too high and failures – as an integral part of learning – are not tolerated, embracing AI might face discarding. The Pre-deployment Circle (Figure 10) can turn into a vicious circle for the company.

On the other hand, this model creates a frame for how companies can start developing their AI deployment path. Exploration can be started with a few resources and a limited set of qualified data. The first steps do not require significant investments. Even the first prototypes can be built with reasonable costs. Entering the frame (Explore) helps to get the learning going, which will take time and can only be done internally – as developing dynamic capabilities in general (Teece, 2019). Together with the analyzed ninety-nine article documents (Appendices A and B), the model helps to understand the Pre-deployment stages and their importance. These stages cannot be bypassed since, according to (Teece, 2019), the needed capabilities are unique and path-dependent. The Pre-deployment Circle must be understood as a training track and run several rounds to ensure learning and attaining the needed capabilities. Without internal capability development, it is hardly possible to enter the deployment successfully.

The Pre-deployment Circle and the time required to build the needed capabilities also explain, at least partly, the gap between company investments and the sparsity of achieved business results. This way, the study brings additional insight into the research purpose and motivation mentioned in Chapter 1. However, for a more comprehensive answer, additional research is needed.

The pre-deployment phase must be led, championed, and supported with clear objectives on what is aimed to be achieved. Active and frank communication and structured, fail-tolerant learning must be enabled to facilitate this. Otherwise, companies risk stalling and stop moving toward actual deployment, learning, and results. The role of management in supporting and encouraging AI pre-deployment is critical, which is consistent with the Dynamic Capabilities theory (e.g., Teece, 2017)

According to our knowledge, the results and the framework described above are a novel and unique contribution to harnessing AI for company success and stakeholder benefits. We have solidly anchored the framework in the Capability theory, the Dynamic Capabilities, and connected it to the theory of company strategy (Peng, 2022). This framework and the research results help us understand that AI is not just a handy tool for solving problems or an IT application package to manage operations or information. The sooner a company can break from the

Pre-deployment Circle to beyond prototyping, the quicker it improves chances to start getting concrete business results. A well-led pre-deployment can be a cost-effective way for the company to prepare for the deployment and later scale-up of AI.

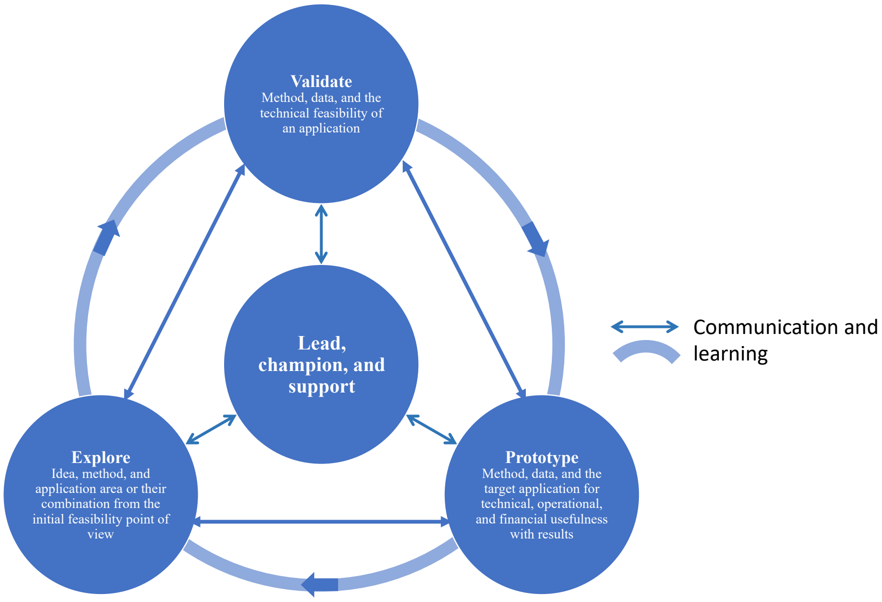


Figure 10. A conceptual framework (the Pre-deployment Circle) for an organization's pre-deployment phase of AI adoption.

Implications from AI, dynamic capabilities and corporate innovation viewpoints

We reviewed recent research literature on dynamic capabilities and innovation management from the AI deployment point of view and outlined the review in the online Appendix E (https://doi.org/10.5281/zenodo.11091404). We summarize the observations as follows:

1. The pre-deployment phase can be explained by and fits well in the sensing phase of the dynamic capabilities model (Schilke et al., 2018; Teece, 2007; 2017; 2014; Eisenhardt and Martin, 2000). The capabilities needed for entering AI deployment rarely exist in companies, but they must be developed. The article (Teece, 2007) also supports points 2 and 3 for the explanation mentioned earlier in this Chapter.
2. The dynamic capabilities and innovation have been discussed in several articles. While Lawson and Samson (2001) presented their innovation capability model and how to build an innovation engine already in 2001, recent reviews maintain that "we still know little about what affects valuable innovation outcomes and how firms come to innovate successfully" (Truong and Papagiannidis, 2022). The comprehensive review by Mendoza-Silva, (2020) supports these findings, identifying 21 research gaps related to innovation capability.
3. AI and innovation have been reviewed and discussed (e.g., by Bahoo et al., 2023; Gama and Magistretti, 2023; Truong and Papagiannidis, 2022; Haefner et al., 2021; Verganti et al., 2020). For example, Truong and Papagiannidis, (2022) and Haefner et al., (2021) both take a conservative stance on the role of AI in innovation and do not expect significant changes soon due to AI's upcoming role in innovation.
4. Gama and Magistretti (2023) identify a dichotomous view presenting an enabling and enhancing role for AI in developing innovation capabilities. Developing AI-enabling capabilities through pre-deployment seems to support the development of innovation capabilities.
5. Verganti et al. (2020) have a more progressive view on the role of AI in innovation. They envision, supported by analysis on Netflix and AirB&B, that AI moves digital automation upwards from manufacturing to design. They continue that we are at the beginning of a transformation in the innovation process, whose extent is difficult to fully capture, and that many fundamental questions are still open.

When summarizing the discussion from the AI and innovation point of view, it seems that developing innovation capabilities can benefit AI pre-deployment, and the efforts put into AI pre-deployment can benefit the development of innovation capabilities. Wide deployment of AI is needed to realize significant results and benefits from AI in innovation. Understanding the innovation process and AI deployment are at early stages in companies, leaving much important space for empirical and theoretical research.

6 Conclusion, limitations, and further research

Deployment of AI has not proceeded as smoothly and painlessly as one would expect based on the interest, private investments, and hype raised by media, consultants, and even governments. To the best of our knowledge, this study is the first academic research focusing on finding concrete business objectives, approaches, results, and learnings of AI deployment in companies through systematic research of peer-reviewed literature.

The key outcome of this research is that AI is still at the early pre-deployment stages in companies. Our analysis of selected 99 articles strongly supports this outcome since no deployment-related business objectives, approaches, results, or learnings were found in the systematic literature research. Potential reasons for this are immaturity in i) digitalization, ii) cognizance, iii) transparency, iv) research, and v) deployment difficulty. Instead of business objectives and results of deployment, we found a lot of activities at earlier, pre-deployment stages, which we named Explore, Validate, and Prototype. Based on the analysis and the results, we developed a conceptual framework to explain the findings on the pre-deployment. For companies, the model builds a basis on which to follow their pre-deployment path. It emphasizes a risk-tolerant, agile, persevering approach to ensure cooperative learning and capability-building. If management does not fully support and encourage the pre-deployment efforts, the company risks discarding the AI efforts too early and too lightly.

Extensive peer-reviewed research related to pre-deployment stages is available. We concretize the outcome at each pre-deployment stage in the online Appendices A, B, and C (https://doi.org/10.5281/zenodo.11091404). These are valuable for researchers and practitioners interested in detailed AI pre-deployment information structured by stages, industries, and company functions. The abundance of pre-deployment research activity is positive and promising for the future of both research and practice.

From the theoretical point of view, we find the pre-deployment results compatible with the Dynamic Capabilities theory. Based on this research, companies are, at best, at the sensing stage of their AI capabilities development. The role of AI in company innovation is still in its infancy, which is not surprising since the understanding of the innovation process is also in high need of further research. There are both cautious and optimistic views of AI's future role and influence on innovation. Learning to deploy AI calls for multi-domain innovation, and harnessing the full potential of innovation needs widely deployed AI. The evolution and benefits of these seem to be intertwined.

The topics of AI deployment, innovation capabilities, and AI in innovation need more theoretical and practical research as stated also by other researchers mentioned in Chapter 5. We encourage company-case, multi-case, and longitudinal studies to establish metrics, analyze results, and improve theories. We have highlighted the most urgent future research proposals from the AI deployment angle in the online Appendix D. Focusing on these would help to condense practical and theoretical wisdom to speed up the deployment, build competitive advantage through AI and innovation, and create stakeholder value via operational and strategic benefits.

This research has its limitations, naturally. For example, the possibility that selecting other databases and different search criteria could have produced differing results cannot be ruled out. We used inductive and iterative analysis to find out a detailed view of the deployment situation in companies. The team has discussed and iteratively reviewed the analysis and results, and we believe they support and justify the findings and results of the synthesis and conclusion. Compared to other research, we identified repeated notes and comments supporting the presented outcomes and conclusion.

Appendices, available in https://doi.org/10.5281/zenodo.11091404 :

Appendix A. Articles at the Prototype and Validate stages with summaries and observations from research questions point of view.
Appendix B. Articles at the Explore stage with summaries and observations from the research questions' point of view.
Appendix C. Analysis of the verbs and objects in the descriptions of the goals and objectives in the articles (Sub-question 1).
Appendix D. Summary of the discussion points by sub-question with reflections on other literature, and further research proposals.
Appendix E. Summary of the review of the relevant recent literature on dynamic capabilities, innovation capabilities, and AI and innovation.

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Literature of the Systematic Literature Research by stage of pre-deployment (the numbers in front refer to Appendices A and B)

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