Strategy and artificial intelligence

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Abstract:
Given the rapid development over the past decade of methods qualified as "artificial intelligence" (AI), questions arise about how these methods might fit into a firm's strategies, or even replace them. This view overlooks the aspects of strategy-making that are marked with a high degree of uncertainty and many an ambiguity. The limitation inherent in building tools for decision-making that massively rely on sets of data restricts somewhat the possibilities. Although it is unlikely that AI will eventually steer a firm's strategic decisions, its use in corporate strategies is already a reality that is modifying the architecture of resources and qualifications within firms. This new architecture of the creation of value requires an internal reorganization for it to be deployed in business process strategies. Given the nature of the decisions automated by AI, it is imperative for firms to set up a body of governance that will define the doctrine for using such a technology.

Deep Knowledge Ventures, an investment fund, announced, in 2017, that artificial intelligence (AI) had been holding a seat on its board of directors for several years; and Mark van Rijmenam, a founder of Datafloq, has confirmed that forms of artificial intelligence will continue sitting in board rooms.[1] Paradoxically however, the firms that use AI the most have not made room for it on the board. Such is the case of Amazon, Facebook, Google, Uber and Apple, all of which won very solid positions in competitive markets in a relatively short time. This paradox clearly illustrates the difficulty of assessing AI's role and its relation to corporate strategies.[2]

The actual progress of AI (evidence of this being OpenAI's GPT-3 or Heron System's unmanned vehicle which beat the pilot of USAF 5-0 in a simulated dogfight)[3] is leading firms to wonder how AI should fit into their strategies. Meanwhile, AI methods are being widely deployed in many operations in several industrial sectors for programmed purchases of advertisement space, medical diagnoses, the allocation of financial assets or the customization of online offers, as well as for taking photographs with a smartphone, setting prices, detecting scams, etc.[4] These many applications are evidence of the actual interest that some companies have shown in using AI as part of their corporate strategy (AI STEERING COMMITTEE 2019).

Nonetheless, do these AI methods and techniques modify corporate strategies as defined by the managerial sciences? How can firms draw a strategic advantage from these methods and tools? How will the development of these methods affect the board of directors and strategic decision-making? The deployment of AI is forcing us to ask these questions.

After discussing AI's strategic value for a firm, I shall draw attention to the reorganization that is necessary to actually draw a competitive advantage from this new technology. I shall then show how uses of AI introduce ethical questions for leaders at the firm's highest level.

[1] Respectively https://asia.nikkei.com/Business/Artificial-intelligence-gets-a-seat-in-the-boardroom
&
https://www.brinknews.com/will-ai-board-members-run-the-companies-of-the-future/.

[2] This article has been translated from French by Noal Mellott (Omaha Beach, France). The translation into English has, with the editor's approval, completed a few bibliographical references. All websites were consulted in March 2021.

[3] https://www.youtube.com/watch?v=NzdhIA2S35w

[4] For example, "AI is now an 'ecosystem' for us" on https://venturebeat.com/2020/07/17/ebay-cto-ai-is-now-an-ecosystem-for-us/.

Strategic decision-making and AI: A new era for corporate strategy?

Many misunderstandings about the exact nature of AI are widespread in economic circles. They often lead economic agents to imagine that AI upends business strategies. AI will, for sure, modify business plans in some industries in the coming years, such as the automobile industry and supply chain businesses in general but also, in part, the health sector and entertainment. After a decade of the advances made in AI however, the real changes in corporate strategies turn out to be much more mundane. Recent studies have shown that firms are using AI tactically rather than strategically, mainly to improve operational processes (MIT TECHNOLOGY REVIEW 2020).

AI is producing powerful predictive models in various fields (vision, language, etc.). Recent progress might lead us to think that such models could, when a board of directors decides to do so, be used for strategic decision-making or even to making strategic decisions as such. This requires defining what is strategic about a corporate decision, an issue widely debated in research for several years now (RUMELT *et al.* 1994, HAMBRICK & FREDRICKSON 2001 VAN DEN STEEN 2017). Those academics who consider strategy to be a matter of how problems are defined or who focus on story-telling or "sense-making" find it hard to admit that any form of AI could play a role in strategic decision-making.

Beyond the question of defining strategic decision-making in corporations, the current methods for developing AI (such as machine or deep learning) all rely on sets of data for training AI to build a predictive model. An AI capable of making strategic corporate decisions depends, therefore, on the availability of a very wide range of relevant, sufficiently varied data to be used for model-building. However what defines strategic decision-making is the lack of information, a high degree of uncertainty and the strong interdependency with decision-makers. Given these characteristics, it is improbable that firms will entrust strategic decisions to AI.

Nonetheless, were such a choice to be made, the AI in question would still run up against two major obstacles that would keep it from replacing decision-makers: the biases stemming from the data sets used (as in the case of patents studied by CHOUDHURY *et al*. 2020) and the inherently unpredictable nature of predictions (*e.g.*, a pandemic like COVID-19). The question of biases is open to discussion insofar as corporate leaders' own cognitive biases affect their decision-making (SCHUMACHER *et al*. 2020). So, biases would not be eliminated, but one set of biases would replace another. The more fundamental obstacle is that the economic, social and political upheaval that heavily affects the drafting of strategies is often inherently unpredictable. It lies outside the scope of any model built, regardless of how powerful it is. Predictive models are limited because they rely on data about the past, which, as we know, does not replicate itself (BROUSSARD 2018). To be convinced of this, we need but observe the failure of the predictive models for policing, which have proven incapable of apprehending the complex social factors underlying criminality (BARABAS 2020).

Therefore, AI will have more to do in applications for defining the contents of strategies and their implementation than in the process of strategic decision-making itself, even though some academics have imagined an AI-assisted strategic piloting (KIRON & SCHRAGE 2019). To proceed from this conclusion, it is necessary to describe the nature of the relations between AI and strategy implementation, especially in terms of the resources, skills and qualifications that shape strategic choices, internal and external.

A resource for corporate strategies

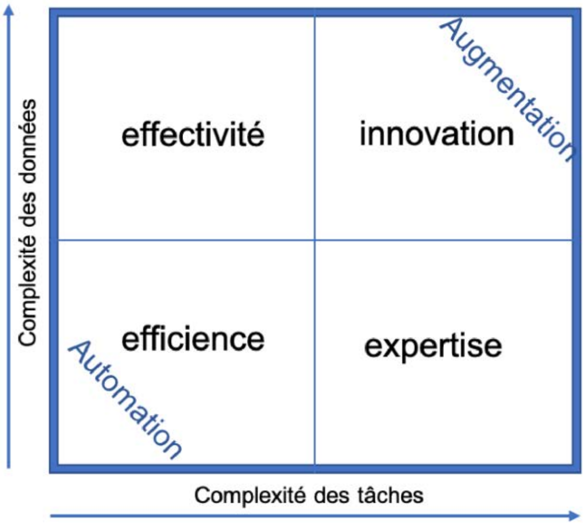

Figure 1: Uses of AI in firms as a function of the complexity of data and of tasks.
Source: Adapted from Accenture 2016

The development of AI depends on the availability of data and, too, on their complexity and the tasks for which they are intended. Current forms of AI stand out owing to their performance of simple tasks, which can be easily automated. AI for more complex tasks is, however, limited to providing assistance, to being a tool that enhances human beings. Between automation and enhancement, we can imagine four uses of AI in corporate strategies (Figure 1):

- AS A TOOL FOR EFFICIENCY. For these uses, the data are not very complex, nor are the tasks to be performed. AI is seen as a further step toward automation, thanks to machine learning. For this, AI often capitalizes on the firm's experiences by accelerating feedback while lowering average production costs (as reflected in the learning curve). As a consequence, the newly invented robots are ideally suited for cost-based strategies of market domination, since they accelerate the lowering of costs in supply chain operations, warehouse management, merchandising and the management of the online user experience. Parallel to this cost reduction, AI could be used for real-time price-setting so as to continuously optimize prices on the supply side (LEVINA *et al*. 2009). For these reasons, AI would be an especially useful tool for strategies in pursuit of efficiency.
- AS A TOOL FOR EFFECTIVITY. In this case, AI is seen as a means for rendering services effectively and making the experience of using a service "fluid" for millions of users simultaneously. Unlike the preceding use case, the data needed are more complex and often unstructured (texts, likes, language, comments). Mainly based on the capacity for detecting customer behavior patterns, automation could be put to work to customize user services. By personalizing the customer experience and making it more fluid, AI becomes a basic tool in customer loyalty strategies. Given the advances made in methods of language recognition, we can foresee an increased use of AI for managing customer relations. Amazon, for instance, systematically uses AI to make the customer experience as smooth as possible (LEVY 2018). Several applications for using AI in pursuit of this sort of strategy can be cited, whether for setting prices, choosing a rental on Airbnb or customizing offers on Spotify, Amazon or Uber. Products incorporate forms of AI in order to improve the user's experience of them, as at Apple, not to mention Amazon or Google, where various forms of AI (image-processing, vocal interfaces, automatic management of the battery range) are embedded in devices (AXON 2020).

● AS A LEVER FOR EXPERTISE. In this case, AI handles tasks while relying on human beings whose expertise is based on a long experience that is hard to replicate. A typical case is a diagnosis in radiology. While we can now imagine using AI to facilitate the detection of certain pathologies, we can hardly imagine letting it make the final diagnosis, since the decision made directly affects a person. As much can be said about financial counseling: banks still dare not let the oversight of their clients' account to robots, however talented the latter might be. With regard to expertise, AI is a complement enhancing human actions.

● AS A LEVER FOR INNOVATION. Using AI for innovation has spawned the most expectations, as in pharmaceutics where more than 200 start-ups have specialized in discovering new molecules for therapy.[5] For this use case, AI's capacity for handling complex data and processing them is superior to what human beings can do. It has opened the way toward new medical treatments.[6] For devices, a potential use of AI would be, for example, to design an original, robust structure for vehicles (HERRERA2019). However the use of AI for designing devices could potentially be disruptive insofar as it deeply alters value-creation processes (BATALLER & HARRIS 2016).

New resources, skills and qualifications

Online platforms are using AI in these four ways in various sectors, such as travel services, hotels, retail businesses and transportation. These platforms, designed in the digital era, have built information systems capable of collecting the data necessary for the predictive models that analyze user experiences. They thus enjoy a competitive advantage over conventional companies, since their business model has (partly) been designed in view of massive data collection (ISAAC 2021). These platforms have turned data into a literal strategic resource and thus upended competition. Without data, competitors have a hard time building any form of AI. The access to data can thus be seen as a market entry barrier (MAHNKE 2015, CASADO & LAUTEN 2019).

Conventional businesses often lack data for competing effectively with these upstarts. This leads them toward strategies for sharing data so as to nurture their own "data pools" and build reliable predictive models. We already observe this in advertising, where alliances (Garivity in France, Skimlinks in the United Kingdom) between various parties have taken shape to form bigger data sets, which can be used to compete with newcomers like Facebook and Google. Although competition law sometimes looks askance at these alliances, they are, in Europe, seen as a means for competing with the American and Chinese platforms (VESTAGER 2016). They are a key element in the European Commission's digital roadmap.[7]

The step after data collection is for AI to use these data to build models. Online platforms have, we must admit, identified the needs for model-building and have recruited experts. In addition, they have purchased specialized firms to speed up the acquirement of know-how in this field. After all, building up such a complex store of knowledge takes a long time and comes at a heavy cost (CROCHET-DAMAIS 2020). These policies have sometimes been seen as a form of predatory competition, since they tend to lessen competition (BOURREAU & DE STEEL 2020, DIGITAL… 2019, ARGENTESI *et al.*2019). But they are also considered to be a response to a dysfunctional labor market and educational system, which do not provide the skills that would match firms' needs.

[5] https://blog.benchsci.com/startups-using-artificial-intelligence-in-drug-discovery

[6] https://www.vox.com/2020/1/31/21117102/artificial-intelligence-drug-discovery-exscientia

[7] See the European Commission's "European data strategy" for "*making the EU a role model for a society empowered by data*" on https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age/european-data-strategy_en.

The maturity of AI methods has modified the field of competition. From a strategic perspective, what now seems decisive for AI's success is a firm's ability to integrate and develop the skills and qualifications necessary for building and operating AI, for making AI its own distinctive competence on the market.

Successfully integrating AI in corporate strategies

AI has mainly been used in new firms in information and communications technology (ICT). The questions we can ask about AI techniques in relation to a company's internal organization are not the same in ICT as in traditional firms.

From an organizational viewpoint (KRETSCHMER & KHASHABI 2020), using AI techniques requires mustering the requisite skills, qualifications and resources (TAMBE 2014, ROCK 2019). Information technology teams are not, by themselves, capable of rolling out these techniques, which depend on a combination of skills and qualifications in mathematics/statistics, computer science and specific business processes. Most firms assign this responsibility to a "data science" team under the authority of a "chief data officer" (CDO). Nonetheless, this new assignment does not produce AI as such.

Two hurdles are recurrently encountered. The first is the lack of data or the poor quality of the data available to the firm. To jump over this recurrent hurdle, the firm's information system has to be reorganized; and more importantly, "data education" has to be provided at all levels in the firm (STRENGOLTH 2020). The second hurdle is to pass from a predictive model built in a "data lab" to a model actually integrated in the firm's operational processes and information system. This phase of industrializing AI is crucial to its deployment. It very much depends on skills and qualifications in digital technology and, too, on the management of changes, since the consequences of introducing AI tend to modify the execution of processes and the relation to customers.

The rollout of AI techniques means choosing between three major alternatives:

- Adopt a ready-made solution proposed by specialized editors (specialized, for example, in the detection of fraud for the insurance industry or the optimization of auctions for online advertizing).
- Use off-the-shelf offers from the digital giants (Amazon, Microsoft, IBM, Alibaba) or from specialized start-ups. These offers rely on pretrained models that have to be improved with inhouse data.
- Build one's own models with open-source software or free-to-use bricks while profiting from the architectures proposed by cloud-providers (Amazon, Microsoft, Google).

The choice between these three has important strategic consequences:

- If the first is chosen, the firm will have the same tools as its rivals; and it will have to use them to design an offer that makes it stand out from the competition. This offer can but be on par with market standards.
- If the second is chosen, building a reliable predictive model will depend on the quality of inhouse data. The data value chain must be fully managed.
- If the third is chosen, specialized skills and qualifications will be crucial for building models specific to the firm.

Corporate governance and AI

The rapid development of AI techniques raises questions not only about the strategic choices to be made by firms but also about the methods for making decisions and how they are used within the firm. These questions concern governing bodies: in the first place executive committees and boards of directors. Without going so far as to introduce AI in these bodies, several issues must be addressed. The first has to do with the professional credentials of corporate executives with regard to this very technical subject. Technology itself too often becomes the focus of discussions whereas the stakes are, on the one hand, the data necessary for AI and, on the other hand, the organization and management of the skills and qualifications of the teams in charge of AI techniques. How can a governing body keep up on the knowledge about such an increasingly strategic topic that requires expert skills that lie beyond its members' qualifications?

In recent years, some firms have introduced a new leadership position centered on the technology (chief digital officer) or on the data (chief data officer). Chief data officers tend to overshadow chief digital officers, but they should not be redubbed chief information officers. They must be data architects who create value and develop AI. Chief data officers should have a solid background in AI so as to enlighten the discussions of governing bodies on this strategic subject.

Is it necessary to use AI? How to compete with other forms of AI? Should the firm use AI techniques already on the market? How to apply them to specific cases? How far to take these uses? Such are the questions to be addressed by governing bodies. These questions soon lead to other, precise questions about the criteria to be used for decision-making. Ethical principles have to be adopted about the uses of data, since predictive models and the AI stemming from big data might have direct effects on the users of these systems and decisions (WHITTLESTONE *et al*. 2019). For example, should a bank make an offer of services based on the ability to reliably predict a divorce? How far to go in managing a customer's account when AI can predict the monthly balance? These questions are more than matters of feasibility and acceptability. They tend to be ethical questions about the meaning of a firm's actions and the customer's free will.

Defining a set of ethical guidelines is absolutely necessary if corporate leaders want to be able to make decisions about AI that they can justify to stakeholders and, above all, to customers and employees. Ethics committee must be set up to define a set of principles with regard to data and AI applications in various policy areas, business processes and training programs.

Table 1:
Major ethical principles about using data

Transparency	Explicability of the models used. Information about how an algorithm makes decisions about persons.
Fairness	Managing the biases stemming from data so as to avoid discrimination.
No malice	Asimov's three laws of robotics: no use of data should endanger human beings or diminish their physical and mental capacities.
Responsibility	Principle of accountability.
Freedom and autonomy	Principle of consent and free will.
Confidence	Principle of confidence.
Dignity	Respect human dignity.

The list of ethical principles in Table 1 has been drawn from various studies on this topic (For an overview, cf. JOBIN *et al*. 2019). Such principles have to be integrated in the methods used to design and produce the algorithms that massively use data (privacy by design, security by design, inclusiveness by design). In addition, they should undergo assessments (privacy impact or equality impact assessments).[8] However ethics and the compliance with these principles should not lead to a permanent censorship of R&D. Instead, they should accompany the development of an AI in compliance with the principles that the firm has chosen to follow and uses to justify its actions to stakeholders.

Current forms of AI usually produce tactical rather than strategic advantages. Their deployment relies on big data — the strategic resource and raw material that firms often have trouble gauging. To take advantage of AI, a major reorganization turns out to be indispensable. The resources and processes necessary for building and managing AI require in-depth changes in the management of the data value chain. These changes are both technical and "cultural", whence the difficulties many firms have had in reaping competitive advantages. Once the resources, skills and qualifications as well as the techniques and processes are mustered, it is important to understand the limits of this technology and establish an employment doctrine that upholds a certain number of values so that AI is as easily accepted as possible.

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