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Managing and Controlling Innovation in the 21st Century Using Artificial Intelligence

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Abstract

Artificial intelligence (AI) is changing companies and how they organize innovation management. In line with the rapid development of technology and the replacement of human organizations, AI may actually force management to rethink the entire innovation process of a company. In response, we explore the implications for future innovation management. Using ideas from the Carnegie School and the behavioral theory of the firm, we examine the implications for innovation management of AI technologies and AI systems based on machine learning. We outline a framework that shows to what extent AI can replace humans and explain what needs to be considered in transforming the digital innovation organization. We conclude our study by exploring future research directions.

1. INTRODUCTION

There is a growing scientific interest in the idea that artificial intelligence (AI) and machine learning can replace humans, take over workplace roles, and transform existing organizational processes. The underlying assumption is that, given certain limitations in information processing, AI can deliver higher quality, greater efficiency, and better results than human experts.

Given the potential of AI to perform traditionally “human” tasks in organizations, we might ask whether AI can be used to pursue one of the most important processes that impact a company’s long-term survival and competitive advantage (innovation). At first glance, the idea that AI and machine learning can and should be used by companies for innovation purposes may seem almost far-fetched. However, innovation has traditionally been viewed as a domain for Humans are considered to be “unique” in their ability to innovate.

Although AI may have its drawbacks compared to humans, there are reasons why companies may want to use AI in their innovation processes. Among the exogenous factors for the innovation process is the fact that innovation managers are increasingly faced with highly variable environments, more competitive global markets, competing technologies, and shifting political dynamics. At the same time, the availability of information has increased and continues to increase.

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These trends provide strong evidence that the basis of competitiveness is based on information and the problem-solving capabilities of organizations. Perhaps more importantly, in many contexts, the negative effects of innovation risk are compounded by rising costs. That is, the cost of each innovation has been increasing dramatically.

For example, while the transistor density in integrated circuits is increasing exponentially in accordance with Moore's Law, this progress has necessitated further efforts by companies such as Intel. Drug development processes in the pharmaceutical industry show similar trends.

This means that the organizational approach to innovation must be challenged by introducing artificial intelligence and machine learning due to their cost advantages in information processing. Consequently, finding ways to apply artificial intelligence and machine learning in companies' innovation processes should be of interest to innovation managers.

On the one hand, this has the potential to create better ways for companies to respond to their increasingly competitive environment and manage the growing volume of information around them. On the other hand, supporting the innovation process with artificial intelligence can create real value for companies by reducing the risk and cost of innovation processes. Today, human-organized innovation management plays a key role in companies and their capacity to reinvent themselves through exploratory initiatives. However, artificial intelligence can provide instrumental assistance beyond the human realm.

Indeed, both academics and practitioners have stated that artificial intelligence may significantly impact corporate innovation processes in the future. The notion that AI can potentially be used in innovation settings is further supported by the rapid development of artificial intelligence and machine learning, which points to significant and exciting changes in the future. However, our knowledge of the limitations of artificial intelligence in the field of innovation is still very limited. Using artificial intelligence and machine learning for creativity and innovation is very different from areas where artificial intelligence has replaced traditional management.

Following on from the discussion above, this article aims to fill the gap in our knowledge by reviewing the literature and providing a framework for examining the management challenges associated with promoting innovation through artificial intelligence. While artificial intelligence has recently gained momentum in management literature, it is not a new phenomenon.

When the idea of computer systems with artificial intelligence was first discussed by specialists in the field in the mid-1950s, the impact of computer processing on organizations was already of interest to management scholars, notably Richard Siret, James March, and Herbert Simon.

The Carnegie School, in particular, the behavioral theory of the firm, has had a close relationship with artificial intelligence since its inception. Simon argued that "if computers are organized to some extent in the image of humans, the computer is an obvious vehicle for investigating the implications of alternative organizational assumptions for human behavior."

Our research provides a framework for explaining how AI can be used for innovative purposes, and calls for moving beyond human participation in the innovation process. In doing so, we build on the core assumptions of the behavioral theory of the firm and its key concepts. We proceed as follows. First, we provide the theoretical background to our study. We describe the link between behavioral theory of the firm and AI, with particular attention to organizational problem solving and information processing in this context.

We also examine information processing in the digital organization by highlighting the need for modern companies to compete on their digital capabilities and by explaining new ways of processing information in the digital organization.

In doing so, we describe the innovation process and the limitations of related information processing. Based on this theoretical background, we then examine the application areas of AI in the innovation process and derive a framework for overcoming the limitations of information processing in the innovation process with AI. We develop a set of AI readiness levels in the digitalized organization by examining the information processing capabilities of AI. We then discuss the derived framework and readiness levels by describing the various challenges in implementing AI in the innovation process. Finally, we draw some brief conclusions.

2. Theoretical Background

BTF has been accepted in organization and management theory as a major basis for understanding organizational decision-making and behavior. In its development, they proposed a set of foundational concepts at the cognitive level, built on the concept of bounded rationality, which includes the ideas of satisfaction, search, and organizational routines.

The theory includes a set of relational concepts that serve as theoretical frameworks for explaining how cognitive concepts emerge in organizations. These concepts include pseudo-conflict resolution, uncertainty avoidance, problem-oriented search, and organizational learning.

There is interest among researchers in reexamining the various concepts presented in the "Behavioral Theory of the Firm" in the context of recent developments in artificial intelligence. The idea originally put forward by BTF was that organizational problem solving could be understood by viewing organizations as information processing systems built by simple “if-then” computational algorithms, which were at the core of artificial intelligence at the time. The logic of viewing an organization as a simple algorithm or combination of algorithms that process information is deeply embedded in BTF.

2.1. Behavioral Theory of the Firm and Information Processing

Information processing is a key component of innovation in organizations. A central activity in innovation management is the decision-making process, which requires the processing of information by managers involved in the innovation process. The role of management in information processing is to make decisions about the inputs to the process in terms of data, edge knowledge and other information.

The information then needs to be processed, in other words, the data, knowledge and information are collected and analyzed. Ultimately, after processing the information, management is responsible for decision-making. With the advent of machine learning, a type of artificial intelligence that allows machines to “learn” from data and experience without explicit programming – the way information is processed in organizations is rapidly changing. All of the above steps in organizational information processing can be supported or, in some cases, taken over by artificial intelligence systems. In fact, modern digital organizations exhibit certain characteristics that fundamentally change the way information is processed in organizations. Interestingly, today’s organizations are changing in a way that makes it difficult for management to access and analyze some information elements.

2.2. Information Processing in the Digitalized Organization

The emerging digital organization has a strong backbone of highly integrated machine learning and computer science. This means that a large number of processes are automated through algorithms. Some authors suggest that this should be an organizational pillar and that organizations should therefore consider their core capabilities as digital capabilities.

These services interact with customers and suppliers and enable the storage of information and knowledge. Therefore, an increasing amount of information and knowledge is stored electronically without human intervention. The digitized organization becomes the main component and the social system of an organization becomes less central.

As a result, it can be said that managers who are responsible for managing innovation and decision-making are less effective, not only because of human limitations, but also because they may be constrained by operating outside the relevant information flow.

It can be assumed that managers who have access to this information are a small subset of the management set, meaning that many managers may have less information, both quantitatively and qualitatively, than they did before the advent of computerized organizations and technological changes in the workplace.

These background realities require a model in which artificial intelligence-based innovation, machine learning, computer information, and processes are integrated into innovation management. As artificial intelligence further advances, it can be said that the role of innovation management will change in line with the advancement of artificial intelligence and machine learning. Therefore, human innovation management is expected to work alongside artificial intelligence and machine learning algorithms in identifying and selecting opportunities as well as exploring the organization's next competitive advantage.

We believe that the increasing implementation of e-services and automation, along with the general transformation to digital organizations, will change the role of innovation management. As in the past, innovation managers faced two specific obstacles when they try to identify or develop new opportunities and ideas.

First, they must overcome information processing limitations that limit the amount of information about new opportunities or potential solutions that the company can pursue. These information processing limitations are often the result of managers' cognitive limitations, that is, the human mental capacities to absorb or process information are biologically limited. The second obstacle that managers face is the result of ineffective or local search routines. This obstacle specifies that managers generally seek solutions in knowledge domains that are relevant to the company's and their own existing knowledge base. This suggests that most solutions are relatively incremental in their innovative direction, as they rely heavily on existing knowledge. However, to generate a more creative and innovative idea or opportunity, managers must expand the search beyond existing knowledge areas to new areas that are more exploratory in nature.

Thus, although access may be more limited in increasingly digitalized organizations, as managers are able to process large amounts of information about possible solution approaches and opportunities, they should be able to narrow down the set of possible solutions, the most promising ones, and identify the truly exciting opportunities. Furthermore, as managers can go beyond their current knowledge base with the help of artificial intelligence, they should be able to generate more innovative solutions and identify more creative opportunities.

The AI solutions that can be deployed are not simple, and AI participation in the innovation process may be challenging. It will also be difficult to replace human participation. Any AI-based system that seeks to support management in these efforts must be able to overcome the same obstacles that human managers face in the innovation process. The above discussion develops the basic perspective used to develop a framework for examining the management challenges associated with promoting innovation through AI.

Table 1 below provides an overview of the literature streams and topics covered in our theoretical background section. We bring together behavioral theory of the firm and its focus on information processing with the literature on the digitalized organization and innovation processes to theorize about the challenges that management faces with AI and innovation. Next, we will discuss specific analysis.

2.3 Areas of Application of Artificial Intelligence in the Innovation Process

By combining the obstacles that both humans and artificial intelligence systems must overcome in the innovation process with the key activities of idea generation and development that must be performed, we can obtain a framework of creative application areas of artificial intelligence in the innovation process.

To understand the possibilities of artificial intelligence, we need to identify where artificial intelligence can help and potentially replace human decision-making in innovation management. Specifically, there are four areas where human decision-making can be theoretically supported:

(1) Developing ideas by overcoming information processing limitations.

(2) Generating ideas by overcoming information processing limitations.

(3) Developing ideas by overcoming local search routines.

(4) Generating ideas by overcoming local search routines. These four areas are illustrated in Figure 1, along with a brief description of what AI in each quadrant should be able to do.

The next section provides an overview of the current capabilities of AI systems in supporting humans in the aforementioned areas of the innovation process, highlighting examples in each quadrant of Figure 1.

3. AREAS OF APPLICATION OF ARTIFICIAL INTELLIGENCE IN THE INNOVATION PROCESS

By combining the obstacles that both humans and artificial intelligence systems must overcome in the innovation process with the key activities of idea generation and development that must be performed, we can obtain a framework of creative application areas of artificial intelligence in the innovation process. To understand the possibilities of artificial intelligence, we need to identify where artificial intelligence can help and potentially replace human decision-making in innovation management. Specifically, there are four areas where human decision-making can be theoretically supported:

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3.1. Overcoming Information Processing Limitations with AI for Idea Development

Current AI systems excel at overcoming human information processing limitations in the areas of idea and opportunity development. Currently, AI systems They rely heavily on deep neural networks that require and are capable of processing large amounts of data. With this feature, we see a large number of artificial intelligence systems that can support humans in developing ideas, opportunities, and solution approaches and discover interesting areas by processing much larger volumes of information than is possible for humans. Research Indeed, these technologies are already creating significant economic value for companies. In this context, referring to quadrant 1 in Figure 1, we find a number of interesting applications of artificial intelligence across a wide range of domains. This development is strongly associated with improved conditions for innovation. There are many exciting applications of artificial intelligence systems in materials discovery.

A review of literary trends and topics

Authors	Subject	Literature Current
Argote and Greve (2007), Cyert and .March.(2012) and Gavetti et al (1963), Piezunka et al. (2019), Posen et al. (2018) and Puranam et al.(2015)	Overview Renewed interest in BTF due to advances in artificial intelligence	Behavioral Theory of the Firm (BTF)
McNally and Schmidt (2011) and van Riel et al (2004) .) Samuel, (1959)	The Importance of Innovation in Organizations. Machine Learning Capabilities.	Information processing
Lenka et al.(2017).George et al. (2014), Lanzolla et al. (2007) , and Zammuto et al.(2018)	Digital capabilities of new methods of knowledge and information management.	Digitalized organizations
Kijkuit and van den Ende (2007); Martin (2003)and Wilson (2016); Shane Eggers and Kaplan (2009), Nelson and Winter (1982), Williams and Mitchell,(2004) Gavetti and Levinthal (2000), Katila and.Ahuja .(2018) , and Posen et al.(2002) Amabile.(2018) and von Krogh(2019)	Stages and characteristics of information processing limitations in the innovation process The ability of artificial intelligence to overcome information processing limitations	Innovation process

For example, AI can be used to optimize battery components and solar cells, or to speed up the process of discovering new catalysts. In order to discover these new materials, machine learning-based methods are used to predict the most promising materials for testing, thereby significantly speeding up the innovation process.

Of course, there are also interesting applications of AI in pharmaceutical research and development. Here, AI systems include those that speed up the process of protein engineering, which is useful in discovering proteins suitable for technical, scientific and medical applications. The reason why machine learning-based methods are interesting for researchers in this field is that the search space of potential proteins is too large to be searched exhaustively with existing methods. In addition, AI applications can be used to identify disease treatments.

For example, deep-domain adaptive neural networks have been trained on single-cell RNA genomic datasets to ultimately develop therapies that stop the transmission of malaria. Finally, there are many areas where artificial intelligence systems can be used to drive process innovations in organizations. For example, Celonis uses process mining to identify organizational processes that are suitable for robotic process automation. Celonis uses artificial intelligence applications that enable organizations to implement significant administrative innovations.

<table>
<tr><td colspan="4">Innovation process</td></tr>
<tr><td colspan="2">Generating ideas</td><td colspan="2">Developing ideas</td></tr>
<tr><td>The AI system is able to identify more problems, opportunities, and threats that may be used to generate new ideas (2).</td><td>The AI system is able to identify and evaluate more information, which can then be used to develop ideas. (1)</td><td>Information processing limitations</td><td rowspan="2">Barriers to innovation</td></tr>
<tr><td>The AI system is able to identify and create more creative/exploratory problems, opportunities, and threats to generate new ideas. (4)</td><td>The AI system is able to identify and evaluate more creative/exploratory ideas. (3)</td><td>Local or ineffective search routines</td></tr>
</table>

Figure 1. Application areas of artificial intelligence in the innovation process

3.2. Overcoming the Limitations of Information Processing with Artificial Intelligence for Idea Generation

There are several AI applications that fall into quadrant 2 of the framework in Figure 1. These AI applications can process much more information to generate new ideas and opportunities that would likely be overlooked by humans working alone. A typical example is an application developed by ai.Outlier. The company uses a set of machine learning methods to process raw benchmark data into human-readable insights.

After analyzing a company's data, Outlier produces a set of customized "stories" that summarize actionable and interesting insights for specific managers. By doing this, Outlier can highlight innovative opportunities for managers. How it can work is illustrated in the following example:

One of Outlier's clients is a large, international quick-service restaurant chain, Tavernet. It sells hundreds of items in thousands of stores, but in one instance, the company found something different. A store that had been closed for three weeks immediately after reopening was selling twice as many sodas as before. This is a big change because sodas are the most common item sold by quick-service restaurants.

Upon further investigation, management learned that the location had been closed for renovations but had not used the previous layout since reopening. The staff had found a better layout for the store, one that coincidentally increased soda sales significantly.

This observation from just one store, a change that was made randomly, can now change the entire company's revenue as it spreads across all locations. As this example shows, the AI-based analytics provided by Outlier was instrumental in developing an innovation at the focal company. Outlier's ability to find significant anomalies and patterns in business data is one of the ways in which AI can help companies generate or identify innovative ideas and opportunities.

These AI methods may not be able to independently develop complete solutions, but they can guide human managers towards the most promising paths to innovation. Another interesting example in this regard is provided by Tshitoyan and colleagues.

They created an AI system that can extract tacit knowledge from the materials science literature. Their system uses an algorithm—vec2word, a popular neural network in natural language processing applications—to extract concepts from text. The algorithm is able to visualize complex materials science concepts, including the underlying structure of the periodic table, without requiring searchers to explicitly include chemical knowledge.

The AI system can also recommend materials for other applications. By censoring the data, the authors can show that the system can actually recommend materials several years before they are discovered. Thus, the method points to opportunities for future innovations in an already existing knowledge area. This study shows potential applications of AI in Quadrant 2 of Figure 1. That is, AI systems that are able to generate or identify ideas and innovation opportunities, where a large amount of information in an existing knowledge area must be processed.

3.3. Overcoming Local Search Routines with Artificial Intelligence for Idea Development

There is early evidence that AI systems may be able to support humans in the types of innovative activities presented in quadrant 3 of Figure 1. These activities involve identifying and developing ideas, opportunities, and solution approaches in which the process goes beyond the application. Local search routines—in other words, remote search—are used. For example, Autodesk used various algorithms to create a new partition for Airbus crew. The generative design methods employed to invent the new partition create product types that designers could not create alone. The algorithms used by Autodesk were based on the growth patterns and bones of mammals.

They enabled the construction of a new, more efficient, but equally durable crew partition. Therefore, by incorporating artificial intelligence methods into the development process, Autodesk and Airbus were able to create a more innovative solution than would otherwise have been possible.

Even more interesting, some applications are based on generative adversarial networks (GANs). The Creative Adversarial Network (CAN) for art creation, developed by El Gamal et al. (2017), is an example of such an AI solution. A CAN is a type of GAN that is capable of generating original art. The network was trained on 81,449 paintings by 1,119 artists from the 15th to 20th centuries. The system trains two competing networks—a discriminator and a generator—to learn to classify artistic style (discriminator) and to learn style ambiguity (generator). As a result, CAN generates new art that deviates from the learned styles.

We argue that this deviation from previously learned styles is precisely where the CAN system can overcome the local search routine and demonstrate its potential for far-field search. From Since the model first learns about existing art styles, it is also aware of current domain knowledge.

However, it is set up to specifically explore beyond existing styles and, therefore, can generate new ideas. Another related research project by Sbai and colleagues is called DesIGN -Design Inspired by Generative Networks.

The system can generate new styles, forms, and shapes for fashion apparel. It deviates from existing fashion styles represented in the training dataset, while generating real pieces of clothing. Therefore, it overcomes the local search routine when developing new ideas for fashion apparel.

3.4. Overcoming Local Search with Artificial Intelligence for Idea Generation

Ultimately, AI systems that hope to address Quadrant 4 of Figure 1 must be able to generate or identify ideas and opportunities for innovation in unrelated knowledge domains. One method in AI that may facilitate the generation or identification of innovative ideas and opportunities is reinforcement learning. Recent advances in reinforcement learning, such as unsupervised reinforcement learning and hyperreinforcement learning, have been useful in generating new ideas. Reinforcement learning generally involves training an agent in a (virtual) environment.

The agent uses the reward signal to learn which actions maximize rewards and which actions minimize them. Reinforcement learning requires humans to manually construct rewards, which is a nontrivial and sometimes suboptimal approach to reward engineering.

As Osindero Simon, one of Google's top AI researchers at DeepMind, explains: "To the extent that you design a reward function, you are also designing a solution […] If it were easy, for us to design a solution, you might not need to learn it in the first place." Unsupervised reinforcement learning attempts to address this shortcoming by allowing the agent to learn its reward function using a stream of observations and actions.

Thus, this approach is the first step towards Enabling algorithms to learn to recognize and achieve goals unsupervised will open up interesting avenues for creativity and innovation. Meta-reinforcement learning tackles a very relevant question regarding how to use learning to improve the learning process itself. Recent work in this area has attempted to devise algorithms that are able to adapt quickly to new arbitrary problems.

Advances in these areas should allow algorithms to become more flexible in terms of solving new problems, which may be useful in generating, discovering, and recognizing new creative ideas and opportunities.

4. LEVELS OF AI READINESS FOR DIGITAL ORGANIZATION DEVELOPMENT

As anticipated above, the various AI systems described in Section 3 are at different levels of complexity in terms of their ability to augment and replace human managers in innovation processes. These levels of complexity can be obtained by looking at the types of capabilities that an information processing system has to complete the functions described in each of the quadrants of Figure 1.

For this, we will consider the "innovation process" and "barriers to innovation" dimensions as the problem space and the solution space. The first dimension, which describes the tasks of the innovation process (idea development and ideation), can also be considered as the problem space that is the subject of the innovation.

According to the information processing view of the innovation process, "the problem space is the internal representation of the working environment" used by the subject, whether the subject is a human manager or an artificial intelligence system.

When going through the innovation process, an information processing system can continue with its current definition of the problem space, which is simply consistent with developing a new idea or solution based on the problem space, or it can decide to include additional data, information, or knowledge.

It thus redefines the problem space and opens up the ability to generate new ideas and solutions. Another way to describe these two options is to describe the first as exploiting an existing problem space and the second as exploring a problem space. redefined, evolving, or different.

To understand the levels of capability of current AI systems in terms of assisting humans in the innovation process, it is important to understand some of the key technical characteristics of these systems. There are two key features of most of today's advanced AI systems that are limited by human capabilities. First, most current AI systems are trained by human AI experts who collaborate with domain experts on the basis of their existing knowledge.

This means that these AI systems must typically attempt to search a broader base of known and relevant knowledge—in other words, most systems are limited in the extent to which they can explore the problem space.

Second, advanced AI systems are tuned in such a way that the learning process is optimized for a given objective function. This objective function is defined by the human AI researchers who implement and train the system.

Furthermore, these objective functions are generally very sparse because the human researchers who calibrate the systems are unlikely to know all possible objectives and therefore tend to fall short in their ability to provide an ideal objective function.

As a result, for most AI applications, the solution space is predefined by humans, and current AI systems therefore have very limited ability to explore the solution space independently. As a result, these two characteristics of AI systems impose technical limitations on the systems' abilities to redefine and explore both the problem space and the solution space.

Furthermore, most current AI systems are limited in their ability to generate or recognize ideas and opportunities and overcome local search routines. However, as explained in Sections 3.2, 3.3 and especially 3.4, some recent developments suggest that AI systems may indeed be able to overcome these limitations.

We can therefore derive a range of what we call "information processing capability levels" for AI systems, which indicate how likely it is that AI systems will replace and complement human decision-making. Broadly speaking, they can be grouped into three capability levels according to the types of information processing capabilities shown in Figure 2 below.

4.1. Level 1 Information Processing Capability: Exploitation

Level 1 information processing capability indicates that an AI system is capable of helping human innovation managers process much larger amounts of information and knowledge than they themselves are capable of doing.

AI systems at this level of capability will primarily be able to support rather than completely replace humans in the innovation process, because by processing more information, they perform a supporting function and do not completely take over the entire innovation process.

Therefore, these AI systems can help humans overcome the limitations of cognitive information processing that often prevent them from fully considering the huge volume of data and paying attention to a large number of data sources.

Properly designed AI systems can both deal with much larger volumes of data and process different data sources. These types of AI systems are located in Quadrant 1 of the Figure 1 framework presented in Section 3.

4.2. Level 2 Information Processing Capability: Developing

Level 2 information processing capability indicates that the AI system can enhance the innovation process by generating ideas or by overcoming local search routines to find new solutions and opportunities.

At this level of capability, AI systems continue to work alongside human innovation managers. These systems excel in supporting managers in two specific ways. First, they help in discovering new ideas and opportunities as described in Quadrant 2 of the Figure 1 framework. Second, they can support innovation managers in developing more innovative and creative ideas and solutions.

These types of AI systems are shown in Quadrant 3 of Figure 1. At present, the technological capabilities of AI systems are still relatively limited, and only a few systems can operate at this level of readiness, as explained in Sections 3.2 and 3.3.

4.3. Information processing capability level 3: Exploration

Information processing capability level 3 indicates that the AI system is capable of discovering new paths in the innovation process. This type of AI system can perform more advanced and difficult tasks in the innovation process and, therefore, can not only support human innovation managers, but can also replace them to a certain extent.

AI systems at the "Explorer" information processing capability level can generate and create new ideas that are particularly innovative and creative. Due to their more advanced information processing capabilities, these AI systems can discover both

new ways to define problems (problem space exploration) and new ways to address the problem (solution space exploration).

As a result, we can expect AI systems with Level 3 information processing capabilities to have a greater chance of taking on a greater share of the tasks traditionally performed by human innovation managers. However, the current state of the art is relatively far from allowing the implementation of such AI systems, as there are few initial efforts for AI systems of this type. This is explained in Section 3.4 with respect to Quadrant 4 in the framework of Figure 1.

5. DISCUSSION

Considering the opportunities for AI to participate in the innovation process, the question arises as to when, how, and to what extent human innovation managers and AI systems can and should work together. Literature often discusses AI's capacity to perform and replace workplace tasks in general terms.

For example, current analyses estimate that proven AI technologies have the potential to replace up to half of all work activities performed by human's 60 percent of all jobs involve approximately 30 percent of automated activities.

Consequently, we think it is important to have a specific discussion about AI's ability to replace humans in the innovation process. Can AI replace the human aspect of innovation management? Initial investment in AI will generate rapid, cheap, and relatively complete manifestations of new ideas that can be innovative.

However, replacing managerial judgment can be difficult, and thus, fully transforming into a digital organization can be problematic. The development and addition of new innovations is often coordinated by a large management team motivated by the discovery of market opportunities.

In this regard, it should be emphasized that innovation management decisions across the organization are inherently complex, and therefore completely replaceable by AI. It requires a set of algorithms that are intertwined, and inevitably, this is done under conditions of significant uncertainty.

It is an art that requires the company to exploit economies of scope, increase and create market power, and create flexible changes and synergies with resources such as the workforce across the company's business areas. Fully utilizing AI is challenging because it requires new ways to address a new industrial environment.

This requires acquiring new knowledge and resources, as well as creating new business areas and new business models to integrate new innovations into existing product portfolios. Companies must create and adjust processes that are aligned with the new product, configure new organizational structures and systems for administrative alignment and governance control purposes.

These are all tasks and activities that can be supported by AI, but within clear and challenging limits. While AI may help with product concept and market analysis, and scheduling resources and systems around it, this is a very complex process. Therefore, AI is likely to be more relevant when new products are launched in areas where the TMT is less familiar. However, its use is likely to be implemented alongside human management.

Previous research has reported that overworked and pressured management may fail to develop sufficient knowledge to familiarize themselves with new products, making uninformed decisions that are difficult to correct and ultimately leading to failure. The use of AI is likely to make a significant contribution to profitability when products are launched that are highly innovative and the role of TMT is different in the future.

Level 3: Exploration	Level 2: Development	Level 1: Exploitation	
Fully capable of exploring and redefining both the problem space and the solution space	Able to explore and redefine the problem or solution space	Able to successfully exploit problem and solution spaces	Search approach
- Discovering new ways in the innovation process - Creating and inventing new and creative ideas - Exploring new ways to define problems - Exploring new ways to address problems	OR: - Able to discover new ideas and opportunities OR: • Supporting people in developing more innovative ideas and solutions	- Used to overcome limitations of cognitive information processing - Can deal with more data - Capable of processing many different data sources	Specifications
Sandbox experiments	Initial implementations	Executable applications.	Maturity level
Al systems with increased machine autonomy	→	Human-designed AI systems	Level of autonomy

Figure 2. Levels of AI information processing capabilities.

How temporary are AI solutions and how difficult are they to implement? There are several challenges associated with implementing these emerging technologies in organizations. Specific challenges lie at the level of the technology itself, as well as at the level of the people tasked with implementing it. Certain challenges also lie at the interface between technology and people.

The first set of challenges, which are closely related to the technology itself, include relatively obvious challenges such as the availability and suitability of data. On the technology side, there is the hardware issue. For example, in terms of computational power, some modern AI applications require very powerful processing functions and large amounts of data to power these processes.

For example, one recent research project that generated fake images using competitive models required the energy that the average American household uses in about six months. Beyond these challenges, the technology is in many ways not mature enough to be applied in professional settings.

Taking reinforcement learning as an example, this area of machine learning is very vibrant, and researchers continue to make very interesting advances. However, while reinforcement learning is a highly researched and interesting area of artificial intelligence, it is mostly applied to developing artificial intelligence systems that can beat human performance in video games.

To date, there are only a few commercial applications of this very interesting type of artificial intelligence. One example of a real-world application of reinforcement learning is its use by Chuxing DiDi, China's largest car rental company. Didi has developed a dispatching algorithm based on reinforcement learning that can adapt to driver demand.

The solution has been tested in a limited number of Chinese cities, where it has shown greater efficiency than previous non-reinforcement learning-based distributed systems. Aside from the fact that many machine learning applications have not progressed significantly beyond sandbox environments, the technology itself is still developing its fundamentals.

Deep learning capabilities were only proven in 2012, and a large portion of patents in AI are still very basic in nature. The second set of challenges is closely related to the humans involved in implementing and using AI solutions in companies. It is well-known that companies often lack the technical skills necessary to successfully implement AI solutions.

Depending on the complexity of the solution to be developed, different skills are required, and since there is a high demand for these skills, companies often have difficulty acquiring the necessary talent. Companies that have employees with the necessary technical skills face the next hurdle. If high-performance AI solutions are to be developed, the team working on the solution generally needs to use technical staff and domain experts.

The problem is that such collaborative approaches to developing AI solutions can be very complex. A recent multi-year project to monitor patients in intensive care units (ICUs) required close collaboration between AI researchers and medical professionals.

This meant that the amount of time required and the level of complexity to conduct the study was much higher than traditional AI projects. But this approach was essential to designing an effective system. Collaborative teams like the one employed in the ICU monitoring project are essential to ensure that the AI solutions developed address the relevant problems that companies currently face.

Finally, there are challenges in linking technology and the humans responsible for implementing it. For example, a limiting factor in the adoption of AI systems in companies may stem from the amount of human intervention required. While AI solutions are intended to automate processes in workflows, it is rare that a complete set of connected tasks can be fully automated.

Furthermore, the solution space that artificial intelligence systems can explore is, in many cases, very much predefined by the algorithm(s) chosen by the humans implementing the system. In addition to limiting the solution space, humans can also be less specific about the solutions.

This is often the case with reinforcement learning machine learning applications, where distributed reward functions lead to highly “creative” problem solving by the algorithm. Machine learning essentially plays the role of the system.

Inadequate human specification can also lead to questionable results in product design. When parameters are not precise enough, the results can be so “creative” that they are largely useless. As a result, human intervention is required, but it has the potential to introduce inefficiencies into processes.

However, human intervention can be beneficial depending on the context. Therefore, one of the biggest challenges is to gain a clear understanding of when to bypass human intervention and when to accept it. Furthermore, it is important to ensure that humans receive actionable information from the AI system so that they can make optimal decisions based on the system’s output.

Another challenge in the human-technology nexus is trust in the AI system. Depending on the design of the AI system, humans can sometimes trust the technology either too much or too little, which creates friction in the use of the AI system. Therefore, designing AI systems that the humans who interact with them can trust sufficiently is an important challenge that must be overcome when implementing AI systems.

6. CONCLUSION

In this paper, we examine how AI systems can support innovation management. Conventional, human-based approaches to innovation management have limitations that are primarily rooted in their incomplete ability to fully address information needs and deal with complexity.

We develop a framework based on the limitations of information processing as presented in the behavioral theory of the firm. We then derive the levels of AI information processing capabilities required for the development of digital organizations.

Finally, we outline the challenges in implementing AI systems that manage innovation in relation to the technology itself, the humans who are tasked with implementing it, and the technology-human nexus. Overall, we note that AI has a constructive role to play where the tried and true benefits of innovation management resources are overshadowed, are impossible due to digitalization, or when AI undeniably emerges as the preferred option.

From our observations, it seems that AI has a clear potential in creating a more systematic approach by integrating AI into organizations that seek innovation. Our research advances the innovation management literature by illuminating the use of AI and machine learning algorithms in organizing the future of innovation.

Our findings point to areas where AI systems can be fruitfully applied in organizational innovation, namely, cases where the development of new innovations is largely hampered by information processing limitations.

For example, AI systems that rely on anomaly detection can be useful when companies struggle with information processing limitations in their search for new opportunities. Finally, we highlight recent advances in AI algorithms that demonstrate the potential of AI to solve more difficult challenges in innovation management. These include overcoming local search and generating entirely new ideas. We look forward to seeing how new advances in AI technology reveal more opportunities and expand the areas where AI can be usefully applied in innovation management.

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