The AI-based Transformation of Organizations: The 3D-Model for Guiding Enterprise-wide AI Change

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Abstract

Artificial Intelligence (AI) is increasingly gaining importance for organizations due to its immense potential for value creation and growth. However, companies struggle to tap this potential, as many AI projects fail in the early stages because of lacking guidance and best practices. To shed light on how AI adoption and transformation can be approached and what challenges organizations face, we analyzed eleven organizations of varying sizes and industries. Drawn on these insights, we identify four transformation types distinguished by different AI transformation stages and journeys. Furthermore, we develop a 3D-Model to guide enterprise-wide AI change and propose concrete recommendations for action on each dimension. Our findings help practitioners navigate, manage, and (re)evaluate their AI strategy for an enterprise-wide transformation.

Keywords: artificial intelligence, AI transformation, AI adoption, multi-case study, practice-based IS research

1. Introduction

AI is a significantly disruptive technology for organizations (Benbya et al., 2020). At this point, 37% of global companies have incorporated AI into their businesses and products (Jovanovic, 2022), marking AI as a fast-growing technology and a fixed point on many more organizations' future agendas (Sagodi et al., 2022).

AI heralds various potentials for organizations, including increased revenues, improved customer interactions, and boosted business efficiencies (Alsheibani et al., 2020). Due to the varied application possibilities, AI is increasingly incorporated as a crucial strategic, innovative, and therefore, IT transformational element in organizations to achieve a competitive advantage (Alsheibani et al., 2019b).

Despite its potential, AI's management and strategic involvement are seen as a challenge in the recent academic discourse for practitioners (Fukas et al., 2021). Organizations have no strategic overview of where to start an AI-based transformation (Fukas et al., 2021). Consequently, AI adoption for many is still in its infancy, and organizations struggle to incorporate AI into their product and IT (service) landscape (Laut et al., 2021; Pandl et al., 2021). Currently, only 5 % have comprehensively integrated AI (Pumplun et al., 2019), while a recent survey outlines that 65% of executives perceived no immediate improved value relating to their AI endeavors (Pandl et al., 2021). In this vein, AI in organizations is frequently closely connected with disappointed and exaggerated expectations, as AI projects presently are highly explorative and remain experimental, often even already failing as pre-production proof-of-concepts (Benbya et al., 2020).

Organizations are increasingly aware that AI management is different from traditional enterprise IT endeavors, as novel approaches are needed to sustain AI-based technologies (Berente et al., 2021). This is because AI comprises a complex bundle of technologies and applications, necessitating a new holistic understanding by managers of how to communicate, lead, coordinate, and control them (Berente et al., 2021). Additionally, it is also due to the different technological properties AI possess in comparison to conventional information systems (IS), such as, for example, being learning systems with black box characteristics and context-sensitivity (Sagodi et al., 2022). As a consequence of these challenges, organizations need to build capabilities for mastering new AI management activities, such as establishing data security and management, AI governance, AI strategic alignment, regulatory approvals for AI-based decisions, and ethical scrutiny of learning systems (Jöhnk et al., 2021; Kruse et al., 2019; Pumplun et al., 2019).

Generally, current research has predominantly focused on AI systems' general design and applications or underlying technological advancements (Nguyen et al., 2022; Pumplun et al.,

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2019). Research from the AI management perspective has been focused on initial AI maturity models as well as structural and psychological prerequisites (Eitle et al., 2022). Further, on the AI management side, organizational readiness and adoption factors have also been studied (e.g., Pumplun et al., 2019).

However, helping organizations systematically develop AI capabilities is still a scarce field of knowledge in research and practice. This is unsatisfactory, given that various organizations face the challenge of establishing enterprise-wide AI programs and initiatives (Eitle et al., 2022). First authors already highlight the importance of thinking broadly when laying the foundation for AI transformation (e.g., Fridgen et al., 2022). Hence, we answer the following research question (RQ):

RQ: What are the key activities for driving enterprise-wide AI change and capabilities?

To answer this RQ, we conducted a multi-case in-depth study. We collected data from eleven organizations implementing AI, ranging from manufacturers to service providers. We draw on our insights to illustrate organizations' different levels and approaches regarding enterprise-wide AI adoption and transformation. Our article showcases three AI transformation dimensions organizations can pursue, containing a broad overview of possible strategic directions and corresponding recommendations to guide AI transformation effectively.

2. Conceptual Background

AI has recently gained much attention in organizations by comprising a set of technologies able to sense, reason, and facilitate conceptual learning and decision-making (Bock et al., 2020). Due to AI's variety of technologies and skills—resulting in several application cases that have changed over time—there exists neither in practice nor science a consensus on the exact meaning of the "umbrella term" AI (Alsheibani et al., 2019b; Nguyen et al., 2022).

Generally, researchers define AI as a generic concept for technologies capable of mimicking human behavior and learning how to solve tasks usually performed by human intelligence (Castillo et al., 2020). In this sense, AI differs from conventional IS by being able to learn and make decisions generally based on input data rather than predefined or deterministic rules (Crowston & Bolici, 2019). While early AI attempts were restricted by limited computing power and data, contemporary AI exemplifies greater autonomy and more profound learning capacity, as it can use cognitive or conversational functions and interact with an immense amount of data (Baird & Maruping, 2021; Berente et al., 2021). As a result, AI technologies possess tremendous potential for organizations and offer a transformative role in various sectors and industries, for instance, by reinventing business models, augmenting or automating work, and providing performance improvements for organizations in general (Collins et al., 2021). AI has applications in manifold application domains, such as chatbots utilizing natural language processing, facial recognition employing image processing, and recommender systems fueled by machine learning (ML) algorithms.

However, despite the general potential of AI and the steep increase of AI applications in organizations, it becomes clear that managing AI *"is unlike information technology (IT) management in the past"* (Berente et al., 2021, p. 2). AI will not simply fit into previous concepts of managing traditional IT technologies. This leads to a situation in which organizations or respectively organizational decision-makers need to adapt their behavior, reinterpret their approach, and understand relevant nuances of AI capabilities and their continuous strategic management (Fridgen et al., 2022). In addition to already investigated fundamental readiness and adoption factors to ensure a secure foundation of AI technologies (cf., Jöhnk et al., 2021; Pumplun et al., 2019), practitioners need a holistic view of AI application as an organizational transformation involving multiple new activities and engagements, that need to be controlled and directed. In this context, research on AI management and transformational change is scarce. The business- and strategy-oriented understanding of the management and long-term value-adding implementation of AI for enterprise-wide change is still new to researchers and organizations even though it is a vital capability in the future (Fukas et al., 2021; Sagodi et al., 2022). Many organizations appear to be at the stage where they are attempting to create a business case for AI. It is stated that many present-day AI initiatives and strategies fail, leading to a more pessimistic outlook (Alsheibani et al., 2019a; Sagodi et al., 2022). To combat this sentiment and help organizations further develop their initiatives, our research gives guidance on how to implement AI as an organization-wide change to help generate its proposed value and sustain AI efforts.

3. Research Design

Our research goal is to understand how different companies with diverse transformation levels approach AI implementation and to examine current best practices and challenges. To obtain a broad picture, we conducted a multi-case study including eleven cases ranging from e-commerce and manufacturing organizations to insurance providers and media companies (Yin, 2003). We purposefully investigated organizations of varying sizes to encompass various AI transformation stages and approaches. Moreover, we selected over 30 study participants, including IT executives, senior managers, chief data scientists, and other IT experts, as well as Chief Information Officers (CIO) and Chief Digital Officers (CDO) (see Appendix for more details).

Our study data was collected in a two-step procedure: First, we conducted six focus group sessions, which ranged from 1h to 1h 15min, with IT executives and experts of four different organizations using video conferencing tools. During these sessions that took place between January and August 2021, organizations in turn presented their AI strategy and their challenges in adopting AI. Afterward, the sessions concluded with open discussions among all company representatives and researchers. Based on these discussions and the material presented, we derived common fields of AI activity, as depicted in Table 1. These fields were iteratively validated in the upcoming focus group sessions to make additions and discuss critique. Second, we conducted seven semi-structured interviews, each with organizations not represented in the focus groups. The semi-structured interviews allowed for adaptability while enabling us to structurally incorporate insights from the focus groups (Myers & Newman, 2007). The interviews took place in August 2021 and lasted a little over 50 minutes on average. Drawing on the observations from the focus groups, we made certain to generally cover the derived fields of activity, enabling us to better compare and categorize the studied cases afterward.

Table 1. Focus group result – Fields of AI activity

1	Strategy & Governance
2	Development Lifecycle
3	Data Management
4	Tools & Platforms
5	Process & Work Design
6	Service Design
7	Capability Building
8	Ecosystem Integration

Two researchers coded the recorded and transcribed interviews along with protocols of the focus group sessions and additional company materials (e.g., slides, internal documents) separately in MAXQDA. We used open, axial, and selective coding to examine interesting aspects, find relationships between these aspects and finally identify aspects explicitly relating to AI strategy and journey (Corbin & Strauss, 1990). During the entire coding process, we repeatedly discussed our codes and interpretations of the material to ensure our results' consistency and validity.

4. Types & Selected Example Cases

In our study, we identified four organization types distinguished by different AI transformation stages and journeys. Namely, *Explorers*, *Intermediates with a focus on process optimization, Intermediates with a focus on customer value creation,* and *Strategic Visionaries*. In the following, we describe what criteria characterize each type and then for each present an exemplary case, highlighting the type's AI approach as well as their findings, realizations, and learnings.

4.1. Explorers

Explorers are companies that are interested in AI but possess little to no experience in dealing with it. They are curious to discover how AI can be employed as a beneficial technology in their organization to create value for internal or external applications. We characterize them as *Explorers* as they are still in the beginning stages, figuring out precisely what AI entails and exploring which use cases might be suitable to gain first practical insights and experiences. Our study shows that *Explorers* score relatively low in terms of overall digital maturity and that they are usually active in traditional industries that are not well known for their digital affinity. Besides finding new use cases, *Explorers'* main challenges are building up the fundamental expertise to get started and sustain their AI efforts, as well as establishing a profound data infrastructure fueling these efforts.

Case Example Explorer

An *Explorer* case example anonymously referred to as BROKER (Case ID 11), is a business insurance broker and employer to over 1,000 people. It provides services on businesses' insurance needs and risk management.

In the insurance industry, there is a plethora of documents like policies, contracts, and reports that need constant analysis and evaluation. For instance, benchmarking insurance offers is a manual and document-intensive task which needs a lot of time and expert knowledge. To improve and automate this process, BROKER's pilot AI project set the goal to automatically turn document content into structured data to subsequently automatically benchmark different insurance offers. BROKER teamed up with an external technology partner who contributed AI skills which BROKER was lacking at the time.

Due to the novel nature of the project as well as the non-deterministic nature of AI, BROKER quickly realized that the prospect of success was not entirely clear. Time, people, and resources would need to be invested even if the company did not know "*if it is generally even possible to solve the assignment with* *the available technology,"* as BROKER's Digital Transformation Manager put it. As a result, the company consciously set its project objective beyond solely implementing an AI-based system. BROKER's CDO described their approach as follows: *"A goal is to especially stake out the technology's general performance and test the collaboration with such a partner. Which in a classic project you would not like to see as an objective."*

By outsourcing AI development, BROKER was able to quickly get started on the AI project. This is in line with BROKER's general bottom-up AI approach, where AI skills are not built in-house but outsourced to external IT providers or, if necessary, incorporated by hiring employees when capability gaps appear.

An early realization BROKER had, is the changed role the domain experts of the functional teams play in the ideation, development, and operation of AI. Specifically, their indispensable part in validating the system's accuracy which necessitates a deeper understanding of the technology used in the project. As the CDO explained: *„In the course of the project, we demand the department in a different way. We concern them a lot with what the technology is doing just at [that moment]."*

Questioned on data management regarding data responsibility, infrastructure, and strategy BROKER's CDO stated: *"We are now at the point where we're asking [ourselves]: What do we have to establish? What do we actually need?"* Facing this challenge by fully assessing all requirements and freeing up resources is an ongoing field of activity for BROKER.

4.2. Intermediates

Intermediates are companies that are beyond the stage of developing proof-of-concepts. They have successfully implemented at least one complete AI system that is up and running. Additionally, they have at least one core AI or data science team, where the company's current collective AI expertise is concentrated. The core AI team is commonly responsible for selecting use cases and managing the project's ideation and incubation phase. Further, the development of AI systems or the management of third-party solutions usually also falls within the responsibility of the organization's core AI team. Generally, *Intermediates* have a data infrastructure that facilitates the development of AI projects, though for some setting up a fully satisfactory data infrastructure is an ongoing process.

On their way to further build expertise and develop new solutions, we found two types of *Intermediates:* (1) Those who focus on using AI to improve the efficiency of internal processes, and (2) those with focus on directly impacting the customer's experience. Though for some *Intermediates* there might be some overlap, we found that most chose either one or the other approach in their AI journey.

4.2.1. Intermediates with a focus on internal process optimization

Many reasons exist for *Intermediates* to focus on internal process optimization. Firms with internal processes characterized by being resource and time-intensive or companies with minimal customer interaction (e.g., manufacturing industry) are more likely to fall in this category. Moreover, we found that organizations, being heavily regulated regarding data use or those working with sensitive data, usually also focus on internal process optimization. This might be due to legal or ethical difficulties connected to using AI for customer-facing applications.

Case Example Intermediate with a focus on internal process optimization

One *Intermediate* case *focused on internal processes* is a statuary health insurance provider in Germany, anonymously referred to as INSURER (Case ID 05). The organization insures several million people and is an employer to over 10,000 employees.

INSURER has successfully developed multiple AI applications, which tremendously improved work and business processes. Notable cases are an inbox classification application, which assigns mails to the responsible employees, a hospital invoice auditing application, and an image processing application for recognizing different stamps on documents.

All of INSURER's AI projects are built and developed in-house. This conscious decision was motivated by the wish to not have its AI ambitions be directed by and dependent on external actors. To realize this, significant effort was put into building a core AI team, even before the first use cases were developed. The core AI team was set up to function as an incubator and a pipeline for AI ideas and AI development. INSURER's head of IT innovations described the function of this team as follows: *"[it's] a group of people that always appears, when an idea or the request for some brainstorming comes up in a business division [...] This squad then starts to think, to analyze [...] and to make a model. But most importantly also starts to implement."*

To cover this wide array of tasks, INSURER turned away from establishing a strict role differentiation often found in AI teams (e.g., data scientists, analysts, or ML engineers). On the contrary, INSURER decided to encourage and even expect AI team members to broaden their skill set while keeping their specialization, allowing for a more flexible use during ideation and development.

One AI-specific challenge is the management of the AI lifecycle. Time and resources need to be invested even after deployment and system rollout. Unlike conventional systems, the monitoring of an AI-based system's performance during operation is of importance, whereby domain experts play a crucial role. As the head of IT innovations described: *„There is a huge difference, because suddenly it's no longer IT monitoring something, but it's the domain experts that have to monitor it."* So even after closely collaborating during the development, domain experts were especially required. This led INSURER to realize that AI expertise and understanding needed to be built outside the developer teams as well. Conveniently, this realization coincided with the business divisions' desire to better *"understand what AI entails and ask the right questions"* as INSURER's AI architect put it.

While for some companies setting up a monitoring framework for AI applications on internal processes might be uncharted territory, for INSURER this was nothing new. Due to the high regulatory requirements for health insurers set out by the German Social Security Code, INSURER already had many monitoring tools in place which surveil their processes and determine quality criteria for these processes. Adding AI into the mix therefore did not significantly raise complexity because as INSURER's AI architect remarked: "*[the domain experts] already monitor [their] processes anyways and AI is an automation component in this process"*. Further, due to the slow-changing nature of the health insurance field INSURER's AI-based applications were less prone to be confronted with abruptly changing environments or input variables, which is a typical challenge such systems might face in other industries. However, when attempting to design services that are customer facing this regulatory-driven advantage turned into a disadvantage. The strict guidelines on the utilization and possible user applications set by the Social Security Code consequently explain why INSURER focused on leveraging AI for internal process optimization rather than customer value creation.

Data management is a field of activity that gained new priority when INSURER further pushed its AI endeavors. As INSURER's AI architect recounted: *"that's when we teased the topic for the first time: […] we need a data lake, because without fast data delivery and regulated but good data access, we won't pick up speed."* Aside from further improvements to its data infrastructure INSURER was faced with numerous new and old questions regarding data management. Like questions on how to manage the data preparation process or on what constitutes good data quality from the perspective of AI. All this goes to show that the topic of data management is a core field of activity which needs continuous attention even after a solid foundation for working with AI is set.

4.2.2. Intermediates with a focus on customer value creation

Intermediates with a focus on customer value creation aim at using AI to enrichen offered products or create new customer-facing services. Thus, use cases are focused on the customer experience and how AI can be a facilitator for improving it.

Case Example Intermediate with a focus on customer value creation

A media group and newspaper publishing house from our case study, anonymously referred to as PUBLISHER (Case ID 08), employs almost 5,000 employees and is in business for more than 5 decades. Because of technological advancements and changes in how information and media are presented and consumed today, PUBLISHER's industry is rapidly changing and experiencing disruption. Following and leveraging this trend is a big challenge PUBLISHER is facing. Consequently, AI-supported efforts are majorly focused on its online publishing platforms and thus content customers read and interact with online.

PUBLISHER has no overarching AI strategy. It follows a rather practical approach to AI. As PUBLISHER's executive board member and head of digital research and development (R&D) explained: *„It's always concrete questions where - independently of a larger strategic context - attempts are being made at developing the best solution for a concrete problem."* Many questions PUBLISHER faced were not necessarily unique, which is why most AI-based applications were bought from outside software providers. Third-party solutions that are successfully in use are text-to-speech and hate speech detection applications. The latter for example monitors PUBLISHER's forums and immediately blocks posts containing hate speech, which in turn removed the need for constant supervision by an employee. These AI applications came pretrained and merely needed to be fed with a minimal amount of PUBLISHER's own data to be fully operational. This way, PUBLISHER only had to invest resources in intermittently checking and retraining the software's algorithm.

Other AI-specific considerations and questions PUBLISHER had in conversations with third-party providers where concerning the database used to train these models. GDPR requirements and potential future regulations could mean that the employment of these applications might not be possible in the future. With third-party cookies for example INSURER had a lot of concerns regarding future-proofing. The potential risk was highlighted by INSURER's head of R&D as follows: *"we all assume that third-party cookies will disappear from the market within the next two to three years. [...] And then of course I ask: 'Do you use third-party cookies as your database? And if so, what will you do?' […] 'How is the data collected?', 'Will there be technological or legal changes that will make the use of this data basis impossible in the future?'"*

Despite the large amount of knowledge on and positive experiences with out-of-the-box AI solutions, PUBLISHER decided to additionally put efforts into building and encouraging their own expertise in developing AI. When considering what project to choose PUBLISHER factored in two main considerations. First, whether the respective field was part of the core business and second, how company-specific the context and especially the data of the problem was. According to the head of digital R&D the subject of churn prediction fit these criteria: *"This is know-how that we would like to have in the company because everything that has to do with […] generating subscriptions and avoiding subscription cancellation is a core business of ours. So that's one of those disciplines that we must master and […] it is all the better, the better we master it also technologically."* Hence, PUBLISHER initiated a churn prediction project in collaboration with an external technology partner. The goal of the project was to develop an AI-based solution which predicts if a customer is likely to cancel their subscription and proposes what needs to be done to prevent this. The team consisted of three PUBLISHER employees and two external team members. This decision enabled the company to outsource some parts of the development while still doing most of the work in-house. The mix of building and outsourcing allowed PUBLISHER to quickly get started on the project yet ensured that AI know-how stayed in the company long term.

In terms of data and data management, a challenge PUBLISHER faced was how to work with multiple data sources. Thinking about this roadblock the head of R&D recounted: *„What we were not able to do in the past is to link data from different data sources because we knew it was going to [lead to] chaos."* To tackle this problem PUBLISHER introduced a new role namely a *„head of data"*. One main task of this role was to ensure data integrity which placed the foundation for PUBLISHER to achieve a more coherent and workable database and infrastructure.

4.3. Strategic Visionaries

In contrast to *Explorers* and *Intermediates, Strategic Visionaries* have numerous running AI-based applications. Questions surrounding data management, tool use, or basic AI functionality are not at the forefront as these are areas *Strategic Visionaries* have already built a high level of expertise. *Strategic Visionaries* go further than the other transformation types, they see AI as a key enabler and a competitive advantage. As a result, they explicitly define AI as a part of the company's business strategy. Extracting best practices, developing guidelines, setting up a comprehensive governance, and pipelining AI incubation are all fields *Strategic Visioners* are highly invested in. These investments in turn facilitate the scaling of AI solutions and thus make large-scale implementation of AI possible.

Case Example Strategic Visionary

A *Strategic Visionary* case example company, anonymously referred to as RETAIL (Case ID 01), employs well over 20,000 employees. The company has been in business for decades and is presently very active in the field of e-commerce.

RETAIL's AI vision is to be a leading AI company by 2030, and it has the best conditions to do so. Presently, a total of 40 ML-based products and services are part of its portfolio. Application scenarios range from general applications like e-mail classification and forecasting to e-commerce-specific ones, like dynamic pricing or image similarity-based outfit recommendations. In terms of AI expertise, RETAIL employs over 20 teams with roughly 100 developers that work on implementing ML as part of their output. Concerning AI governance RETAIL concerned itself with defining development standards for example regarding system architecture and coding best practices or understanding regulatory requirements. RETAIL also gave special attention to the development of ethical guidelines, which entailed ensuring fit with its corporate values and considerations on public image and impact.

One main pillar of RETAIL's strategy is the expansion and reinforcement of AI knowledge and know-how. At RETAIL this was approached *"in depth, in the form of a high level of excellence among all data scientists and engineers [and] in breadth, in the form of a solid basic knowledge among all roles that are indirectly involved"* (RETAIL internal documents). In other words, all levels starting from (top) management down to employees that are not in direct contact with AI use cases are educated on AI.

Starting with process automation RETAIL established a framework for streamlining AI ideation and incubation. In RETAIL's approach AI incubation teams were set as the heart of the operation. Their task was to first discover, prototype, and validate ideas. After validating an idea, the incubation team would get together with the product team to plan, develop, and then implement and automate the application. This centralized approach helped RETAIL deploy automated processes more quickly and increase its general expertise on the incubation of AI innovations.

A major bottleneck RETAIL repeatedly encountered was its engineering capacities. In view of this bottleneck, RETAIL set the goal to build its own cloud-native AI platform. This meant that establishing development standards and best practices gained an even greater priority, as the answers to this would be the foundation of the platform.

In contrast to *Explorers* and *Intermediates* RETAIL as a *Strategic Visionary* utilized partnerships and collaborations not only to develop use cases but also to enable the general exchange on knowledge, processes, and technologies. Potential partners were not limited to IT service providers but included actors in other industries, in education, and in research.

5. Recommendations for Action

The cases in our study illustrate different AI transformation stages of organizations. Before setting up a comprehensive AI strategy it is advisable for companies to first assess which one of the four transformation types they are. Main factors in assessing this are AI expertise, the existence of AI enabling data infrastructure, the number of successful AI projects, and the scope of the organization's AI governance. Knowledge of the company's transformation type allows the company to determine its positioning among competitors, manage expectations and set appropriate goals when initiating AI projects. For example, BROKER as an *Explorer* had to realize that one main objective for them is to generally experiment with AI and test the collaboration relationship with their new external IT partner. In contrast, new projects for a *Strategic Visionary* would not be focused on experimenting but would be very result-oriented with a focus on finding and defining best practices like in RETAIL's case.

As a result, it is only after assessing the transformation type, that an organization is ready to set up a strategy for enterprise-wide AI change.

Based on our research and the companies' experiences, we present a 3D-Model for guiding AI transformation. As depicted in Figure 1 the three dimensions for strategic action are (1) *Core Capability Building*, (2) *Value Stream Embedding,* and (3) *Organizational Enabling*. These dimensions span the space of possible AI activities and configurations.

In the following section, we explain the dimensions and for each present recommendations for possible actions practitioners setting up an AI transformation strategy can take.

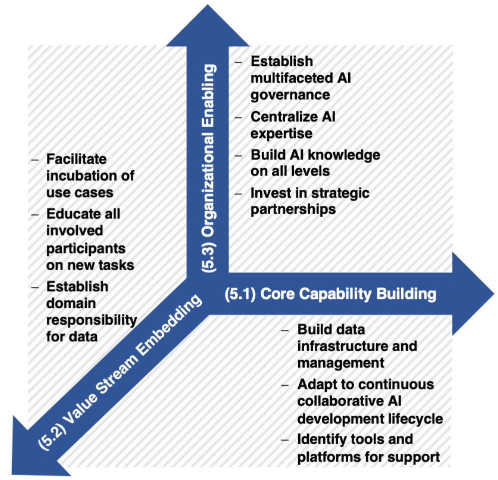

Figure 1. 3D-Model for guiding AI transformation

5.1. Recommendations on Core Capability Building

A company's AI core capability is comprised of activities and infrastructure an organization must have to successfully initiate, implement, and maintain AI activities and applications. As some level of capability is necessary to get started on an AI project *Explorers* must especially set this dimension as a top priority. Nevertheless, *Intermediates* and *Strategic Visionaries* must continually (re)evaluate their core capabilities to determine if existing and planned AI activities are still sufficiently supported. Consequently, companies must set aside long-term resources for managing and observing these new and changing requirements.

Build data infrastructure and establish data management. Concerning data management, AI introduces novel requirements. Structured and unstructured data must be centrally accessible and working with multiple actors requires regulated data access. Moreover, when consolidating multiple data sources, data quality and integrity become crucial to identify items across different data sources. To ensure this, companies should set up a data infrastructure, that facilitates regulated and fast provisioning of different kinds of data (e.g., data lake and data hubs). Additionally, if absent, organizations should introduce a new role, such as head of data or data officer whose main job is to manage the data infrastructure and keep track of ongoing and upcoming needs.

Adapt to AI's continuous and collaborative development lifecycle. The non-deterministic nature of many AI algorithms introduces a new volatile variable into the development and operation of AI-based systems. Unfavorable changes in continually learning AI applications or changes in the application's environment (e.g., shifting input data) require monitoring and regular maintenance. Companies must recognize this and set aside resources in terms of time and people during development and beyond.

Additionally, the development process calls for close interdisciplinary collaboration of product teams, AI developers, system engineers, and legal teams. To address this, organizations should establish fixed and flexible possibilities for exchange between those involved in the development lifecycle.

Identify tools and platforms that support and best fit AI ambitions and capabilities. In our research, we observed that most companies use cloud-based solutions to set up their infrastructure for AI development. This is advisable as it allows for more flexibility and supports the collaborative nature of AI development.

In terms of development tools, there is an abundance of tools to choose from when working with AI. For many case organizations, we noticed an uncontrolled development regarding AI tool use, as most developers are often free to select preferred tools. However, we suggest organizations, especially when moving from the *Explorer* to the *Intermediate* stage, to decide how much they want to control tools, and if tooling should be limited to a consolidated set. At the very least companies should ensure compatibility inside collaborating teams and with existing systems.

5.2. Recommendations on Value Stream Embedding

AI projects are initially highly experimental and often already fail as proof-of-concepts. A reason for this is that organizations focus on conceptual or technical aspects, leading to a disconnect from the concrete value stream or actual process environment. However, AI adoption and change require seamless integration of existing business processes, knowledge systems, user interfaces, and customer channels. Thus, value stream embedding is a key dimension as it describes the sum of all endeavors and measures taken to seamlessly optimize and automate specific services, internal processes, and workflows.

Actively facilitate incubation of use cases. During project incubation, different teams with diverse perspectives and responsibilities interact and communicate on specific needs relating to a (potential) AI solution. These exchanges not only act as a catalyst and accelerator for innovation but are also an enabler for value stream embedding and seamless integration – if all perspectives are considered. For this reason, companies should provide numerous touch points and opportunities for interdisciplinary and interdivisional collaboration and design during this process. Possible formats can be workshops or periodic brainstorming and discussions with product teams, AI and software developers, system engineers or other affected parties.

Regarding resource management, it is advantageous for companies to separate the incubation process from general operations. In doing so, firms ensure that investments and efforts into new use cases do not interfere with daily business operations.

Educate all involved participants on new tasks and responsibilities. Uncertainty on how AI changes the workflow of the involved employees can be a reason for poor integration. To combat this, we recommend that companies educate the teams on how the introduction of AI or the AI development process itself changes their duties. For instance, affected departments must be educated on their role as a critical asset for validating and monitoring their AI applications. Where possible, companies should routinize these new tasks, as introducing them as a part of a daily, weekly, or monthly routine appropriately consolidates them.

Establish domain responsibility for data. Identifying the correct and necessary data and in part obtaining it, is a task that falls within the responsibility of the domain experts as it necessitates a deep understanding of the domain-specific processes. Our research suggests that especially for data-intensive or data-driven departments this task is reoccurring throughout the project duration which necessitates particular attention and sufficient resources. For such cases, it is advisable to appoint a department member that is responsible for this task. This role defined as data steward by one of our study's cases does not need to be filled by someone who is overly technically versed, as this role should mainly concern itself with data content and contextualization of the data. Technical considerations and issues still mainly fall within the responsibility of AI developers and members of the data management team.

5.3. Recommendations on Organizational Enabling

Organizational enabling describes the strategic and enterprise-wide integration and establishment of AI. Primarily initiated by and in the responsibility of the company's (top) management, activities in this dimension are not focused on the individual AI solution or process but are concerned with strategically enabling the organization.

Establish multifaceted AI governance. Firms are confronted with a multitude of challenges that arise when they leave the explorative stage to move on to implement truly embedded AI systems and scale their development. Establishing best practices for AI development as part of a company's technical governance is just one area of governance with which a company must concern itself. Other types of governance owing to the AI transformation are regulatory governance, dealing with legal requirements, organizational governance, entailing the business' structure, and ethical governance, which reflects company-specific ethical guidelines.

Centralize AI expertise & knowledge in the AI core team. On the one hand, we observed that organizations often have a hard time finding AI experts but on the other hand we also found that they struggle to leverage existing AI expertise. Considering these difficulties, we suggest companies concentrate their AI expertise on one AI core team. This core team works as a foundation for mutual education and knowledge transfer. Additionally, the team is valuable for managing AI efforts and can function as a point of contact for company-wide AI-related ideas and propositions. Thus, this centralizing knowledge approach helps streamline AI efforts, even for smaller companies. Larger companies with many AI experts can either continue with this centralized approach by allowing for multiple AI core teams with different specializations or can alternatively experiment with decentralized approaches where AI experts might be embedded into functional teams.

Build AI skills and knowledge on all employee levels. Knowledge in general and employee capability specifically are concerns for all transformation types. While some companies primarily focus on certain employees or specific teams, teaching AI to enable the entire organization must address all company levels. Consequently, we suggest that companies go beyond directly involved product and developer teams. Software developers, system engineers, and other actors directly involved in developing or using AI applications should at least have a basic understanding of AI methods and standards. Further, the (top) management must be educated on AI potential and needs, to ensure sufficient resources are allocated for developing and maintaining AI-based systems. We advise businesses to offer seminars and information workshops open to the general staff. Programs like this demystify AI, reduce hesitations, foster an open-minded innovation culture, and promote interdisciplinary interactions, which constitutes an ideal foundation for launching new AI projects.

Invest in strategic partnerships. AI change does not need to be an isolated process. Collaborating, outsourcing, and communicating with other players enable significant and competitive advantages. We suggest collaborating with external IT providers for companies that have little expertise but want to quickly get started on their AI transformation. This way, the entire development, or at least those parts the company has not mastered yet, can be outsourced.

Beyond outsourcing and collaborating on projects, we recommend organizations that want to advance their AI endeavors to look for fresh impulses. Having an exchange on AI activities with industry peers can be an impulse. Additionally, connecting with businesses from other industries or startups as well as players in education, and research can also be beneficial for companies to gain new insights and keep pace with the continuously changing AI landscape.

6. Concluding Remarks

Owing to rapid advancements in AI, organizations today are presented with a myriad of exciting AI technologies and application scenarios. Thus, many companies are actively investing in utilizing and developing AI. Reducing cost, increasing productivity, and creating new services are just a few potential avenues (Alsheibani et al., 2020). However, despite great interest and initiated efforts, many companies fail at adopting and thus levering AI for their organizations (Jöhnk et al., 2021; Pumplun et al., 2019). In this vein, we conducted a multi-case study to gain insights from eleven organizations with differing AI profiles. Based on our research, we highlight four AI transformation types reflecting different transformation stages and journeys. Further, we develop a 3D-Model for AI transformation and present concrete recommendations for action on each dimension. Our insights on transformation types and dimensions for action equip practitioners with the necessary knowledge to assess their current practices and develop a roadmap for future AI endeavors. Hereby, becoming AI-savvy organizations that can unlock AI potential and retain an AI-enabled competitive position long term.

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Appendix – Table Research Method

ID	Industry	Employees	Position of Participants		Duration
01	Retail	> 20,000	CIO, Vice President Business intelligence, Head of Data Science, Head of System Services, Corporate Responsibility Lead, Head of IT and Process Management, Technical IT Consultant	FOCUS GROUPS	Σ= ~6h
02	Consumer Goods	> 20,000	Director Data & Analytics, Head of Data Science Hub		
03	Health insurance	5,000-10,000	CDO, Head of AI, Product Owner		
04	Public sector	1,000-5,000	AI Consultant, Head of Data Science & AI, Board Member (Digital Transformation)		
05	Health insurance	10,000-20,000	Head of IT-Innovations, AI Architect, Scrum Master, IT Division Head	INTERVIEWS	45 min
06	Medical Technology	5,000-10,000	CIO, IT Demand Manager		30 min
07	Financial services & insurance	5,000-10,000	Head of Data & Data Analytics, Product Owner Data Analytics Platform		1h 5 min
08	Publishing/ media	3,000	Head of digital research & development		50 min
09	Public sector	> 20,000	CDO, Advisor Digital Strategies		1h 10 min
10	Publishing/ media	1,000-5,000	Head of Data, Head of Data Intelligence		50 min
11	Insurance brokerage	1,000-5,000	CDO, Consultant Digital Corporate Development, Digital Transformation Manager		50 min