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The Impact of Artificial intelligence in Innovation and Business Management

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Abstract

The **role of AI in innovation and business management** is indispensable. In recent years, Artificial Intelligence (AI) has evolved around 12.9% globally into a landmark technology transforming the private and public sectors. An organization that adopts and invests in Artificial Intelligence technology is going to need to evolve a new management style that combines a leader's vision with a scientist's expertise over a growing body of specialized knowledge. Business productivity has increased by 40% because of AI. Artificial Intelligence (AI) reshapes companies and how innovation management is organized. Consistent with rapid technological development and the replacement of human organization, AI may indeed compel management to rethink a company's entire innovation process. In response, we review and explore the implications for future innovation management. We outline a framework showing the extent to which AI can replace humans and explain what is important to consider in making the transformation to the digital organization of innovation. We conclude our study by exploring directions for future research.

Keywords

Artificial Intelligence (AI), Speech Recognition, Technology, Decision Making, Enhance Business Activity.

INTRODUCTION

Artificial intelligence (AI) has had a profound impact on innovation and business management across various industries. Here are some key ways in which AI has influenced these areas:

Enhanced Decision-making: AI technologies, such as machine learning algorithms, can process vast amounts of data and identify patterns that humans might overlook. This capability enables more informed decision-making in areas like product development, market analysis, and resource allocation.

Automation and Efficiency: AI has automated repetitive and mundane tasks, freeing up human resources to focus on more strategic and creative endeavors. Intelligent automation streamlines processes, reduces errors, and improves overall operational efficiency.

Predictive Analytics: AI-powered predictive analytics models can analyze historical data to forecast trends, customer behavior, and market demands. This helps businesses make data-driven decisions, optimize their strategies, and stay ahead of the competition.

Personalized Customer Experience: AI enables businesses to deliver personalized experiences to their customers. Chatbots and virtual assistants powered by AI can interact with customers in real-time, addressing their queries, recommending products/services, and enhancing overall customer satisfaction.

Improved Productivity and Innovation: AI technologies enable businesses to automate tasks, perform complex computations, and generate insights at a speed and scale that would be challenging for humans alone. This enhanced productivity allows organizations to innovate more rapidly and bring new products and services to market faster.

Risk Management and Fraud Detection: AI can analyze data in real-time, helping businesses identify potential risks and detect fraudulent activities. By monitoring patterns and anomalies, AI algorithms can flag suspicious transactions, protect sensitive data, and mitigate various risks.

Supply Chain Optimization: AI-powered algorithms can optimize supply chain management by analyzing data related to inventory, demand forecasting, logistics, and distribution. This helps businesses reduce costs, minimize wastage, and improve overall supply chain efficiency.

Enhanced Market Insights: AI can analyze vast amounts of data from diverse sources, including social media, customer feedback, and market trends, to provide valuable insights into consumer preferences, competitor strategies, and emerging market opportunities. This helps businesses make more informed decisions and develop effective marketing strategies.

New Business Models: AI has the potential to create entirely new business models. For example, the rise of AI-powered platforms, such as ride-sharing and food delivery services, has disrupted traditional industries and created new opportunities for innovation and entrepreneurship.

Ethical Considerations: The adoption of AI in business management raises ethical considerations related to privacy, bias, and transparency. It is crucial for organizations to address these concerns proactively and ensure responsible AI deployment to maintain public trust.

Overall, AI has revolutionized innovation and business management by enabling data-driven decision-making, automating tasks, enhancing productivity, and fostering new opportunities for growth and competitiveness. Its continued development and integration into various business processes are likely to reshape industries and drive future advancements.

2.THE OBJECTIVE OF THE STUDY

The Following are the main objectives of the paper:

Detailed Explanation of Artificial Intelligence; Machine Learning and Deep Learning.

Artificial Intelligence, Machine Learning, and Deep Learning at Work Place.

Artificial intelligence and Organizations in Today's Scenario.

The Future Scenario of Artificial Intelligence in the Working Place

Artificial intelligence has a wide range of uses in businesses, including streamlining job processes and aggregating business data. AI is expected to take digital technology out of the two-dimensional screen and bring it into the three-dimensional physical environment surrounding an individual.

This article is for business owners and employees who are looking to understand how the use of artificial intelligence transforms the business sector.

Considering AI's potential to take on traditional 'human' tasks in organizations, we may ask whether a role for AI can be used in pursuing one of the most important processes affecting a firm's long-term survival and competitive advantage – innovation. Prima facie, the idea that AI and machine learning could and should be used by firms for innovation purposes may seem almost far-fetched. After all, innovation has traditionally been seen as a domain for humans, given their 'unique' ability to be innovative. Scholarly interest in the idea that artificial intelligence (AI) and machine learning can replace humans, take over workplace roles, and reshape existing organizational processes has been growing steadily. The central premise is that, given certain constraints in information processing, AI can de- liver higher quality, greater efficiency, and better outcomes than human experts.

Although AI may have downsides compared to humans, there are several non-trivial reasons why firms may want to use AI in their in- novation processes. Among the factors exogenous to the innovation process is the fact that innovation managers are increasingly faced with highly volatile and changing environments

We proceed as follows. First, we provide the theoretical background to our study. We describe the link between the behavioral theory of the firm and artificial intelligence, paying special attention to organizational problem solving and information processing in this context. We also examine information processing in the digitized organization by elucidating the need for modern firms to compete on their digital capabilities and by explaining the new modalities of information processing in the digitized organization. In doing so, we describe the in- novation process and the associated information processing constraints. Building on this theoretical background, we then examine potential AI application areas in the innovation process and derive a framework for overcoming information processing constraints in the innovation process with AI. We develop a set of readiness levels of AI in the digitized organization by looking at AI's information processing capabilities. Then, we discuss our derived framework and the readiness levels by describing the different challenges in implementing AI in the innovation process. Finally, we draw some brief conclusions.

3.THEORETICAL BACKGROUND

The BTF has been acknowledged in organization theory and management as a major foundation for understanding decision making and organizational behavior. In developing it, Cyert and March (1963) proposed a set of foundational concepts on the cognitive level that are built on the concept of bounded rationality, which encapsulates the ideas of satisficing, search, and organizational routines. The theory includes a set of relational concepts that serve as theoretical mechanisms to explain how cognitive concepts unfold in organizations. These concepts include the quasi-resolution of conflict, uncertainty avoidance, problematic search, and organizational learning. There is renewed interest among researchers in re-examining the various concepts put forward by Cyert and March in 'A Behavioral Theory of the Firm' in the context of recent developments in AI.

The idea originally posited by the BTF is that organizational problem solving could be better understood by looking at organizations as information-processing systems constructed by simple computational 'if-then' algorithms, which were at the core of AI at that time. The logic of viewing the organization as a simple algorithm or a combination of algorithms that process information is deeply embedded in the BTF.

3.1 THE BEHAVIORAL THEORY OF THE FIRM AND INFORMATION PROCESSING

Information processing is a key component in innovation in organizations. A central activity in innovation management is the process of decision making, which requires information processing by managers involved in the innovation process. The role of management in information processing is to decide upon inputs into the process in terms of data, knowledge, and other information. Then, information must be processed – in other words, data, knowledge, and information are gathered and analyzed. Finally, once information has been processed, management has the responsibility to take decisions.

With the advent of machine learning – a type of AI that allows machines to 'learn' from data and experience without being explicitly programmed – the way information processing occurs in organizations is changing rapidly. All the above stages of organizational information processing can be supported or, in some cases, taken over by AI systems. Indeed, the modern digitized organization exhibits certain characteristics that substantially change the way information processing occurs in organizations. Interestingly, the organizations of today are changing in a way that makes it difficult for management to obtain and analyze certain elements of information.

3.2 INFORMATION PROCESSING IN THE DIGITIZED ORGANIZATION

The digitized organization that has now emerged features a strong backbone of highly integrated machine learning and computerized knowledge. This means that a vast number of processes are automated through algorithms. Some authors suggest that this needs to be an organizational mainstay and, therefore, organizations should consider their core capabilities as digital capabilities. These services interact with customers and suppliers, and enable the storage of information and knowledge. Thus, an increased amount of information and knowledge is stored electronically and without human involvement. The digitized organization becomes the major constituent, and the social system of an organization becomes less pivotal. Consequently, one can say that executives and directors who are responsible for innovation management and decision making are less efficient not only because of human limitations but also because they may be constrained by operating outside the relevant flow of information. It can be assumed that those managers who do have access to this information are a small subset of the managerial pool, which means that many managers may have quantitatively and qualitatively less information than they had prior to the computerized organization and the technological changes in the workplace.

These background realities call for a model where innovation-oriented AI and machine learning of computerized information and processes are integrated into innovation management. As AI advances further, it can be said that the role of innovation management will change in step with progress made by AI and machine learning. Thus, human innovation management will be expected to work side by side with AI and machine learning algorithms in identifying and selecting opportunities as well as investigating what could be the organization's next competitive advantage.

3.3 INFORMATION PROCESSING IN THE INNOVATION PROCESS

To better understand how AI augments organizational innovation, we need to examine how information is processed for innovation. The innovation process – which is at the core of innovation management's attention – is commonly understood to comprise a series of stages including (1) the recognition, discovery, creation, and generation of innovative ideas, opportunities, and solutions; (2) the development or exploitation of various ideas, opportunities, and solutions; and final.

Therefore, even though access may be more limited in increasingly digitized organizations, the more managers are able to process a large amount of information on possible solution approaches and opportunities, the more they should be able to whittle down the set of possible solutions to the most promising ones and to recognize truly exciting opportunities. Furthermore, since managers are able to go beyond their current knowledge base with the assistance of AI, they should be able to develop more innovative solutions and recognize more creative opportunities. The AI solutions that could be employed are not straightforward however, and it may be challenging to involve AI in the innovation process. It will also be difficult to replace human involvement. Any artificial intelligence-based system that seeks to support management in these endeavors must be capable of overcoming the same barriers encountered by human man- agers in the innovation process.

The above discussion develops the fundamental perspective used for a framework to examine 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 the behavioral theory of the firm and its focus on information processing with the literature on digitized organization and innovation processes to theorize about the challenges that management faces with AI and innovation. Next, we turn to the specific analysis.

Table 1
Overview of literature streams and topics.

Literature stream	Topic	Authors
Behavioral theory of the firm (BTF)	General overview	Argote and Greve (2007), Cyert and March (1963), and Gavetti et al. (2012).
	Renewed interest in BTF due to developments in artificial intelligence	Piezunka et al. (2019), Posen et al. (2018), and Puranam et al. (2015).
Information processing	Importance for innovation in organizations	McNally and Schmidt (2011) and van Riel et al. (2004).
	Machine learning capabilities	Samuel (1959).
Digitized organizations	Digital capabilities	Lenka et al. (2017).
	New modalities of knowledge and information management	George et al. (2014), Lanzolla et al. (2018), and Zammuto et al. (2007).
Innovation process	Steps and characteristics	Kijkuit and van den Ende (2007); Martin and Wilson (2016); Shane (2003).
	Information processing constraints in the innovation process	Eggers and Kaplan (2009), Nelson and Winter (1982), Williams and Mitchell (2004), Gavetti and Levinthal (2000), Katila and Ahuja (2002), and Posen et al. (2018).
	Ability of AI to overcome information processing constraints	Amabile (2019) and von Krogh (2018).

4.POTENTIAL AI APPLICATION AREAS IN THE INNOVATION PROCESS

Here are some potential AI application areas in the innovation process:

1. **Idea Generation**: AI can assist in idea generation by analyzing large volumes of data, identifying patterns, and providing suggestions based on user input. Natural Language Processing (NLP) techniques can be used to extract insights from text documents, research papers, and customer feedback.
2. **Market Research**: AI-powered analytics can analyze market trends, customer behavior, and competitor strategies to provide valuable insights for identifying new market opportunities and consumer needs. AI can process and interpret vast amounts of data from various sources to support decision-making.
3. **Product Design and Development:** AI can enhance product design by using generative algorithms to create optimized and innovative solutions. Computer Vision techniques can assist in automated object recognition and feature extraction, enabling faster prototyping and design iterations.
4. **Data Analysis and Modeling**: AI algorithms, such as machine learning and data mining, can be used to analyze complex datasets and identify correlations, trends, and patterns that may lead to innovative insights. These insights can inform decision-making during the innovation process.
5. **Predictive Analytics**: AI can leverage historical data to build predictive models that forecast market demand, customer behavior, and product performance. This enables businesses to make informed decisions about resource allocation, pricing strategies, and product positioning.
6. **Collaborative Innovation**: AI can facilitate collaboration and idea-sharing among teams by providing platforms for real-time communication, knowledge sharing, and brainstorming. Virtual assistants and chatbots can also assist in managing collaborative innovation processes.
7. **Intellectual Property Management**: AI can support intellectual property management by analyzing patent databases and identifying prior art. It can also help in monitoring trademarks and detecting potential infringements.
8. **Automation and Optimization**: AI-powered automation can streamline and optimize various tasks in the innovation process, such as data collection, documentation, and analysis. This frees up human resources to focus on more creative and strategic aspects of innovation.
9. **Customer Insights and Personalization**: AI can analyze customer data, including browsing behavior, purchase history, and social media interactions, to provide personalized recommendations and improve the customer experience. This helps businesses tailor their innovation efforts to meet customer needs effectively.
10. **Risk Assessment and Mitigation**: AI can assist in identifying and mitigating risks associated with innovation initiatives. It can analyze data to assess project feasibility, evaluate potential risks, and recommend risk mitigation strategies.

These are just a few examples of how AI can be applied in the innovation process. The specific applications may vary depending on the industry, organization, and the nature of the innovation being pursued.

4.AI READINESS LEVELS FOR DEVELOPING THE DIGITIZED ORGANIZATION

As foreshadowed above, the different AI systems described in section 3 are at different levels of sophistication in terms of their ability to augment and replace human managers in innovation processes. These levels of sophistication can be derived by looking at the kinds of cap- abilities that an information processing system must have in order to complete the functions described in each of the area in Fig. 1. For this, we will consider the 'innovation process' and the 'barriers to in- novation' dimensions as the problem space and the solution space, respectively.

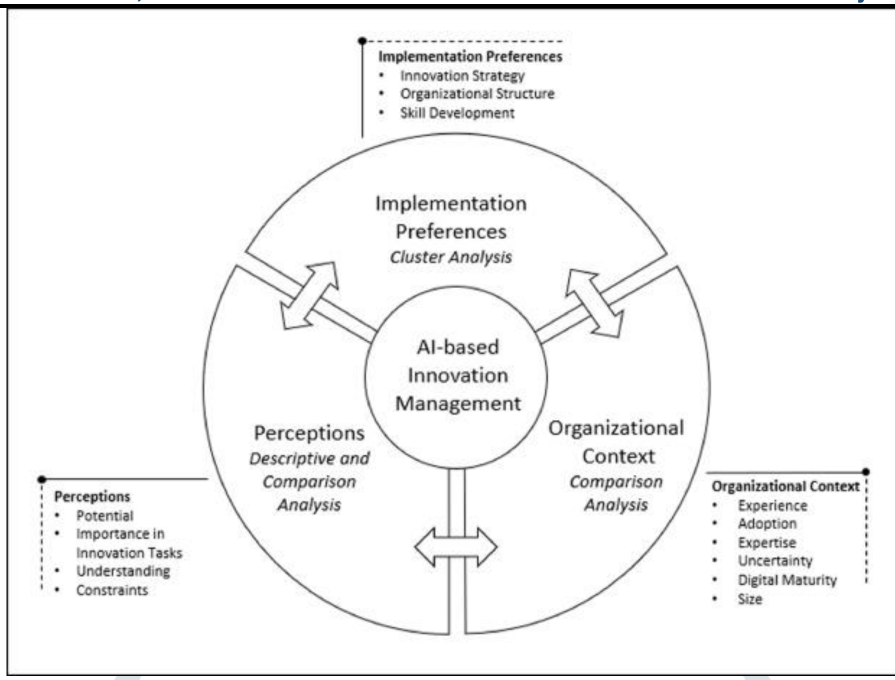

Fig-1 innovation process in management

The primary aspect, which portrays the errands in the advancement cycle (thought improvement and thought age), can likewise be seen as the issue space that is the subject of development. In accordance with a data handling point of view on the development cycle, the "issue space is the inside portrayal of the undertaking climate" utilized by the subject, the subject being a human director or a simulated intelligence framework. While going through the advancement cycle, a data handling framework can either go on with its ongoing meaning of the issue space, which would relate to just fostering a novel thought or arrangement in light of the issue space, or it could choose to incorporate extra information, data, or potentially information, consequently rethinking the issue space and opening up the capacity to create groundbreaking thoughts and arrangements. One more method for portraying these two choices is consider the previous as the Double-dealing of a current issue space and the last option as the Investigation of a reclassified, developing, or different issue space.

The second dimension, describing the barriers to be overcome in the innovation process (information processing constraints and ineffective or local search), may be interpreted as the ways in which the solution space for innovation can be altered. Overcoming information processing constraints does not require any change in the specification of the solution space, since this barrier to innovation 'merely' indicates that the solution space is searched more efficiently and quickly. In other words, overcoming information processing constraints indicates that the solution space is more effectively and efficiently *exploited*. In order to overcome local and inefficient search routines, however, it is necessary to *explore* the solution space so that more distant and creative solutions can be found.

To comprehend the capacity levels of current man-made intelligence frameworks as far as helping people in the advancement cycle, it is vital to under-stand a few critical specialized elements of these frameworks. In particular, there are two vital qualities in most man-made intelligence frameworks grew today that are obliged by human capacities. In the first place, latest simulated intelligence frameworks are prepared by human artificial intelligence specialists who join forces with space specialists depending on their current information base. This implies that these simulated intelligence frameworks ought to by and large attempt to look through a known, related information base to a greater extent - in other words, most frameworks are restricted in the degree to hand planning a prize capability, you're likewise in some sense hand de-marking an answer […] In the event that it was simple as far as we were concerned to plan an answer, perhaps you would have no need to learn it in any case". Solo support learning attempts to address this inadequacy by permitting the specialist to Become familiar with its prize capability utilizing a flood of perceptions and activities. Consequently, this strategy is an initial move toward empowering calculations to figure out how to perceive and accomplish objectives with next to no management, which will open up intriguing roads for innovativeness and development. Meta-support learning handles a firmly related question concerning how learning can be utilized to work on the most common way of learning itself. Ongoing work in this space has endeavored to devise calculations that can adjust quickly to erratic new issues. Progressions around there ought to permit calculations to turn out to be more adaptable as far as taking care of new issues, which might demonstrate supportive in producing, finding, and perceiving new imaginative thoughts and potential open doors.

5.DISCUSSION

Considering the opportunities to involve AI in the innovation process, the question of when, how, and to what extent human innovation managers and AI systems can and should work together arises. This has been discussed in the literature but usually from the perspective of simply understanding AI's ability to perform and replace human workplace tasks in general. For instance, current analyses estimate that proven AI technologies have the potential to replace up to half of all work activities carried out by humans – 60 percent of all occupations consist of approximately 30 percent automatable activities. Consequently, we think it important to undertake a more specific discussion of AI's ability to replace humans in the in- novation process.

Could AI ever replace the human side of innovation and business management? An initial investment in AI will generate fast, inexpensive, and relatively thorough manifestations of new ideas that can be innovative. However, the judgement of managers may be difficult to replace and, therefore, a full transformation to a digitized organization may be problematic. Developing and adding new innovations is often co- ordinated by a large management team that is motivated to explore market opportunities. In this regard, we must stress that innovation management decisions throughout the organization are inherently complex and, therefore, difficult to fully replace by AI. It would require a host of algorithms to be interwoven and, inescapably, this would be done under conditions of significant uncertainty. This is an art that would require the company to exploit economies of scope, increase and build market power (Caves, 1981), and create flexible shifts and synergies with resources such as labor throughout the business areas of the company. The full use of AI is challenging because it demands new ways of addressing a novel industry environment

It entails the acquisition of new knowledge and resources, as well as creating new business logics and new business models to meld the new innovations into the current portfolio of products. Companies would need to create and adjust routines that align with the new product, configure new organizational structures and systems for the purposes of administrative alignment, and buttress governance control. These are all tasks and activities that can be sup- ported by AI but within clear and challenging boundaries.

While AI may help with the product concept and market analysis, and the scheduling of resources and the systems around it, it is a highly complex process. Thus, AI is likely to be more relevant when new products are launched in areas where the top management team (TMT) is less familiar. However, its use is likely to run alongside human management. Previous research has reported that overburdened and stressed management may not be able to develop sufficient knowledge to become familiar with new products, taking ill-informed decisions that are difficult to revise and that ultimately spell failure. The use of AI will likely make an important contribution to profitability when radically innovative products are launched and when the role of the TMT is different in the future How provisional are AI solutions and how difficult are they to implement? There are several challenges associated with implementing these emerging technologies in organizations. The specific challenges are located on the level of the technology itself as well as on the level of the individuals tasked with implementing it. Certain challenges are also located at the technology–human nexus.

The first set of challenges, which are closely related to the technology itself, include some rather more obvious challenges such as the issue of data availability and suitability (for an extensive discussion of this, see. On the technological side, there is the issue of hardware. For instance, in terms of compute power, some modern AI applications require extremely powerful processing functionalities and vast amounts of data to power these processes. For instance, one recent research project that generated fake images using generative adversarial models required as much energy as the average American household would use in approximately six months. Beyond these challenges, the technology is in many ways not mature enough to be applied to professional settings. Taking reinforcement learning as one example, this area of machine learning is highly vibrant, and researchers are continuing to make very interesting progress. However, while reinforcement learning is a highly researched and interesting area of AI, it is mostly applied to the development of AI systems that can beat human performance in video games. To date, there are only a few commercial applications of this very interesting type of AI. One example of a real- world application of reinforcement learning is its use by DiDi Chuxing, China's biggest ride-hailing company. Didi has developed a reinforcement learning-based dispatching algorithm that is able to adapt to rider demand. The solution has been tested in a limited number of Chinese cities where it showed greater efficiency than prior non-reinforcement learning-based dispatching systems. Aside from the fact that many machine learning applications have not progressed substantially beyond sandbox environments, the technology itself is still undergoing development of its fundamentals. Deep Learning was arguably proven to be viable only in 2012, and a large portion of the patents in AI are still very much foundational in nature.

The second set of challenges are closely related to the humans in- volved in implementing and using AI solutions in firms. It is quite well documented that firms often lack the necessary technical skills to successfully implement AI solutions.Depending on the complexity of the solution to be developed, different skills are necessary and, since there is very high demand for these skills, companies often have trouble acquiring the necessary talent. Companies that do have employees with the necessary technical skills then encounter the next hurdle. If high-performing AI solutions are to be developed, the team working on the solution should generally comprise both technical employees and domain experts. The problem is that such collaborative approaches to developing AI solutions can be quite complex. A recent multi-year project to monitor patients in intensive care units (ICUs) necessitated close collaboration between AI researchers and medical professionals. This meant the amount of time required and the complexity level of conducting the study were much higher than traditional AI projects. But this approach was critical in order to design an effective system. Collaborative teams such as the one employed in the ICU monitoring project are essential to ensure that the AI solutions developed address relevant problems that firms are currently facing.

Finally, there are some challenges located at the nexus of the technology and the humans in charge of implementing it. For example, a limiting factor in applying AI systems in firms may stem from the amount of human intervention required. While AI solutions are in- tended to automate processes in workflows, it is seldom the case that a whole series of connected tasks can be fully automated. Furthermore, the solution space that AI systems can explore is, in many cases, very much pre-defined by the algorithm(s) chosen by the humans implementing the system. In addition to limiting the solution space, hu- mans can also underspecify solutions. This is often the case with the sandbox applications of reinforcement learning where sparse reward functions lead to very 'creative' problem solving by the algorithm – the machine essentially ends up gaming the system. Inadequate specifications by humans can also lead to questionable results in generative design. When parameters are not stringent enough, the results can be so 'creative' as to be largely useless. Consequently, human intervention is required but that has the potential to spawn inefficiencies in the processes. Nonetheless, human intervention can be beneficial depending on the context. One of the biggest challenges is, therefore, gaining a clear understanding of when to circumvent human intervention and when to embrace 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 machine output. Another challenge located at the human–technology nexus is that of 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 using the AI system. Therefore, designing AI systems that humans who interact with them can adequately trust is an important challenge to overcome when implementing AI systems.

6.CONCLUSION

In this article, we review how innovation and business management may be supported by artificial intelligence systems. Human-centered, conventional approaches to innovation and business management have limitations that are primarily rooted in their imperfect ability to fully address information needs and cope with complexity. We developed a framework based on information processing constraints as presented in the behavioral theory of the firm. From that, we then derived the information processing capability levels of AI needed to develop digitized organizations. Finally, we delineated the challenges in implementing AI systems that innovation management faces in relation to the technology itself, the humans 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 over- whelmed, are impossible because of digitization, or when AI emerges irrefutably as the preferred option. From our observations, it appears that the clear potential of AI resides in creating a more systematic approach by integrating AI into organizations that are pursuing innovation. Our research advances the innovation management literature by shedding light on the use of AI and machine learning algorithms in the future organization of innovation. Our findings point to areas where AI systems can already be fruitfully applied in organizational innovation – namely, instances where the development of new innovations is primarily hampered by information processing constraints. AI systems that rely on anomaly detection, for instance, can be helpful when firms are struggling with information processing constraints as they search for new opportunities. Finally, we highlight recent advancements in AI algorithms that are indicative of AI's potential to resolve the more difficult challenges in innovation and business management. These include over- coming local search and generating completely novel ideas. We look forward with interest to see how new developments in AI technology open up further possibilities and extend the areas where AI can usefully be applied in innovation and business management.

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