Artificial Intelligence: A Strategy to Harness its Power Through Organizational Learning

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Abstract: Although artificial intelligence (AI) has become a crucial component of digital transformation efforts tied to organizational strategy, many firms struggle to articulate the strategic value of emerging AI systems. In this article we argue that the power of AI as a strategic resource lies in its self-learning capabilities. Such learning capabilities are only realized in partnership with humans through mutual learning. By building on a learning-centered framework, we elaborate on how AI can contribute to organizational learning to create a competitive advantage. We formulate the concept of artificial capital and the ways artificial and human capital can together drive routinization and strategic learning processes that connect internal and external environments of the organization. Finally, we use this conception to formulate practical recommendations for managing and developing AI to meet strategic business goals.

Introduction

In recent years, new waves of artificial intelligence (AI) systems empowered by breakthroughs in deep learning have made great technological strides, propelling many firms to speculate about the strategic significance of these systems. Even though these firms see the rising importance of AI as a strategic asset, many have yet to realize its potential. As a result, there is a sizable gap between AI capabilities presented by vendors and actual impacts of the intelligent technology within organizations.

A 2019 survey of over 2,500 executives conducted by MIT Sloan Management Review and Boston Consulting Group found that most companies have begun to invest in and employ AI capabilities. Yet seven out of ten of those companies reported minimal or no impact from AI (Ransbotham, Khodabandeh, Fehling, *et al.*, 2020). One potential reason companies struggle to generate value from AI is the tendency among executives to perceive and integrate AI as a point technology for specific and siloed operations within the organization (e.g., customer service). Seen this way, AI is primarily used for tactical and fragmented purposes, such as lowering the costs of certain operations. Rarely does AI implementation encompass a long-term strategic perspective that can lead to sustained business gains (Joshi and Wade, 2020).

Journal of Business Strategy: https://doi.org/10.1108/JBS-11-2021-0182

Additionally, many companies fail to recognize the unique nature and breadth of capabilities that emerging AI systems can offer (Ransbotham, Khodabandeh, Kiron, *et al.*, 2020). In contrast to the previous waves of computing, the power of AI lies in its self-learning capabilities, which are enabled by better computational power and access to big data within and outside organizations. Because of AI's unique characteristics, even a minimally viable AI system could be different in practice from standard IT projects commonly implemented in businesses in the past (Davenport and Seseri, 2020). For example, the 'expert-in-the loop' approach could take a different shape as the human expert does not necessarily feed the system with the problem-solving logic (and the system itself could develop it).

The technological advancement that has led AI to become more pragmatically viable is deep learning. This subset of machine learning is driven by artificial neural networks and can perform analyses and solve problems that are not possible with traditional machine learning approaches (Jarrahi, 2019). While traditional machine learning approaches rely on a human expert to identify the features upon which a machine learning model should be trained, models based on deep learning will self-learn those features during the training process.

As such, to harness the strategic value of emerging AI systems, organizations may need to adopt a different approach than used with previous IT systems because deep learning AI systems are increasingly performing tasks considered exclusively human-centered such as those requiring tacit knowledge, perception, and judgment (Brynjolfsson and Mitchell, 2017). In this article, we argue a way to understand AI strategic value is by directing attention to its links to organizational learning processes. Thus, we will focus on how AI systems can contribute to learning processes that transform knowledge into core capabilities, offering strategic benefits to organizations.

A Learning-Centered Approach

To account for the unique self-learning capabilities of emerging AI technology, we adopt a learning-centered approach to embrace the link between AI and organizational strategy. To discuss our framework, we first describe how self-learning capabilities offered by AI systems may contribute to organizational learning and why such capabilities must complement human learning to fulfill the ultimate goal of mutual learning between humans and AI. Next, we describe a learning-centered perspective to frame the contribution of this AI-empowered learning to organizational strategy.

Through its ability to recognize complex patterns and perform powerful analytics, deep-learning-based AI systems can potentially transform knowledge resources into new capabilities that facilitate organizational learning. AI systems have rapidly advanced in their capability to discover patterns in big data, including patterns that are unknown to humans and organizations. For example, deep learning models can analyze unstructured text in contracts, invoices, and point-of-sales data to flag erroneous charges, making audit processes much more cost and time efficient (Davenport and Mahidhar, 2018). Unlike traditional rule-based intelligent systems, which operate within a defined set of rules, these AI systems learn from each transaction and use this information to develop the model and provide more effective inferences.

Mutual Learning between Humans and AI

Humans are instrumental in contextualizing AI-generated knowledge, integrating it into organizational learning processes, and transforming it into organizational capabilities. Understanding organizational context requires social intelligence and is a tacit, human-centric competency (Jarrahi, 2019). Humans are unique in their capability to put knowledge into perspective and can extrapolate learning from one context to another even when situations or problems have few similarities (what is called analogical thinking).

When mutual learning occurs between deep learning systems and knowledge workers — as opposed to the two learning independently — it can create a new organizational capability (Barro and Davenport, 2019). On the one hand, human workers bring their prior education, knowledge, and experience in an industry and topic domain to their job. On the other hand, technological advances that enable embedding of prior domain knowledge (e.g., financial audits) are allowing deep learning systems to do a more thorough analysis resulting in a set of observations, questions, and proposed conclusions a human teammate can use for further analysis.

When the human worker provides updated analysis back to the deep learning system, the AI system becomes smarter and can deliver a deeper analysis to the business than would have been delivered by the knowledge worker alone. For example, UPS uses an AI-empowered network planning tool that organizes packages based on measures such as the time of year, destination, and content. The system provides human operators with choices that can be accepted or rejected. The human and AI partners can learn from one another: The human operator's feedback is provided to the AI system to fine-tune its model while the system serves as a check on the human’s decision-making (Latinovic and Chatterjee, 2019). Developing the processes and routines that enable this mutual learning environment will become a core of a company's differentiated capability.

How can a human-AI Partnership Drive Organizational Learning and Strategy?

To examine AI and its role in organizational strategy, we draw on the knowledge-based perspective, which views knowledge as a strategic source for gaining competitive advantage (Grant, 1996). The framework presents the strategic leveraging of internal knowledge resources and firm-specific capabilities as key to achieving competitive advantage. These competitive advantages are driven by knowledge capabilities that are valuable, rare, and difficult to imitate. This perspective directs attention to learning as a core organizational action through which internal knowledge resources are transformed into core competencies. We argue that this learning process can be augmented and enhanced by implementing new AI capabilities.

The transformation of knowledge-based assets to core competencies is a continuous and path-dependent learning process. That is, the learning process is dependent on the path the firm adopts and perfects (Grant, 2006). Because of this unique path, the learning and the dynamic knowledge capabilities generated are proprietary and hard to imitate by competitors. Competitive advantage does not last forever and requires constant learning and adaptation. As such, the learning culture that sustains over time and nurtures continuous mutual learning between AI and human workers can serve as a source of advantage.

Path-dependent learning involves two interlaced processes (Andreu and Ciborra, 2009). The first is a learning process that takes an internal orientation and is geared toward more effective and efficient organizational processes and routines (e.g., speeding up or reinventing service delivery). The second learning process takes a more external orientation and is geared toward market orientation and growth (e.g., creating new revenue streams and enabling new business models). The two learning processes span and connect internal knowledge resources and the external environment of the firm and, together, reflect an organization's ability to present a dynamic competitive advantage based on path dependencies and the organization's position in its external environment, as depicted in the Learning Model (Figure 1).

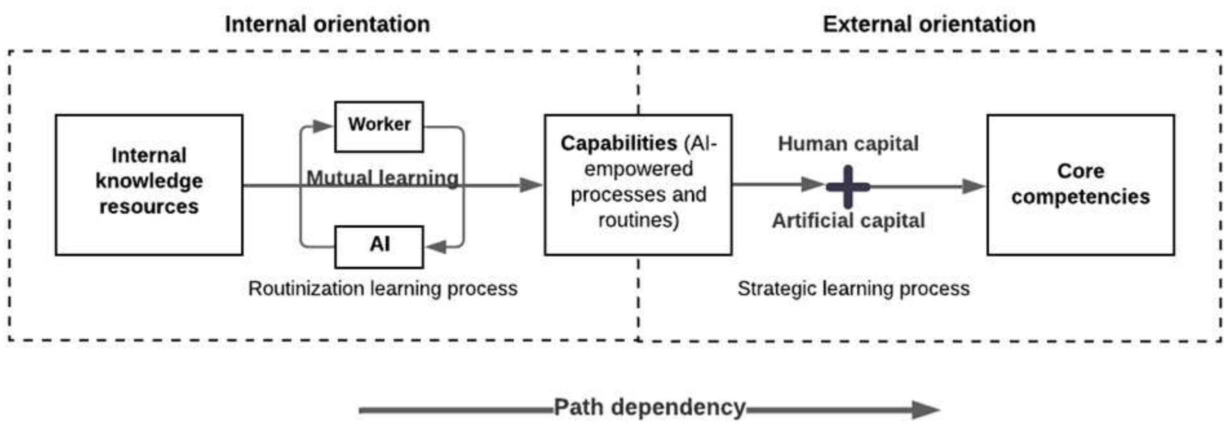

Figure 1: The Learning Model: AI and its role in learning processes that transform internal resources to strategic core competencies.

Resources are valuable, but to sustain a competitive advantage, organizations must transform them into inimitable capabilities (Barney, 1991; Grant, 2006). Common technological ingredients of AI systems such as training data available in the organization or off-the-shelf AI systems are valuable resources but do not automatically translate to new knowledge that can be used for strategic purposes. Generating meaningful knowledge and, more importantly, taking advantage of it in learning processes requires close collaboration of knowledge workers.

First Learning Process (Routinization Learning Process)

The first learning process has an internal orientation and is focused on embedding and internalizing knowledge resources in organizational routines. This process emphasizes improving organizational capabilities or the internal value chain through more effective and efficient organizational processes and routines (Grant, 2006). The organization can combine and exploit internal knowledge resources to develop capabilities; and, therefore, it is clearly linked with management of knowledge and know-how (Teece, Pisano and Shuen, 1997). Through this learning process, workers and AI technology work and learn together to arrive at more effective and adaptive organizational practices and routines. Internal work processes and routines are the first step in the organization's internalization of resources.

A key interim outcome of routinization is higher levels of human and artificial capital and a more intelligent decision making as both actors arrive at a better understanding of problems and internal context while gaining awareness of the evolving capacity of each other. The value of AI is often realized in practice through continuous experiment and in close interaction with knowledge workers and data.

Capabilities

Capabilities are interim outcomes (see Figure 1) that are created through the innovative combination of the organization's internal resources in developing, carrying, analyzing, and exploiting internal knowledge resources. Capabilities embody the company's key organizational routines and processes, which represent knowledge that stems from earlier organizational learning in the form of "rules, procedures, conventions, strategies, and technologies" (Levitt and March, 1988, p.320). These are the true means through which a business delivers value to its stakeholders. Because of its crucial role in transforming internal resources to capabilities and then to core competencies, learning becomes a fundamental strategic issue in the knowledge-based view of the firm.

AI capabilities can help optimize processes and routines. For instance, certain customer experiences are fragmented because data and operations relevant to these services are housed in different units. Such a siloed perspective can be transformed by AI-empowered learning into a comprehensive and cohesive picture of a customer, bringing together pieces of data to inform a decision. A clear example of using AI-enabled learning for process improvement comes from Hitachi Corporation's implementation in accordance with the *kaizen* philosophy of constant improvement. The system in Hitachi monitors workers' approaches to problems and discerns the most efficient alternatives in their routines. It then delivers instructions to workers that take fluctuating demands into account. The system has been said to increase the productivity of logistic activities by 8 percent (Daugherty and James Wilson, 2018).

Although AI can improve current processes, its disruptive power lies in enabling completely new things by creating processes that are impossible without it. AI can not only transform the services and products firms offer but also create new ways of operating through customization and personalization. Netflix's algorithm uses viewing history to understand individual preferences and then offers customized recommendations based on this information (Iansiti and Lakhani, 2020). AI is also revitalizing management workflows through what is known as algorithmic management. Platform businesses such as Amazon or Upwork are scaling operations in an unprecedented way (e.g., matchmaking between service recipients and service providers) by building on algorithms that undergird the process of assigning, aggregating, and evaluating tasks.

According to the knowledge-based perspective, capabilities are gained through combining and exploiting knowledge resources. Mutual learning between humans and AI can be used to combine knowledge resources and put them into distinct and new uses. For example, the petroleum company Repsol used AI to analyze millions of data points on a daily basis (e.g., on drilling productive wells) to reduce inefficiencies by finding root causes and areas that could be improved. Human experts either use the recommendations generated by the AI system or feed them back to the AI system for revision. This type of relationship between managers and the AI creates opportunities to learn and continuously optimize organizational processes (Ransbotham, Khodabandeh, Kiron, *et al.*, 2020).

Human and Artificial Capital

Building capabilities rests on and contributes to already accumulated human and artificial capital**,** knowledge that facilitates the execution of organizational routines and processes. This knowledge is not limited to individual workers or systems but also has an important collective dimension that lives in organizational routines, structures, and culture.

Human and artificial capital can both be regarded as the capability to integrate, analyze, and combine information into new ideas and services, forming and refining core competencies. Human capital can be understood as the accumulation of training, experience, judgement, intelligence, relationships, and insights of individuals within the firm (Barney, 1991, p. 101). It embraces the unique insights of humans that help in strategic decision-making that requires foresight about dynamism of the market. Humans are more competent than intelligent machines in making pragmatic decisions in situations without historical precedents and many unknown factors, such as the global pandemic.

We define artificial capital as contextually enriched AI-generated knowledge, meaning it is sensitive to the specific organizational context and not only universal context-free best practices. In essence, artificial capital embraces the unique analytical capabilities of AI systems that are gained through continuous analysis of data and feedback. For example, artificial capital provides a comprehensive overview of all historical precedents relevant to a problem or situation and, based on this past data, can help an organization predict future events. This is possible because of the knowledge that AI systems amass about the organization, culture, processes, and key sources of information. Artificial capital derives from mutual learning between humans and AI; specifically, humans attach contextual meaning by feeding back insight into the system.

Human and artificial capital are related but cannot be reduced to one another. As organizations experiment with AI, neither form of capital will be self-sufficient because effective decisions tend to incorporate both elements. For instance, in the early days of the COVID-19 pandemic, AI algorithms needed to be overhauled as they had not witnessed any precedent similar to the massive scale of upheaval in consumer behaviors. Thus, humans had to play more crucial roles in making sense of what was changing in consumer behaviors. However, as months passed the predictive algorithms had access to more data about these patterns and could thus play a more prominent role (Pressman, 2020).

Second Learning Process (Strategic Learning Process)

The strategic learning process has an external orientation since firms turn outside to explore what is happening, particularly in relation to consumer behaviors and demands. Based on changes in the external environment, internal processes and capabilities are dynamically developed, adjusted, and redeveloped. The ability to respond to evolving opportunities in the competitive environment, and thus build core competencies, depends on effective work processes as capabilities are built over time.

This learning process requires leveraging a symbiotic combination of human and artificial capital to identify and transform capabilities to core competencies. By constantly analyzing the internal environment of the organization and the competitive environment within which the organization operates, individuals and teams decide what internal knowledge-based capabilities have strategic potential to act as a sustainable competitive advantage. In this learning process, organizations find the right balance between internal capabilities and opportunities in the external environment and market.

For example, for a company like Ticketmaster, recognizing and rewarding legitimate buyers is part of its core competencies. It needs to constantly confirm that real fans, and not bots or fraudulent actors, have easy and early access to tickets. To do this, the company uses AI to construct a holistic view of buyers' behaviors and to facilitate access for legitimate buyers (Joshi and Wade, 2020). However, resellers will then adapt their strategy by figuring out how the algorithm may work, creating a strategic threat to the integrity of the platform. To counteract this threat, Ticketmaster uses human capital to scan the market and identify changes that can be used to retrain AI algorithms to combat threats.

Core Competencies

Core competencies come from the collective knowledge across the firm about alignments among products and services, technologies, internal capabilities, and the competitive market (Hamel and Prahalad, 1993). Core competencies are built over the long run, are hard to imitate, and, as a result, can serve as foundations of competitive advantages that differentiate a firm from its competitors.

For instance, a core competency of the German car maker Porsche is its ability to predict shifting demands in different regional markets and find the balance between the right product and the right market. AI helps the firm develop more adaptive processes, customize car configurations out of thousands of options, and deliver unique inventories based on region-specific dynamics (Ransbotham, Khodabandeh, Kiron, *et al.*, 2020). This new AI technology, named Recommendation Engine, improves a highly individualized car customization experience. Although many car company websites offer the ability to build a customized car, Porsche used deep learning and over 270 training models to develop a tool that takes this a step further. As a customer selects car options, the Recommendation Engine populates with other car suggestions based upon the customer's previous answers (Vornehm, 2021). This not only provides a personalized car shopping experience, but Porsche also claims the technology is about 90% accurate in suggesting accurate selections. As another example, a core competency emerging in the lending industry involves providing credit opportunities in countries where comprehensive credit systems are lacking or underdeveloped. AI has helped companies employ alternative swells of data (with sometimes more than 1000 data points) to predict creditworthiness in unconventional ways and provide swift loans to more borrowers.

Discussion and Implications

AI is transforming business by impacting both internal operations and the delivery of external services. As the technology continues to advance and integrate, it will be critical for business executives to prepare their workforces and organizations to take advantage of all of AI's strategic capabilities. Economic research on digital transformation shows that 90% of the investment necessary to transform a business is not spent on technological capabilities but directed toward reinventing processes and training people (Brynjolfsson, 2021). Our framework echoes this and the sentiment that organizational learning, not machine learning, drives organizational strategy (Ransbotham, Khodabandeh, Kiron, *et al.*, 2020). Organizational learning brings a competitive advantage and acts as a foundation on which a firm can develop the capability to adapt to an ever-changing environment. As such, AI can be understood as a strategic asset because it may help the firm continually learn and reposition itself in the competitive environment rather than serving merely as a tool for automating processes, cutting costs or moderately adding to the firm's revenue streams. In what follows, we discuss the implications of our framing of AI and ways corporations can harness the self-learning power of AI.

Align AI with the Corporate and Learning Strategy

One way to harness the power of AI is to align AI systems with the learning strategy and overall strategy of the organization. Recent surveys indicate most organizations still implement AI in a single business process using a piecemeal approach (Fountaine, McCarthy and Saleh, 2019). Strategic uses of AI will involve implementing it to create new organizational directions, not just for isolated business functions. "Companies that treat AI as a 'technology thing' struggle to deliver value: An IT focus on AI tends to generate less value than a broad strategic focus," as stated by Roaborham et al (2020).

Strategic application of AI requires broader organizational orchestration and initiatives that are impossible if looking only at short-term gains. Given the strategic importance of AI, C-level managers need to be involved in developing and deploying AI strategy and connecting it with the business strategy. In addition, those involved in strategic planning need to have a clear awareness of major AI technologies and ways to connect AI with the internal and external environments of the organization. AI champions should be able to communicate with other managers and stakeholders in nontechnical terms and clarify the relationship of AI with corporate strategic directions as well as where it stands in relation to the current portfolio of legacy systems and infrastructures (Davenport and Mahidhar, 2018). For example, the ambitious deployment of IBM's Watson in MD Anderson Cancer Center was halted in 2017 partly due to a lack of integration with the current electronic medical record system.

Harness Self and Mutual Learning

Leaders and organizations must recognize the power of AI as a learning technology rather than an approach to cut cost and labor. AI may not immediately impact 'here and now' operations. To reap the self-learning benefits of AI, organizations need to avoid the common pitfall of "learning myopia," which refers to the intolerance toward the unpredictability of exploring new ideas that do not appear directly related to immediate business profits and operations of the organization (Levitt and March, 1988). AI's strategic benefits and its contribution to organizational learning take place through the long-term, path-dependent process depicted in Figure 1. For example, pharmaceutical companies have shown the strategic patience needed to integrate AI into the process of drug development. Even though AI has the potential to speed up drug development and lead to the discovery of novel treatments, the process still requires laborious and continuous back and forth between human researchers and the predictive technology to identify potential compounds for synthesis and further study (Preuer *et al.*, 2019).

Using AI to adapt to an environment that constantly changes may require moving away from creating fully formed learning objectives for AI before it is deployed for strategic purposes. AI applications rarely begin with all the desired functionally and are best developed through a test-and-learn mentality where early user feedback is incorporated, and mistakes are reframed as a source of discovery (Bughin *et al.*, 2017). Mutual learning between humans and AI systems (and creation of artificial capital) requires experimentation and, as early iterations show, a need for change or improvement. Leaders can highlight what is learned from each pilot and encourage appropriate risk taking.

AI can contribute to strategy through its unique capabilities in self-learning, but the strategic value of AI's self-learning is realized only when it contributes to human learning and, therefore, human capital. One scenario for such mutual learning in automated processes is when humans accept, reject, or revise AI decisions. This approach allows humans to learn more about how AI logic works in practice based on different inputs and outputs, its rationale, and ways to inform their own work. In turn, AI can use the feedback loop (decisions provided by the human expert) as a source of learning for fine tuning its model.

Adopt an Inside-out Approach

Because AI systems that analyze massive amounts of data are now available to many organizations, they do not produce a competitive advantage unless effectively integrated into organizational routines and processes that generate new forms of human and artificial capital.

Such integration only happens when there is mutual learning of knowledge workers and AI systems, making the learning process path-dependent and enabling a sustainable advantage.

As noted, the process of mutual learning is deeply rooted in organizational routines, processes, and culture. To understand which AI resources must be acquired or amplified to support organizational learning and capability building, managers must first explore and understand the internal environment of the organization. To facilitate the learning process, organizations should look outward and inward and ask key questions about the environment in which they compete and the types of resources they can access. This will allow them to decide how AI can be used best to connect the firm's unique internal processes/resources and its external environment (as indicated in Figure 1).

Whether to buy or develop AI in-house is a vexing question. Firms will have to evaluate whether they need to hire and train employees with specific AI expertise to develop internal AI systems or if they may use "AI as a service" which means building on AI capabilities provided by third parties; this decision requires considering how AI will align with the overall company strategy (Beck *et al.*, 2019).

Develop AI Literacy

Company-wide AI literacies are vital for successful implementation of AI strategies and forming an AI-centered learning culture. AI literacy encompasses skills and competencies that allow human capital to harness the power of artificial capital by facilitating effective partnerships with AI systems. This includes (1) technical, analytical skills (2) business acumen and (3) critical mindsets.

AI technical and analytical skills include engineering-centered abilities such as AI product and application development, writing and implementing software, and integrating AI with existing systems. However, general data expertise in areas such as data aggregation, data cleaning, and transformation are also important for ensuring the quality of the data fueling AI that is applied to achieving corporate learning strategies (Long and Magerko, 2020).

Another crucial component of AI literacy is the ability to connect AI capabilities with strategic needs. Workers with this business leadership skill act as key translators between those with AI expertise and those who understand the broader business goals. These roles are integral in interpreting the AI system results and determining how these outputs affect learning goals and organizational strategies (Beck *et al.*, 2019). These mediators need to be able to interpret AI results, understand the overall business strategy, and be in a position of power within the company so they can influence decisions and share AI insights. If AI experts do not have a deep enough understanding of the firm's learning goals and corporate strategies, it can lead to a "tail wagging the dog" scenario.

Conclusions

As is often the case with new technologies, strategic gains go well beyond the technology itself; the value of digital transformation never comes from the technology but from doing business differently with it. As a result, AI's strategic values are not automatic; they are realized only if self-learning capabilities are integrated, magnified, and made sense of by knowledge workers. Organizational learning and the strategic gains that it undergirds require elaborate coordination between human learning and machine learning.

The framework presented here delineates how AI can be leveraged as a strategic resource. Rather than treating AI as a point technology and breaking down its role in revolutionizing specific functions and specific departments; its strategic value should be understood in the context of its contribution to the overall organizational learning and the corresponding process of learning and capability development. Instead of a functional technology, AI should be seen as a comprehensive form of capital that builds on and complements human capital, together helping organizations derive new strategic knowledge.

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