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Competitive advantages through generative AI: expertise as the key to implementation

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Competitive advantages through generative AI: expertise as the key to implementation

Abstract

The Problem
In order to understand generative AI and its mechanisms of action, players need a high level of abstraction (Saitta and Zucker, 2013). However, many companies lack the necessary expertise for the technology. In addition to cultural factors, this lack of expertise is the main barrier to a results-oriented implementation of the technology (Campos Zabala, 2023).

The Solution
To identify valuable fields of application, companies need to understand the expertise in the decision-making processes of their own activities. The article shows concrete examples and steps that companies can use to test and apply new technological possibilities to their own use cases.

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1 Introduction

Many companies are discussing the potential applications of generative artificial intelligence (AI). However, in order to understand generative AI and its mechanisms of action, the actors involved need to have the appropriate technological expertise. However, many companies of all sizes lack precisely this (Campos Zabala, 2023). This article provides an overview of selected technological possibilities of generative AI, which help companies to carry out value creation activities more efficiently and effectively.

However, technological expertise alone is not enough to achieve competitive advantages with generative AI. In order to identify valuable fields of application, companies need to understand the expertise in the decision-making processes of their own activities. In addition to the new technological possibilities, the article shows concrete examples and steps that companies can use to test and apply these to their own use cases.

2 New technological possibilities

Technological advances in the areas of computing power (Moore, 1965), transmission speed (Butter) and memory (Kryder, 2005) follow exponential growth curves. The fact that technological possibilities are continuously and significantly improving on this basis is therefore nothing new. The problem is that humans are not able to intuitively understand exponential growth. A fact that is impressively described by the rice grain legend surrounding the creation of the chessboard in India. The impact of generative AI on the consciousness and strategic considerations of decision-makers in all industries was correspondingly great.

One observation is that the revolutionary nature of the publication of new technological capabilities is often followed by a more evolutionary phase of optimization of this technology. Agrawal, Gans and Goldfarb describe a direct consequence of this relatively silent and continuous improvement in their book "Prediction Machines" as follows: "This is simple economics: when the cost of something falls, we do more of it. [...] More significantly, because it [artificial intelligence] is becoming cheaper it is being used for problems that were not traditionally prediction problems." Technological progress is therefore not only making the technology more capable, but also considerably cheaper. The result is that new fields of application are being opened up in which the use of artificial intelligence was previously too complex or simply too resource-intensive. (Agrawal, Gans and Goldfarb, 2018)

Companies are asking themselves how they should deal with generative AI, i.e. how they should use it.

Dealing with generative AI

According to McKinsey (Lamarre, 2024), companies can choose and combine three basic archetypes (Maker, Taker and Shaper) to integrate generative AI into their business models:

I. **Maker:** Makers are investing heavily in the development of their own AI technologies and platforms. A process model that is likely to exceed the resource availability of most companies many times over and is therefore primarily pursued by large technology companies such as OpenAI or Google.

II. **Taker:** Takers use and integrate existing, widely available AI technologies into their business processes. While this offers a more cost-effective way to implement AI, it rarely enables sustainable medium-term competitive advantages to be achieved as the same technologies are also available to competitors.

III. **Shaper:** Shapers use basic models and modify them with their own company's data and specifications in fields of application that affect the company's core processes. This approach offers the greatest potential for companies to achieve significant competitive advantages.

Before the question of how companies can use generative AI in selected value creation activities is answered in chapters 5 and 6, the technological foundations are briefly outlined in the following chapter.

3 Multi-agent AI and graph neural networks: revolutionizing the way we deal with complexity and knowledge

The autosapient model of AI applications

A common mistake when formulating the goal of an AI project is that AI solutions are designed with the aim of providing a final "right" solution and automating decision-making. The assumption that generative AI completely relieves decision-makers of their work and independently presents decisions that are undoubtedly correct is definitely wrong. AI is an auxiliary tool that can support managers in the decision-making process.

The concept of "autosapient" AI, as described in the Harvard Business Review article "Leading in a World Where AI Wields Power of Its Own", brings with it a different perspective on the formulation of goals for AI systems. Autosapient systems are designed to learn autonomously, continuously improve and interact with human actors. (Heimans and Timms,2024) This can take place at different levels with varying degrees of complexity.

Four levels of AI models

In order to better understand the transformation of AI systems, it is necessary to look at the development from simple models to complex multi-agent systems. Four levels can be distinguished, which correlate with increasing task complexity. (Guo et al. 2024; Parthasarathy et al. 2024):

I. **Simple models**
These are basic language models (LLMs) that process and generate natural language. They are suitable for general information queries and simple decision-making processes. LLMs can analyze large amounts of text and provide simple answers. However, their capabilities are limited to processing static information.

II. **Specifically trained models**
These models are tailored to specific tasks or domains and provide more detailed and contextual insights based on industry or company-specific data. The focus is on optimized output that goes beyond generic answers and includes specific expertise.

III. **AI agents**
An AI agent can perform complex, specialized tasks autonomously and interact with third-party systems via interfaces. It acts as an advanced decision-making assistant for a specific area of application.

IV. **Multi-agent AI**
These systems consist of several specialized agents that work together to perform highly complex tasks with a high degree of reliability. Each agent contributes its own partial expertise, resulting in comprehensive and coordinated decision-making.

Each agent can be based on different technological foundations. Graph neural networks in conjunction with graph databases, which are explained in the necessary depth below, are particularly relevant to the central idea of this article, which is to transfer company expertise into AI models.

Graph neural networks and graph databases

Graph neural networks (GNN) are a form of deep learning specifically designed to process complex data structures in the form of graphs. A graph consists of nodes (entities) and edges (relationships) that represent connections between the nodes. GNNs make it possible to understand and process both individual nodes and the relationships between them, which distinguishes them from conventional neural networks. The underlying graph data can come from a variety of sources, including social networks, molecules, or even graph databases specifically designed to store and query graph structures. (Khemani et al., 2024)

A specific form of graph database is knowledge graphs, which accumulate domain-specific knowledge and make it explicitly accessible for AI applications. (Peng et al., 2023) By integrating knowledge graphs, especially deep information, AI models can be improved in their performance. (Elnagar and Weistroffer, 2019) Chapter 5 graphically illustrates a specific use case.

How the innovative technological possibilities outlined in this chapter can be used to support the execution of value creation activities is described below.

4 The impact of new technological opportunities on business activities

Businesses are driven by activities that are carried out within core, support and management processes. According to Agrawal, Gans and Goldfarb (2018), these activities follow a generic architecture, which is illustrated in Figure 1:

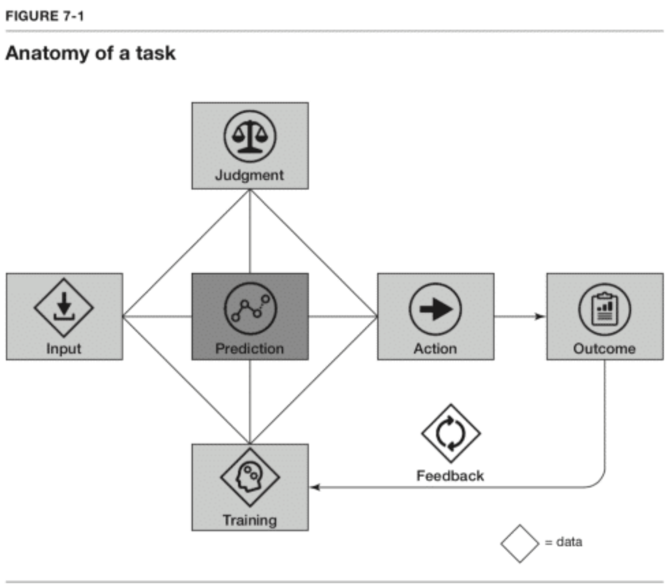

Figure 1: Anatomy of an activity according to Agrawal, Gans, and Goldfarb (2018)

At the center of the architectural model is the prediction element, in which the situation is assessed and possible outcomes are predicted. It is the basis for human judgment and subsequent action. The prediction element can be carried out by both humans and machines, explicitly by predictive AI models. The book published in 2018 describes cases as suitable for AI support if they involve large amounts of historical data, repeatable, consistent situations and clear, measurable goals (Agrawal, Gans and Goldfarb, 2018).

The availability of generative AI in the form of large language models, especially in conjunction with graph databases, expands the types of possible use cases in which the prediction module can be executed by machine. Increasingly complex, knowledge-based questions can be processed explicitly. (Elnagar and Weistroffer, 2019)

A distinction is first made between experience and expertise based on Malhotra and Bazerman (2008). Experience describes the frequency with which an activity is carried out and therefore has a direct effect on efficiency, but only an indirect effect on the quality of the activity. Expertise, on the other hand, comprises the methodological component of a decision, specifically the explicit knowledge in the assessment of a situation. Expertise has a corresponding effect on the quality of the result and the effectiveness of the activity.

This distinction between experience and expertise is particularly relevant when it comes to the expansion of machine-aided decision-making. In this context, two types of cases can be identified, which are explained in more detail in the following chapter using specific application examples.

I. **Cases in which the expertise is not explicitly available in the company**
This expertise can be developed using generative AI on the basis of unstructured internal and external data. To do this, the unstructured data is converted into a knowledge graph using a language model, which is then used in the predictive model and improves the result (Elnagar and Weistroffer, 2019). Specific sources can be processes from a customer support ticket system, machine manuals or email correspondence.

II. **Cases in which there are no measurable results of the activities**
In activities that do not focus on classic predictive issues, the integration of expertise in language models can be used to support decision-making. Specifically, for example, expertise on strategic management methods can be integrated into autosapient AI assistants that support decision-makers in strategy development and implementation. (Csaszar et al., 2024)

The consequence for companies

Companies must understand these new opportunities and reflect them on their activities in order to develop competitive advantages and new forms of value creation by shaping the technology (see chapter 2). Two key questions arise explicitly:

I. How great is the potential for expertise: What expert knowledge is available in the company in an unstructured or incomplete form and can be made accessible and integrated in a scalable way using forms of AI?

II. How can the new technological possibilities be used to convert existing expertise into new forms of value creation?

The following chapter describes two examples of use cases that illustrate the advantages of the innovative process approach.

5 Application examples of generative AI

5.1 Use case I: Monitoring and assessment of machine states

Technology-based implementation of the partial expertise of a ship manager

The core activities of a ship manager focus on the technical management of the ship under their care. A key area of responsibility here is the monitoring of machinery on board the ships and the procedural handling of planned and unplanned repair tasks.

This expertise has been substituted by technology providers for several years now, for example through the establishment of predictive maintenance approaches. However, multi-agent AI systems offer a more in-depth basis for mapping the expertise of a ship manager.

The specific approach

The system comprises the following components and features:

I. **Identification of anomalies:** Agent 1 continuously monitors sensor data from the machines on board the ships and identifies deviations. The task is a classic question for an AI-based time series analysis that requires a manageable amount of training data.

II. **Derivation of the faulty system component:** Agent 2 receives the identified anomalies and determines the faulty system component. This is a task that requires a large amount of legacy data. Generative AI can be used to make existing data usable in a different form and reduce the amount of legacy data required. Specifically, event chains are derived from machine manufacturers' manuals and fault reports from service technicians in the past. The event chains include both the inference from anomalies in the measuring points and the consequence of the malfunction of one system component on another. In addition to the reduction in training data, the transfer of this expertise into the algorithm also ensures that the agent can justify the result achieved. Figure 2 shows the transfer of knowledge from a manual to the corresponding event chains.

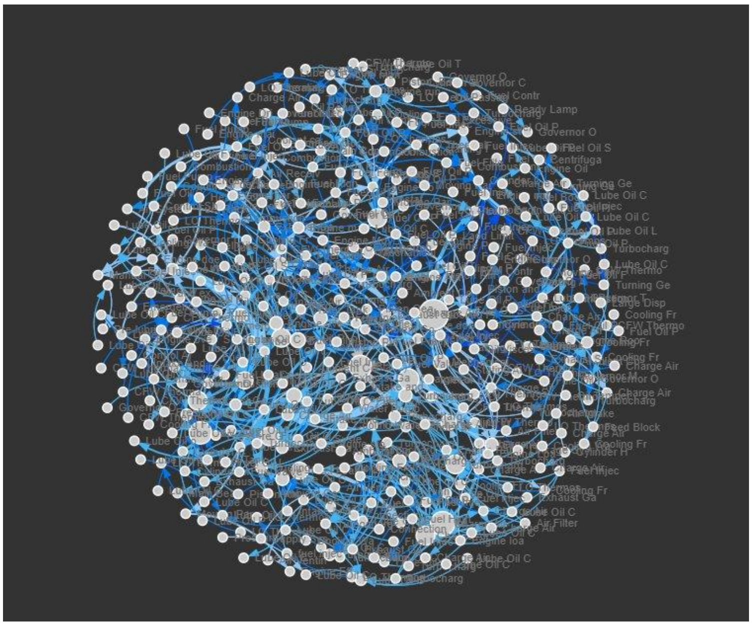

Figure 2: Expertise extracted from the manual of a machine type using generative AI (own illustration)

III. **Quality control of the issued assessment:** Agent 3 acts as a gatekeeper with the task of quality assurance in the process and the corresponding avoidance of cascading errors in the outcome of the respective agents. Using the expertise it has built up, the agent evaluates the results of the previous agent, taking previous activities into account. It assigns a value for the probability that the assessment made is correct.

IV. **Triggering the follow-up action:** Agent 4 initiates the follow-up action based on the assessment of causality and its certainty. This agent explicitly takes over the interaction with the responsible actors, explains and justifies the proposed measures and adjusts them according to the feedback received. The source of knowledge for dealing with the detected faults lies primarily in the reports from service technicians on previous repair measures.

The effect for the ship manager

Three specific consequences for the ship manager can be derived from the implementation:

I. **Improved service quality:** The model makes it possible to detect damage to machinery at an early stage. The consequential damage from the malfunction of the first system component could have been completely avoided.

II. **Knowledge retention and expansion:** By transferring the unstructured data from external manuals and internal reports into structured event chains, the manager ensures the retention and expansion of their own expertise compared to a variant in which an external solution provider implements a predictive system solution.

III. **Increased effectiveness and vertical integration in the value chain:** Based on the outcome of the system described above, further sub-activities, such as spare parts logistics, can be successively integrated and systematically controlled. The approach of transferring external unstructured knowledge into structured internal expertise also offers various approaches for new forms of value creation.

5.2 Use case II: Multi-agent AI in marketing

Scalability of a marketing agency's expertise

Identifying, researching and approaching potential new customers is a field of activity for many small and medium-sized companies that can only be managed to a limited extent with internal resources. Consulting an appropriate marketing agency is not necessarily feasible for many of these companies, especially in economically challenging conditions, and is therefore not commissioned. This has the following direct consequences: A lack of marketing strategy and implementation for the company and a reduced market for the marketing agency.

Multi-agent AI offers the basis for counteracting this situation by making parts of the marketing agency's expertise scalable and significantly cheaper. A corresponding set-up could look like this:

I. **Agent for market segmentation and positioning**
Agent 1 is trained with the methods and evaluation criteria for the market segmentation and positioning of a company in a target market. The integrated expertise enables targeted feedback in the context of iterative loops with the users within the user company and supports with impulses for differentiation in the market.

II. **Agent for content strategy and creation**
Agent 2 creates the content strategy for the respective market segment based on the output of the previous agent. The integrated expertise of this agent explicitly ensures the selection of a suitable channel for making contact and the content formulation of the customer approach. Based on the results of the subsequent agents, the content can be dynamically adapted and optimized with the involvement of the users of the user company. In expansion stages, this agent can select customer-specific addresses based on individual

web research, provided the potential customer is addressed directly.

III. **Agent for campaign management and optimization**
Agent 3 plans the campaigns and evaluates them according to key figures and reference values that are common for the respective channel. In the event of deviations from target values or the identification of negative trends, the agent interacts with the previous agent and the users in order to adapt the generated content. The agent supports the analysis of causality and validates new content from the previous agent against success criteria derived from previous campaigns. The agent also analyzes the profitability of each campaign.

IV. **Agent for customer feedback analysis**
Agent 4 analyzes the mood and content feedback from customers and contacted leads. Based on the findings, the agent can provide feedback to the second and third agents in order to immediately take the insights gained into account. Both positive and negative feedback can be clustered in this agent in order to optimize its own service provision on this basis and adapt the customer approach used accordingly.

Even if the services provided by a marketing agency go beyond the service packages mentioned above and are still differentiated in terms of the quality of the output, at least at present, the application of the technology in the rough concept described above offers relevant added value in a customer segment that was not previously addressable for the marketing agency in question. The translation of the agency's own expertise, at least in part, therefore offers a short-term opportunity to penetrate new market segments and at the same time make the agency's own service provision more efficient within the markets it already serves. In the medium term, however, this poses a considerable risk of substitution, particularly for small market players and those who are slow to react to new technological opportunities.

The two use cases demonstrate the advantages of using the technological possibilities of generative AI presented in this article in selected value creation activities of the company. How suitable fields of application can be identified is described in the following chapter.

6 Identification of areas for the implementation of multi-agent AI in the company

Evaluation of current activities

In order to effectively implement multi-agent AI in your own company, it is crucial to identify the right areas of application. The key question that companies need to ask themselves is: “What is the expertise at the core of the company's value creation?” Four key questions that help to identify an initial pilot project or derive new use cases are:

I. **What activities are at the core of the value proposition to the customer?**
As already described, the answer to this question often requires a deeper process-related understanding than originally assumed. Of particular interest are those activities that can only be carried out by long-serving employees.

II. **What expertise is required to carry out this activity?**
The focus here is on expert patterns in decision-making in order to identify specific modules that can be mapped using AI. A missing or imprecise architecture is a strong signal for potential effectiveness through the implementation of explicit expertise.

III. **What is the communication intensity of the activity?**
Activities with high communication intensity between different human and machine

actors are an indicator of existing potential. The ability of generative AI to map interaction with human actors and the multi-agent concept open up new potential for mapping these activities.

IV. **Who owns this expertise?**
As already explained in the example of the ship manager, technology providers have been mapping expertise in corporate activities for many years. Implementing this expertise in-house is generally not efficient, especially as a competitive advantage can only be achieved if the in-house solution is significantly better than the existing solutions that are already available on the market. Therefore, in-house expertise in a specific module and expertise in the interaction of the individual modules are relevant for gaining a competitive advantage.

Applying these four key questions usually leads to a series of possible use cases which, once identified, can be evaluated using traditional methods of profitability analysis and developed on a small scale using an agile approach.

7 Conclusion

In light of advancing technological developments, decision-makers have a responsibility to re-evaluate and implement their business models and forms of service provision. In particular, generative AI in conjunction with knowledge graphs and multi-agent structures offers new opportunities for integrating new and existing expertise into corporate activities. The necessary task for companies is to penetrate and reflect on their own expertise. One mistake that players should avoid in their mental orientation is the approach of completely substituting human action. Rather, the right question for opening up a new area of application should be: Where can the capability of artificial intelligence integrate new or existing expertise into the decision-making process and thus positively influence the quality of human judgment and the resulting actions. This applies to both existing and new players within and outside the company.

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