Examining heterogeneous patterns of AI capabilities

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Abstract. This study explores the heterogeneous patterns of companies in terms of their AI capabilities by analyzing various combinations of AI-specific resources. Drawing on the resource-based theory of the firm, we develop an analytical framework comprising two key dimensions: AI infrastructure and AI competencies, and employ two scores to quantify these dimensions. We apply this approach to a dataset of 215 companies and categorize them into four distinct groups: beginners, followers with strong AI-infrastructure, followers with strong AI-specific human resource, and leaders in terms of AI capabilities. Our analysis provides insights into the companies' sectoral affiliation, size classes, fields of usage of AI, and make or buy decisions regarding the uptake of AI solutions. Our findings suggest that the manufacturing and construction industry had the highest proportion of beginner companies with low AI capabilities, while the services and IT industry had the largest share of leader companies with strong AI capabilities. The study also shows that companies with different levels of AI capabilities have distinct motives for adopting AI technologies, and leading companies are more likely to use AI for product innovation purposes. Overall, the study provides a comprehensive analysis of the various AI-specific resources that contribute to a company's AI capabilities and sheds more light on configurations of AI-specific resources. Our analytical framework can help organizations better understand their AI capabilities and identify areas for improvement.

Keywords: AI capabilities, heterogeneous patterns, manufacturing, survey

1 Introduction

In the recent years, artificial intelligence (AI) has gained significant attention and become a top technological priority for organizations, mainly due to the availability of big data and the emergence of advanced techniques and infrastructure [1]. Different studies have also shown a significant increase in the number of companies implementing AI [2]. However, despite the potential business value that AI can deliver, organizations face numerous challenges that prevent them from realizing performance gains [3]. Several studies have highlighted that many companies are yet to realize the expected benefits of AI [4]. One of the main reasons for this is the implementation and restructuring lags that organizations face in leveraging their AI investments, leading to a modern productivity paradox [5]. To overcome this challenge, organizations need to invest in complementary resources that will help them build an AI capability [6, 7]. This raises the so far under-addressed question of what these complementary resources are and how companies can orchestrate them to effectively build AI capabilities. In this paper, we contribute to filling this gap by examining combinations of AI-specific resources to better understand heterogeneous patterns of companies regarding their AI capabilities.

As a theoretical background, we draw on the resource-based-view (RBV) of the strategic management literature [8–12] and its recent implementation in the field of information systems research [13–18]. We use this literature to explain how relevant resources to information technologies (IT) can be leveraged in order to form the so-called IT capabilities, which in turn can conditionally influence competitive performance [19, 20]. More precisely, we use the recent studies on more specific AI capabilities, which provide valuable insights into the organizational resources needed for firms to develop their AI capabilities and achieve performance gains [21]. Following the RBV the authors have identified some key types of AI-specific resources and grouped them into three categories based on the framework of Grant (1991): tangible resources (data, technology, basic resources), intangible resources (inter-departmental coordination, organizational change capacity, risk proclivity) and human resources (business and technical skills). Moreover, they examined the impact of AI capabilities on organizational creativity and performance. However, what we do not know from previous studies is how companies differ in their AI capabilities and if there are some distinctive patterns of firm's AI-specific resource combinations. Knowing more about such patterns of AI-specific resources would contribute to a better understanding of the micro-foundation of AI capabilities, thus contributing significantly to both, research and practice.

In order to investigate the micro-foundations of AI capabilities, we first develop an analytical framework for systematizing AI-specific resources using RBV and the recent literature on AI capabilities. We start with the theoretical notion that the mere implementation of AI techniques alone is unlikely to lead to competitive gains, as these techniques are widely available and easily replicated in the market. Similarly, relying solely on data to fuel these techniques will not be sufficient to create distinctive AI capabilities. Companies thus need to develop and implement a unique blend of human resources and combine them with other intangible and tangible resources to create an AI capability. Hence, on the one hand, our framework focuses on human resources, including employees' knowledge and abilities. On the other hand, given the diverse range of AI applications, each with unique technical requirements, data needs, and organizational contexts, we examine the relevance of tangible and intangible resources, as AI infrastructure, using companies' capabilities as general criteria for introduction, implementation and development of AI solutions. We subsequently apply this framework to analyze a comprehensive dataset obtained from a long-term research project investigating the adoption of AI for work and learning in organizations. Specifically, we examine a sample of 215 companies to identify diverse combinations of AI-related resources and elucidate distinct patterns of AI capabilities. Our study sheds more light on configurations of AI-specific resources and thus provides support for the heterogeneity assumption concerning AI capabilities. Thus, by showing its potential to capture the heterogeneity in an empirical analysis, our framework can serve as a comprehensive basis for deeper understanding of the concept of AI capability and thus for improving existing or even developing new measurement for different patterns of AI capabilities. It also has the potential to support managers in understating the position of their companies in terms of AI capabilities.

2 Theoretical Foundation

2.1 From RBV to AI Capabilities

The idea of the role of complementary and unique firm-level resources and their orchestration for gaining competitive advantage has its roots in the resource-based-view (RBV) of the strategic management literature [17, 18]. While the RBV generally encompasses a broad definition of resources that includes assets, knowledge, capabilities, and organizational processes, Grant's (1991) framework provides a more nuanced understanding of resources by distinguishing between resources and capabilities and classifying resources into tangible, intangible, and personnel-based categories. Tangible resources refer to financial and physical assets, while intangible resources include reputation, brand image, and product quality. The third group represents personnel-based resources that encompass technical and other knowledge assets as well as employee skills. Organizational capabilities, on the other hand, are an organization's ability to integrate and deploy valuable resources to achieve a competitive advantage [22] or with other words to orchestrate resources to create competitive advantage [23]. Grant (1995) proposes a hierarchy of organizational capabilities that range from specialized capabilities to broader functional capabilities such as marketing, manufacturing, and IT capabilities. These functional capabilities, in turn, can be integrated to form cross-functional capabilities, such as customer support capabilities that result from the integration of marketing, IT, and operations capabilities.

Recent literature in the field of information systems adopted this approach to explain how information technology (IT) related resources can be leveraged in order to form the so called IT capabilities, which in turn can conditionally influence competitive performance [19, 20, 24]. There are different kind of IT-capabilities examined in this term, for instance social media capabilities [25] or business analytics and big data capabilities [14]. In this context, a firm's IT capability is characterized as its capacity to effectively utilize IT-based resources in conjunction with other resources and capabilities [17]. Following the Grant's classification of resource types, the IT-based resources might be: IT infrastructure (hardware) and data for tangible, organisational and managerial characteristics for intangible and technical and managerial IT skills for human resources. While tangible resources, for instance IT equipment and software, can be bought on the market, and thus do not represent factors of competitive advantage per se, intangible and human resources, as enablers of IT application in organizations, are valuable sources of heterogeneity, and therefore of competitiveness on the market [8, 21].

More recent studies have explored the development and management of AI-specific capability as imperative for organizations seeking to realize performance gains from AI solutions [21, 26, 3, 7]. They identified the organizational resources necessary for firms to develop their AI capabilities and achieve performance gains. Building on the theoretical underpinnings of the RBV and recent studies in the information systems literature, Mikalef and Gupta (2021) propose eight resources that jointly constitute an AI capability: (1) tangible resources (data, technology, and basic resources), (2) human resources (business and technical skills), and (3) intangible resources (inter-departmental coordination, organizational change capacity, and risk proclivity). According to the RBV, the simple implementation of AI techniques alone is unlikely to lead to competitive advantage, as these techniques are widely available and easily replicated in the market. On the other hand, relying solely on data to fuel these techniques will not be enough to create distinctive AI capabilities. Companies thus need to develop and implement a unique blend of tangible, intangible, and human resources to create an AI capability which in turn implies a firm’s ability to select, orchestrate, and leverage its AI-specific resources [13].

2.2 AI Capabilities as Bundle of Tangible, Intangible and Human Resources

Tangible resources represent the IT infrastructure needed for AI applications, in terms of the necessary hardware for storing and processing data as well as software for (big) data processing required by AI [27, 28]. These resources cover data [29, 30]. Due to the key fact that AI-based systems learn through different data types and large amounts of data, this topic plays not only one of the most important, but also one of the most challenging roles concerning the implementation of AI [28].

Intangible resources are highly unique and heterogeneous resources due to the mix of organizational history, people, processes, and conditions that characterize organizations. Studies on firms' readiness for AI emphasize the high relevance of intangible resources for both, adoption of AI solutions for improving companies' performances, as well as for reaping business benefits from adopted technologies. Because of the high complexity of AI implementation projects resulting from high purpose- or context-specificity of AI [29], typical organizational features, like for instance firm or project team size, interdisciplinarity, cross-functional collaboration and boundary spanners [31, 32] play a crucial role for implementation and leveraging value of AI.

Human resources cover collective knowledge and skills of employees, as well as their training, experience, and professional connections [9, 8, 10]. Considering the field of IT, besides the technical IT skills essential for introducing and application of IT solutions in the company, for instance hardware development, software development, data science etc. [33], managerial IT skills plays also a crucial role for implementing IT solutions in companies. IT managerial skills encompass the capacity to conceptualize, create, and utilize IT applications to bolster and improve other operational aspects of a business [24]. Those skills include for instance abilities of the management to understand the needs of the company and to implement the suitable IT solution, as well as to coordinate IT activities in the company. Hence, project management, moderating skills and leadership paly crucial role here [17]. Technical and managerial skills evolve over long period of time through the accumulation of experiences. Hence, they are often tacit in nature and thus organization specific [34]. Therefore, differences in benefits companies gain from IT has been attributed largely to their managerial IT resources [17, 24]

2.3 The Framework for Analyzing Patterns of AI Capabilities

For researching into different patterns of AI capabilities, we adopt the RBV logic of the relevance of different resources for introduction and usage of AI solutions in companies [21]. We start with the premise that tangible resources are freely acquirable by most firms through the market and thus are not adequate on their own to develop AI capabilities that can provide a competitive edge. Whereas, intangible resources represent those that are, due to their evolutionarily organizational character for the company [35–37], unique and heterogeneous [21]. Therefore, for analyzing patterns of companies with respect to their AI capabilities, it makes sense to consider them together with the intangible resources, i.e. as one dimension, representing AI infrastructure as enabling factor for adopting AI solutions in the company. Moreover, we understand that there might be different combinations of tangible and intangible resources enabling successful introduction of an AI solution in one companies' processes, as one phase of the AI adoption process, and for effective implementation of this solution in the everyday work, as the another phase.

To gain a deeper understanding of the crucial role that human resources play as the third group of AI-specific resources in enabling AI capabilities, it is essential to explore the competence of employees in working and learning with AI. In conjunction with the AI infrastructure, we propose a comprehensive two-dimensional framework (see **Fig. 1**) for analyzing the patterns of AI capabilities across different industries and organizations. This framework serves as an effective tool for identifying best practices and areas for improvement in AI adoption and implementation. Additionally, it offers valuable insights into the correlation between varying degrees of AI capabilities and their impact on organizational performance.

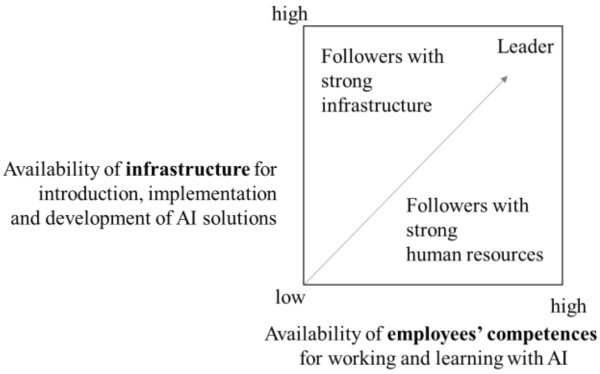

Fig. 1. Framework for analyzing patterns of AI capabilities

Integrating two critical dimensions representing different AI-relevant resources, the framework classifies companies into four distinct groups, each representing a different level of AI capability. Companies categorized as beginners exhibit a low level of AI-relevant skills and knowledge and possess limited AI infrastructure. These organizations are just embarking on their AI journey and have yet to fully leverage the potential of AI technologies. Followers with strong infrastructure have invested heavily in tangible resources, such as digital equipment, necessary for AI implementation. However, their focus on infrastructure development often comes at the expense of enhancing AI-relevant skills and knowledge among their employees. Companies falling into the category of followers with strong human resources recognize the importance of nurturing talent and cultivating a deep understanding of AI within their organization. While their AI infrastructure may not be as advanced as that of leaders, their strong human resources lay a solid foundation for future growth. Finally, leaders represent the pinnacle of AI capability within the framework. These companies have effectively combined tangible and intangible resources to achieve a significant competitive advantage in the AI landscape. With this resource-based systematization, the framework also elucidates two distinct paths that companies follow on their journey from beginners to leaders. The first path involves heavy investment in tangible resources, primarily focusing on AI infrastructure. This approach prioritizes the acquisition of digital equipment and tools necessary for AI implementation. The second path emphasizes the development of AI-relevant skills and knowledge among employees, recognizing the significance of human resources in AI capability. This path aims to create a skilled and knowledgeable workforce capable of driving AI initiatives within the organization.

3 Methodology

Our work follows a mixed methods approach, combining qualitative and quantitative methods. First, to explore the required tangible, intangible and human resources that companies need for effectively implementing AI in their processes, and thereby to develop a fundament for our conceptual framework, we conducted qualitative expert interviews with various practitioners. We targeted interview partners with sound knowledge of the AI solutions used by companies as well as the areas of their implementation. To obtain a broad heterogeneous picture, interviewees from different domains were recruited including four representatives of companies developing AI technologies, four representatives of companies applying AI technologies, and two representatives of companies developing AI training. Each interview lasted between 45 and 60 min and with the permission of the interview partners we recorded and transcribed for subsequent coding. The guideline for the interview consisted of two main categories of questions: 1) skills and knowledge of employees required for introduction, implementation and development of AI solutions, 2) AI-related infrastructure, which includes challenges and other required resources related to the adoption and use of AI. In order to systematically analyze the data collected, we used these main categories to systemize the various competences and related infrastructure identified. We found that there are four typical categories of competences in the context of AI that represent different skills and knowledge in organizations:

1. *AI-specific competences* include all skills and knowledge directly related to AI.
2. *Leadership and moderation competences* include all skills and knowledge needed to engage people and coordinate the project.
3. *Project management competences* include additional skills and knowledge that should be available in the project team to successfully implement AI projects.
4. *AI usage competences* include the skills and knowledge that future AI users should have.

Moreover, we identified four distinct organizational AI capabilities that manifest AI-specific combinations of tangible and intangible resources in companies. Hence, these capabilities represent the **AI-related infrastructure** that enables the successful introduction and implementation of AI solutions for various tasks related to AI deployment:

a. *AI use case identification* describes the organization’s current capability to find appropriate application areas for AI within the organization using existing resources.
b. *AI process integration* describes the organization’s current capability to embed AI solutions into established business processes using existing resources.
c. *AI utilization* describes the organization’s current capability to adequately use AI solutions within the organization with given existing resources.
d. *AI development* describes the organization’s current capability to develop AI solutions independently within one's own company using existing resources.

In the second stage of our research, we employed a quantitative online survey to further develop and expand upon our qualitative findings. A total of 215 participants were recruited for the study. We specifically targeted companies that require strategic alignment of their human resources structure and other tangible and intangible resources. To ensure that the participants met our inclusion criteria, we only included individuals who (a) were employed in enterprises with at least ten employees and (b) had personnel or decision-making responsibility regarding the introduction of new technologies. Screening questions at the beginning of the survey ensured participant eligibility. The survey was conducted in German, and only German-speaking residents of

Germany were recruited. Participation in the survey was voluntary, and participants were compensated in accordance with the panel provider's terms of service.

Out of the total companies surveyed, 35 (16.3%) were small companies with less than 50 employees , 77 (35.8%) medium-sized companies with 50 to 249 employees, and 101 (47.0%) large companies with 250 or more employees. In terms of industry distribution, 90 companies (41.9%) were from the manufacturing and construction sector, 75 companies (34.9%) were from the services and IT industry, and the remaining 47 companies (21.9%) were from other industries.

For each company, we calculated two scores to assess its level of artificial intelligence (AI) capabilities (see **Fig. 2**). The first score is the AI Competence Score, which is measured by questions about the availability of AI-related competences within the companies. Thereby, we refer to 35 competence items, which are the result of our qualitative research (cf. [38]). Of these 35 competence items, 1) eleven items are grouped as AI-specific competences, 2) nine items are grouped as leadership and moderation competences, 3) ten items are grouped as project management competences, and 4) five items are grouped as AI usage competences. Responses were rated on a 5-point Likert scale for each question. By averaging the scores of each group, we calculated an average for each competence category, ranging from zero to four. By adding up these mean values, we calculate the AI Competence score. The second score is the AI Implementation Score, which assesses the availability of AI infrastructure. It is determined it by summing the responses to four questions that assess the extent to which AI infrastructure is in place to a) identify AI use cases, b) integrate AI into processes, c) use AI, and d) develop AI. Again, responses to these questions were given on a 5-point Likert scale.

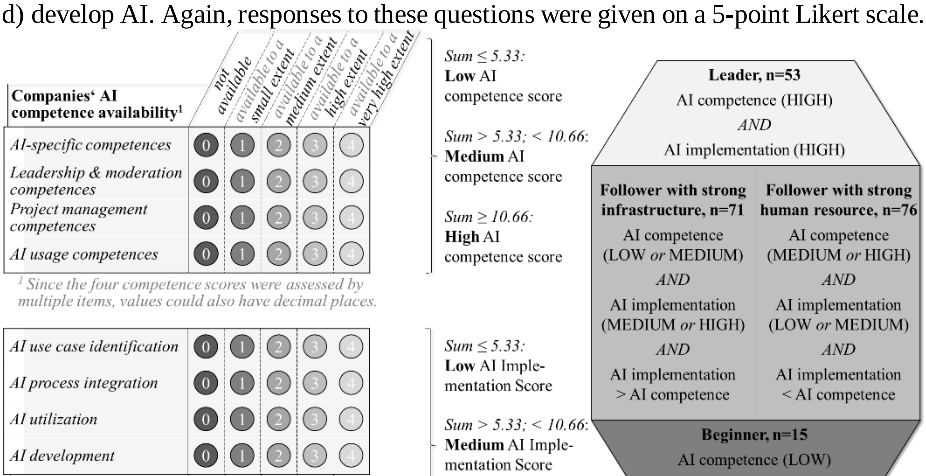

Fig. 2. Classification of Companies Based on their AI Capability Patterns

The scores for both criteria can range from 0 to 16, with *low* capability scores less than or equal to 5.33, *high* capability scores greater than or equal to 10.33, and *medium* scores in between. These values can be used to evaluate the overall AI capability of a company and compare it with other examined companies. As shown in Fig. 2 we categorized the 215 companies of our survey into four groups: beginners, followers with strong infrastructure, followers with strong human resource and leaders. While *beginners* (n=15) have both a low AI competence score and a low AI implementation score, *leaders* (n=53) have high scores in both. *Followers with strong infrastructure* (n=71) have high or medium AI implementation scores and low or medium AI competence scores, with the AI implementation score always higher than the AI competence score. On the other hand, *followers with strong human resource* (n=76) have high or medium AI competence scores and low or medium AI implementation scores, with the AI competence score always higher than the AI implementation score.

4 Results

As elucidated in Chapter 2.3, the AI capability index evaluates the association between the degree of a company's AI infrastructure (including both tangible and intangible resources) and the proficiency of their employees (i.e., their skills and knowledge) in working with and learning from AI. This framework enables not only the categorization of companies based on their AI capabilities but also a comprehensive analysis of the resources that facilitate those capabilities.

The **Fehler! Verweisquelle konnte nicht gefunden werden.** shows three distinct groups of companies in terms of their AI capabilities: beginner, follower, and leader. The majority of companies surveyed fall into the follower group, which is further divided into two sub-groups: those with developed AI infrastructure and those with stronger employee competencies in working with AI. This suggests that companies can take different paths towards becoming leader AI users, either through investing in their AI infrastructure or in their employee competencies.

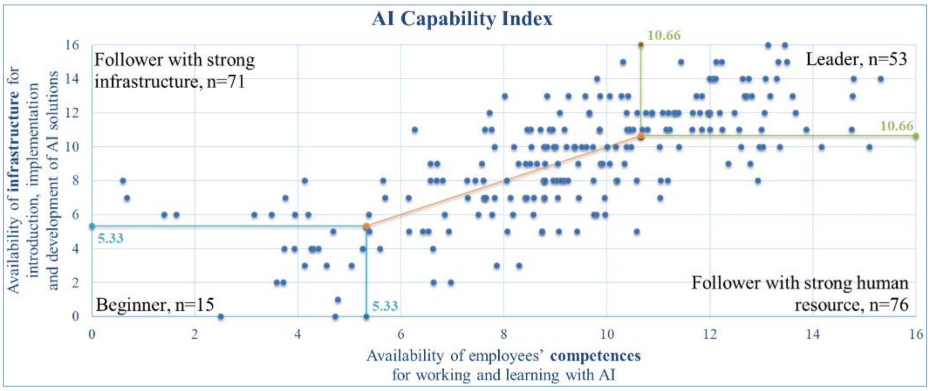

Fig. 3. AI capability index - general statistics

Based on the available data, it seems that the development of both AI infrastructure and employee competencies are equally crucial for attaining higher levels of AI capability. This is evident from the noticeable concentration of companies along the diagonal line. Hence, these findings imply that companies must allocate their resources towards both areas, ideally in tandem, to effectively adopt AI technologies. This outcome highlights the importance of considering both tangible and intangible resources, as well as human resources, when implementing AI solutions in organizations.

We conducted a detailed analysis of the distribution of companies based on their AI capabilities across three different sectors: manufacturing and construction, services and IT, and other industries relevant to the manufacturing value chain (see Fig. 4, left). We classified the companies into three categories, namely beginners, followers, and leaders, based on their AI capabilities, using the same categories as mentioned above. Our findings indicate that the manufacturing and construction industry has the highest proportion of companies with low AI capabilities among beginners, while the services and IT industry has the largest share of leader companies with strong AI capabilities. Within the group of follower companies, more manufacturing companies prefer investing in AI infrastructure compared to investing in building strong human resources for adoption of AI. In other words, these manufacturing companies are more likely to have allocated resources towards acquiring and implementing AI technology rather than investing in developing the skills and knowledge of their human workforce in relation to AI. Finally, among leader companies, the dominant group is the service and IT providers, representing 58% of the total. This suggests that the service and IT industry is leading the charge in terms of AI adoption and innovation, while manufacturing companies are still in the early stages of embracing AI technology.

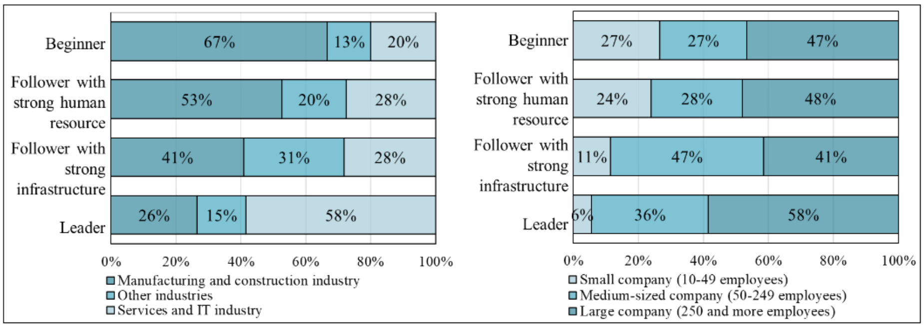

Fig. 4. AI capability index - overview of industries (left) and company sizes (right)

After examining AI applications that are specific to certain sectors, we proceeded to investigate AI capabilities categorizing the companies based on their size (see **Fig. 4**, right). As expected, larger companies have higher AI capabilities compared to smaller companies. Among leaders, 58% of large companies have AI capabilities compared to 6% of small companies. However, our data reveals a surprising result that a substantial proportion of large companies belong to the group of beginners. This underscores the need for increased investment in both AI infrastructure and competencies, irrespective of company size. Upon analyzing the group of followers, our statistics demonstrate that small and medium-sized companies invest significantly more in AI infrastructure than in the skills and knowledge of their employees, while this gap is less pronounced among large companies in the followers group.

After analyzing sector- and size-specific AI applications, our research delved into specific purposes of AI use, categorized by the level of AI capabilities (see **Fig. 5**, left).

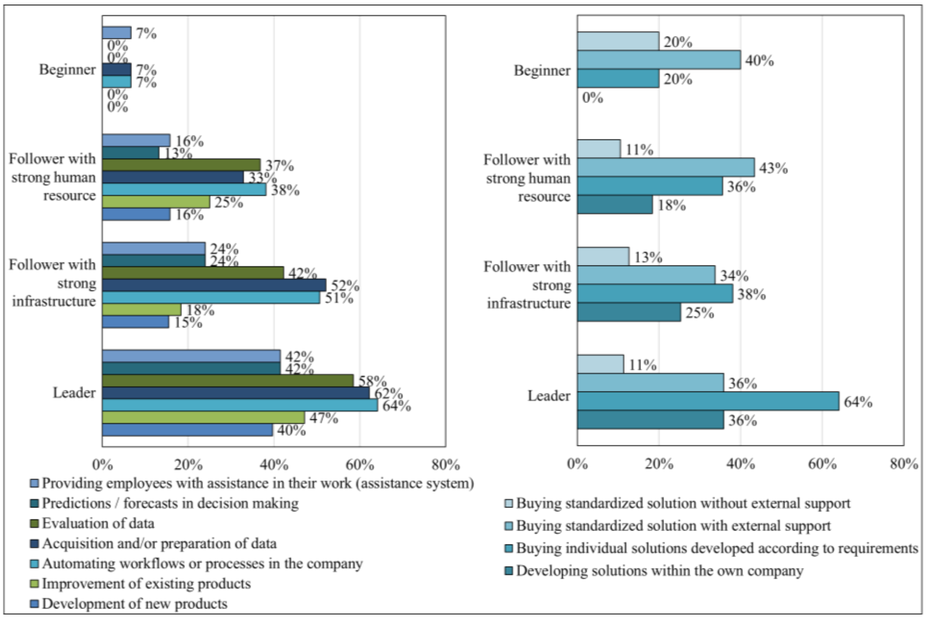

Fig. 5. AI capability index - overview of fields of implementation (left) and whether companies are developing or buying AI solutions (right)

For this analysis we used the same classification of three groups of companies: beginners, followers, and leaders. Generally, our data reveals that companies with varying levels of AI capabilities have distinct motives for adopting AI technologies. Novices have just begun utilizing AI in select areas, such as providing employee support, data evaluation, or workflow automation. Companies following with stronger human resources are likely still developing their AI infrastructure, resulting in lower percentages across all categories compared to those with robust infrastructure and leading companies. As expected, the leading companies exhibit the highest percentages of AI usage across all purposes, indicating their advanced and comprehensive AI capabilities. Notably, they demonstrate a significant increase in the usage of AI for product innovation activities, particularly in developing new products, compared to other groups.

Finally, we analysed how companies approach the development of AI solutions, i.e. whether they purchase AI solutions technology companies on the market or develop those themselves (see **Fig. 5**, right).

The result indicates that a majority of the surveyed companies prefer to buy AI solutions instead of developing them in-house. Only a minority of companies reported developing their solutions by themselves, with the leader category having the highest percentage at 36%; this was also expected due to their high level of infrastructure and competences for developing AI solutions. In contrast, none of the beginner companies reported developing their solutions in-house. The most common approach among the analysed companies is to buy individual solutions that are developed according to their specific requirements. Furthermore, the result shows that a significant number of companies buy standardized solutions with external support. The highest percentage of companies that buy standardized solutions with external support is found in the follower with strong human resource category at 43%, followed by the beginner category at 40%. Lastly, the result reveals that the percentage of companies that buy standardized solution without external support is the lowest across all categories of companies. Among those, the beginner category has the highest percentage at 20%.

5 Concluding Remarks

In this paper, we aim at exploring various combinations of AI-specific resources to gain a deeper understanding of the heterogeneous patterns of companies regarding their AI capabilities. Therefore, we build on previous research on AI-specific tangible, intangible, and human resources [21, 26, 3, 7] and develop an analytical framework, as shown in **Fig. 1**, for analyzing the AI capabilities of companies. Our framework comprises two key dimensions: AI infrastructure and AI competencies. We employ two scores to quantify these dimensions: the AI Competence Score, which measures the availability of AI-related competencies (human AI-specific resources), and the AI Implementation Score, which assesses the availability of AI infrastructure (tangible and intangible AI-specific resources). We apply our approach to a comprehensive dataset of 215 companies that we gathered from investigating the adoption of AI for work and learning in organizations. Based on their AI capabilities, we categorize the companies into four distinct groups: beginners, followers with strong AI-infrastructure, followers with strong AI-specific human resource, and leaders. We further analyze the AI capabilities of these groups with respect to their sectoral affiliation, size classes, field of usage of AI, and their make or buy decisions regarding the uptake of AI solutions. This analysis provides us with additional insights into these groups, ultimately advancing our understanding of the heterogeneous patterns of companies in terms of their AI capabilities.

Overall, our analysis suggests that the manufacturing and construction industry had the highest proportion of beginner companies with low AI capabilities, while the services and IT industry had the largest share of leader companies with strong AI capabilities. Within the follower category, manufacturing companies tended to invest more in AI infrastructure than in developing human resources for AI adoption. The dominant group among leader companies were service and IT providers, suggesting that this sector leads in AI adoption and innovation while manufacturing companies are still in the early stages of embracing AI technology. Further, our findings indicate that larger companies tend to have higher AI capabilities compared to smaller companies. This is consistent with the expectation that larger companies have more resources to invest in AI infrastructure and competencies. However, the data also reveals that a significant proportion of large companies are still in the early stages of AI adoption, highlighting the need for increased investment in AI infrastructure and competencies across companies of all sizes. We also found that small and medium-sized companies invest more in AI infrastructure than in the skills and knowledge of their employees, while this gap is less pronounced among large companies in the followers group. This suggests that small and medium-sized companies may need to prioritize investing in their employees' skills and knowledge to fully realize the benefits of AI technology.

We also show that companies with different levels of AI capabilities have distinct motives for adopting AI technologies, and the leading companies are more likely to use AI for product innovation purposes. This suggests that the adoption of AI technologies is positively associated with product innovation and thus with competitiveness [21]. Finally, we found that companies are more likely to buy AI solutions rather than develop them in-house, and that buying custom or off-the-shelf solutions with external support is a common approach. This could indicate a lack of in-house AI expertise or resources among companies. It could also highlight the complexity of emerging AI applications and the difficulty of providing people with such specialized skills.

We contribute to theory by developing an analytical framework that combines tangible, intangible, and human resources to analyze the AI capabilities of companies [21, 26, 3, 7]. This framework provides a comprehensive understanding of the heterogeneous patterns of companies in terms of their AI capabilities, including the factors that influence their adoption and use of AI technologies. In terms of resource-based view, we emphasize the importance of a company's resource base as a bundle of tangible, intangible and human resources in shaping its AI capabilities [21, 14, 26, 8, 39, 24, 17]. In doing so, we show the relevance and adaptation of the RBV in the context of today's business environment that requires organizations to invest in digital technologies such as AI. By analyzing a comprehensive dataset of 215 companies, our study highlights the differences in AI capabilities among companies of different sizes, sectors, and field of usage of AI. For instance, we show the relevance of AI capabilities for product innovation and thus competitiveness. This finding indicates that the RBV in its adapted form can explain competitive variations among companies that leverage digital technologies to gain an edge. In turn, the findings also challenge our understanding concerning the key drivers of competitive success, which over the last years are becoming increasingly embedded with digital technologies and particularly AI. Moreover, we provide insights into the relevance of different levels of AI capabilities for companies' make or buy decisions regarding the uptake of AI solutions. Overall, our framework can thus be practically used to assess a company's strategic fit with AI and help firms identify opportunities for competitive advantage based on their resource combinations.

To expand upon the findings and increase the scope of inquiry, we suggest following directions for further research. Firstly, longitudinal studies could be conducted to examine the changes in AI capabilities over time and establish causal relationships between single types of resources and overall AI capabilities. Secondly, further studies could use objective measures of AI capabilities, such as data from AI applications or patent filings. This would provide a more accurate and detailed assessment of AI capabilities and enable researchers to identify trends and patterns in AI development. Thirdly, future research could examine additional factors of AI capabilities, like ethical and social implications of AI adoption. Finally, it would be beneficial to expand the scope of the study with more comprehensive, multivariate research into how different AI capabilities affect various aspects of a company's performance, such as productivity, profitability, and innovation.

References

1. Davenport TH, Ronanki R (2018) Artificial intelligence for the real world. Harvard business review 96:108–116
2. McKinsey (2022) The state of AI in 2022—and a half decade in review. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review
3. Fountaine T, McCarthy B, Saleh T (2019) Building the AI-powered organization. Harvard business review 97:62–73
4. Ransbotham S, Khodabandeh S, Fehling R et al. (2019) Winning with AI. MIT Sloan management review
5. Brynjolfsson E, Rock D, Syverson C (2018) Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In: The economics of artificial intelligence: An agenda. University of Chicago Press, pp 23–57
6. Ambati LS, Narukonda K, Bojja GR et al. (2020) Factors influencing the adoption of artificial intelligence in organizations–From an employee's perspective
7. Chui M, Malhotra S (2018) AI adoption advances, but foundational barriers remain. Mckinsey and company
8. Barney JB (1991) Firm resources and sustained competitive advantage. [s.n.], [S.l.]
9. Barney JB (2001) Is the resource-based "view" a useful perspective for strategic management research? Yes. Academy of management review 26:41–56
10. Grant RM (1991) The Resource-based theory of competitive advantage: Implications for strategy formulation. California Management Review reprint series. California Management Review, University of California, Berkeley, CA
11. Makadok R (2001) Toward a synthesis of the resource-based and dynamic-capability views of rent creation. Strategic management journal 22:387–401
12. Helfat CE, Peteraf MA (2003) The Dynamic Resource-Based View: Capability Lifecycles. SSRN, S.l.
13. Conboy K, Mikalef P, Dennehy D et al. (2020) Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. European Journal of Operational Research 281:656–672
14. Mikalef P, Pappas IO, Krogstie J et al. (2018) Big data analytics capabilities: a systematic literature review and research agenda. Information Systems and e-Business Management 16:547–578
15. Mikalef P, Pateli A Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. Journal of business research
16. Wamba SF, Gunasekaran A, Akter S et al. (2017) Big data analytics and firm performance: Effects of dynamic capabilities. Journal of business research. https://doi.org/10.1016/j.jbusres.2016.08.009
17. Bharadwaj AS (2000) A resource-based perspective on information technology capability and firm performance: an empirical investigation. MIS quarterly:169–196
18. Schryen G (2013) Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. European journal of information systems
19. Melville N, Kraemer K, Gurbaxani V (2004) Review: Technology Information An Performance: Organizational Integrative Model of IT Business Value. MIS Q 28:283–322
20. Zhang MJ (2005) Information systems, strategic flexibility and firm performance: an empirical investigation. Journal of Engineering and Technology Management 22:163–184

21. Mikalef P, Gupta M (2021) Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management 58:103434
22. Amit R, Schoemaker PJH (1993) Strategic assets and organizational rent. Strategic management journal 14:33–46
23. Sirmon DG (2011) Resource Orchestration to Create Competitive Advantage: Breadth, Depth, and Life Cycle Effects. SAGE Publications, [ ]
24. Mata FJ, Fuerst WL, Barney JB (1995) Information technology and sustained competitive advantage: A resource-based analysis. MIS quarterly:487–505
25. Benitez J, Castillo A, Llorens J et al. (2018) IT-enabled knowledge ambidexterity and innovation performance in small US firms: The moderator role of social media capability. Information & Management 55:131–143
26. Sjödin D, Parida V, Palmié M et al. (2021) How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. Journal of business research 134:574–587
27. Najdawi A (ed) (2020) Assessing AI Readiness Across Organizations: The Case of UAE. IEEE
28. Heimberger H, Horvat D, Schultmann F (2022) Assessing AI-readiness in production – a conceptual approach: Conference Proceedings. 26th International Conference of Production Research (ICPR)
29. Jöhnk J, Weißert M, Wyrtki K (2021) Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. Bus Inf Syst Eng 63:5–20
30. Mikalef P, Fjortoft SO, Torvatn HY (2019) Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value. Conference Paper
31. Tornatzky LG, Fleischer M (1990) The processes of technological innovation. Issues in organization and management series. Lexington Books, Lexington, Mass.
32. Horvat D, Dreher C, Som O (2019) How firms absorb external knowledge—Modelling and managing the absorptive capacity process. Int J Innov Mgt 23:1950041
33. Kinkel S, Baumgartner M, Cherubini E (2021) Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. Technovation 110:102375
34. Sambamurthy V, Zmud RW (1994) IT management competency assessment: A tool for creating business value through IT (working paper). Financial Executives Research Foundation
35. Kogut B, Zander U (1992) Knowledge of the firm, combinative capabilities, and the replication of technology. Organization science 3:383–397
36. Dierickx I, Cool K (1989) Asset stock accumulation and sustainability of competitive advantage. Management science 35:1504–1511
37. Grant RM (1999) Prospering in dynamically competitive environment: organizational capability as knowledge and strategy resources for the knowledge-based economy woburn
38. Baumgartner M, Horvat D, Kinkel S (2023) Künstliche Intelligenz in der Arbeitswelt – Eine Analyse der Kompetenzbedarfe auf Unternehmensebene. In: Gesellschaft für Arbeitswissenschaft e.V. (ed) Nachhaltig Arbeiten und Lernen. GfA-Press, Sankt Augustin
39. Wang N, Liang H, Zhong W et al. (2012) Resource structuring or capability building? An empirical study of the business value of information technology. Journal of management information systems 29:325–367