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Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation?

Prince Chacko Johnson [a], Christofer Laurell [c], Mart Ots [a], Christian Sandström [a,b,*]

[a] Jönköping International Business School, Box 1026, Jönköping 55111, Sweden
[b] The Ratio Institute, P.O. Box 3203, Stockholm SE-10364, Sweden
[c] Einride, Regeringsgatan 65, Stockholm 11156, Sweden

A R T I C L E I N F O

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A B S T R A C T

Digitalization has altered many assumptions underpinning research on innovation management. At the early innings of exploring how digital innovation management stands out, there is a need for further studies in this area. Previous research on how firms use artificial intelligence has distinguished between automation and augmentation of human activities. In this paper, we explore how firms implement artificial intelligence within research and development. Utilizing an international news database spanning 956 articles from 122 newspapers published in 2020, we find that artificial intelligence is primarily adopted to augment human activities (55%) within research and development, rather than to automate matters (11%). We observe differences across sectors where automation is more common in government, information and communication technology (ICT), and technology and software. Our systematic coding shows that artificial intelligence is primarily adopted for exploration research and development (64%), rather than exploitation (5%). Based on these findings, we conclude that research and development from artificial intelligence primarily focuses on novel markets and areas of operations, rather than enhancing existing product markets and activities. Moreover, it augments human labor rather than replaces it; hence, job losses related to artificial intelligence do not seem to be taking place within research and development.

1. Introduction

How does digitalization affect the ways firms organize and manage their innovation processes? With digitalization, innovation is no longer a delimited phenomenon with a central locus of agency that is bounded by space and time. Therefore, scholars increasingly explore digital innovation management as a new avenue for research. Previous studies have highlighted the effects of digital technologies on innovation agents, such as organizations or individuals (Nambisan et al., 2017).

This paper addresses one such aspect of the interrelationship between innovation management and digitalization, namely how and to what extent artificial intelligence (AI) results in the automation or augmentation of research and development (R&D) work. A recent paper on whether AI results in automation or augmentation draws on paradox theory and argues that these two effects are not necessarily mutually exclusive, but rather interdependent over time and across functions (Raisch and Krakowski, 2021). These findings emphasize the importance of looking more closely at AI's effects on innovation management and R&D to find out whether this is also the case in such a setting.

We also address whether the implementation of AI is primarily related to exploration R&D or exploitation R&D (March 1991) – that is, whether AI is employed with the objective of creating new product areas and expanding markets or increasing efficiencies. As these different modes of R&D are usually associated with varying managerial routines and organizational structures (O'Reilly and Tushman, 2011), an investigation into AI's impact on R&D may have important managerial implications.

We investigate these issues by performing a content analysis of international news press, specifically articles covering AI in R&D. Using the Proquest ABI/INFORM database, which covers many of the world's leading news outlets related to business, technology, and trade, a structured search identified 1 287 newspaper articles on AI in R&D

* Corresponding author at: Jönköping International Business School, Box 1026, Jönköping 55111, Sweden.
E-mail address: christian.sandstrom@ju.se (C. Sandström).

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published in 2020. By qualitatively coding these articles and classifying them into different industrial applications, we describe the present state of AI in R&D processes concerning automation/augmentation and exploration/exploitation, while also addressing the interrelationship between these two categorizations.

In the next section, we review recent literature on AI and look at our research question in greater detail. We then describe our employed method. Subsequently, our results are presented and discussed, followed by a concluding remark.

2. Theoretical background: artificial intelligence and innovation management

AI-based solutions can be defined as systems with the ability to act intelligently, correctly interpreting external data, and using these objectives to execute particular tasks by a flexible configuration, even to the extent of reproducing human behaviors with cognitive, social, and emotional intelligence (Di Vaio et al., 2020). AI has become a major area of research in almost every field, including engineering, medicine, business management, science, law, and marketing, in the 21st century (Oke, 2008). AI refers to machines performing cognitive functions usually associated with human minds, such as learning, interacting, and problem-solving (Nilsson, 1971). The application of AI is rapidly diffusing into organizational tasks previously considered exclusive for humans, such as performing human cognitive and non-routine work (Brynjolfsson and Mitchell, 2017). Due to technological development and increasing computational power, AI has been progressing from solving "narrow" tasks and well-specified objectives towards "broader" tasks and more ambiguous or multifaceted ends, for instance, in social interaction, design, arts, science, or creativity and innovation (Amabile, 2020; Tegmark, 2017). Recent advances in computation capabilities, the extensive increase in data availability, and new machine learning techniques will allow organizations to execute managerial activities with the help of AI-based solutions (Brynjolfsson and McAfee, 2014). Beyond the centrality of data for operating and competing in the age of AI (Gregory et al., 2021; Iansiti and Lakhani, 2020), the accessibility and ownership of organizational and customer data has been recognized as a fundamental advantage for firms to learn faster (Iansiti and Lakhani, 2020) and create innovation using AI (Hartmann and Henkel, 2020).

AI solutions now play major roles in a range of processes for customer selection, human resources, risk assessment in banking and insurance, advertising, scheduling, and routing (Kaplan and Haenlein, 2019; O'Neil, 2016; Ransbotham et al., 2017). Examples of AI solutions in organizations include Unilever's talent acquisition process, Netflix's personalized movie suggestions, and Pfizer's drug discovery processes (Raisch and Krakowski, 2021). Most individuals use some form of AI-based solutions on a regular basis through speech-based assistants (e.g., Siri, Alexa, Google Assistant), smart cars, drones or even some modern computer games (Kaplan and Haenlein, 2019; Krogh, 2018). As AI is becoming increasingly accessible in terms of technological cost, computing power, distribution of competence, and availability to data, more companies employ AI in some of their processes. At the same time, fewer companies look to make AI-driven data analysis an omnipresent core component in how their firms operate and are organized, which is how large tech firms like Amazon, Facebook, Alibaba or Tencent work (Iansiti and Lakhani, 2020; Webb, 2019). These advancements and increasing innovation within the technological domain have resulted in practitioners, researchers, and scholars debating how this would impact the human labor and organizational R&D (Agrawal et al., 2018; Krogh, 2018).

Recently, critical questions have been raised about AI implementation in practice, including asking whether the rapid performance gains that have been made on the technological side through advances in machine learning are slowing down (Furman and Seamans, 2019; Marcus, 2018), whether promised economic performance gains are really materializing (Brynjolfsson et al., 2017), and whether cognitive capacity of firms are really expanding (Keding and Meissner, 2021). Hence, as knowledge about the role/function of AI in firm-level R&D is still in its infancy, there is a lack of empirical research on firm-level use of AI (Furman and Seamans, 2019) and whether firm-level innovation work is aimed at efficiency gains or expansion and growth.

2.1. AI and digital innovation management

AI is central to the digital innovation debate (Appio et al., 2021), as it is part of a wider influence of digitalization on innovation and R&D (Nambisan et al., 2017; Yoo et al., 2012). AI asks new questions (Haefner et al., 2021), forces innovation processes to critically challenge the foundation for existing product and service portfolios (Nylén and Holmström, 2015), and shapes how R&D work is conducted and organized (Cockburn et al., 2018).

Numerous factors have been said to drive this transformation. The modular nature of digital technologies has enabled the creation of new innovations by recombining existing elements in novel ways (Lyytinen, 2021). An AI-driven solution to collect and process in one area can be used in a seemingly unrelated product or service. This has also changed the mode of innovation and R&D into a more distributed and open process, where exploration and variation increasingly occur across firm borders (Benner and Tushman, 2015; Nambisan et al., 2017).

Abundant access to information (Altman et al., 2013) is characteristic of innovation in a world where actions are continuously monitored and tracked, increasing the speed and observability of the innovation process (Bogers et al., 2021). AI is accentuating the network effects of data in R&D processes as firms are increasingly pushed to develop their capabilities to exchange, combine, and process digital information across products, units, and firms (Gregory et al., 2021).

Specifically, AI has features that allow information about process performance, product usage, and customer needs to be sourced (Burström et al., 2021), analyzed, and recombined in novel ways in the innovation process (Trocin et al., 2021). Additionally, AI-enabled data flows are said to shorten the process cycle, thus reducing the time needed to market new innovations (Bughin et al., 2017). Research is only beginning to explore AI's capacity to explore information and provide recommendations in innovation processes, and what it will do to augment strategic decision-making and enable innovative business solutions (Keding and Meissner, 2021; Leyer and Schneider, 2021). The modes in which AI is implemented in R&D work will depend on the technological mindsets and skills among innovation workers (Holmstrom, 2021; Solberg et al., 2020) as well as changing collective understandings about what innovation entails in firms and industries (Lyytinen, 2021).

2.2. Automation, augmentation or both?

It is predicted that AI will affect almost every job function (Iansiti and Lakhani, 2020). Long before the advent of AI, there were fears that automation and robotization would make humans redundant, assuming that there is only a certain amount of work and if it is automated then there is less for humans to do (e.g., Jarrahi, 2018). Contrastingly, while Bughin et al. (2017) concluded that most jobs consist of tasks and routines that could be automated, they also suggested that automation could create more opportunities for humans to work more closely with upcoming technological advancements, providing more time to use human capabilities and innate human skills, as machines would take over more of the predictable activities of a normal work day (Maier et al., 2018). Accordingly, when it comes to the field of AI and management, AI can be categorized broadly into two different applications within organizations: automation and augmentation (Brynjolfsson and McAfee, 2014; Daugherty and Wilson, 2018; Davenport and Kirby, 2016). Automation refers to machines taking over human tasks, whereas augmentation implies that humans work in close collaboration with machines to perform a particular task (Raisch and Krakowski, 2021).

Discussions concerning the role of AI as a complement or substitute in existing organizational tasks and activities are frequent across academia and policy debates (e.g., Furman and Seamans, 2019). At the core of the debate are questions regarding whether “robots”, via *automation*, will make human workers and certain skill sets redundant, or whether AI will mainly be assistants or co-workers doing groundwork, such as data collection, systematization, analysis, and recommendations, thereby *augmenting* process performance and human capabilities and preparing humans to make more well-informed decisions. While recent contributions to research suggest that AI may *both* automate and augment human activities (Raisch and Krakowski, 2021), researchers in the area of innovation and strategy find it increasingly relevant to ask where and when AI is beneficial for product and process performance (Agrawal et al., 2019; Jarrahi, 2018; Verganti et al., 2020).

As automation and augmentation are not mutually exclusive and they interact over time, a recent study concluded that it is not necessarily meaningful to regard them as separate (Raisch and Krakowski, 2021). If automation is applied, a machine is handed the task with little or no involvement by humans and the benefits of this could be the avoidance of human bias (Davenport and Kirby, 2016). On the contrary, augmentation is the process when there is close interaction between humans and machines, allowing the user to complement a machine’s ability with the unique human capabilities, such as intuition and reasoning (Daugherty and Wilson, 2018; Jarrahi, 2018).

The choice of whether to apply AI for automation or augmentation purposes depends on the nature of the task at hand, since narrowly defined routine and structured tasks can more easily be automated, whereas complex, uncertain tasks and broadly defined objectives are (still) more difficult for AI to solve alone (Tegmark, 2017). The latter points to an augmentation approach where humans and machines contribute somewhat different strengths when solving complex tasks. AI is a general purpose technology (Cockburn et al., 2018) and emerging AI innovation discourse shares how AI is promising simultaneous development on several dimensions (Bughin et al., 2017). Some suggestions point at AI being used for R&D work to replace workers in more automated solutions (Brynjolfsson and McAfee, 2014; Krogh, 2018), while others indicate an opportunity to let AI augment human judgment in decision-support systems (Keding and Meissner, 2021; Leyer and Schneider, 2021).

The increased implementation of automation is currently changing the character of innovation management (Haefner et al., 2020), but it is unclear how. To better understand the role of AI in R&D processes that drive towards automation and/or augmentation of firm operations, deeper and more specific explorations of how different firm activities are affected by AI are needed across sectors of the economy.

2.3. Artificial intelligence, exploration or exploitation?

The distinction between exploration and exploitation constitutes an important challenge for organizational R&D. *Exploration* concerns activities aimed to generate new knowledge and includes, for instance, search, experimentation, and systematic efforts to develop innovations that are more uncertain and beyond an organization’s established base of skills. *Exploitation* deals with the refinement of existing assets and execution of activities aimed at monetizing established capabilities (March 1991).

Regarding innovation, the exploration-exploitation typology is often described as the difference between the refinement of an existing technology or the invention of a new one (Winter, 1971). However, it has been noted that AI is not merely a technology, but that it centrally calls for firms to develop and adapt their value-creating processes, business models, and entrepreneurial activities to realize the potential of the technology (Burström et al., 2021; Chalmers et al., 2021). R&D activities related to AI importantly serve to arrange or organize firms’ capabilities and processes/activities to explore or exploit market value, for instance, by engaging with new groups of customers or relating to existing customers in new ways (Garbuio and Lin, 2019; Gregory et al., 2021; Kumar et al., 2019). Decisions on how to focus R&D and use new technology (e.g., AI) for exploration or exploitation purposes are strategically crucial and will influence short- and long-term earning capacity and how firms are perceived by financial markets (Mc Namara and Baden-Fuller, 2007).

While March (1991) and scholars like O’Reilly and Tushman (2011) have highlighted that the ability of organizations to simultaneously explore new domains and exploit existing ones is critical for firms’ survival and growth, it is clear that firms frequently struggle to do so. This challenge is at times referred to as the productivity dilemma (Utterback and Abernathy, 1975). Previous research has identified various factors contributing to firms failing to strike this balance, including established resource allocation procedures (Christensen, 1997), organizational structures (Henderson and Clark, 1990), managerial cognition (Tripsas and Gavetti, 2000), and existing skill sets (Tushman and Anderson, 1986).

It could be hypothesized that the modular nature of digital technologies that allow components to be decomposed and reused in radically new contexts (Lyytinen, 2021) would encourage firms to break existing mental models and focus their R&D efforts on venturing into new territory (Ceipek et al., 2021). Likewise, since the data that feeds the algorithms benefits from wider network economies (Gregory et al., 2021; Lyytinen, 2021), unexpected partnerships between stakeholders from different industries would speak for more exploratory R&D. When asked, most firms tend to see AI as a key to new business and new markets (Ransbotham et al., 2017), yet other reports highlight that firms use AI’s power to exploit their current operations in more efficient ways (Bughin et al., 2017).

Although AI has been said to promise “vast” opportunities for productivity increases and new products and services (Makridakis, 2017, 46), little is known about what firms actually do with AI (Furman and Seamans, 2019). Central to this paper, there is a shortage of knowledge on how firms see the potential of AI and how it guides their R&D activities and priorities. Concerning AI and its application to R&D processes, an issue of critical importance is whether organizations primarily adopt AI to explore new domains of knowledge or to exploit an existing set of skills. As exploration and exploitation require different sets of capabilities, AI may require different sets of capabilities depending on whether it is adopted for exploration or exploitation.

2.4. Synthesis and research problem

The two classifications, namely exploration/exploitation and automation/ augmentations, are useful tools that allow us to explore firms’ strategic choices regarding AI in innovation processes and their realization of AI’s value-creating capacity. Extant research has highlighted that the adoption of AI may result in the automation of human work or the augmentation thereof, even though these two facets of AI adoption are not necessarily mutually exclusive (Raisch and Krakowski, 2021). Although augmentation seems to dominate at present, there is a need for further empirical investigation into automation/augmentation, especially concerning R&D processes.

Moreover, little is known concerning whether AI is primarily applied for exploration or exploitation R&D. As exploration and exploitation demand different organizational routines and behavior, an enquiry into this issue is essential to understand how AI can be managed for R&D processes. Therefore, this paper asks two central research questions:

(1) Is AI primarily adopted for augmentation or automation of R&D activities?
(2) To what extent is AI applied for exploitation and exploration activities in R&D? Additionally, we set out to explore the intersection between automation/augmentation and exploration/ exploitation.

3. Method

3.1. Data collection

To understand the role of AI within firms' R&D in detail, we chose to utilize the international news press, specifically articles containing AI in R&D along with synonyms by using ProQuest's ABI/INFORM database. The ABI/INFORM database features thousands of publications spanning journals, newspapers, wire feeds, and blogs, and is also one of the world's leading databases for research and academic studies. In this study, we decided to look at newspaper publications alone. With the aim of carrying out an international study that could add value to researchers and industries across the globe, we only selected publications in English that also enabled us to analyze the collected data on a larger scale across demographic and regional constraints. AI and R&D were used as keywords when searching the database. Newspaper articles that contained words like AI, R&D, and their synonyms were used.

Newspaper articles published from January 2020 to December 2020 were collected to analyze their contents. A total of 956 articles from 122 newspapers published in this period were collected. The data covered major leading newspaper publications, such as *The Wall Street Journal, The Telegraph, Daily Mail, Business Insider, The Financial Express, The Sun*, and *Times of India*. While the validity of secondary sources, such as newspapers, can be discussed, these sources are internationally recognized as credible. Moreover, the sources were primarily used to provide information on what different firms are doing – for example, descriptive data on the implementation of AI in the R&D process of a pharmaceutical company may be biased in different ways, but whether we observed an augmentation/automation and/or exploration/exploitation is still an analysis that should be possible to do. We welcomed both in-depth case studies and further statistical analysis, our approach can be regarded as open, exploratory, and concerned with general patterns of AI implementation within R&D.

3.2. Data analysis

After data collection, the articles were analyzed by applying qualitative content analysis (Silverman, 2015), which helped us understand the content and code them accordingly. The content analysis was done sequentially, considering the unit of analysis as different industries and starting by analyzing the AI aspect and then the R&D aspect. Each entry was read and categorized into the industry that was being discussed. Thereafter, all articles within the dataset were analyzed and categorized into automation, augmentation, or both, based on the description provided within the news entry and what was written in it. As outlined in Section 2, *automation* is referred to as machines taking over human tasks, while *augmentation* implies that humans work closely with machines to perform a particular task (Raisch and Krakowski, 2021), which guided this step of the coding process.

In the next step, the dataset was categorized into exploration, exploitation, or both, based on the content of the respective articles. As outlined in Section 2, *exploration* concerns activities aimed to generate new knowledge and includes search, experimentation, and systematic efforts to develop innovations that are more uncertain and beyond an organization's established base of skills. Contrarily, *exploitation* deals with the refinement of existing assets and the execution of activities aimed at monetizing established capabilities (March 1991). Considering an industry-level analysis followed by the frequency and percentage of each parameter – that is, (1) Automation, (2) augmentation/automation, or (3) augmentation; and (1) exploration, (2) exploration/exploitation, or (3) exploitation – were analyzed according to their respective industries. Finally, an aggregate of the occurrences of the parameters in relation to AI was analyzed. This helped us understand and get a holistic view of the economy in terms of what parameter is the most important when it comes to AI within firms' R&D.

4. Results and analysis

The results are presented in three steps. First, we look at the overall results where the aggregated data are analyzed. Second, we take a closer look at results concerning automation/augmentation and exploration/exploitation. In the third step, industries like technology, healthcare, and manufacturing are utilized to illustrate the nuances between the six different parameters industry by industry. A few excerpts from the data are shown in Table 4.

4.1. Overall findings

Table 1 depicts the frequency of automation, augmentation, or both concerning R&D activities, such as exploration, exploitation, or both. As the table illustrates, most momentum is found in the intersection between augmentation and exploration, even though a considerable number of initiatives are taken in the intersections between (1) automation and augmentation, and exploration; (2) automation and augmentation, and exploration and Exploitation, and (3) augmentation, and exploration and Exploitation. Tables 2 and 3 depict the classification of each industry corresponding to AI and R&D, respectively.

Two illustrative examples drawn from the dataset on how AI influences R&D in a more general sense were:

Table 1
Automation, augmentation, exploration and exploitation distribution.

	Exploitation	Exploration	Exploitation and exploration	Total
Automation	4%	4%	3%	11%
Augmentation	1%	43%	11%	55%
Automation and augmentation		17%	17%	34%
Total	5%	64%	31%	

Table 2
Industry classification based on AI.

Industries	Automation	Augmentation	Automation and augmentation	Grand total
Software technology	3	108	62	173
Government	2	100	44	146
ICT	33	48	60	141
Healthcare	6	80	36	122
Research	3	27	45	75
Education		54	12	66
Finance		26	12	38
Manufacturing	22	8	3	33
Astronomy	3	15	12	30
Pharma	12	9	6	27
Government		20	3	23
Automobile		3	14	17
Biotechnology		3	6	9
Agriculture			9	9
Agriculture		9		9
Manufacturing	8			8
Transport		6		6
Archaeology	3			3
Fitness	3			3
Environment		3		3
Recruitment		3		3
Humanities and music		3		3
Food engineering			3	3
Media		3		3
Mining			3	3
Grand total	98	528	330	956

Table 3
Industry classification based on R&D.

Industries	Exploitation	Exploration	Exploration and exploitation	Grand total
Software technology		110	63	173
Government	3	94	49	146
ICT	30	69	42	141
Healthcare	3	101	18	122
Research		42	33	75
Education		57	9	66
Finance		29	9	38
Manufacturing	3	13	17	33
Astronomy		24	6	30
Pharma		21	6	27
Government		11	12	23
Automobile		6	11	17
Biotechnology		3	6	9
Agriculture		6	3	9
Agriculture			9	9
Manufacturing		8		8
Transport		6		6
Archaeology	3			3
Fitness			3	3
Environment		3		3
Recruitment			3	3
Humanities and music		3		3
Food engineering			3	3
Media		3		3
Mining		3		3
Grand total	42	612	302	956

> Inventing AI, found that the number of patent applications received annually with AI subject matter more than doubled from 2002 to 2018, from 30,000 to 60,000 applications. Also, a whopping 42% of our technology classes contained AI-related subject matter. This is a clear indication of both the importance of the technology and of how much it has permeated our society. As the world adopts 5G, as sensors and transmitters continue to be embedded into every known product, and as quantum computing is commercialized, this number will only rise. (Targeted News Service, 2020)
>
> AI that understands the world as well as humans — will eventually speed up the pace of research and development and cause an exponential increase in innovation. Many believe this is the real threat to international peace and stability. Countries know this. Already in 2017 Russian president Vladimir Putin said AI was "the future not only of Russia but of all of mankind" and proclaimed that "whoever becomes the leader in this sphere will become the ruler of the world". US and Chinese policy documents reveal a similar worldview. The executive order on AI signed by US President Donald Trump in early 2019 states that "continued American leadership in AI is of paramount importance to maintaining the economic and national security of the US". China's New Generation Artificial Intelligence Development Plan notes that "AI has become a new focus of international competition" and that "AI is a strategic technology that will lead in the future" (Lynge, 2020).

4.2. *Automation, augmentation, or both?*

Fig. 1 presents the industries identified in our data, namely 20 industries. Entries that contained activities of various industries or joint ventures are mentioned under multiple industries. As seen in the figure, technology, government, healthcare, and education were the most dominant industries. The figure also illustrates that augmentation is adopted in most industries. An exception can be noted in both the manufacturing and the electronics industries, where automation stands out. Furthermore, it can be seen that the technology and software industry along with government and healthcare considerably emphasize the importance of automation and augmentation.

4.3. *Exploration, exploitation, or both?*

Fig. 2 presents the identified industries and the R&D activities AI is applied to. As depicted in the figure, the healthcare, technology and software, government, and education industries dominate in the exploration side of R&D activities. The rise of exploration with healthcare during this period could be explained by COVID-19. A certain level of exploitation can be seen in electronics and manufacturing. A combination of exploration and exploitation can be seen within the technology and software, government, and ICT industries. Moreover, a rise in exploration within the educational industry is noticeable.

4.4. *Illustrations from different industries*

In the sub-sections that follow, the technology, healthcare, and manufacturing industries are utilized to illustrate the nuances between the six different parameters as they manifest industry by industry.

4.4.1. *Healthcare*

Fig. 3 presents the occurrences of AI with respect to R&D activities within the healthcare industry, with the focus on the exploration aspect of R&D. Within the exploration area, more than 60% is augmentation, while the rest is seen to use both automation or automation and augmentation. With COVID-19 hitting the world in 2020, almost every healthcare company has been working or researching to explore new ways of finding vaccines and drugs, which would explain the rise in the exploration side, compared to other R&D activities like exploitation. One of the entries stated, "AI is being utilized in biotech to help create drugs and vaccines at lightning speed."

However, there is still some importance given to automation. This is especially the case in articles recounting how companies used automated machines to make capsules for certain drugs. It was also noted that these firms used a mix of automation and augmentation for such cases.

4.4.2. *Software technology*

Fig. 4 depicts the R&D activities regarding AI within the technology and software industry. This figure shows that a lot of attention was given to augmentation with respect to the exploration side of R&D. In one illustrative example, a company representative stated:

> We're excited about what this [exploration] means for the industry. It really accelerates R&D to warp speed, but it is also capable of making kilograms per day of high-value, precisely engineered quantum dots. Those are industrially relevant volumes of material.

Within exploration, there was no sign of automation, yet a little emergence could be seen while considering a mix of exploration and exploitation happening simultaneously. The technology and IT sector has been thriving over the last couple of years and the implementation and adoption of AI escalates the exploration process of R&D activities within firms. A joint approach of automation and augmentation happening simultaneously can also be observed.

4.4.3. *Manufacturing*

Fig. 5 illustrates the R&D activities regarding the adoption of AI within the manufacturing industry. As it can be seen, automation stands out in this industry. Under every process of R&D, automation has the highest number of occurrences. Most of these were firms involved in making parts for automobiles or other machines. Within exploitation, it can be seen that automation is the only form of AI implementation that occurs.

5. Discussion

Table 1 along with Figs. 1–5 provides important observations and

Table 4
Excerpts and examples of different occurrences of AI in R&D.

	Exploitation	Exploration	Exploitation and exploration
Automation	"A new technology, called Artificial Chemist 2.0, allows users to go from requesting a custom quantum dot to completing the relevant R&D and beginning manufacturing in less than an hour. The tech is *completely autonomous*, and uses artificial intelligence (AI) and *automated* robotic systems to perform multi-step chemical synthesis and analysis. Quantum dots are colloidal semiconductor nanocrystals, which are used in applications such as LED displays and solar cells…. 'We're excited about what this means for the specialty chemicals industry. It really accelerates R&D to warp speed, but it is also capable of making kilograms per day of high-value, precisely engineered quantum dots. Those are industrially relevant volumes of material'." (Targeted News Service, 2020)	"Exscientia, a clinical-stage Artificial Intelligence (AI) drug-discovery company and SRI International (SRI), a research center headquartered in Menlo Park, California announced today that the companies have entered into a drug-discovery collaboration agreement to implement a new approach to drug discovery by integrating AI design with automated compound synthesis. Through the collaboration, the companies will combine SRI's fully automated SynFini™ synthetic-chemistry system with Exscientia's Centaur Chemist™ AI platform to expedite discovery of selective molecules for a high value oncology target." (Targeted News Service, 2020) "FinHub has spearheaded agency efforts to encourage responsible innovation in the financial sector, including in evolving areas such as distributed ledger technology and digital assets, *automated* investment advice, digital marketplace financing, and artificial intelligence and machine learning. Through FinHub, market and technology innovators as well as domestic and international regulators have been able to engage with SEC staff on new approaches to capital formation, trading, and other financial services within the parameters of the federal securities laws. Designating FinHub as a stand-alone office strengthens the SEC's ability to continue fostering innovation in emerging technologies in our markets consistent with investor protection." (Asia News Monitor, 2020)	"'Traditionally, sampling is labor-intensive and done manually, with growers and their agronomists having to closely monitor the changes in the numbers of pests across hundreds of cotton plant leaves on a weekly basis to determine if control action is required,' Dr McCarthy said. 'We identified that machine vision could automate the pest counting on each leaf by using infield cameras and image analysis software. We have since enabled these vision detection algorithms to be used on a smartphone device.' 'Through an app, agronomists can then use real-time photo capture for pest counting which offers reduced sampling times, more precise detection and recording of pests, increased sampling consistency between field personnel and improvement for the timing of control decisions'" (Walker, 2020).
Augmentation	"IIT Jodhpur has set up an Incubation and Innovation center in its campus to nucleate a cluster of new age ventures. The Incubation and Innovation center will play a key role in this ecosystem, he added. The focus is on the Deep Tech innovations to nurture start-ups/ entrepreneurs *exploiting scientific discoveries* or meaningful engineering innovations to make transformational changes in technology landscape." (Asia News Monitor, 2020)	"Boston Scientific, a 41-year-old medical device manufacturer. Like other healthcare companies, it had to pivot nearly overnight to address the surge of interest in telemedicine. Prior to the outbreak, many patients, doctors, and insurers still viewed telemedicine with skeptical eyes. Now, Boston Scientific's chief digital health officer thinks it could replace up to 80% of the nearly 884 million in-person physician visits each year. And the company is quickly changing its focus to prepare for that. An augmented-reality-powered application, for example, can superimpose an expert's hand over a user's real-world view to help them set-up new products or even oversee the insertion of devices like pacemakers and catheters. That's just one example of the many to come as emerging technology like automation, AR, virtual reality, and artificial intelligence provide a path forward for companies and customers alike to adapt to the 'new normal'." (Williams, 2020). "Delhi-born Arnav Kapur's Artificial Intelligence-enabled headset, which 'augments human cognition and gives voice to those who have lost their ability to speak', has been named as one of the 100 Best Inventions of 2020 by *Time*. Kapur, a 25-year-old post-doctoral scholar at Massachusetts Institute of Technology (MIT), invented the device called AlterEgo at the MIT Media Lab. He made it to the list under the experimental category. *Time* described AlterEgo as something which 'does not read your thoughts, but it can enable you to communicate with your computer without touching a keyboard or opening your mouth'." (Ray, 2020).	"A $960,000, nine-month National Science Foundation (NSF) Convergence Accelerator grant has been awarded to Penn State researchers to explore faster and more cost-efficient methods of discovering pharmaceuticals using quantum artificial intelligence." (Small, 2020)
Automation and augmentation		"In a hi-tech lab in Seattle, a robot called Isaac has been helping researchers make remarkable breakthroughs in machine learning. Built by Nvidia engineers at its 50-person facility, Isaac uses advanced computer vision to see the world and complete difficult tasks, such as cooking a meal in the lab kitchen. The technology may sound frivolous, but it is just one example of the $300bn (£231bn) US graphics chip company's aggressive research and development agenda in artificial intelligence and robotics. As part of its $40bn takeover of Britain's	"From virtual medical assistance to data analytics, artificial intelligence enhances productivity and frees up time for tasks that require human insight, by augmenting and automating routine activities. Artificial intelligence (AI) is a powerful workforce multiplier that is changing the business landscape. From virtual medical assistance to data analytics, AI enhances productivity and frees up time for tasks that require human insight, by augmenting and automating routine activities." (

(*continued on next page*)

Table 4 (*continued*)

Exploitation	Exploration	Exploitation and exploration
	Arm, Nvidia has laid out its plans for another research laboratory, this time an artificial intelligence lab and world-leading supercomputer in Cambridge." (Field, 2020).	Yeok, 2020). "In a building at the former hospital site in Adelaide there are 130 incredibly skilled artificial intelligence experts quietly working on industries of the future. The University of Adelaide's Australian Institute of Machine Learning (AIML) at the Lot Fourteen innovation precinct wants to revolutionize advanced manufacturing, medicine, agriculture and defense with next-level productivity gains. AIML Director Professor Anton van den Hengel says machine learning will underpin the future of almost all industries, enabling efficiency and productivity changes to keep Australia on the international stage. 'Over the course of the last decade computer vision has gone from a mathematical research area to being the core of modern artificial research intelligence, ' van den Hengel says. 'It's the technology of the future of driverless cars, of mining, of agriculture; almost every application you can think of, this technology will revolutionize it.'" (Barrett, 2020).

managerial implications on the current state and effects of AI on firms' R&D. It appears that AI has resulted in the augmentation of human work within R&D, potentially transforming current jobs and imposing demands on new skill sets.

This finding suggests that firms do not primarily use AI within R&D to improve and perform existing operations more cost-efficiently. Rather, our results suggest that the studied AI-based R&D initiatives are undertaken with the aim to improve and extend the value-creating potential of organizational activities. Around 90% of the articles in our dataset represented initiatives where augmentation was a central

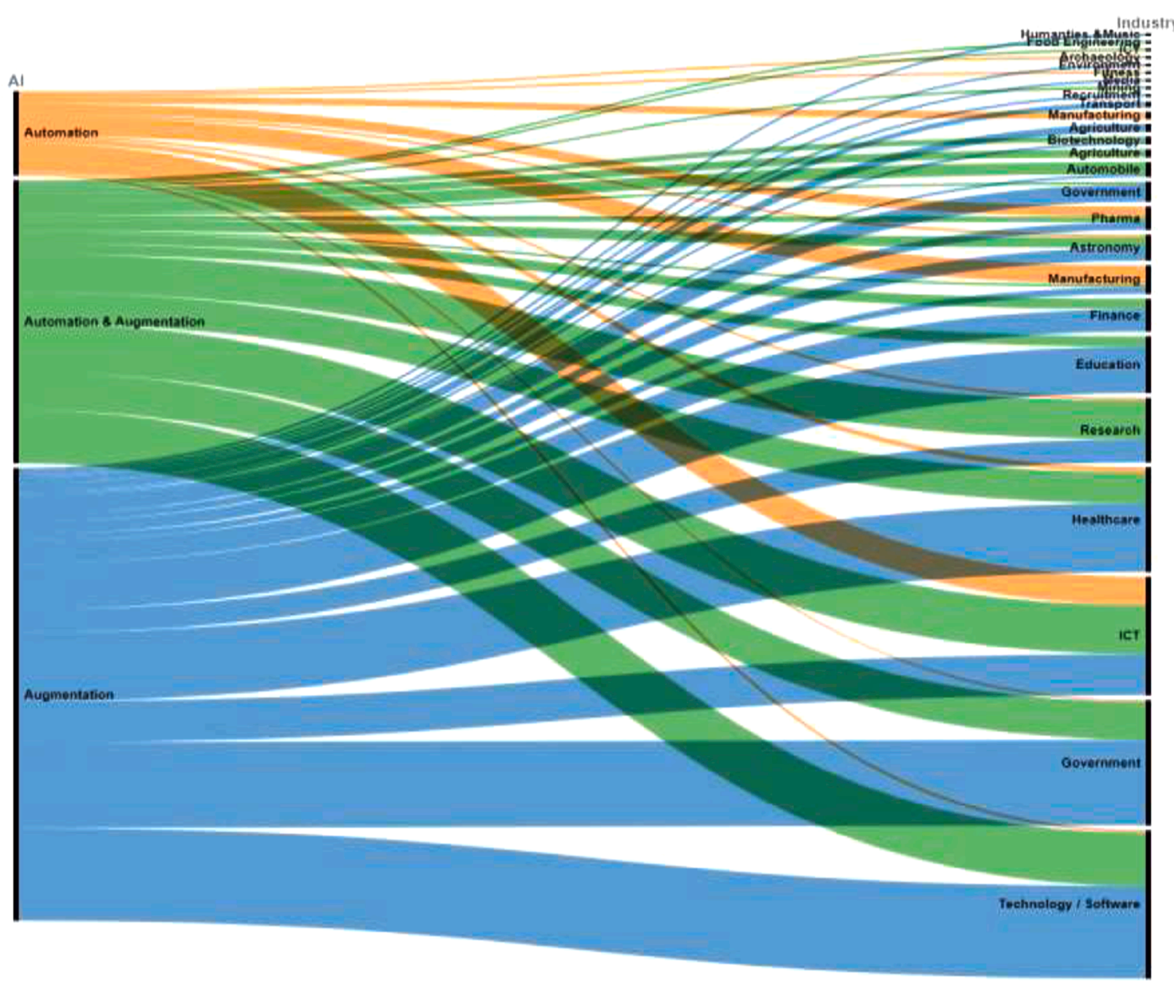

Fig. 1. AI in different industries.

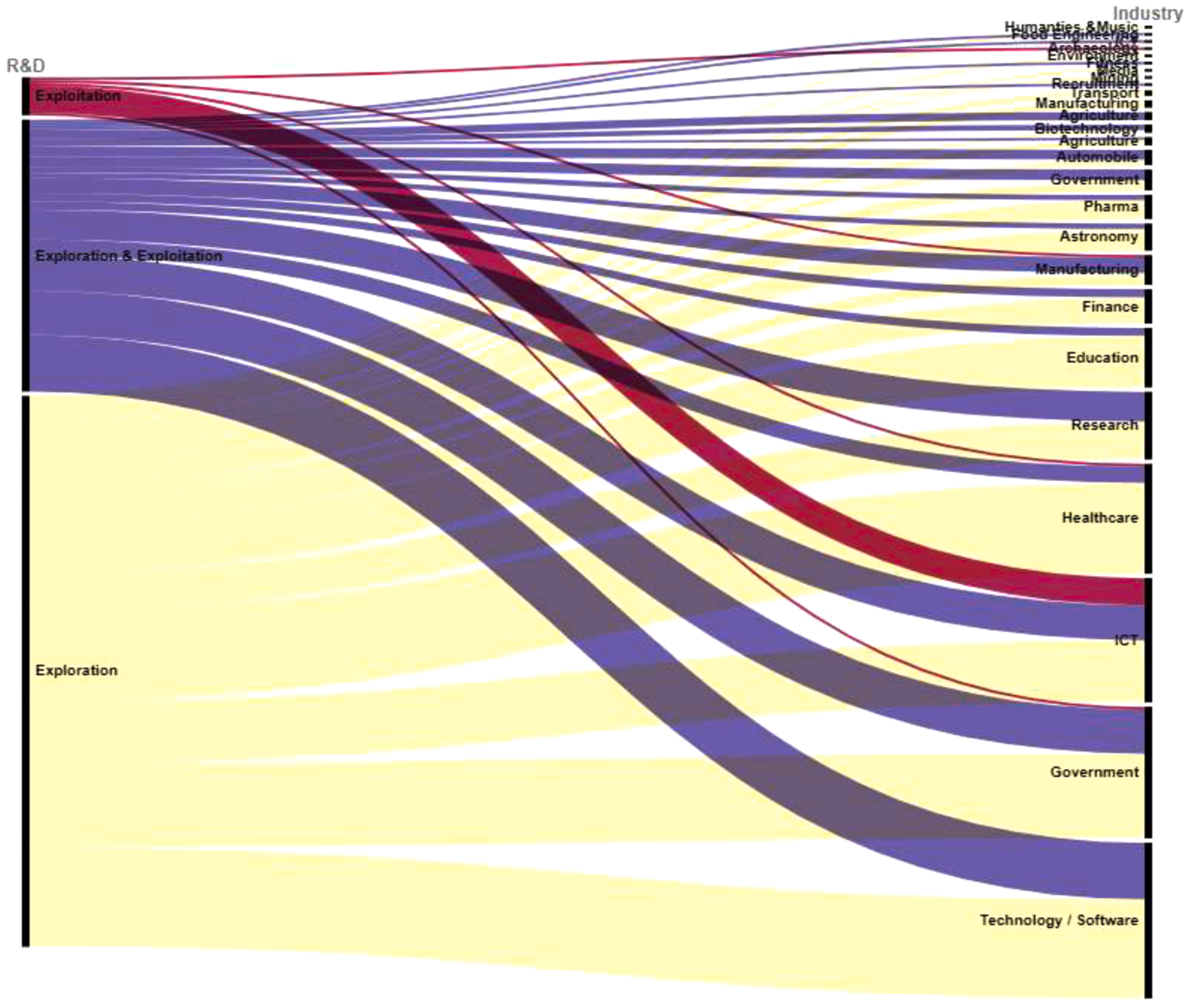

Fig. 2. R&D in different industries.

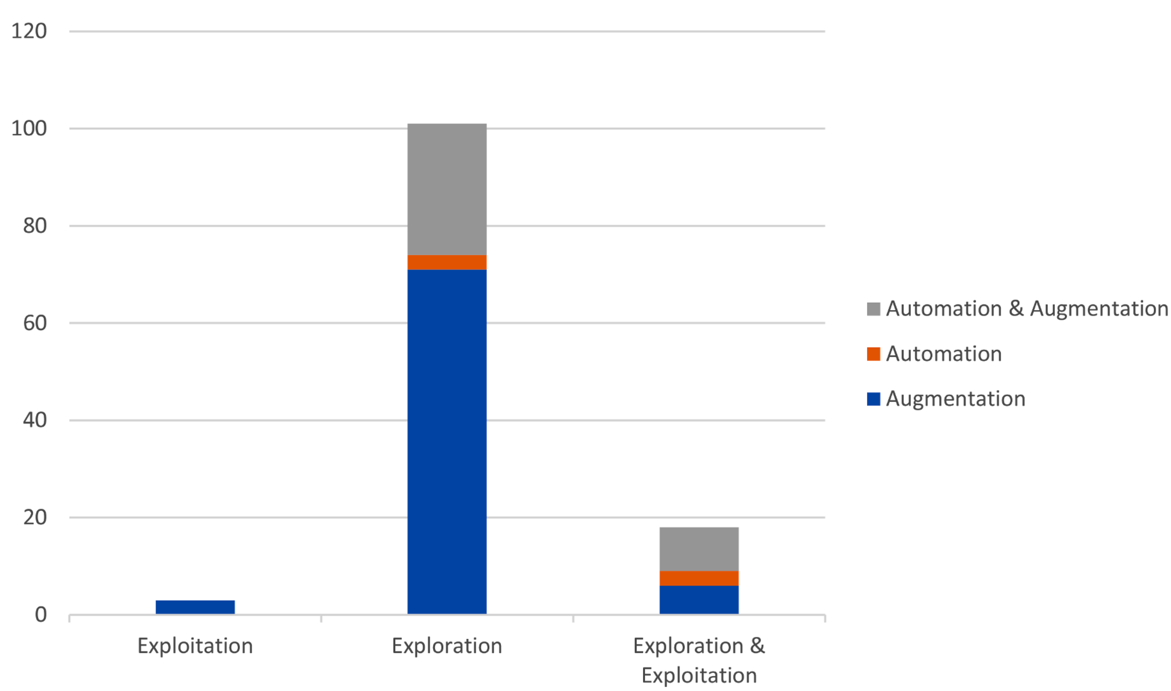

Fig. 3. AI and R&D in healthcare.

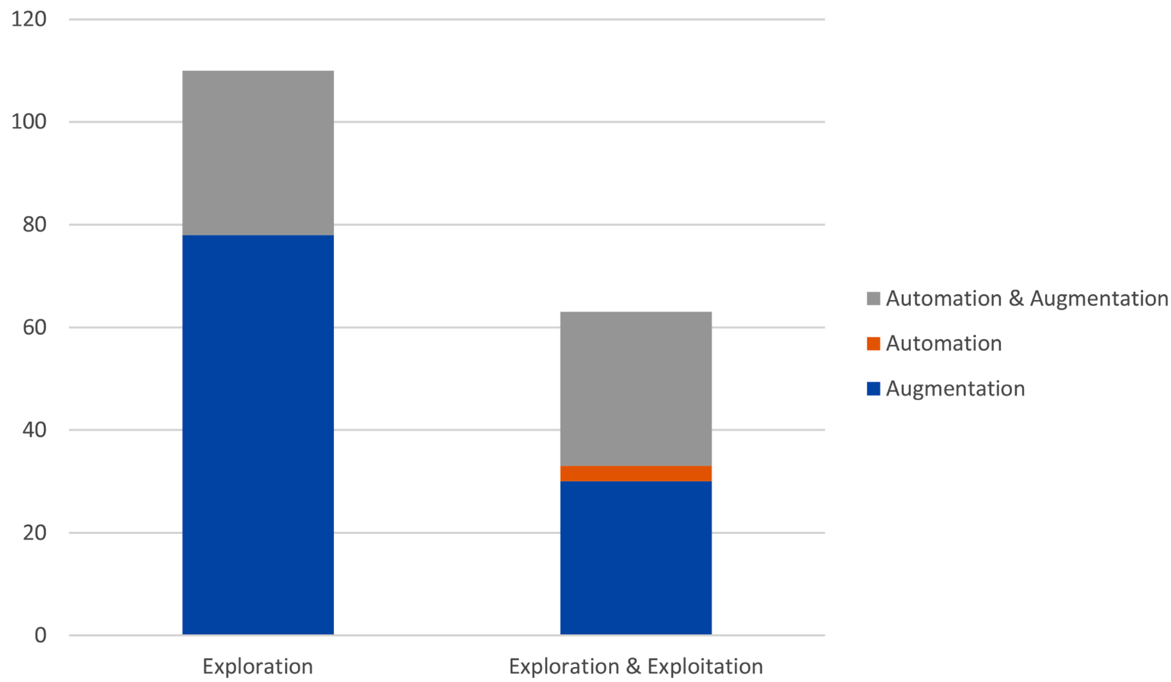

Fig. 4. AI and R&D in software technology.

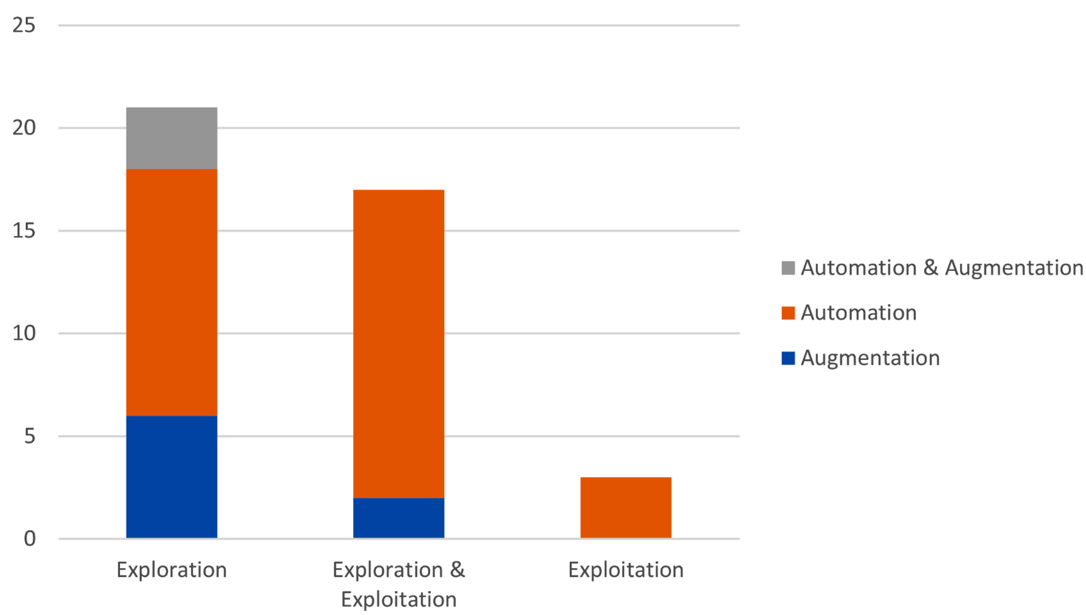

Fig. 5. AI and R&D in manufacturing.

component, with AI complementing, supporting, and facilitating existing human-led processes and practices. Consequently, concerns regarding the displacement of human jobs seem to have been exaggerated, at least within R&D, since only 10% of our data concerned automation. These findings are in line with recently published work (Raisch and Krakowski, 2021) and support earlier observations that the use of fully automated AI-enabled processes are still rare outside specific, controlled, and predictable environments in industrial manufacturing (Cockburn et al., 2018).

Examples of data-driven firms like Google, Baidu, and Uber (Iansiti and Lakhani, 2020) show how their organizational designs and processes are built from the management of data, but they are not void of humans. Likewise, based on our data, we can expect more firms to aim their innovations to integrate AI-enabled data processing in their various operations, and gradually organize themselves to accommodate this (not the same as being automated organizations). Moreover, the process of firms' R&D will uncover the need for new human jobs and functions that are yet to be invented (Acemoglu and Restrepo, 2018).

The consequences of AI-augmented innovation work include significantly lowered search costs and increased speed in R&D processes (since AI continuously processes vast amounts of information, for instance, in the search for improved product formulae, or product/process performance), but also that human R&D competences and knowledge will need to be less specialized and sector-specific (Cockburn et al., 2018). Such projections can cause some concerns in relation to studies showing R&D managers to develop greater trust in and reliance on AI than the accuracy the algorithm sometimes deserves (Keding and Meissner, 2021; Leyer and Schneider, 2021). However, for the foreseeable future, the environments of innovation management that are open to (and increasingly require) external influence will contain too many uncertain factors to make it suitable for AI automation (e.g., Cockburn et al., 2018). Nevertheless, as more firms implement and test AI to augment R&D activities, we could expect two things to happen. First, AI as a decision support improves due to improved algorithms and more input data in the machine learning models; and second, organizational workers with gained experience become more experienced and aware of the merits and limitations of AI as decision support in R&D processes.

These findings are consistent with the arguments by Raisch and Krakowski (2021), in the sense that tensions between automation and augmentation seem exaggerated and that, in many cases, AI implementation is a matter of automation *and* augmentation. As can be seen in Table 1, about a third of the covered material concerns an overlap between automation and augmentation. Raisch and Krakowski (2021) argued that the trade-off argument is overly simplistic as it is limited to a specific task and a certain point in time.

AI is primarily related to exploration. In fact, the majority of articles in the study point solely toward exploratory efforts, wherein firms gear their R&D processes to leverage the opportunities of AI to equip themselves with new competencies or enter new product or market segments. While literature has suggested that AI implementation serves well for exploitation purposes, such as through automated sales bots and more efficient sales prediction and targeting (Chalmers et al., 2021; Liebregts et al., 2020), we see relatively little of this in our data. The focus on exploration could suggest that firms that are not yet data-driven in their organizational designs have difficulties integrating AI with their existing operations, but prefer to focus their AI-related R&D initiatives in areas and teams, separate from the core organization.

Therefore, this study's findings are more in line with predictions that due to the challenges of radically changing established value ecosystems and the incremental development of technology-based competencies and capabilities, (incumbent) firms will initially use AI primarily in limited exploratory and experimental R&D efforts (Burström et al., 2021; Rachinger et al., 2019). While the exploratory application of AI in our R&D data may signal that firms do not know exactly what it can be used for, there is also a hope from managers that AI will open up for novelty, business renewal, and unrelated expansion (Bughin et al., 2017). In addition, we recognize that there are fundamental mechanisms from digitalization on innovation management that include more distributed and open-ended R&D processes drawing on collaborative input from a wider range of external stakeholders (Nambisan et al., 2017). Specifically, networked data exchanges across firm boundaries can enrich AI and improve its performance (Gregory et al., 2021), stimulating the formation of new R&D alliances. Such forces can, beyond the mere novelty of AI, suggest a strategic intent in the dominance of exploratory efforts in our empirical data, indicating a structural change in how R&D work is configured in the digital age.

This leads to the final point of discussion, which focuses on the considerable overlaps between exploration R&D and exploitation R&D in about 20% of the dataset (Table 1). This overlap seems to be greater in certain sectors, such as government, ICT, and technology and software. Previous research has noted that firms tend to pursue not only one, but several different AI functionalities in parallel (Burström et al., 2021). This overlap between initiatives is likely to lead to challenges related to ambidexterity – that is, an organization's ability to simultaneously explore and exploit a certain technology. While some AI initiatives can be seen mainly as learning efforts, the challenges of inducing real business innovation with simultaneous exploration and exploitation R&D should be seen against the rigidities caused by existing internal structures for value creation and the reliance on the external ecosystem to co-evolve. Previous research has documented this issue as a critical challenge for management of R&D (O'Reilly and Tushman, 2011). Our results imply that this challenge may exist regarding R&D and further studies on whether this is the case are welcomed.

We encourage research into how different managerial challenges prevail when implementing AI within the R&D process. As stated in the literature review, previous research has identified a collection of challenges for firms that try to strike a balance between exploration and exploitation, including resource allocation procedures (Christensen, 1997), organizational structures (Henderson and Clark, 1990), managerial cognition (Tripsas and Gavetti, 2000), and the relation between established and new skill sets (Tushman and Anderson, 1986). As existing literature has identified a collection of factors contributing to firms failing to strike this balance, future research could be conducted on how these factors manifest in the case of AI adoption within R&D. As our findings are exploratory and draw on a large set of qualitative sources, further statistical analysis of these results is needed.

6. Conclusion

The purpose of this paper was to investigate the effects of AI on firms' R&D. Specifically, we studied whether AI is adopted in R&D efforts for automation or augmentation and whether it is applied for exploitation or exploration purposes. We compared the results across different sectors of the economy. Taken together, our results contribute to existing literature on this issue (e.g., Raisch and Krakowski, 2021) by presenting empirical illustrations of how the interplay between AI and R&D activities manifest across industries and by showing how AI is being used by organizations worldwide in the context of innovation processes and firms' R&D.

Drawing on a dataset spanning 956 articles from 122 international newspapers, we found that AI is so far primarily adopted for the augmentation of R&D work. Relating to R&D exploration and R&D exploitation, AI is primarily used for exploration rather than exploitation. Therefore, the augmentation of exploration R&D seems to be the most common way to use AI within R&D. Automation is so far limited and concentrated to certain sectors, such as government, ICT, and technology and software. Thus, this study's findings seem to suggest that AI has a role in R&D that is largely in line with recent publications on digital innovation management, where it has been argued that digitalization results in more distributed and open-ended R&D.

This and the fact that 34% of the data reports on a combination of automation and augmentation suggest that AI is presently not adopted for automation purposes. Consequently, we conclude that fears concerning humans being displaced by AI have so far seemed somewhat exaggerated, at least in the case of R&D work.

Author statement

Prince Chacko Johnson contributed with method, data analysis, theoretical framing, writing and presentation of results.

Christofer Laurell contributed with methods, data analysis and framing.

Mart Ots contributed with framing and theory and discussion.

Christian Sandström had the overall responsibility, took part in the framing, literature and discussion.

CRediT authorship contribution statement

Prince Chacko Johnson: Methodology, Formal analysis, data collection, writing, review and framing. Christofer Laurell: Methodology, Formal analysis, data collection. Mart Ots: Conceptualization, theoretical framing. Christian Sandström: Writing review & editing, Conceptualization and theoretical framing.

References

Acemoglu, D., Restrepo, P., 2018. Artificial intelligence, automation and work. National Bureau of Economic Research Working Paper Series, 24196. 10.3386/w24196.

Agrawal, A., Gans, J.S., Goldfarb, A., 2019. Exploring the impact of artificial intelligence: prediction versus judgment. Inf. Econ. Policy 47, 1–6. https://doi.org/10.1016/j.infoecopol.2019.05.001.

Amabile, T.M., 2020. Creativity, artificial intelligence, and a world of surprises. Acad. Manag. Discov. 6 (3), 351–354. https://doi.org/10.5465/amd.2019.0075.

Appio, F.P., Frattini, F., Petruzzelli, A.M., Neirotti, P., 2021. Digital transformation and innovation management: a synthesis of existing research and an agenda for future studies. J. Prod. Innov. Manag. 38 (1), 4–20. https://doi.org/10.1111/jpim.12562.

Barrett, R., 2020. Innovation precinct transforming industry. The Australian, 12 November. Available at: https://www.theaustralian.com.au/special-reports/innovation-precinct-transforming-industry/news-story/846eb69184f6900b3cdc7e2dd4ebc406.

Benner, M.J., Tushman, M.L., 2015. Reflections on the 2013 Decade Award – "exploitation, exploration, and process management: the productivity dilemma revisited" ten years later. Acad. Manag. Rev. 40 (4), 497–514. https://doi.org/10.5465/amr.2015.0042.

Bogers, M.L.A.M., Garud, R., Thomas, L.D.W., Tuertscher, P., Yoo, Y., 2021. Digital innovation: transforming research and practice. Innovation 1–9. https://doi.org/10.1080/14479338.2021.2005465.

Brynjolfsson, E., McAfee, A., 2014. The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. WW Norton & Company, New York, NY.

Brynjolfsson, E., Mitchell, T., 2017. What can machine learning do? Workforce implications. Science 358 (6370), 1530–1534. https://doi.org/10.1126/science.aap8062.

Brynjolfsson, E., Rock, D., Syverson, C., 2017. Artificial intelligence and the modern productivity paradox: a clash of expectations and statistics. National Bureau of Economic Research Working Paper Series 24001. https://doi.org/10.3386/w24001.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., Trench, M., 2017. Artificial Intelligence: The next Digital Frontier? McKinsey Global Institute. Available at. https://www.mckinsey.com/~/media/mckinsey/industries/advanced%20electronics/our%20insights/how%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/mgi-artificial-intelligence-discussion-paper.ashx.

Burström, T., Parida, V., Lahti, T., Wincent, J., 2021. AI-enabled business-model innovation and transformation in industrial ecosystems: a framework, model and outline for further research. J. Bus. Res. 127, 85–95. https://doi.org/10.1016/j.jbusres.2021.01.016.

Ceipek, R., Hautz, J., De Massis, A., Matzler, K., Ardito, L., 2021. Digital transformation through exploratory and exploitative internet of things innovations: the impact of family management and technological diversification. J. Prod. Innov. Manag. 38 (1), 142–165. https://doi.org/10.1111/jpim.12551.

Chalmers, D., MacKenzie, N.G., Carter, S., 2021. Artificial intelligence and entrepreneurship: implications for venture creation in the Fourth Industrial Revolution. Entrep. Theory Pract. 45 (5), 1028–1053. https://doi.org/10.1177/1042258720934581.

Christensen, C.M., 1997. The Innovator's Dilemma: When new Technologies Cause Great Firms to Fail. Harvard Business Review Press, Boston, MA.

Cockburn, I.M., Henderson, R., Stern, S., 2018. The impact of artificial intelligence on innovation. National Bureau of Economic Research Working Paper Series, 24449. 10.3386/w24449.

Daugherty, P., Wilson, H.J., 2018. Human + Machine: Reimagining Work in the Age of AI. Harvard Business Review Press, Boston, MA.

Davenport, T.H., Kirby, J., 2016. Only Humans Need Apply: Winners and Losers in the Age of Smart Machines. HarperCollins, New York, NY.

Di Vaio, A., Palladino, R., Hassan, R., Escobar, O., 2020. Artificial intelligence and business models in the sustainable development goals perspective: a systematic literature review. J. Bus. Res. 121, 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019.

Field, M., 2020. Takeover may help UK tech darling reach new heights – but doubts remain in Silicon Valley. The Sunday Telegraph, 20 September.

Furman, J., Seamans, R., 2019. AI and the economy. Innov. Policy Econ. 19, 161–191. https://doi.org/10.1086/699936.

Garbuio, M., Lin, N., 2019. Artificial intelligence as a growth engine for health care startups: emerging business models. Calif. Manag. Rev. 61 (2), 59–83. https://doi.org/10.1177/0008125618811931.

Gregory, R.W., Henfridsson, O., Kaganer, E., Kyriakou, S.H., 2021. The role of artificial intelligence and data network effects for creating user value. Acad. Manag. Rev. 46 (3), 534–551. https://doi.org/10.5465/amr.2019.0178.

Haefner, N., Wincent, J., Parida, V., Gassmann, O., 2021. Artificial intelligence and innovation management: a review, framework, and research agenda. Technol. Forecast. Soc. Chang. 162 https://doi.org/10.1016/j.techfore.2020.120392. Article 120392.

Hartmann, P., Henkel, J., 2020. The rise of corporate science in AI: data as a strategic resource. Acad. Manag. Discov. 6 (3), 359–381. https://doi.org/10.5465/amd.2019.0043.

Henderson, R.M., Clark, K.B., 1990. Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. Adm. Sci. Q. 35 (1), 9–30. https://doi.org/10.2307/2393549.

Holmström, J., 2021. From AI to digital transformation: the AI readiness framework. Bus. Horiz. https://doi.org/10.1016/j.bushor.2021.03.006.

Iansiti, M., Lakhani, K.R., 2020. Competing in the age of AI. Harv. Bus. Rev. 98 (1), 59–67.

Jarrahi, M.H., 2018. Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making. Bus. Horiz. 61 (4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007.

Kaplan, A., Haenlein, M., 2019. Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus. Horiz. 62 (1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004.

Keding, C., Meissner, P., 2021. Managerial overreliance on AI-augmented decision-making processes: how the use of AI-based advisory systems shapes choice behavior in R&D investment decisions. Technol. Forecast. Soc. Chang. 171 https://doi.org/10.1016/j.techfore.2021.120970. Article 120970.

Krogh, G.V., 2018. Artificial intelligence in organizations: new opportunities for phenomenon-based theorizing. Acad. Manag. Discov. 4 (4), 404–409. https://doi.org/10.5465/amd.2018.0084.

Kumar, V., Rajan, B., Venkatesan, R., Lecinski, J., 2019. Understanding the role of artificial intelligence in personalized engagement marketing. Calif. Manag. Rev. 61 (4), 135–155. https://doi.org/10.1177/0008125619859317.

Leyer, M., Schneider, S., 2021. Decision augmentation and automation with artificial intelligence: threat or opportunity for managers? Bus. Horiz. 64 (5), 711–724. https://doi.org/10.1016/j.bushor.2021.02.026.

Liebregts, W., Darnihamedani, P., Postma, E., Atzmueller, M., 2020. The promise of social signal processing for research on decision-making in entrepreneurial contexts. Small Bus. Econ. 55 (3), 589605 https://doi.org/10.1007/s11187-019-00205-1.

Lynge, H., 2020. Robot nationalism has arrived, and SA will have to plug in too. Business Day, 10 December. Available at: https://www.businesslive.co.za/bd/opinion/2020-12-10-robot-nationalism-has-arrived-and-sa-will-have-to-plug-in-too/.

Lyytinen, K., 2021. Innovation logics in the digital era: a systemic review of the emerging digital innovation regime. Innovation 1–22. https://doi.org/10.1080/14479338.2021.1938579.

Maier, M., Ebrahimzadeh, A., Chowdhury, M., 2018. The tactile internet: automation or augmentation of the human? IEEE Access 6, 41607–41618. https://doi.org/10.1109/ACCESS.2018.2861768.

Makridakis, S., 2017. The forthcoming artificial intelligence (AI) revolution: its impact on society and firms. Future 90, 46–60. https://doi.org/10.1016/j.futures.2017.03.006.

March, J.G., 1991. Exploration and exploitation in organizational learning. Organ. Sci. 2 (1), 71–87.

Marcus, G., 2018. Deep learning: a critical appraisal. arXiv ePrint archive. 10.48550/arXiv.1801.00631.

Mc Namara, P., Baden-Fuller, C., 2007. Shareholder returns and the exploration-exploitation dilemma: R&D announcements by biotechnology firms. Res. Policies 36 (4), 548–565. https://doi.org/10.1016/j.respol.2007.02.012.

Nambisan, S., Lyytinen, K., Majchrzak, A., Song, M., 2017. Digital innovation management: reinventing innovation management research in a digital world. MIS Q. 41, 223–238.

Nilsson, N.J., 1971. Problem-Solving Methods in Artificial Intelligence. McGraw-Hill, New York, NY.

Nylén, D., Holmström, J., 2015. Digital innovation strategy: a framework for diagnosing and improving digital product and service innovation. Bus. Horiz. 58 (1), 57–67. https://doi.org/10.1016/j.bushor.2014.09.001.

Oke, S.A., 2008. A literature review on artificial intelligence. Int. J. Inf. Manag. Sci. 19 (4), 535–570.

O'Neil, C., 2016. Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy. Allen Lane, St Ives.

O'Reilly, C.A., Tushman, M.L., 2011. Organizational ambidexterity in action: how managers explore and exploit. Calif. Manag. Rev. 53 (4), 5–22. https://doi.org/10.1525/cmr.2011.53.4.5.

Rachinger, M., Rauter, R., Müller, C., Vorraber, W., Schirgi, E., 2019. Digitalization and its influence on business model innovation. J. Manuf. Technol. Manag. 30 (8), 1143–1160. https://doi.org/10.1108/JMTM-01-2018-0020.

Raisch, S., Krakowski, S., 2021. Artificial intelligence and management: the automation-augmentation paradox. Acad. Manag. Rev. 46 (1), 192–210. https://doi.org/10.5465/amr.2018.0072.

Ransbotham, S., Kiron, D., Gerbert, P., Reeves, M., 2017. Reshaping business with artificial intelligence: closing the gap between ambition and action. MIT Sloan Manag. Rev. 59, 1–17.

Ray, M., 2020. Delhi-Born MIT Scholar's AI-Headset is one of *Time's* 100 Best Inventions of 2020. Hindustan Time, 22 November. Available at: https://www.hindustantimes.com/science/delhi-born-mit-scholar-s-ai-headset-is-one-of-time-s-100-best-inventions-of-2020/story-EghAZTqVspWTn0kZW97RQI.html.

Silverman, D., 2015. Interpreting Qualitative Data. Sage, London.

Small, S. 2020. Researchers use NSF convergence accelerator to shorten drug discovery timeline. Available at: https://www.psu.edu/news/research/story/researchers-use-nsf-convergence-accelerator-shorten-drug-discovery-timeline/#:~:text=%E2%80%94%20A%20%24960%2C000%2C%20nine%2Dmonth,pharmaceuticals%20using%20quantum%20artificial%20intelligence.

Solberg, E., Traavik, L.E.M., Wong, S.I., 2020. Digital mindsets: recognizing and leveraging individual beliefs for digital transformation. Calif. Manag. Rev. 62 (4), 105–124. https://doi.org/10.1177/0008125620931839.

Tegmark, M., 2017. Life 3.0: Being Human in the Age of Artificial Intelligence. Alfred A. Knopf, New York, NY.

Tripsas, M., Gavetti, G., 2000. Capabilities, cognition, and inertia: evidence from digital imaging. Strateg. Manag. J. 21 (10–11), 1147–1161. https://doi.org/10.1002/1097-0266(200010/11)21:10/11≤1147::AID-SMJ128≥3.0.CO;2-R.

Trocin, C., Hovland, I.V., Mikalef, P., Dremel, C., 2021. How artificial intelligence affords digital innovation: a cross-case analysis of Scandinavian companies. Technol. Forecast. Soc. Chang. 173 https://doi.org/10.1016/j.techfore.2021.121081. Article 121081.

Tushman, M.L., Anderson, P., 1986. Technological discontinuities and organizational environments. Adm. Sci. Q. 31 (3), 439–465. https://doi.org/10.2307/2392832.

Utterback, J.M., Abernathy, W.J., 1975. A dynamic model of process and product innovation. Omega 3 (6), 639–656. https://doi.org/10.1016/0305-0483(75)90068-7 (Westport).
Verganti, R., Vendraminelli, L., Iansiti, M., 2020. Innovation and design in the age of artificial intelligence. J. Prod. Innov. Manag. 37 (3), 212–227. https://doi.org/10.1111/jpim.12523.
Walker, K., 2020. Silverleaf Whitefly Detection Apps Under Trial. Queensland Country Life, 22 July. Available at: https://www.queenslandcountrylife.com.au/story/6835675/detecting-crop-pests-with-artificial-intelligence/#!.
Webb, A., 2019. The Big Nine: How the Tech Titans and Their Thinking Machines Could Warp Humanity. Hachette, New York, NY.
Williams, J., 2020. Innovation Inc: the telemedicine push and how the digital era will impact businesses and consumers. Business Insider, 6 July. Available at: https://www.businessinsider.com/innovation-inc-how-the-telemedicine-surge-signals-our-digital-future-2020-7?IR=T.
Winter, S.G., 1971. Satisficing, selection, and the innovating remnant. Q. J. Econ. 85 (2), 237–261. https://doi.org/10.2307/1880703.
Yeok, C.S., 2020. Changing the Business Landscape with AI. The Business Times, 9 October. Available at: https://www.businesstimes.com.sg/opinion/changing-the-business-landscape-with-ai.
Yoo, Y., Boland, R.J., Lyytinen, K., Majchrzak, A., 2012. Organizing for innovation in the digitized world. Organ. Sci. 23 (5), 1398–1408. https://doi.org/10.1287/orsc.1120.0771.

Prince Chacko Johnson is an engineer by background and has worked in the IT industry prior to obtaining his MSc in management. He is presently a PhD candidate at Jönköping International Business School with a special interest in Artificial Intelligence and its application in mature industries.

Christofer Laurell is associate professor of innovation management at the Royal Institute of Technology in Stockholm Sweden and senior vice president at Einride. His research concerns the interplay between innovation and institutional change in sectors such as fashion, the sharing economy and crowdfunding.

Mart Ots is associate professor in marketing at Jönköping International Business School. His research concerns media management, artificial intelligence and branding.

Christian Sandström is Senior Associate Professor at Jönköping International Business School in Digital Business and affiliated with the Ratio Institute. His research interests concern digitalization and the managerial challenges related to it.