The evolution of managerial skills towards the rise of Artificial Intelligence.

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Abstract

***Purpose* -** This study investigates how the rise of AI in organizations may affect managerial skills.

***Design/methodology/approach* –** To answer our exploratory research question, we will use a mixed-methods design. We first conduct a qualitative thematic content analysis on semi-directive interviews to come up with research proposals. Then, those proposals are tested on a wider scale through quantitative questionnaires. Data collection targets each time AI experts and managers working with AI, in a variety of sectors and countries.

***Findings* -** Our qualitative data show how and which managerial skills are to be replaced, augmented or not affected. In parallel, our data points out specific technical as well as non-technical skills that managers are expected to develop in order to successfully accompany the growing presence of AI.

***Practical implications* –** The paper discusses implications for theory and practice.

***Originality/value* –** The originality of this study lies in the mixed-methods research allowing for a deep investigation of the links between managerial skills and AI, as well as their potential evolutions.

Keywords: Artificial Intelligence; Manager; Skills; Evolution; Qualitative.

Introduction

Artificial Intelligence (AI) is "a computer science aiming to perform tasks that replicate human or animal intelligence and behavior (Fiske & Kazdin, 2000)". It impacts public relations (Galloway & Swiatek, 2018), national performance (Alexandre, 2018), sectors (Tredinnick, 2017), jobs (Morikawa, 2017), finance (Wall, 2018), the workplace (Agrawal *et al.*, 2017) and therefore Human Resource Management (Meijerink *et al.*, 2018). In spite of ethical risks (Helbing, 2019), AI has been spotted as an opportunity for many businesses (Scarcello, 2019). It is indeed a significant source for better performance, notably through the enhancement of products, decision-making and internal business operations (Davenport & Ronanki, 2018). It should consequently generate new occupations (Mokyr *et al.*, 2015) and make existing jobs evolve (Manyika *et al.*, 2018).

Training soft skills to AI is the most problematic type of training transfer, just like for humans (Botke *et al.*, 2018), particularly with regards to emotional intelligence (Mattingly & Kraiger, 2019). Yet, the fast-growing capabilities of AI (Lu *et al.*, 2018) are likely to leave a "gaping hole in the continuity of progress" (Malabou, 2019, p. 74), as illustrated by the yearly increase in AI patents by 11% between 1991 and 2015 (OECD, 2017). Actually, "it is quite plausible that it could also take on many of our most human capabilities such as intuition, empathy and creativity" (OECD, 2019, p. 31). It is delicate to anticipate on "how fast the change will happen" (Carlos *et al.*, 2018, p. 497). This sustained and exponential trend suggests that AI is likely to imitate managerial skills one day and might be capable of planning, organizing, leading and controlling (Fayol, 1916; Robbins & Coulter, 2012). Recently, Frey and Osborne (2017, p. 272) estimated that general managers had a 25% probability to be replaced by AI.

In parallel, the rise of AI in organizations will require new skills from managers in order to grant its effective implementation. Yet, university and executive training on that matter seem insufficient as there is already a critical shortage of technical staff and managers who are able to relate to AI, whether it is in the USA (Marr, 2018; Saphir, 2018) or in France (Goya, 2018).

The managerial skills to be affected by AI and to be developed for effective AI implementation therefore deserve further investigation in order to enable universities and companies to fine-tune training efforts to meet operational needs. We also answer the call of Felten *et al.* (2018, p. 4) for whom "more work needs to be done linking advances in AI to occupations and skills". Thus, the present paper is interested in *how can the rise of AI in organizations affect managerial skills*. The deriving research questions that we examine through mixed-methods research are:

- How and which managerial skills are likely to be affected by AI?
- What are the needed managerial skills to successfully accompany the growing presence of AI in organizations?

We first review the academic literature on managerial skills in relation to Artificial Intelligence. In the second section, we outline our methodology and the results of our empirical study. Finally, we discuss our findings and present our conclusions.

1. Literature Review

1.1. Managerial skills

Fayol (1916) is well-known for his classification of management functions in planning, organizing, commanding, coordinating and controlling. Robbins and Coulter (2012) later condensed these functions into four: planning, organizing, leading and controlling. Managers function from setting goals and developing plans; organize the resources and on how to get it done; leading the team and actions; and controlling the implementation to finally purposed in achieving organization's objectives. Overall, they see manager as someone who coordinates and oversees the work of other people so that organizational goals can be accomplished.

Later on, Mintzberg (1973) underwent observational studies of managers at work to understand what they conduct and act on the field. In result, instead of understanding managers in their functions, he then proposed other view to describe managers through their roles. He formulated three interpersonal roles: figurehead, leader, liaison; three informational roles: monitor, disseminator, spokesperson; and four decisional roles: entrepreneur, disturbance handler, resource allocator, negotiator. Interpersonal roles are about involvement with people, informational roles involve receiving, gathering and distributing information; and decisional roles impose making choices and taking decisions.

Table 1: Managerial skills according to Gentry et al. (2008, 172).

Managerial skill	Description
1. Getting information, making sense of it; problem identification	Seeks information energetically; probes; creates order out of large quantities of information; defines problems effectively
2. Communicating information, ideas	Crisp, clear, articulate; good public speaker; strong communicator on paper; adept at disseminating information to others
3. Taking action, making decisions, following through	Action-oriented; presses for immediate results; does not procrastinate on decisions; follows up well
4. Risk-taking, innovation	Has vision; entrepreneurial; consistently generates new ideas; creates significant organizational change
5. Administrative/organizational ability	Establishes and conveys a sense of purpose; team builder; resourceful; can organize and manage big long-term projects
6. Managing conflict; negotiation	Effective at managing conflict; confronts others skillfully; negotiates adeptly
7. Relationships	Builds warm, cooperative relationships; is not abrasive; makes good use of people; has good relationships; readily available to others
8. Selecting, developing, accepting people	Attracts talented people; patient with people as they learn; brings out the best in people; good coach, counselor, mentor
9. Influencing, leadership, power	Inspirational; good at promoting ideas; able to inspire, motivate people; delegates effectively; works effectively with people over whom he or she has no direct authority
10. Openness to influence; flexibility	Listens well; accepts criticism well; collaborates well with others; thinks in terms of trade-offs; creates good give-and-take with others
11. Knowledge of job, business	Shows mastery of job content; effective in a job with a big scope; a quick study; understands numbers
12. Energy, drive, ambition	Good initiative; high energy level; goal-directed
13. Time management	Sets priorities well; makes the most of time available; avoids spreading self too thin
14. Coping with pressure, adversity; integrity	Capable in high pressure situations; has integrity, trustworthy; willing to admit ignorance
15. Self-management, self-insight, self-development	Understands own strengths and weaknesses; learns from experience; aware of his/her feelings; makes needed adjustments in own behavior

On the other hand, Katz (1974) proposed three critical managerial skills such as technical, human and conceptual. Technical skills are job specific knowledge to perform work tasks and are especially needed by first line managers. Human skills are ability to relate with humans including communicating, motivating, leading and inspiring and these skills are needed in all levels of management. Meanwhile conceptual skills are abilities to conceptualize complex situations and to understand several relationships within and outside organizations.

After the booming of digital era in the 2000s, Gentry *et al.* (2008) carried out a survey-based research to more than 14,000 managers to study changes of managerial skills since the 1980s. They found that managerial skills in 1980s are still relevant in 2000s even if administrative/organizational ability, relationships and time management may have undergone a relative evolution (see Table 1). In a similar way, Bhanugopan *et al.* (2017, p. 1703) studied three categories of managerial skills which they classified into personal attributes, managerial skills and business skills. Robbins and Coulter (2012) added that due to fast globalization, competition and technology pace, managers now face other integrative issues such as managing in global environment, diversity, social responsibility, as well as change and innovation.

The literature review implies that if basic managerial skills are likely to remain stable, the complexity and level of importance of each skill might slightly change over the time depending on the situation and context. With a possible industrial revolution coming from an ever stronger AI, managerial skills are to evolve accordingly.

1.2. Artificial Intelligence

Farrow (in press, p. 2) recalls that Artificial Intelligence (AI) is “a computer science aiming to perform tasks that replicate human or animal intelligence and behavior (Fiske & Kazdin, 2000)”. If it includes machine learning, robotics, computer vision, automated reasoning, machine perception and knowledge representation (Marsh, 2013; Mehta & Devarakonda, 2018; Tractica, 2017), Rhines (1985, p. 50) would yet recommend “to think of AI as the ‘branch’ of computing… [as] it may be wise at this point not to define it, because to define is to limit its possibility”.

AI was first developed in the field of Robot Technology. Decker *et al.* (2017) categorized the different kinds of machine tasks according to two dimensions: (1) manual/cognitive and (2) routine/non-routine tasks. Yet, the substantial heterogeneity of tasks within occupations already hinders possible automation which would finally only concern 9% of the US jobs today (Arntz *et al.*, 2017), if minimum wages do not increase (Lordan & Neumark, 2018).

AI also concerns Information Communication Technology and encompasses *prediction* (ability to take information you have to generate information you didn’t have) or *decision-making* skills. Indeed, “modern robots have a system of AI with the help of which they can take decisions (to a limited extent - semi-autonomously)” (Decker *et al.*, 2017, p. 352). These decision-making skills are usually heavily dependent on big data, lack self-idea function and remain quite complicated to use (i.e. Decision Tree, Support Vector Machine, Neural Network and Deep Learning). Yet, this kind of AI already has concrete managerial applications in Supply Chain Risk Management (Baryannis *et al.*, 2018), Knowledge Management (Boulanger *et al.*, 2015) and HRM (Strohmeier & Piazza, 2015).

As of 2019, AI is mostly synonymous with Artificial Narrow Intelligence (ANI = weak intelligence) in the way that AI can only overcome the human at a specific and isolated task (i.e. playing chess or solving equations). More sophisticated, Artificial General Intelligence (AGI = strong intelligence) is about mastering a wide range of cognitive tasks. In that perspective, and maybe “endowed with subjectivity” (Malabou, 2019, p. 73), it might advance to Superintelligence which is defined as “general artificial intelligence greatly outstripping the cognitive capacities of humans” (Bostrom *et al.*, 2018).

Eventually, in line with the Superintelligence approach, current developments concern a new form of AI which is Brain Intelligence (Lu *et al.*, 2018); where the machine might be able to generate new ideas about events without having experienced them (i.e. by using artificial life with an imagine function). Provided that optimistic scholars like Kurzweil (2005) anticipated that “on the horizon for the 2020s, cybernetic intelligence will be indiscernible from human biological intelligence” (Malabou, 2019, p. 74), the literature today announces different horizons. While academics write that human-level machine intelligence is to be developed by 2050 (Müller & Bostrom, 2016) or 2060 (Grace *et al.*, 2018), “it is likely (75%) that superintelligence would be developed within 30 years” (Bostrom *et al.*, 2018). In parallel, Lichtenthaler (2018) depicted all the possible relationships between human and artificial intelligence as being standard, substitute, superiority and synthesis.

Given the exponential increase in public and private research on AI (OECD, 2017, 2019), an updated investigation on the interplays between managerial skills and AI seems necessary.

1.3. Managerial skills and AI

1.3.1. Managerial skills to be duplicated by AI

Since AI can handle simple and repetitive cognitive tasks (Decker *et al.*, 2017), it may soon take over most administrative tasks (Kolbjørnsrud *et al.*, 2016). AI might as well act as personal assistant for managers in coordinating meetings, managing emails or resources, following-up, reporting, reading report or extracting data (Dejoux & Léon, 2018). As a result, managers would then have more time to concentrate towards more value-added missions and human relation development. In the short-term perspective, AI could then be supportive to employees for repetitive tasks and “give them more opportunity to focus on work which requires their core competencies” (Hagemann *et al.*, 2019, p. 160).

However, humans still seem to have the lead on complex and non-standardized tasks (Lichtenthaler, 2018). When it comes to general adaptive intelligence and performance, AI cannot yet cope as it is “typically limited to a single frame or type of problem” (Lu *et al.*, 2018). Creativity, empathy, judgment, storytelling and motivational speeches (Plastino & Purdy, 2018; Wilson *et al.*, 2017) and imagination such as *knowing what questions to ask* and *imagining a thing that does yet exist* (Rometty, 2016) are not yet replicable via AI.

1.3.2. Managerial skills to accompany the spread of AI

If AI already has the lead on prediction in an abundant and inexpensive way, then managers may need to decide in which way prediction should be implemented: this relates to judgment. AI seems so far unable to show advanced ethical judgment, emotional intelligence, artistic taste and ability to define tasks well (Agrawal *et al.*, 2017). If emergent AI will soon be capable to automatically generate initial production system configurations (Hagemann *et al.*, 2019) and to optimize the production (Mohammadi & Minaei, 2019), it might still lack good judgment. Good judgment for instance comes from the knowledge of organizational history (Kolbjørnsrud *et al.*, 2016); a dimension that AI usually fails at considering and which is to be checked by humans.

Managerial training may then shift from a focus on prediction-related skills to judgment-related skills where the human contextual role in defining strategy is to remain (Pistrui, 2018). Organizations will surely show constant demand for people who can make responsible decisions (requiring ethical judgment), engage customers and employees (requiring emotional intelligence) and identify new opportunities (requiring creativity) (Agrawal *et al.*, 2017). Therefore, the new managerial skills to be trained should also be based on prediction, as augmented by AI (Jarrahi, 2018).

In consequence, future managerial skills are likely to be about determining how best to apply AI regarding the opportunities for prediction, what should be predicted and how should the AI agent learn in order to improve predictions over time (Agrawal *et al.*, 2017). Training managers to basic AI management (Dejoux & Léon, 2018) and human teamworking with AI (Norman, 2017) should then be contemplated. From a more macro perspective, several business schools like the MIT Sloan School of Management have already taken that direction with an online program on AI implications for Business Strategy[1].

Moreover, a certain level of organizational maturity is probably needed before generalizing AI (Baldwin, 2019) both on technical and non-technical dimensions (Gunsberg *et al.*, 2018). Harrison and O'Neill (2017) explained that AI could not be performed if the organization is not ready and that it needs two most important basics before adopting AI: automation and structured analysis. AI works on data and having advanced AI will be quite impossible if related data processes are not yet automated and collected. Structured analytics is also needed before getting to next steps to more complicated AI. Afterwards, once organization decided to pursue AI, commitment to change is essential in all levels of management (Chui & McCarthy, 2017). Like any implemented change and beyond the technical skills required, employees also need to be psychologically ready to work with AI.

Additionally, when humans work along with AI, there are new interactions from both sides: machine assisting human and human assisting machine (Wilson & Daugherty, 2018). The manager then has to prepare and inspire its team members to embrace this change, to develop the necessary skills and to define new job descriptions and organizational structures if needed (Knickrehm, 2018). Dejoux and Léon (2018) illustrated manager metamorphose into an augmented manager in the era of AI with five main skills: digital, agility, design-thinking, collaborative and AI skills. These AI skills consist of interaction with machine including creating, educating and controlling the AI.

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[1] https://www.getsmarter.com/courses/us/mit-artificial-intelligence-online-short-course?utm_campaign=MIT-AI_INT-APLHA&utm_medium=automatic&utm_source=email&_ke=eyJrbF9lbWFpbCI6ICJsYXVyZW50LmdpcmF1ZEB0c20tZWR1Y2F0aW9uLmZyIiwgImtsX2NvbXBhbnlfaWQiOiAiZHZLdVpxIn0%3D

Eventually, the literature suggests that managers do play a key role in the AI implementation, like in any change implementation (Kotter, 2012). This key part requires new skills in order for instance to identify the rationale for using AI (Fiore *et al.*, 2018), to understand cognitive technologies and how they work, to analyze the business case, to drive the construction process until implementation and to drive adoption (Henke *et al.*, 2018), to weigh costs and benefits, as well as to evaluate the misleading production result of the application (Schrage, 2018). Some scholars even suggest that future managers might need to possess foundation skills in logics, coding and mathematics to be able to comprehend the functioning of AI (Dejoux & Léon, 2018; Ellenberg, 2017). More especially, managers may eventually have to take on new roles as trainers, explainers and sustainers to ensure effective collaboration with AI (Wilson *et al.*, 2017).

2. Empirical study

The first step of our data collection is made through exploratory and semi-structured interviews. The research proposals that will be extracted from this exploratory data collection are then to be tested with quantitative questionnaires administered to AI experts (the top 100 authors quoted in the field), just like other scholars did on close but distinct topics (Grace *et al.*, 2018; Müller & Bostrom, 2016). Combining quantitative data from questionnaires with qualitative evidence gained from interviews (Eisenhardt & Bourgeois, 1988) allows more holistic understanding of the phenomenon being studied (Baxter & Jack, 2008). Mixed methods indeed provide "a better understanding of research problems" (Molina-Azorin, 2012, p. 33), they are deemed necessary in organizational research (Molina-Azorin *et al.*, 2014; Wright & Sweeney, 2016) and encounter growing popularity worldwide (Heyvaert *et al.*, 2013; Munce & Archibald, 2017).

1.4. Exploratory data collection (Step 1)

1.4.1. Justification of the research design

Yin (2014) defends the idea that the "how" questions should be addressed through qualitative research methods. Therefore, we will begin our investigation through semi-directive interviews with research experts and managers working with AI in a variety of sectors and countries. Furthermore,

1.4.2. Data collection - Semi-structured interviews

Within the qualitative design, the most popular method of data collection is interview (Buchanan, 2012). Semi-structured and unstructured interview are mostly used in qualitative research (Bryman & Bell, 2015). Qualitative interviews put more interest in interviewee's point of view than in researcher's concerns with objective to get rich answers. It sometimes causes flexible order of questions and even adding new questions which are intrigued by interviewee's replies (Bryman & Bell, 2015) although Bryman and Bell (2016) suggest that an interview guide can help to structure a semi-structured interview (see appendices). Resorting to respondents is one type of structuring available approaches to interviewing (Lindlof & Taylor, 2002). It is considered the most common tool of data collection wherein participants are asked to share about their experiences and perspectives (Alvesson & Ashcraft, 2012).

To augment credibility of qualitative research, member validation was conducted by sending summary of findings to each participant to seek corroboration of interpretations of the interviews (Bryman & Bell, 2016). The summarizing of findings was preferred to the sending of the whole scientific writings to participants. This choice allowed to avoid difficulties of understanding and participants' unfamiliarity with theories, concepts and contextual issues (Skeggs, 1994).

Eventually, in order to guarantee dependability (reliability), we also kept complete records of all phases in the research process including selection of research participants, fieldwork notes, interview transcripts, data analysis and others in case further verification and justification are needed (Bryman & Bell, 2016).

1.4.3. Sampling

If it is rarely feasible in qualitative research to collect sufficiently large samples for statistical analysis, it remains possible to collect the data from randomly-selected participants (Kvale & Brinkmann, 2009). Patton (2002) argues that non-probability (non-random) samples are appropriate if the chosen sample can enable to gain understandings and insights. Through a non-probability sampling, our respondents were identified based on our judgement of the characteristics of the population which we think is importantly related to the data required to address our research question (Saunders, 2012). This sampling technique is indeed recommended for exploratory study so as to obtain rich understandings (Saunders, 2012).

Table 2: Profile of the respondents.

Respondent	**Domain**	**Expertise**	**Location**	**Sector**
Exp1	AI	Statistics, architecture & monitor	Toulouse	Automotive industry
Exp2	AI	AI strategist, reinforcement learning, project	Toulouse	Research
Exp3	AI	Machine learning & project management	Toulouse	Consulting
Exp4	AI	Supervised learning, management	Toulouse	Automotive industry
Exp5	AI	General AI & deep learning	Toulouse	Automotive industry
Exp6	AI	Multi-agent system	Toulouse	Automotive industry
Pract1	HR	Recruitment & skills management	Toulouse	Aerospace industry
Pract2	IT (network)	System & network administrator + Architect	Toulouse	Energy industry
Pract3	Operations	Digital transformation	Toulouse	Energy industry
Pract4	Business	Data exploitation	Toulouse	Consulting
Pract5	AI	Project management	Toulouse	Consulting
Pract6	Business	Business analyst	Toulouse	Consulting
Pract7	Business	Business & functions	Toulouse	Consulting
More respondents to be interviewed, notably from the USA and Japan.				

The choice of research participants is based on literature review, professional experiences and pre-assumptions. For example, companies which create its own AI is usually found in high-tech companies merely because they tend to have more readiness of abundant data availability and structured data analysis (Harrison & O'Neill, 2017), as well as more budget. Different levels of management are to provide different managerial skills (1974). Our sampling conducted through a variety of management levels, sectors and countries should increase transferability and dependability (Guba & Lincoln, 1994). Table 2 shows a non-probability sampling of participants as particularly fitted to exploratory purposes (Saunders, 2012). In summary, there is a total of 13 participants from 8 different companies and 5 different industries.

We sought to increase external reliability and external validity through the variety of management levels, sectors and countries to which respondents belong – even if external reliability is usually difficult to grant in qualitative research (LeCompte & Goetz, 1982).

1.4.4. Data analysis

Computer-Assisted Qualitative Data AnalysiS (CAQDAS) (Lee & Fielding, 1991) will be utilized to help facilitating analysis of qualitative data. Despite its limitation or drawbacks, CAQDAS supports coding and retrieval process faster and more efficient (Bryman & Bell, 2015) and offers new opportunities (Paulus *et al.*, 2013) in the process of analyzing data (Mangabeira, 1995).

In that perspective, The NVivo software is widely used in business research (Bryman & Bell, 2015) and will allow a thematic content analysis to be realized on a full transcript of interviews, as recommended by Roulston (2014, p. 301). This method of analysis is indeed the most common in Human Resource Management (Point & Retour, 2009) and the most adapted to that kind of data (Thiétart, 2014). Eventually, the interpretation and the analysis of the data will be made in parallel by each of the researchers and finally confronted in order to improve internal reliability (Bryman & Bell, 2016).

1.5. Testing of research proposals – Step 2 (to be performed in 2020)

1.5.1. Justification of the research design
1.5.2. Data collection - Online questionnaires
1.5.3. Sampling

3. Results of qualitative data collection (Step 1)

In line with our research questions, step 1 has come up with proposals about (3.1) how the rise of AI is likely to affect managerial skills and (3.2) which skills should be developed to accompany the growing presence of AI in organizations.

The literature evokes the terms "replaced" or "augmented" to qualify the impact of AI on jobs, tasks and skills (Bughin *et al.*, 2017; Dejoux & Léon, 2018; Farrow, in press; Frey & Osborne, 2017; Hagemann *et al.*, 2019; Morikawa, 2017; OECD, 2019; Pistrui, 2018; Plastino & Purdy, 2018; Rometty, 2016; Wilson *et al.*, 2017). We will use those qualifications to structure our results in the chapter 3.1.

3.1. Managerial skills likely to be affected by AI

3.1.1. Managerial skills likely to be replaced by AI

- Simple decision/action- taking

Our respondents suggest that taking simple decisions and actions could be replaced by AI, allowing more time for managers to perform elsewhere. Simple tasks usually relate to a logical sequence of actions which could be programmed and automatically done.

"We still have human decision to be taken and, in some cases, it would be replaced because the task is simple enough and the AI is able to do it." (Exp4).

"Simple process steps […] for example […] this can all be automatized." (Pract6).

"You can automate some other tasks which are repetitive, boring and it saves times.*" (Exp5).*

"AI will really do a lot of things. Because it's the processes that are pretty regular routines." (Pract3).

"So, all the things that we'll do and require time but it's not the added-value will be taken by AI and our intelligence will be lots more added-value." (Pract4).

"Because all simple tasks, let's say will be done by the AI. So, people will be pushed to learn higher skills in order to have an added-value in the work." (Pract6).

- Administrative ability

According to our data, basic administrative skills are likely to be replaced by AI. For example, organizing calendars and schedules planning for meetings between several persons, to check the time availability of everyone and combined with room availability or other factors. AI can perform this task more efficiently.

"The university, the schedules: it can be generated with AI." (Exp1).

"[AI can do] The basic administrative tasks, organize the agenda, respond to messages quickly." (Exp6)

- Information search & gathering

Respondents suggest that managers might struggle to search, gather and compute an ever-increasing amount of information. With its computing power and method, AI is likely to outperform managers on this kind of skills.

"[…] to take many more variables than just the age, the last credit data of real estate. So, we will be able to take all their behavior and even their behavior in stores." (Exp3).

"A man will not be able to go through terabytes of data but AI can. So, it's just a tool to gather information altogether to figure out the main points and maybe which article is the most valuable to read." (Exp4).

3.1.2. Managerial skills likely to be augmented by AI

- Complex decision/action- taking

Our respondents point out that AI can identify certain problems faster, can analyze gathered information and predict the future based on history, and eventually propose solutions and actions. Assisted by relevant and pre-determined parameters, AI can augment complex decision- and action- taking.

"Identify some classes in the data, not any human can do this work. Yeah maybe it could take one million people, statisticians to do the same thing. It's just pure question of power and computing capabilities." (Pract7).

"Based on statistics that allow with past data and lots of data and variables to define the decision trees." (Exp3).

"A capacity to have analysts on the machines, to predict the breakdown, to predict wear, to predict a decrease of production et cetera." (Pract5).

"It gives a diagnosis or it proposes an action and it explains why to consider this." (Exp2).

"[AI is able] to completely automatically find the right correlations and to provide the algorithm." (Exp5).

"With system of algorithm and comparison, it will give you the compatibility of the profile of the candidate with the team occupation in which he can fit." (Pract1).

- Innovation

According to our data, AI might help to uncover alternative spectrum of analysis or elements which have not been anticipated or imagined before.

"Today AI will bring another spectrum of analysis […]: it allows to evaluate a notion of potential and things that I will not think of." (Pract1).

"AI is finding those things that you can't see obviously." (Pract4).

"You can identify easy issue, easy problems but once there are specific human interferences which can cause the problem, it's harder to identify." (Pract6).

- Knowledge of job/business

According to our data, AI can also help managers and team members to increase knowledge of their jobs and business.

"It will allow us to see if there are singularities in the team which stand out and to be able to train on their development axes." (Pract1).

"AI can get more relevant information faster so that it helps you to keep posted and to potentially learn the job faster." (Exp5).

- Communication (translation)

If our respondents remain doubtful regarding the ability of AI on oral translation, they believe written translation significantly improved even though it does not yet match the quality of a human-made one. Thus, AI may augment communication skills when it comes to translation.

"[AI can] correctly translate from one language to another so that you don't have translation gap […] for improving the communication in between teams." (Exp4).

“It will facilitate exchanges […] between people of different nationalities.” (Pract3).

“I think [translation] can be replaced for all written parts, but not for the oral parts.” (Exp6).

In the future, AI might even be able to rephrase sentences and to polish communication so that managers become even better communicators.

“In the future too for instance, rephrase your email, make it less angry, figure out ways to… At some point, it's also able to re-read, so it's just not grammar or vocabulary correction but it could be just a rephrasing of what you want to express […] it can be used to polish our communication at some point.” (Exp4).

3.1.3. Managerial skills unlikely to be replaced by AI

- Critical decision-making

The interviewees believe that final decisions should stay at manager’s call due to several reasons such as ethics and judgement.

“When it's the critical tasks, when it's purely human tasks like management, it will never be the AI that has the last word.” (Exp1).

“Disconnect the analysis and the taken actions. And the connection can only be made by human decision.” (Pract7).

“The final decision, it is human being who makes the decision.” (Exp2).

“The information must be treated finally with the context […] The machine, it can better capture the information but it does not know how to use it properly.” (Pract2).

- Imagination

Our respondents agree on the fact that AI cannot yet invent, neither imagine and think out of the box for complex concepts.

“It will reproduce what we tell it to say, what we tell it to do, it will not invent.” (Pract4).

“It's just a playing stupid formula in the end, right?” (Exp5).

“You have to know how to interpret […] I'm not sure that innovation goes through.” (Pract5).

“Everything is decided in advance. […] it cannot imagine on its own.” (Pract2).

3.2. Managerial skills to develop in order to optimize the use of AI

Participants suggested several managerial skills needed to create or develop in order to optimize the implementation and the utilization of AI. These skills are divided into *technical* (3.2.1) and *non-technical* (3.2.2) wise.

3.2.1. Technical managerial skills to optimize the use of AI

- Basic AI knowledge

Our respondents first agree to say that one of the most important points that managers have to develop is to understand the basic of AI: the mechanisms, the potentials and the limits.

“[Managers need] to know the basics of AI and what is the AI.” (Pract2).

“I need to understand and someone to explain to me how it functions.” (Pract1).

“We must demystify the AI […] we must understand the reasons for performance, it is necessary so have a culture to understand what it is.” (Exp2).

“Not to think it's a magic box which works.” (Exp4).

“Knowing what is behind the technology, knowing that it was trained on some data and it's only able to work on those data.” (Exp4).

“Actually, the work we did is to build the learning bases. It's like educating a child. If we always educate it in a single way and when we put it in real life, well it will do that we make it to do.” (Exp6).

“[Managers need] to know what is data, to know how to use data.” (Exp2).

“You can actually do nothing if you do not have lots of data, lots of structured data. [Managers] don't really understand.” (Pract4).

Managers do not have to understand computer programming or coding as this part will be handled by the computer scientist, the data scientists which are involved in the AI project. Moreover, the interface to use AI will be more and more user-friendly.

“The basics to know how it works […] it is the logic which is a bit advanced.” (Exp6).

“People will not be behind the calculation, they will use the app, use the interfaces.” (Pract6).

“What it can do, what it cannot do and what it can bring us.” (Pract7).

“It's not complex at all. It's just know how it works, what are the strengths, what is the limit of the system.” (Exp4).

“[Managers] have not understood the potential or they imagine things that are not possible, so the first step is to say that's possible, that’s not possible.” (Pract7).

“We must understand what does it do, we must understand the possibilities.” (Pract5).

Even human can be wrong, the data is input by human and so there will be risks of errors consequently. Managers need to also discern that it does not mean because AI is a machine so it will not contain bias. In the contrary, AI will definitely have bias which come from the data feed and trained by human. That is why it is important to understand the concept so not to misuse it and that validation and judgment will be required during the utilization.

“You probably need to understand what's data has been trained on, what bias is introduced and what are the risks.” (Exp5).

“You have to understand perfectly the concept.” (Pract7).

- Define needs & business case

Once basic knowledge of AI is acquired, managers may need to identify in which case AI can bring added value.

"So, all industries need to understand if it will impact them." (Exp2).

"To know how we can use IA for our needs, to analyze needs and in which occupation we can use it." (Pract2).

"Abusive excitement that is made around the AI that leads to many AI projects with quite limited relevance." (Pract5).

"The hard point that you have people using your AI […] and it's not useful. It must be part of the strategy I think." (Pract3).

"We see huge potential but not lots of use case at the moment." (Pract7)

"The utilization idea […] but what we really are going to do, it is harder, it requires a bit of projection." (Pract5).

- Judgment & Ethics

Interviewees stress the importance of judgment and ethics regarding AI usage. Human judgment seems paramount to ensure a relevant implementation of AI, as well as when it comes to ethical issues either the potential of sensitive uses of AI.

"If [AI] doesn't work, they have to figure out that the problem is not the AI, it's what's put in the AI." (Exp4).

"Basically, data was really biased so it's like you build tools and if you rely blindly on the tools without really understanding, it can do really stupid things, right?" (Exp5).

"That we cannot trust 100% about the tool. But there's always specific human conditions that generate output that are different from what the logic wants." (Exp6).

"The manager sometimes says oh it's ok, it's good, I can validate it *or he sees that it's not correct and then he challenges it." (Exp6).*

"It will always be a human behind to control what the AI does, to adapt it." (Exp3).

"We use the answer of the user to train the model […] it's supervised by the user." (Exp4).

"[…] experts rejected it, it is a data that will feed the database that will allow the system to improve." (Exp2).

"It is important to put in the model for that it learns about this refusal […] that machine learning becomes more relevant." (Exp 3).

"It's very important when you use these tools to understand the limits and to not misuse them." (Exp5).

"Ethical issues could be taught as we see that the AI is a problem on this matter: because of the large amount of data we have on everyone." (Exp6).

3.2.2. Non-technical managerial skills to optimize the use of AI

- Risk-taking

Apart from technical skills, managers need to hold change and acceptance skills to adopt and maximize utilization of AI. First, managers need to be keen on tasking risks because the developmental forms of AI are likely to produce errors or lack of results.

“One strong point is the culture of risk taking or not […] The act of accepting risks.” (Exp2).

“It can be difficult for them in fact, not to have any result, to start something and to have a result that is not valid.” (Exp3).

“But in the end, you have to accept errors, again, errors, you have errors in the end” (Pract4)

“Because people are afraid I think of AI. Yeah, I think either they're afraid of wasting time” (Pract6)

“There is a resistance in not knowing how it works is because it might not work […] even man can have a failure.” (Exp4).

“For big companies, they are not yet out the culture of risk management and the conduct of change.” (Exp2).

- Open-mindedness

Our data suggest that being flexible and open-minded looks necessary as well in order to accept that AI can augment or even partly replace managers.

“Now if you want to make a good use, you must try this ability, to challenge your humility, develop your flexibility, your openness of mind.” (Pract1).

“That you have to open your mind by saying that machine is able to digest even if it's not like how I’m doing it.” (Pract3).

“The ability of introspection to relativize his own analysis […] to mix what is given by AI and what I give of my cognitive capacities.” (Pract1).

“We have customers especially with lots of experience, so they use to see the world by their way […] I saw that the older people get, the more reflective to change.” (Pract6).

“That's why we did the training for people between 35-45 years old who are able to understand these issues but for that, it's really change drive because it will generate transformations.” (Exp2).

- Organizational change management

Respondents point out the necessity to manage basics of organizational change management so that AI is successfully implemented and used.

“We need to put in place the elements of change management.” (Exp2).

“The main thing that will slow down everything is that people are not ready yet and will take lots of time to be ready.” (Pract6).

“French culture, we really like intuition and experience in knowledge instead of through data.” (Pract4).

Interviewees usually have to deal with resistance to the change that AI implementation implies.

“There are many people against the use of computer for example.” (Pract6).

“[Managers] don't really believe in numbers. I think numbers could be better than their feeling, their intuition and their knowledge of the market and of the business. So, it's really a whole culture reprogramming to actually imagine that AI will really help their business better than they would on their own.” (Pract4).

“[Managers have] to accept to be augmented by the AI, meaning that we finally delegate some tasks to the machine.” (Pract4).

AI can indeed be seen as a threat to some occupations.

“It can replace another job. It can also do, can also be a brake.” (Pract7).

“They may take out some human jobs so I don't think especially in France, we don't use it enough. There are plenty of stuffs that can be done automatically, really.” (Pract6).

“I think it's a bit of fear, bit of pride […] not going to let the machine or something like that to take my job.” (Pract6).

One of the main tactics seems to be extensive argumentation through communication, potentially supported by training.

“I have to convince employees of the interests of AI […]” (Exp3).

“I explain to managers that [..] the job market is evolved. So, our way of doing things, our working methods, our diagnostic methods must evolve over time.” (Pract1).

“To accompany the people in training, to convince them to put things in place.” (Exp2).

“It's good to communicate and explain.” (Exp4).

- Communication & Collaboration skills

Our respondents add that the definition of the business case is probably to be done in association between managers and AI technicians, with a strong two-way communication process. As there are several parties from different background involved, communication becomes one of crucial skills to maximize the realization and use of AI.

“We need the operational expert to help the AI expert always improving AI.” (Exp6).

“It's complicated, an engineer with mathematicians is complicated, mathematicians with experts in the field is still very complicated too. So here, we have 3 phases, 3 different types of population to communicate. It is the problem of background is there.” (Pract5).

“To present to consumers of data, well, it is still necessary to be a good communicator because there is the conduct of change.” (Pract3).

“I organized webinars for all managers or I explain, on a recruitment, I will call the manager directly. There are several levels of communication and information.” (Pract1).

“We would need to have a strong connection between the employee who knows the business and the one who can apply this technic.” (Exp4).

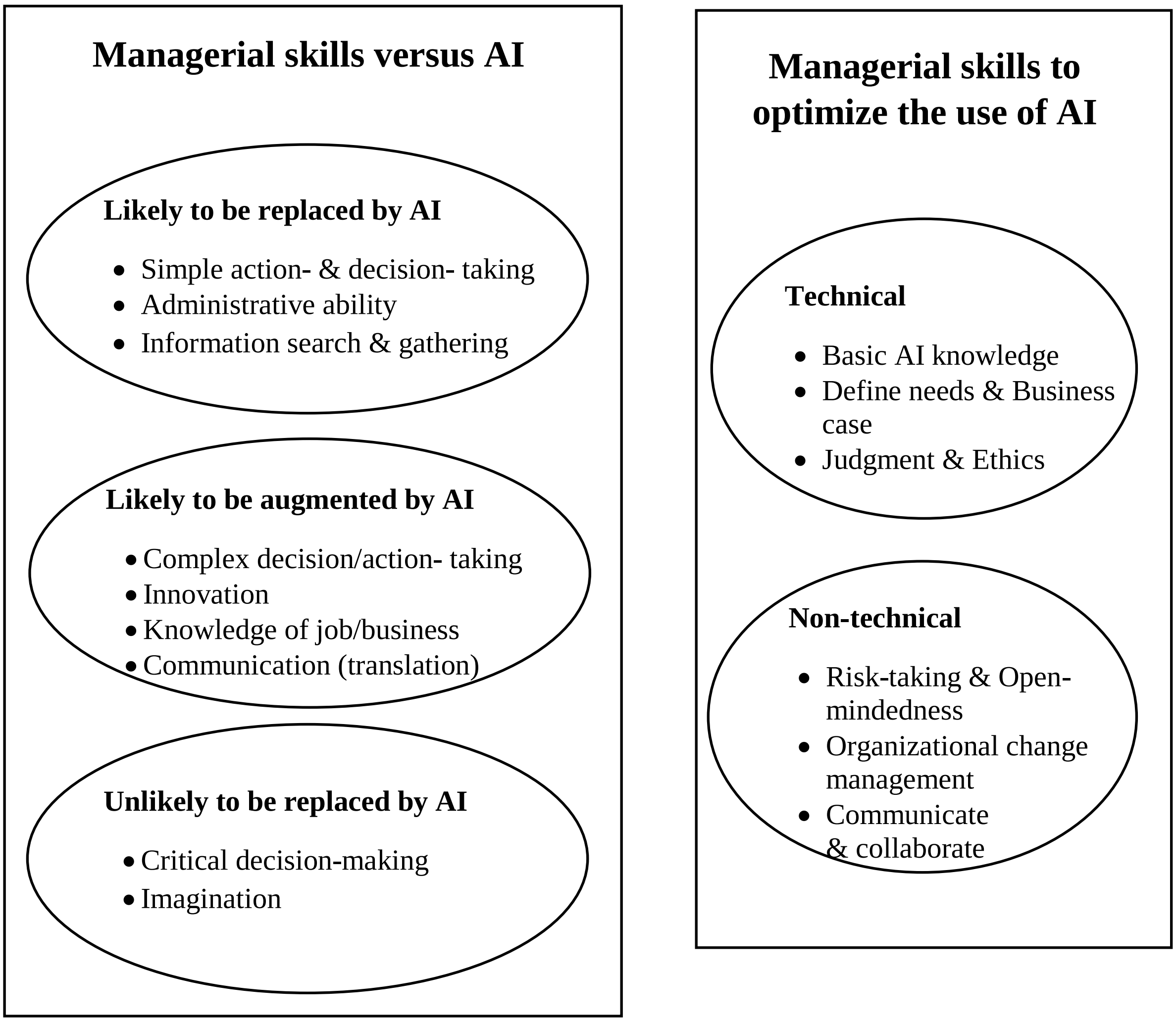
“It's really working in common between the AI expert and the expert of the profession.” (Exp6).

There may also be a need to clearly organize the collaboration between the different occupations.

”We may need to have a clearer separation between the research for algorithms and the use of those in a particular case […] So that maybe there are more exchanges between these people in order for AI to become more reliable.” (Pract4).

The **Erreur ! Référence non valide pour un signet.** below synthesizes our empirical findings.

Figure 1 : Synthesis of the results



4. Discussion

Our study first answers the call of Felten *et al.* (2018) regarding "more work […] to be done linking advances in AI to occupations and skills" as far as managerial skills are concerned.

4.1. Managerial skills versus AI

4.1.1. Managerial skills likely to be replaced by AI

- Simple decision/action- taking

Our data confirm that simple decision-taking, even action-taking, may be outsourced to AI which is to become more effective on that matter (Lichtenthaler, 2018). We confirm that simple tasks such as repetitive, regular and routine tasks are to be replaced or duplicated by AI (Decker *et al.*, 2017; Kolbjørnsrud *et al.*, 2016). The question is then about monitoring those tasks and building acceptance towards that change as it will affect job contents.

- Administrative ability

In terms of simple tasks, AI is faster in planning tasks involving many technical variables, such as organizing schedules or matching room and time availabilities. Just like for simple tasks, Hagemann *et al.* (2019) mentioned that in a short-term perspective, it gives managers more opportunity to focus on work which requires their core competencies which eventually adds more value (Dejoux & Léon, 2018). Yet, some conditions for this enabled focus on added-value creation should probably be granted. Aftermaths in terms of managerial skills to optimize the use of AI on simple tasks will be discussed in section 4.2.

- Information search & gathering

Searching and gathering information, as well as creating order out of large quantities of information, are likely to be replaced. With its computing capacities and its training model in this information era, AI plays a key role for this kind of managerial skills. This is coherent with the work of Lichtenthaler (2018) where he categorized this automating jobs with limited complexity in the "substitute" matrix which is an advanced automation to replace human work with focus on efficiency.

4.1.2. Managerial skills likely to be augmented by AI

- Complex decision/action- taking

Complex problem identification and solving are more likely to be augmented. As depicted by literature that AI cannot cope with general adaptive intelligence and performance, as it is "typically limited to a single frame or type of problem" (Lu *et al.*, 2018, p. 371). As Decker *et al.* (2017) wrote, modern robots have a system of AI with the help of which they can take decisions but only to a limited extent (semi-autonomously). Again, AI capability allows to gather information faster, to predict and to propose solutions and actions. Consequently, AI will augment managerial skills in taking actions and making decisions for more complex problems more efficiently and faster. In that way, AI becomes a significant source for better performance for the enhancement of product or in decision-making (Davenport & Ronanki, 2018).

- Innovation

If creativity (Plastino & Purdy, 2018) is not yet replicable via AI, our results show that systematic correlation analysis can provide managers with perspectives and figures that they would not have though of. The use of AI then increases their innovation skills by potentially widening they perspectives.

- Knowledge of job/business

Several regular and time-consuming tasks been replaced by AI hence will augment manager's time management. AI makes the most of time available which as result, manager can set better their priority to focus on more added-value tasks or to learn new core competences. These findings are coherent with those of Dejoux & Léon (2018) about more added-value coming along with AI, in line with the statement of Hagemann *et al.* (2019) about opportunities to focus on work which requires manager's core competencies.

AI's capability to gather information fast and to predict based on past histories, which is also depicted by Agrawal *et al.* (2017): AI is able to make abundant and inexpensive prediction, which will enable managers to more efficiently analyze their job and enable them to learn faster.

- Communication (translation)

Due to fast globalization, managers now face other integrative issues such as managing in a global environment (Robbins & Coulter, 2012) which might provoke communication issue caused by language differences. AI is more and more advanced in language translation especially in term of text, notably thanks to its learning method. AI is then likely to assist managers to communicate with foreign team members or other interlocutors. oral communication is considered as a complex task, this is aligned with Lichenthaler (2018) where he depict that humans still have the lead for complex and non-standardized task.

4.1.3. Managerial skills unlikely to be replaced by AI

- Critical decision-making

Our respondents confirm that humans still however have the lead for complex and non-standardized tasks (Lichtenthaler, 2018) which makes it very unlikely for AI to take on critical decision-making. Indeed, Good judgment for instance comes from the knowledge of organizational history or context (Kolbjørnsrud *et al.*, 2016): a dimension that AI usually fails at considering. We confirm that the human contextual role in defining strategy is therefore to remain (Pistrui, 2018).

- Imagination

Our respondents confirm that imagination such as knowing what questions to ask and imagining a thing that does not yet exist (Rometty, 2016) may not be replicable by AI. Despite its winning against world champion of GO game board, it is believed that AI does not innovate or invent directly but instead just replicates based on the data it is trained with. Agrawal *et al.* (2017) also evoked that AI is not creative to find new opportunities by itself. In that sense, we confirm that storytelling and motivational speeches are unlikely to be duplicated by AI (Lichtenthaler, 2018; Wilson *et al.*, 2017).

4.2. Managerial skills to be developed to optimize the use of AI

Our results show that existing repositories (Bhanugopan *et al.*, 2017; Fayol, 1916; Gentry et al., 2008; Mintzberg, 1973) should be updated with new managerial skills like *basic knowledge of AI*.

4.2.1. Technical managerial skills to optimize the use of AI

- Basic AI knowledge

While some scholars suggested that future managers might need skills in coding to be able to comprehend the functioning of AI (Dejoux & Léon, 2018; Ellenberg, 2017), our respondents insist that only basic knowledge logic should be taught.

- Define needs & business case

Respondents insist on the necessity to keep human intervention regarding the definition of the needs and the business case. Our results then confirm that managers plays key role to identify the rational for using AI (Fiore *et al.*, 2018), to analyze the business case (Henke *et al.*, 2018) and to weight costs and benefits, as well as to evaluate the misleading production result of the application (Schrage, 2018).

- Judgment & Ethics

Our data confirms that AI is likely to lack good judgment (Agrawal *et al.*, 2017; Kolbjørnsrud *et al.*, 2016). Final decisions related to critical and ethical issues are less likely to be replaced and should still be at human's or manager's hand. We are then able to confirm that managerial training may then shift from a focus on prediction-related skills to judgment-related skills (Pistrui, 2018) and that future managerial skills are likely to be about determining how best to apply AI regarding the opportunities for prediction, what should be predicted (Agrawal *et al.*, 2017).

4.2.2. Non-technical managerial skills to optimize the use of AI

- Risk-taking

Manager needs to accept of taking risk to innovate. Then to drive the change to its team members in the organization. This is coherent when Chui & McCarthy (2017) depicted that commitment to change is essential in all levels of management and that employees are also psychologically ready to work with AI.

- Openness-mindedness

In our data, being open-minded looks necessary to make the best use of AI. This is coherent with literature saying that managerial training may then shift from a focus on prediction-related skills to judgment-related skills (Pistrui, 2018).

- Organizational change management

Our data show that change management skills (through communication and training) are needed. Manager indeed have to develop leadership skills (Kotter, 2012) to drive the change within the organization. Knickrehm (2018) added that managers had to develop the necessary skills and to define new job descriptions and organizational structures if needed.

- Communicating & Collaboration skills

Our participants highlight that a good communication on the change implied by AI is needed. Commitment to change is actually essential in all levels of management and that employees are also psychologically ready to work with AI (Chui & McCarthy, 2017).

Our data also suggest that to maximize the utilization of AI, communication and collaboration will also paramount in continuous AI use. Clear role descriptions and separation might also be needed to enhance more effective and efficient collaboration. Thus, it might be needed to define new job descriptions as well as modernized organizational structures (Knickrehm, 2018), notably because human teams working with AI should then be contemplated (Norman, 2017).

Our respondents eventually agree on the fact that collaboration between operational managers and AI technicians is necessary in order to grant the best use of AI. This relates to the work Agrawal *et al.* (2017) who evoked on how should the AI agent learn in order to improve predictions over time.

Conclusion

Summary

Thanks to qualitative interviews with AI experts and practitioners, our qualitative data show how and which managerial skills are to be replaced, augmented or not affected. In parallel, our data points out specific technical as well as non-technical skills that managers are expected to develop in order to successfully accompany the growing presence of AI.

Limitations

Despite our limited sample size for the qualitative data collection, our research is still believed to have a certain generalizability (Buchanan, 2012) such as moderatum generalization (Eisenhardt, 1989), naturalistic generalization (Stake, 1994), isomorphic learning (Toft & Reynolds, 2005) or analytical refinement (Tsoukas, 2009). As it is almost impossible for qualitative research to come up with findings that can be applied to other situations, places and people (Bryman & Bell, 2016), it is then more important to produce rich accounts of experiences of people called “thick description” (Geertz, 1973) providing other researchers with database needed to assess the possibility of transferability of findings to other contexts (Lincoln & Guba, 1985).

Contributions

Our research first brings empirical contribution by combining views of AI experts and managers working in the continents (Europe, America and Asia) where investments, practice and research in AI are both diverse and the most advanced (OECD, 2019).

Secondly, our paper brings theoretical contributions in the way that it enriches existing taxonomies of managerial skills (Bhanugopan *et al.*, 2017; Fayol, 1916; Gentry *et al.*, 2008; Mintzberg, 1973) with new technical and non-technical skills to grant an optimized use of AI, as this tool is entering organizational life.

Thirdly, our article orientates companies towards the right direction in terms of training investments at a historical moment where AI is getting installed in many sectors and occupations. For instance, our data shows that training efforts should be directed towards what can now be considered as basic technical managerial skills. In a way, we further specify what Dejoux and Léon (2018) called basic AI management: (1) basic AI knowledge, (2) defining needs and business case of AI as well as (3) judgment and ethics in using AI. Corporations should also support the development of non-technical managerial skills in order to optimize the use of AI: (1) risk-taking, (2) open-mindedness, (3) organizational change management as well as (4) communication and collaboration skills. Our data then suggests that the job descriptions of managers and AI specialists are likely to evolve so that AI is used in the best possible way. If an industrial revolution is actually happening thanks to AI (a revolutionary tool), training plans and organizational structures are on the verge of being significantly restructured for companies to adapt to competition. Our article provides companies with some valuable directions in that perspective.

Perspectives for future research

Future research could investigate training methods which are effective into teaching the new managerial skills that are hereby identified, specifically in relationship with AI.

Parallelly, there is a possibility that specific managerial positions and/or specific sectors call for different relationships between managerial skills and AI. Therefore, the existing managerial skills' repositories (Bhanugopan *et al.*, 2017; Fayol, 1916; Gentry et al., 2008; Mintzberg, 1973) are likely to be updated in different ways according to different contexts.

Eventually, future research should explore how organizations are to be restructured (Knickrehm, 2018) to accompany the evolution in managerial skills that we show AI is likely to produce and to grant an optimal functioning, notably with more managers working directly with AI (Norman, 2017).

Appendices

Appendix 1: Interview guide for AI Experts

Interview Guide - AI Expert

PROFILE OF THE RESPONDENT	
1	What is your Title/Department/Organization?
2	What is your Age/Gender/Tenure in position/organisation?
3	Do you have a specific AI expertise?

CURRENT AI	
4	How would you qualify the evolutions in the use of AI? What do you think would be the future trends in the use of AI?
5.	Do you think current AI has AFFECTED some managerial skills? How?

FUTURE AI	
6.	How far do you think AI is likely to AFFECT managerial skills in the future? At which horizon (when)?

FUTURE MANAGERIAL SKILLS TO BEST USE AI	
7	According to you, are there specific managerial skills to be developed/created in order to complement the rise of AI and to maximize its efficiency? If yes, which ones? Why?
8	Any additional comments?
9	Do you know any other AI practitioner/expert that could be interviewed as well? If yes, would you please have his/her contact information?

Notes:

- *Artificial Intelligence is defined as "a computer science aiming to perform tasks that replicate human [...] intelligence and behavior (Fiske & Kazdin, 2000)".*
- *Managerial skills can for instance be "Replaced (even partially)/Supported/Augmented/Not affected at all" by AI.*

Appendix 2: Interview guide for AI practitioners

Interview Guide - AI Practitioner

PROFILE & RELATIONSHIP TO AI	
1	What is your Position/Department/Organization?
2	What is your Age/Gender/Tenure in Position/Organization?
3	Do you have specific AI expertise?
4	Which specific AI technologies are you using? For which purpose?
5	When did you start using AI in your job?
6	After having introduced AI, what was the biggest change(s) that you have experienced in your job?
7	What are the challenges while working with AI?
8	How do you address those challenges?
9	Do you think you have maximized utilisation of AI in your job? Why?
10	Did you receive Ai-related training? If yes, please specify.

CURRENT & FUTURE AI	
11	How would you qualify the evolutions in the use of AI in your job/sector? What do you think would be the future trends in the use of AI in your job/sector?
12	Do you think AI HAS AFFECTED managerial skills IN YOUR JOB? Please specify which skills.
13	Do you think AI WILL AFFECT managerial skills IN YOUR JOB - in the future? Please specify which skills. At which horizon (when)?

FUTURE MANAGERIAL SKILLS TO BEST USE AI	
14	According to you, are there specific managerial skills to be developed/created in order to complement the rise of AI and to maximize its efficiency IN YOUR JOB? If yes, which ones? Why?
15	Any additional comments?
16	Do you know any other AI practitioner/expert that could be interviewed as well? If yes, would you please share his/her contact information?

Notes:

- *Artificial Intelligence is defined as "a computer science aiming to perform tasks that replicate human […] intelligence and behavior (Fiske & Kazdin, 2000)"*
- *Managerial skills can for instance be "Replaced (even partially)/Supported/Augmented/Not affected at all" by AI.*

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