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Identification, innovation and application of artificial intelligence in the field of economics

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Abstract

The range of themes and theories raised about artificial intelligence is so broad and extensive that it requires clarity regarding the fundamental principles, opportunities and challenges it creates. For this purpose, the present research provides an overview of the six manufacturer segments of artificial intelligence: built data, unstructured data, pre-processes, core processes, knowledge tracks, and valuable output information. A typology is then presented, as an analytical tool for managers in the field with artificial intelligence stabilization. This typology examines the impact of emerging innovations on artificial intelligence from two perspectives of innovation boundaries and their impact on organizational capabilities. The first view deals with the difference between product innovation (which affects the company's output) and process innovation (that affects companies' operations). The second view describes innovation as an empowerment enhancer or destroyer. This means that innovation enhances or destroys existing knowledge and skills. This framework enables industry managers to evaluate existing markets and opportunities or threats arising from them and create a valuable context and structure for relevant strategic decisions.

Keywords: artificial intelligence, machine learning, disruptive innovation, product development, strategic policy making, situation awareness

1 Introduction

When Amos Tversky (the most cited psychologist of the 20th century) was asked about artificial intelligence, he joked that he didn't know much about it, while his expertise was "natural stupidity."(Vallmuur, 2020) . Until recently, artificial intelligence was recognised as a good idea but more suitable for sublime scientific fields. Over the years, the decline in investment and public perception of the liability of AI promises has led to the rise of artificial intelligence (Paschen et al., 2019). However, in the last 3 or 4 years, artificial intelligence has emerged as a topic of the day, both in industry and in the university. As searches recorded on Google Trends indicate, the topic's popularity has reached its highest in the last 3 years (Forsyth & Ponce, 2003).

Progress in artificial intelligence has always faced pleasure and fear. Warnings from prominent technologists such as Elon Musk, Steve Wozniak, Bill Gates, and Stephen Hawking have been widely issued, expressing concerns that artificial intelligence could eventually lead to end-of-life events against humanity(Hochstetter et al., 2023). John Maynard Keynes's predictions of the replacement of human power by artificial and robotic intelligence, or "technological unemployment" due to the discovery of cost-efficient tools in the use of labor, It may be realized for its grandchildren(Keynes, 2010).

More Optimistic Views Point to the Prevalence of Artificial Intelligence in Personal and Commercial Use. Face and speech recognition has become common thanks to smartphones and devices connected to the Internet of Things. These devices, using Amazon's Alexa or Apple's series, can take everything from door locks to control music playback and categorize photos based on facial recognition technology. Business applications are just as extensive as well. Banks use artificial intelligence to identify fraudulent credit cards, AI helps hospitals diagnose and treat severe illnesses, and traders use AI in targeted advertising or delivering services to customers through Chatbots (Canhoto & Clear, 2020). Optimistic people believe that artificial intelligence will soon help improve our daily lives (Aleryani, 2019), and there is a possibility of synergies between artificial and human intelligence (Jarrahi, 2018).

Organizations and managers need to judge whether their business capabilities will increase by taking advantage of opportunities associated with artificial intelligence or if they will become weakened and worthless. It is necessary to simplify this assessment, to explore the opportunities for innovation in the field of artificial intelligence(Aleryani, 2019). Based on the concepts of innovation literature, the present study introduces analytical tools that managers can use to evaluate emerging artificial intelligence innovations in their organizations. For this reason, the current research, aimed at providing better understanding to policymakers, executives and senior executives, first briefly describes the building blocks of AI systems and their interrelationships, and then, based on this understanding, draws their attention to AI-based innovation opportunities. In the continuation of current research, it provides analytical tools that assess and predict situations and how artificial intelligence innovations impact organizational capabilities for managers (Lee & Lee, 2015). The research also discusses the limitations of artificial intelligence and provides a summary of managerial concepts in the field of AI.

2 Components of Artificial Intelligence Systems

(David L. Poole and Alan K. Mackworth, 2023), define artificial intelligence as intelligent computational agents that perceive the environment and take actions to maximize the chances of success. This definition represents a shift in perspective from previous views that introduced artificial intelligence as a manifestation of human intelligence. This new definition highlights the importance of environmental perception and makes the computational performance of artificial intelligence evident not only in theory but also in practice and problem-solving.

Every information system consists of hardware, software, data, people, and procedures (Silver et al., 1995). While being considered separate from its environment. These systems interact with their environment in a basic input-process-output manner. In this interaction of inputs, the raw data is derived from human or physical resources, the process is the valuable manipulation of this data, and the outputs contain meaningful information that is fed back into the environment (Ndemo & Thegeya, 2023).

Given the role of artificial intelligence as a theory and practice in the development of systems that work to achieve the desired optimal results, artificial intelligence systems can be divided into six constituent parts (figure1): structured data, unstructured data, pre-processes, main processes, knowledge base, and information (Paschen et al., 2019). The following is a brief introduction of each of these sections and their role in artificial intelligence systems.

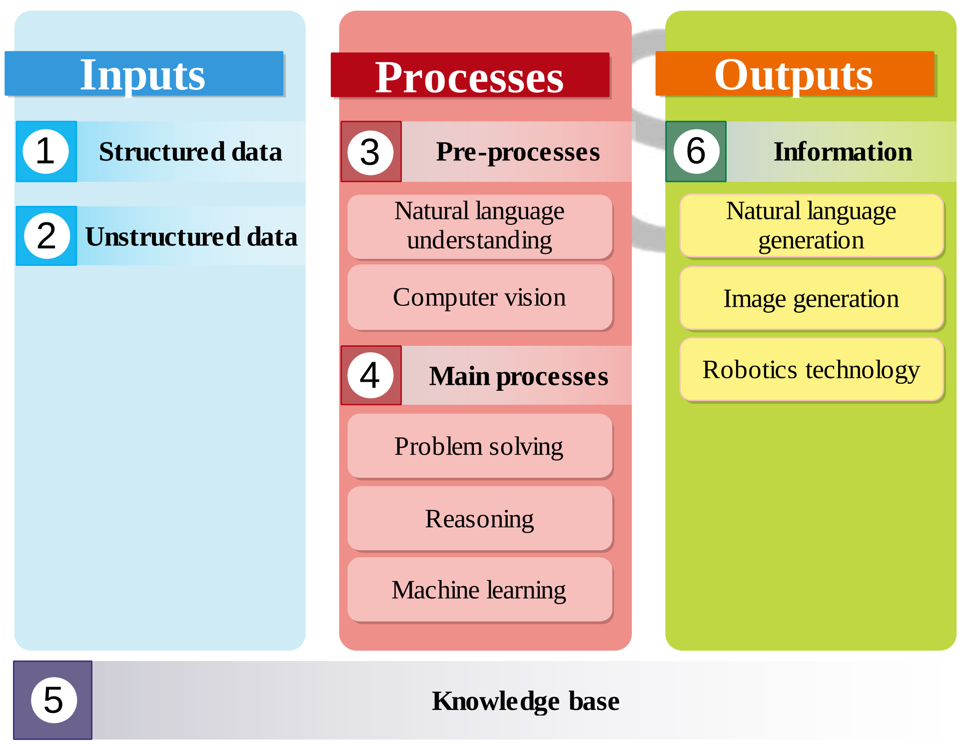

Fig.1 Components of Artificial Intelligence Systems (Paschen et al., 2019)

2.1 Inputs

2.1.1 Structured data

Structured data, standardized data, and organized data are outstanding elements that form the core of business analytics and intelligence. For example, it can be existing figures, sales data or production levels, as well as these data can be found with external access in web browsing or stock exchange data. Artificial intelligence can help analyze this data instantly (Paschen et al., 2020)(Zhuang et al., 2017).

2.1.2 Unstructured data

Unstructured data is not standardized or organized and therefore more difficult to analyze. Much of the data generated by social media, the Internet of Things (IoT), and mobile devices, such as blog posts, Instagram, or tweets (X) with their associated captions, falls into this category, each of which can contain a text, audio, or image file. It is uniquely capable of handling this type of input data (Morse et al., 2024).

2.2 Processes

2.2.1 Pre-processes

Pre-processing of unstructured data, including cleaning, transforming, and selecting data, in a way that makes the data more processable. Examples include natural language understanding and computer vision.

Artificial intelligence systems use natural language understanding to interpret spoken and written language. In the first step of recognizing speech, human language is translated into text. This operation allows the system to recognize spoken words, but has not yet assigned meaning to them. Attributing meaning to words is the primary challenge of understanding natural language. Because factors such as context, vocabulary, and disciplinary terms create considerable fluctuations, most natural language applications use a vocabulary and a set of dictionary rules to analyze the structure, relationships, and weight of words or phrases in natural language. Then they create the most likely meaning of the speech text using statistical modeling and machine learning. Outstanding current users understand natural language, including summarizing text, analyzing emotions, and extracting relationships (Zhuang et al., 2017).

Computer vision signals images so that they can communicate with artificial intelligence systems. This processing has been a very complex task and represents a cornerstone for artificial intelligence systems that work based on results. Computer vision uses machine learning to recognize patterns and extract meaning. For example, the use of facial recognition software for searches and in surveillance videos to track criminal suspects significantly corresponds to human recognition. (Kamkar et al., 2020)

2.2.2 Main processes

the core processes in artificial intelligence include three types of intelligent behavior: problem solving, reasoning, and machine learning. Machine learning uses the process of gaining new knowledge and refining existing knowledge to the expected and more efficient results.

Problem solving means finding the optimal solution to achieve a goal. When the best solution does not exist, divergent problem solving generates and evaluates alternative solutions that may be equally valuable. On the other hand, convergent problem solving attempts to discover a unique and best answer. This process is greatly simplified by artificial intelligence systems working with big data. Both divergent and convergent solutions are stored in artificial intelligence systems, updating the knowledge base accordingly (Gheorghe Tecuci, n.d.).

Reasoning uses logic to draw conclusions from available data. Artificial intelligence systems work beyond traditional methods in reasoning under conditions of uncertainty. Deductive or top-down reasoning attempts to arrive at new conclusions based on hypotheses it believes to be true. Inductive or bottom-up reasoning seeks to build general propositions from individual observations. With both types of reasoning, artificial intelligence systems look for patterns and rules that can be applied to current or future problems (Pecora, 2014).

Machine learning allows artificial intelligence systems to increase their performance without depending on pre-defined rules existing in the system (Lee & Shin, 2020). Early machine learning was overseen by humans who defined pre-programmed rules for systems to follow, but the limitations of this approach soon became apparent. As a result, AI researchers developed algorithms capable of extracting new knowledge from massive amounts of data, making machine or "deep" learning a key component of contemporary AI systems. Deep learning increases the system's ability to solve problems more efficiently and increases the accuracy of solutions to repetitive problems. Artificial neural networks are one of the powerful tools used in machine learning today. They are a sequence of computational steps known as network layers. Each layer of the network performs relatively simple calculations and then presents the results to the next, deeper layer. This cascading design leads to the formation of a powerful system that can depict complex mappings, even if the nonlinear calculations are mathematically simple (Sebag, 2014).

2.3 Data structure: Knowledge base

Intelligent behavior is based on storing past data, information, or knowledge so that experiences in knowledge can influence subsequent behavior. In earlier information systems, hierarchical or relational databases contained structured data that made it possible to store and retrieve content from past processes. In AI systems, these representations can be unstructured data, structured data, or prepaid data, as well as information generated by the system itself for AI processes. Deep learning leads to the production of implicit knowledge, whereby information stored from one layer of the network cannot be interpreted without another layer. In this way, artificial neural networks act as implicit knowledge bases (Huang et al., 2006).

2.4 The Output: Information

A designated intelligence system must provide meaningful information from the completion of processes to its surroundings, either as a basis for human decision making or as input to other information systems. In addition, the information generated by artificial intelligence for non-human affairs is also used in a variety of business applications.

Natural language generation, essentially the reverse of natural language understanding, produces full conversational narratives as output. These narratives can be in the form of text, such as when an AI system transforms large data sets into reports and business intelligence insights. It can also take a more sophisticated form of speech, such as the chatbots that use this technology and are now widely used in marketing and customer service. As the latest version of Google Assistant can participate in meaningful two-way conversations, it is not different from human interaction (Heinonen et al., 2020).

Image generation is the opposite of image recognition, and the output is complete images, even if the information is incomplete (such as when there is no background). Although the technology has not yet evolved enough, drawing robots can generate images based on text descriptions (Ruqian Lu, 2002).

Robotics technology allows machines to use information to physically interact and change their environment. Machines based on artificial intelligence can move in complex physical environments, choose items in the warehouse, move flexibly and smoothly, and even run or jump with perfect balance and coordination (Sennott et al., 2019).

3 Typology of innovations based on artificial intelligence and their effects on capabilities

As part of intelligent systems, AI can be used to help organizations find creative solutions to business problems and take advantage of valuable opportunities. AI can bring about significant changes in the performance of organizations, processes, and products, increasing the capabilities of companies and thereby changing how they compete in the industrial environment.

By combining different manufacturing sectors and artificial intelligence applications, companies can create different value-creating innovations. Understanding this diversity is important for managers and researchers' knowledge. From the perspective of researchers, structural diversity leads to the complexity of knowledge, and this complexity affects how theories and approaches are applied to a variety of artificial intelligence-based innovations. From the perspective of managers, structural diversity affects how companies use artificial intelligence to build organizational capabilities for future competitive advantages (Abonamah et al., 2021).

Figure 2 is derived from the concepts in the innovation literature, and especially from Tushman and Anderson's (1986) research on technology discontinuities, to show the typology of artificial intelligence-based innovations. As an analytical tool for managers, this typology looks at the variety of innovations based on artificial intelligence and their potential effects from two dimensions: innovation boundaries and their effects on organizational capabilities (Granstrand et al., 1997). What Tushman and Anderson refer to as "discontinuities" are major technological innovations that no increase in scale, efficiency, or design of older technologies can compete with. The boundaries of innovation explain how innovations can be product-oriented (affecting an organization's partnerships) or process-oriented (affecting intra-organizational operations)(Tushman & Anderson, 1986). In the field of artificial intelligence, an example of product-oriented innovation is the emergence of self-driving vehicles in urban transportation, while an example of process-oriented innovation is the use of artificial intelligence to predict and support companies' decisions about target markets.

A disruptive innovation invalidates existing capabilities, skills, and knowledge and fundamentally changes the set of capabilities of an organization or even the entire industry (Tushman & Anderson, 1986). For example, self-driving vehicles could be disruptive to taxi drivers and other transportation providers. In contrast, a capability-enhancing innovation enhances an organization's current knowledge and skills. Like when artificial intelligence applications greatly reduce the duration of drug discovery processes and increase biochemical capabilities. In short, capability-disruptive innovations undermine existing skills and knowledge, while capability-enhancing innovations build on existing capabilities and improve them.

These two dimensions can help managers recognize and understand the four types of innovations that AI can create, along with their effects on products, processes, and organizational capabilities. The following examples describe each of these four types of innovation.

Capacity-enhancing process innovations based on artificial intelligence lead to performance upgrades in internal processes. These advancements have been based on knowledge and skills and provide the core for future improvements to internal processes. For example, KONE Corporation offers services related to more than one million electric lifts and stairs worldwide. The company's experts identify regular repairs and maintenance, including inspections of materials, parts, and critical components, inform experts and carry out further diagnoses, and initiate necessary preventive reconstruction. In this way, the capabilities of the expert process are increased by using artificial intelligence.

Capability-enhancing product innovations bring better product performance to customers by improving existing capabilities in an industry. Such innovations replace older technologies but do not eliminate the skills needed to master them. For example, when automakers use AI in navigation applications, automotive or alarm systems, they improve the driving experience for car owners, but these advances do not fundamentally change the set of capabilities associated with the automotive industry (Granstrand et al., 1997).

Disruptive product innovations based on artificial intelligence create a new offering group or replace existing goods or services. For example, the use of self-driving buses in urban transport, such as those currently deployed in some regions of Switzerland, could, if successful, replace public transport bus drivers, just as taxi drivers are there is a possibility of driverless cars becoming popular. This type of AI-based innovation may fundamentally change the capabilities of the public transportation industry, while potentially augmenting previously critical capabilities, such as human driving skills and geographic knowledge.

Capability-disruptive process innovations represent a fundamentally new way of producing a particular offering, such that existing knowledge and skills in a particular organization or industry become obsolete. For example, in advertising, companies use artificial intelligence to suggest digital media purchases. Based on multivariate testing of audiences, bids, keywords, targeting, domains, and locations, AI-based machines provide tailored purchase suggestions to the target community. This completely changes the previous process of buying digital media and makes digital media buyers without the need for specialized skills. Regardless of whether capability-disruptive innovations create new offerings or enable entirely new processes, they can profoundly change the capabilities associated with an industry, thus displacing previous skills, capabilities, and technologies.

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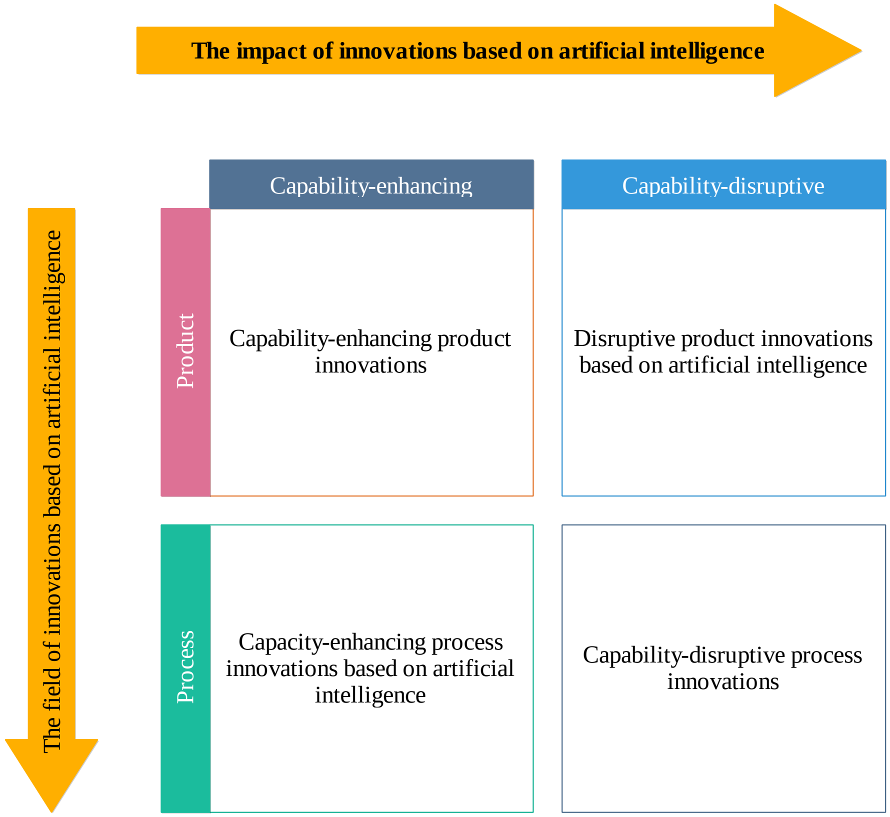

Fig. 2 Typology of innovations based on artificial intelligence and their effects on capabilities

4 Application of Artificial Intelligence Typology

The presented typology of this research will be useful for decision makers in at least four important areas. a) Managers can use the typology as an analytical tool to predict how artificial intelligence-based innovations will affect their organization's capabilities. When managers examine which of their processes or products will be affected by AI and whether the results can enhance or destroy capabilities, they can more fully understand their company's exposure to AI-based risks or opportunities. Be informed and plan accordingly.

b) Managers can use this framework to chart how AI affects the competencies of their strategic partners. Just as switching partners to a supplier that has been identified as AI can lead to increased competence in products or processes, it can also be beneficial for downstream or upstream value chain supply companies. For example, a retailer that predicts customer demand more accurately with AI can not only improve cash flow and inventory management for itself, but also offer better programs for transportation companies that supply its warehouse inventory (Adobor et al., 2023). Managers can benefit from understanding the diversity of AI innovations and creating a competitive advantage. Even if they never embrace AI, they collaborate with people familiar with increasing abilities and methods.

c) Executives and senior managers can use this typology as a framework to discuss their organization's set of strategic innovations. For successful AI-based innovation, a consumer goods manufacturer may invest in projects that enhance capabilities in products, processes, or both. Companies with higher technology, such as Amazon, may struggle to undermine existing capabilities in the industry and implement greater risks in bolder initiatives. This typology can help managers decide which AI-driven innovation situation is best for their particular success.

d) Managers can use this typology as a tool to identify valuable or disruptive changes in AI-based innovations in their industry's products and processes. Companies have been victims of the innovation dilemma in the past, which occurs when new and unexpected competitors adopt new technological innovations and take over the market of existing companies, and in some cases even cause the failure of large companies (Birnbaum, 2024). Improvements based on artificial intelligence happen quickly, and monitoring the impact of artificial intelligence in a company and its competitors on product and process capabilities should be part of the company's continuous strategic planning more than once (Kakatkar et al., 2020).

Many of the most widely used management tools and frameworks have stood the test. They are easy to use and useful, allowing managers to focus on the key elements. According to the research of Toshman and Anderson (1986), the typology presented in the present study provides direct knowledge of the effects of AI-based innovations on the organization and industry in the hands of people who seek to identify such an effect.

5 Limitations of Artificial Intelligence

Artificial intelligence systems can bring profound and pervasive changes to companies, fundamentally reshaping the way they operate, compete, and thrive. Today's significant research and development efforts in artificial intelligence have widely addressed this field (Mirbabaie et al., 2022) Generalized artificial intelligence, also known as strong artificial intelligence, aims to develop machine intelligence that can turn its hands to anything. This goal is too ambitious and some might argue that it is not worth pursuing. The current research focuses on applied artificial intelligence, which is sometimes known as weak artificial intelligence (Armstrong et al., 2014). These systems simulate human intelligence for specific tasks to produce business intelligence programs or machines. The third type of artificial intelligence, artificial Superintelligence, has so far been known mainly from science fiction and from the predictions of Stephen Hawking and Elon Musk that we will reach a point where artificial intelligence will far exceed the knowledge and abilities of humans (Mirbabaie et al., 2022). This may lead to "technological singularity" and profound and incomprehensible changes in human civilization.

While the AI cloud may still be a reality in the near future, warnings from people like Musk and Hawking should neither be ignored nor treated as mere speculation. Designing and implementing this generation of computational tools presents diverse legal, normative, and ethical challenges to existing social, economic, and political institutions (Cellan-Jones, 2014). Changes or even the relocation of a wide range of jobs, the capacity of AI to exacerbate economic, racial, or other inequalities, and the challenges of AI to existing rights and freedoms in societies are just a few of these concerns (Wheeler, 2013).

Managers should consider three limitations of business-specific artificial intelligence systems.

1. In addition to the significant time and expense required to implement AI, decision makers should consider its interoperability with other information systems and platforms (James et al., 2015) . Currently, the lack of standards leads to a mismatch between collaboration and use in the AI application. McKinsey estimates that for this reason, 40% of the potential benefits of artificial intelligence may not be realized (Southgate, 2020)

2. Managers should be careful, consider the quality of data used to train artificial intelligence systems. Educational data can be incomplete, deliberate, or invariable, as it is usually extracted from limited, non-representative, or poorly defined samples. This deficiency may lead to the implementation of deliberate learning algorithms that, in addition to the full outputs of the handouts, can lead to statistically irresistible output. For example, since most educational data is labelled by humans, human conspiracies and cultural hypotheses can be transferred to algorithms and thus to the output of an artificial intelligence system.

3. Decision makers should also carefully design privacy measures. The intelligence of any artificial intelligence system depends on receiving the right amount of training data, and the development of more complex systems increasingly depends on the nature of the training data. Therefore, managers should be ready to answer questions such as how to provide information, obtain consent, or access to personal data. Also, since learning algorithms are constantly changing, even the scientists who created them sometimes face challenges from the results (Chappell & Teven, 2023).

6 Conclusion

Despite the limitations of AI, managers and entrepreneurs who want to take advantage of the capabilities of applied AI need to understand the fundamental parts and implications for organizational capabilities. It is hoped that the present study will provide enlightening perspectives on these sectors and implications, helping CEOs and senior managers to take advantage of the innovation opportunities associated with AI, while warning them about its risks and limitations.

In describing the six constituent parts of artificial intelligence and providing a typology to help predict the effects of artificial intelligence, it is hoped to motivate more rigorous research on artificial intelligence in the organizational context. Artificial intelligence has already changed the way businesses work and do business. While many current applications of artificial intelligence enable capability-enhancing innovations, continued and massive advances in machine learning, reasoning, and problem solving are leading to capability-disrupting innovations that will fundamentally change how businesses operate, compete, and thrive. They change but also rebuild.

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