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Master in Information Technologies and Innovation Management

THE CHANGES OF SALESPERSON’S SKILLS AND KNOWLEDGE CAUSED BY THE FOURTH INDUSTRIAL REVOLUTION

Master’s Thesis by the 2nd year student

Concentration — Master in Information

Technologies and Innovation Management

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**ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ**

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29.05.2017 (Date)

**АННОТАЦИЯ**

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| Описание цели, задач и основных результатов  | Цель данной работы состоит в том, чтобы ответить на вопрос как компании должны изменить подход в работе со специалистами по продажам в контексте наступающей промышленной революции. Четвертая промышленная революция приносит технологии, которые в конечном итоге автоматизируют задачи. В ответ, компании меняют свою систему работы с кадрами. Специалисты по продажам являются основой бизнеса, и они будут также выполнять свои функции в контексте четвертой промышленной революции, но их ежедневные задачи будут отличаться. Чтобы определить, какие навыки понадобятся в будущем, мы сначала определяем, какие навыки уже используются специалистами по продажам, используя опрос Министерства труда США. В рамках следующего этапа мы сравниваем представленные навыки, знания и использование программного обеспечения, которые, как ожидаются, будут соответствовать названиям позиций. Мы используем модель вероятностей автоматизации задач, разработанную McKinsey Global Institute для тех же регионов США, чтобы оценить долю задач в рамках этих рабочих мест, которые могут быть компьютеризированы. Используя повторные статистические корреляционные тесты, мы обнаруживаем, какие из навыков, знаний и программного обеспечения, о которых сообщается в профессиональном опросе, коррелируют с задачами, наименее поддающимися автоматизации. |
| Ключевые слова | Четвертая индустриальная революция, компьютеризация, продажи, человеческий ресурс, будущее работы |

**ABSTRACT**

|  |  |
| --- | --- |
| Master Student's Name | Charles Beraza |
| Master Thesis Title | “The Changes of Salesperson’s Skills and Knowledge Caused by The Fourth Industrial Revolution” |
| Main field of study | 080200 “Management” (specialization: Information Technologies and Innovation Management) |
| Year | 2017 |
| Academic Advisor’s Name | Tatyana A. Gavrilova, Doctor in Technical Sciences, Professor |
| Description of the goal, tasks, and main results | The purpose of this paper is to address the question: How the companies should adapt the human management of their sales workforces in a context of an incoming industrial revolution? The fourth Industrial Revolution is bringing technologies that eventually automatizes tasks. In reaction, companies change their employ of people. Salespersons are the core of the businesses, they will continue to exist after the incoming industrial revolution, but their daily tasks will be different. In order to define which skills are going to be needed in the future, we first define which skills are already used by the salesperson, using the US Ministry of Labour Occupational survey, we match presented the skills, knowledge and software usage expected to fit the job title. We use a reviewed model of tasks probability of computerisation developed by McKinsey Global Institute for the same US region in order to estimate the proportion of tasks within these jobs likely to be computerized. Using repeated statistical correlation tests, we find which of the skills, knowledge, and software reported in the occupational survey are correlated with a fewer share of tasks automatable.  |
| Keywords | Fourth Industrial Revolution, Computerisation, Sales, Human Resources, Future of Work |

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# INTRODUCTION

In 2015, Klaus Schwab the founder and executive chairman of the World Economic Forum exposed the concept of 4th Industrial Revolution (4th IR) developed in an eponym book (Schwab “The Fourth Industrial Revolution” 2016). The term does not refer to a specific innovation but rather covers the whole framework of technologies likely to be unlocked for industrial use in the future. The overall impact of the 4th IR on the economy will be “monumental”, “so vast and multifaceted that it makes it hard to disentangle one particular effect from the next.” (Schwab, 2016, p. 28). The set of tasks or skills needed to achieve a given work is tremendously going to change.

Meanwhile, stability is the key factor for businesses’ success. There are different strategies for businesses to prepare themselves for such technological shocks. The first basic preparation for changes is to be informed, but we can easily assume that the most successful businesses will be the ones who transformed the information about change into a decision and decided to *reskill* their workforces. The report made by the World Economic Forum in 2016 brings us some information regarding the current trends in term of skills requirements by the companies, and that industry-wise. “Responses to the Future of Jobs Survey indicate that business leaders are aware of these looming challenges but have been slow to act decisively. Just over two-thirds of our respondents believe that future workforce planning and change management features as a reasonably high or very high priority…” (World Economic Forum 2016, 26) In order to be disruptive, companies would have to start the redeployment of their workforce alongside the process of computerization of tasks. We can assume that the more synchronized these processes are, the less likely jobs losses are to be.

My paper is motivated by the work of Carl Benedikt Frey and Michael A. Osborne in 2013 “The Future of Employment: How susceptible are jobs to computerisation?”. This paper is one of the first investigating the consequences of the 4th IR from an economical point of view brought the conclusion that 47% of the jobs included in the list used by the US ministry of labor might be subject to computerisation in the years to come from this same fourth industrial revolution. This question has been later developed by a team from the OECD, “The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis” (Arntz, Gregory, & Zierahn, 2016). While the paper of Frey and Osborne described the impact of the 4th IR for each job in the USA, Arntz, Gregory and Zierahn adapted their counterparts’ findings for OECD countries. They also criticized the assumption taken by Frey and Osborne to consider the computerisation job-wise, arguing that the task approach is more realistic. Both of these studies brought economical conclusion relevant to the public discussion, but difficult to interpret for businesses’ decisions makers. In early 2017, the consulting company McKinsey published through its research institute a white paper continuing the tradition of computerisation estimation. As detailed later, we use their findings as they are the *state-of-the-art* regarding this question. The purpose of this paper is to shift these approaches toward the 4th IR from macroeconomy to practical human resources problematics, trying to bring useful insight for businesses. As a general trend, we can simple notice that the proportion of tasks related to physical and repeated work decreased along the last decades (Levy, 2010). Finally, the 4th IR is going to also affect intellectual non-repetitive tasks, changing the rules of the game.

For this study, we took the decision to focus the findings of this paper on sales position for several practical reasons that we are going to develop in detail later. Sales position are existing in all the industries, making our findings relevant for most of the business deciders. Meanwhile, sales tasks have been highly disrupted in the previous decades by the implementation of computers.

In order to evaluate the reality of salespeople, we use data extracted from the US Ministry of Labor, confirming the national scope of this study. The database O\*NET provides an important sample of different professions which we are going to compare with the proportion of computerizable tasks.

# DISCUSSIONS ABOUT INDUSTRIAL REVOLUTIONS, LABOR SUBSTITUTION, THEIR IMPACT ON WORK

## The economic history of the Industrial Revolutions

### The First Industrial Revolution

A first step into the problem would be to consider how this process already occurred in the past. Four industrial revolutions have paved the last two centuries as milestones. Each of them has changed the way the society is balanced, leading to new business environments and practices. “Revolution have occurred throughout history when new technologies and novel ways of perceiving the world trigger a profound change in economic systems and social structures.” (Schwab, 2016, p. 6). This paper doesn’t aim at any historical analysis, but patterns and opinion that happened in the past help us to understand the future of the current trends.

The first industrial revolution evolved from 1760 to the 19th century, it marked the transition from an economy based on food sustainability to a monetary based one. It included innovations such as the steam engine, the train and the embryo of the modern industry through the textile industry. Its social, economic and political consequences were tremendous and drove the modern idea of capitalism. It showed the first documented phenomenon of massive skills reallocation, with the rural exodus from farms to factories (Harari, 2014). One of the first known movement of resistance against technologies undertaken for jobs sakes happened in this context. The *Luddites* were a group of highly specialized textile workers located in the north of England. During 1811 and 1812, they attacked newly installed machines weaving machines, fearing that they might steal their jobs. Similar situations happened in France during the 1789 revolution, and it is known that Queen Elizabeth I refused to grant a patent for a machine, fearing for the country’s stability (Connif, 2011). The term now defines the fear for jobs induced by technologies, which might be developing nowadays as a whole political ideology regarding the possible impact of the incoming technologies.

### The Second Industrial Revolution

The Second Industrial Revolution which happened refers to the development of mass production in the beginning of the 19h century, accompanying the development of mass consumption[[1]](#footnote-1). This change came along societal evolutions, which took time to benefit all the society (mass education, insurance), the time IR took to benefit the society put in light the different paces between technology development and public adoption (Fujimori, Brynjolfsson, Pissarides, George, & Poulsen, 2016, p. 11:50). The two first industrial revolution led to massive unemployment because of the rural exodus. The public policies addressed the issue by launching the first massive reskilling of the population through the public school permitting a huge amount of people to access the knowledge they needed in order to achieve higher value in the economy. From a sociologic point of view, the 3rd IR brought the fundament of the company as a key element of social interaction and one of the most important cement of the society, on an extent comparable with religion. The concept of the company became an element embedded in the human culture (Harari, 2014).

### The Third Industrial Revolution

The third IR (Industrial Revolution) was a more contemporary transition, referring to the introduction of computers, green energy and ecological consciousness in the economy – and by. The way, order and the consequences of events occurred in this period help us to understand the possible impact of the 4th IR. While the exact definition of the Third Industrial Revolution is variable (the term has been coined in 2011 by Jeremy Rifkin, defining the green economy, while Schwab considers it to be the first wave of digitalization, including the first computer and the internet). This period vectored, as the others, industrial revolution vectored important tasks relocation and jobs mutation. It marked the end of the jobs of mathematical clerks and administrative secretary, whose jobs are now – somewhat – do by the Microsoft Office suite. Industrial drawer, Statisticians assistants use to be a position requiring an intermediary level of education, they now do not longer exist in the same way. We will develop later the idea that the 3rd and the 4th IR are polarizing the jobs market.

### The Fourth Industrial Revolution – Technological Overview

The fourth industrial revolution is referring to the present and future development of usable innovations from a set of different technologies that are now being developed. The lag between the technology development and its acquisition by the society could highly change, depending on the country and the societal assumptions. For example, the development of technologies required for the automation of 80% of the actual existing could happen between 2030 (at the earliest) and 2055 (at the latest), while its adoption by companies should happen at the earliest, not before 2050 (Bughin, Manyka, & Weetzel, 2017, p. 12). The book of Schwab provides a view on the different technologies encompassed in the 4th IR and their outcome for both businesses and society. We will assume this book as a tool to comment the set of practitioners’ actual skills produced by our research. The technologies are described in the book following different categories: *Implantable Technologies, Our Digital Presence, Vision as the New Interface, Wearable Internet, Ubiquitous Computing, A Supercomputer in Your Pocket, Storage for All, The Internet of and for Things, The Connected Home, Smart Cities, Big Data for Decision, Driverless Cars, Artificial Intelligence and Decision Making, AI and White-Collar Jobs, Robotics and Services, Bitcoin and the Blockchain, The Sharing Economy, Governments and the Blockchain, 3D Printing and Manufacturing, 3D Printing and Human Health, 3D Printing and Consumer Products, Designer Beings and Neurotechnologies.*

As this list shows, the scope of technologies included in the fourth industrial revolution is very wide. Moreover, the interaction between two new technologies is extremely difficult to imagine. For example, the merging between 3D printing and Biotechnologies will lead to the 3D Printing and Human Health. There is room for other combinations of technologies, creating an important and large framework whose limit are difficult to apprehend. That is why we will focus on the idea that the comprehension of technologies individually is impossible, and the already existing set of technology is a relevant introduction to the later discoveries to come.

### The Fourth Industrial Revolution - Context

 The actual economic context raises, even more, uncertainties about the possible impact of the 4th IR. Some trends seem to be strong enough to have an impact for at least the next decades, shaping, therefore, the integration and the usage of the previously mentioned technologies. The aging of the population is probably one of these strongest trends from the macro economical point of view. In most of the western countries, the average age of the population is increasing, shifting the needs of the public toward specific activities such as nursing of day-care. While many argue that its effect on the economy is negative, causing stagnation, it seems that the situation is more complex and that there is no negative correlation between the economic growth and the aging (Acemoglu & Restrepo, 2017). In the case of Japan, the Robotisation is clearly defined by the government as a political choice to address the effect of the aging population, therefore this trend should be considered in questions related to the computerisation. The emergence of a middle class in the emerging markets is also likely to enforce the need for clear ecological regulation about the consumption of products since the overall available resources are not likely to be able to sustain a North-American style of resource consumption in the future.

### The Artificial Intelligence

Among the various ascending developments of the 4th IR, the Artificial Intelligence (AI) might be considered as the most serious, and its overall impact might result in grave consequences in society. The development of Machine Learning, which uses a Darwinian approach to copy human behave or improve gradually processes, coupled with the access to vast data through the internet - the Big Data – unlock previously unseen potential for the artificial intelligence development, ending the decades-long period of stagnation in the artificial intelligence’s evolution. The idea of the technological singularity defines the hypothetical event when the artificial intelligence would reach a human level. The precise definition of what would be an Artificial Intelligence is complex to define and related to both philosophical and technological questions. “Superintelligence: Paths, Dangers, Strategies” (Bostrom, 2014) brings a framework of reflection about AI. In this book, Bostrom made an aggregation of opinion polls answered by specialists in AI which showed that by 2040 there are 50% of chance that the singularity would happen. To encompass even a glimpse of the final impact of AI is still impossible, but we can assume that from an economist point of view, it would be the “ultimate automation”, completely redefining the place of the human in the economy changing our definition of value, service, and skills. During the last decades, the most valuable skills were related to the mastering of extremely technical and specific skills (medicine, laws, engineering). Regarding the probable predominance of robots in these fields, a possible shift of added value could be imagined, favoring skills related to communication and interpersonal services.

As a conclusion for this part, we should remind how uneven the diffusion of these technologies is across countries. They are far from being evenly integrated into some regions, some sub-Saharan countries have not yet embraced the second industrial revolution. In the region of the great lake near Zambia, the main mean of transportation used by the people to get to one place to the other one is a steam-powered boat brought by the German at the beginning of the 20th century – an emblematic technology of the first industrial revolution (The Economist, 2017). We can observe how African startups are trying to leapfrog the First and Second IR with the Third and Fourth IR because they are less costly in term of infrastructure. We should also not forget how the computerization is changing the core nature of the economy, by constantly increasing the companies’ productivity. As we will develop in the next part, this core evolution within the economy might lead to a need to revamp some core elements of the system.

## Review of cases and theory about the contemporary automation of the economy

According to the Cambridge dictionary, the computerisation is “to use a computer to do something that was done by people or other machines before”. Since the notion of the computer is changing, we will focus on the idea that the computerisation is the phenomena that turn a task previously done by a human to a task achievable with the help of the technologies. In this paper, the computerisation is naturally applied in the context of the fourth industrial revolution as defined previously.

The economic benefit for a business to integrate automation is dividable in two aspects. On one hand, it permits to substitute labor. On the second hand, it unlocks performance gain from the very use of more efficient robots. In their paper “A future that works”, the McKinsey consulting company describes five cases of automation, estimating for each of them the economic benefit resulting of the automation and the share of labor substitution and performance gain involved in it (The different aspects of their method is developed in 2.4).

Table - Estimation of Automation for 5 cases - McKinsey

|  |  |  |  |
| --- | --- | --- | --- |
| Case | Total Estimated Economic Gain | Share of Labour Substitution  | Share of Performance Gain |
| Hospital Emergency Dpt | 11% | 70% | 30% |
| Aircraft Maintenance | 25% | 66% | 34% |
| Oil and Gas Operations | 17% | 15% | 85% |
| Grocery Store | 14% | 32% | 68% |
| Mortgage application processing | - | 88% | 12% |

*Retrieved from* (Bughin, Manyka, & Weetzel, 2017)

### Truck Drivers and Simple Tasks

Taking the assumption that the development of the AI would happen gradually, we understand how this technology is going to growingly impact business. A simple example of that is the work of teleconsultant. These low skills employees are vital for business operations. They operate for different functions, such as sales, assistance, administrative tasks. The emergence of Chatbots systems confirms the findings evoked by Frey and Benedikt, which ranked telemarketers as the most possible threaten job in their list, scoring a 99% of chance of computerisation. (Frey and Osborne 2013, 72) Today, one of the most numerous occupations in the USA is truck drivers, an occupation which is likely to be computerized by the growing development self-driving technologies. There are 3.5 millions of trucks drivers in this country, and the level of technological replicability would make possible rather quickly to automatize the whole function of truck driving, making therefore irrelevant a big share of these millions truck’s driver. This exact profession brings an interesting case study to understand the factors and the outcome of computerisation. The job is simple to describe in term of tasks, driving is almost the only task deployed by the worker in term of economic value. Alongside, the economic metrics - such as the cost of the driver and its impact on customers’ final pricing for delivery - are pretty easy to understand. Therefore if the technology can be integrated and represents a cheaper option for this task execution, the computerisation is likely to happen. In opposition, we can imagine that if the metrics are not clear for the businesses’ decision makers, the integration of the computerisation might be harder to happen. The whole impact of this technology on this given task would have an important impact on the American economy, a total of 1% of jobs might be concerned.

### Predictive Maintenance

One of the most practical and least abstract usages of the artificial intelligence is the different declinations of the “predictive maintenance”. Algorithms permit to estimate precisely failures before they happen, therefore allow more precision and efficiency for the tasks of maintenance. In that case, the impact on jobs volume is not so clear. While the reduction of tasks related to “find” the next failure might lead to an increase in the workforce efficiency, it is not so sure how the whole jobs are going to be disrupted. In the case of aircraft maintenance, the usage of predictive maintenance, automated survey drones, and maintenance robots would highly reduce the overall cost of operations. It would lead to fewer technicians on the ground, but more work on problem solving and management of the maintenance itself, since more interdependent technologies are going to be involved in these operations. In a similar way, the maintenance of Oil and Gas operations is developing its automation. The maintenance and the operations around raw material extraction sites are hazardous, leading to high rate of casualties among the workers.

### The example of health care sector

Being the recipient of extremely important investments, the medical sector would probably is already “hosting” the first great innovation of the 4th IR. This sector might raise the first great ethical issues caused by the 4th, notably through the question of nursing the elders with robots, creating the topic therefore entitled “the Bioethics”. The healthcare sector will probably continue to serve as an example for the previously developed idea that the different regions of the world are implementing the technologies on different paces, mean and purposes. For example, some of the African countries are using the mobile technologies in order to leapfrog the costly approaches of centralized infrastructure developed in western countries during the 3th IR. Many of these countries highly beneficiated from the mobile network, since they lacked transport infrastructures and the western centralisation of the population. Therefore these mobile technologies enabled the possibility to operate previously complex operations of diagnostic or the administrative task underlying the medical acts through the help of smartphones (African Health Observatory, 2015). Meanwhile, the western world is continuing to develop its medicine toward a service now designed to improve the comfort and extend the lifetime of patients rather than address basic problems. One of the difficulties of the hospital emergency department is the volume of complex tasks requiring massive human workforce. The different layer of involved professions and data makes the case of hospitals ideal for the integration of automation (Bughin, Manyka, & Weetzel, 2017). The development of automated diagnostics through the usage of Big Data to monitor different human variable – or predictive healthcare - is going to disrupt the processes of the industry, reducing the difficulty of hospitals and naturally changing the skills and the tasks accomplished by the medical workforces. Previously on the core of the daily medicine, the task of diagnostic starts to be computerized. The IBM’s artificial intelligence “Watson” is now able to produce diagnostics from medical imagery. According to Ned Sharpless of the University of North Carolina, “Watson was tested on 1,000 cancer diagnoses made by human experts. In 99 percent of them, Watson recommended the same treatment as the oncologists” (Lohr, 2016). In the future, the role of doctor might follow the previously described “O-rubber” pattern. Therefore, automation of diagnostic would lead to decrease the importance of complex tasks of diagnostics, underlying the importance of prevention, relationship building with patients, which is already a respectable part of doctor’s worktime. The value of medical practitioners would become different, being the intermediary between patient and automated technology (Vallancien, 2017). While tasks such as surgery cannot be automated, the use of robots able to deploy higher manual dexterity casts another case of computerisation, when rather than replacing a task, the technology transforms it. It goes without saying that robots are not (in a near future) going to operate patients without any human action, but the usage of this assistance would continue to expand.

### The Industrial robots impact

 Being one of the basic examples of the automation, the results of the implementation of industrial robots in industries shows effects confirming the O-Rubber effect previously described. It has been estimated that the implementation of industrial robots raised the annual growth of GDP by 0.37 points and the labor productivity by 0.36 points (Graetz, 2015). Meanwhile, other findings similarly found that the implementation of robots increased the “employment to population ratio by about 0.18-0.34 points and wages by 0.25-0.5 percent” (Acemoglu & Restrepo, 2017).

### The O-rubber explains the technology’s impact on the job market

In order to introduce a further discussion about the automation, it is necessary to introduce the different key concepts related to the automation of tasks. The work of David A. Autor (Why Are There Still so Many Jobs? The History and Future of Workplace Automation) give us explanation about the economical patterns of this computerisation. He showed how banks adapted to the third IR and the disappearance of clerics position. Computers made obsolete numerous positions within the branches, permitting the bank to use drastically reduce the number of employees needed to sustain units’ operations. Thanks to this newly unlocked manpower, banks could multiply the number of branches resulting in an augmentation in the number of banks employees, while virtually the number of tasks needed by the banks decreased. As Autor explains, this situation is economically described by the O-Ring theory (Kremer, 1993). Let’s consider any industrial or service production as a chain of added tasks. The O-ring theory refers to the failure of the space shuttle Challenger, caused by a problem caused by a single O-ring. While this O-ring costs few cents in the market, its cost in this context is multiplied by its importance in the chain of values. In the case of third IR, Autor argues that the shift of the share of the human labor in the chain of tasks. It conversely increased the importance of human based tasks in the same chain of value which was the sales and negotiation skills needed to commercialize banks’ products. This example is showing how reskilling can permit not only to keep manpower but also to use it to access bigger business opportunities. This effect adapted to the economy shows that wages might be increased by the automation of tasks.

### The idea that automation is affecting tasks rather than people

This liquidity of tasks in the job market explains why jobs are more likely to evolve than to be totally automated, simply because of the complex set of tasks involved in any job. As we will develop in the second chapter, the most comprehensive approach toward the job market movements is based on task-wise labor division than job-wise. David Autor proposed in “The Task Approach” to Labor Markets: and Overview” the idea that jobs should be considered task-wise rather than skills-wise. The author considers that the classical canonical function is limited, following an anthropomorphic approach to the reality. He argues that the canonical distinction between labor and job does explain the detail of the value creation. Precisely, he argues that the classical model does not make a distinction between the tasks and the resources (human skills, capital…) needed to achieve it. He argues that this distinction is needed to make an accurate description of the substitution of a given task by either computers (Capital) or the foreign workforce. In order to palliate the flaws in the canonical model, Autor defines both skills and output: “A task is a unit of work activity that produces output. A skill is a worker’s stock of capabilities” (Autor, 2013, p. 5) Autor divides tasks into two categories. The tasks that are formalized and codified are computerizable (Routine tasks). The tasks that are new are not possible to computerize “Non-routine tasks”, and therefore allocated only to human. He considers that time permit the shift of Non-routine tasks to Routine tasks. The author also assumes that the cheapest solution to deliver a task would be logically selected by the economic actor. This division permits a new approach to encompassing the production of value, making it easier to explain how domestic workers, foreign workers, and computers may substitute to each other. “Even when a task is fully codified, however, this does not mean it will be automated. When Nissan Motor Company builds cars in Japan, it makes extensive use of industrial robots to reduce labor costs. When it assembles cars in India, it uses robots far more sparingly. The key difference between production in India and Japan is not technology but cost: labor is comparatively cheap in India” (Autor, 2013, p. 5).

### The middle-class jobs are the most threaten

A strong opinion among scholars studying the phenomena of Industrial Revolution is that the jobs’ market is growingly polarizing between two trends, the jobs requiring a highly specialized degree of education and the ones requiring a low degree of education (Frey & Osborne, 2013).

This is a serious treat for the balance of the economy because it casts a doubt on one of the basic ideas of the liberal economic system that education helps to get a better position. In this hypothetical case, the barrier between low and high profiles roles is stronger, jeopardizing the social ascension and making obsolete many middle-class classifications, how this question is approached by public power is going to be discussed in the next subchapter.

## The discussions about the possible “End of the Economy”

In 1989, Francis Fukuyama coined the expression of “The End of History?” explaining that the end of the soviet-capitalistic rivalry will induce the end of wars. While this idea is questioned by the post 9/11 chain of events, we can imagine that the 4th IR is going to bring a similar disruption of Cardinal theories that have for far paved our vision of the economy. Several authors are arguing that our actual economic model should change in order to face the growing ecological challenges as well the 4th IR. Maybe these technologies are going to provoke the End of the known Economic.

### The role of Institutions, the threat of Jobless Future

According to the site “shift happens”, more than 50% of the skills taught during curriculums are useless just few years after the graduation. Many universities are investing in providing cross formations, aiming at providing the most flexible curriculum. The 4thIR is likely to disrupt required skills in a way quite unpredictable that is why formation courses should aim at developing cross-functional skills rather than simply train people on extremely precise topics. According to the white paper “Realizing Human Potential in the Fourth Industrial Revolution,” the educational ecosystem should change from the early childhood to the retraining of already working professionals. Therefore, they advise that the exposition to the work should be earlier and wider. This is supported by the simple idea that reducing the gap between the workplace and the educational system is likely to reduce the risk of teaching already obsolete knowledge.

While many acknowledge the importance of emerging technologies, its impact on the work market is still discussed. “Techno-pessimists argue that the critical contributions of the digital revolution have already been made and that their impact on productivity is almost over. In the opposite camp, techno-optimist claim that technology and innovation are at an inflection point” (Schwab, 2016, p. 28). Similarly, the pool conducted by Aaron Smith and Janna Anderson for the Pew Research Center in 2014, “AI, Robotics and the Future of Jobs” shows how expert of this topic express divergent opinions about how the 4th IR will change the jobs’ market situation. Therefore, this research shows that “Half of these experts (48%) envision a future in which robots and digital agents have displaced significant numbers of both blue- and white-collar workers” while “The other half of the experts who responded to this survey (52%) expect that technology will not displace more jobs than it creates by 2025.” (Smith & Anderson, 2014). This divergence of opinions about the future of jobs is widespread in this question regarding the difficulty to assess the different factors involved in such predictions. Some interesting opinions emerge from this paper, such as the development of a traditional method of creation that are valuable for the customer or the fact the split between highly skilled employees and other will continue to increase. The group of idea concluding the report is that finally, the society through the political choices will decide the extent of the computerisation.

There is a growing opinion among economists that the fourth industrial revolution might seriously change the definition of work. The previous waves of innovation created jobs creation while destroying other following the concept of “destructive creation” theorized by Schumpeter “Capitalism Socialism and Democracy”, 1942. Nevertheless, the possibilities reachable by Artificial Intelligence might change dramatically the balance between jobs creation and destruction. The 4th IR may lead to huge unemployment, convincing some economist and politician to advocate universal basic income. I quote this opinion, but we do not consider as a possible outcome on the scope of this paper since it is too much unpredictable. The 20th January 2016 the World Economic Forum in Davos gathered several experts on this topic, in order to discuss the possible settings and outcomes of a world without work, in term of societal and economic impacts. The discussion involved *Erik Brynjolfsson(MIT), Christopher Pissarides (Recipient of Nobel price, LSE), Dileep George (CTO of Vicarious FPC) and Troels Lund Poulsen (Ministry of Employment of Denmark)...* The discussion starts with two pieces of information, the findings of Osborne and Frey that the computerisation threats 47% of jobs and a quote from the club of Rome in 1993 “Man Struggle from subsistence, may be solved due to technologies improvement, for the first time in history, man life would consist in choosing his leisure”. AI (Artificial Intelligence) might be summarized through different approaches toward the AI, general AI – able to proceed any type of tasks – and specific AI – able only to deal with a precise type of tasks (play chess, improve supply chain…). According to Dileep (7:27), the key element of achieving human-level AI is the ability to predict. The discussion continues with the idea that the wave of unemployment caused by the emergence of 4th IR would be extremely big, and that universal basic income would be a possible strategy to address it. “Few winners and many losers” (9:21) are expected from the 4th IR. According to Brynjolfsson, the inequality is growing because the increasing productivity does not benefit the whole society. Again he explains that the already quoted idea that public policies are able to shape the impact of 4th IR and computerisation, underlying that while the pace of technological expansion fastens exponentially, institutions are struggling to follow. This is due to the lack of flexibility of traditional public institutions. According to Troels Lund Poulsen, the market will not be able to bring a fair and even development to the society. The threat of the IR is that the low skilled ones are going to struggle to adapt themselves. Therefore, it is necessary to consider sectors that are not possible to automate because of their intrinsic human value, such as nursing and caring roles. The proportion of elders is constantly growing in both developed and developing economies, therefore the age caring sector would possibly counterbalance the effect of the 4th IR. As well the leisure industry is dependent on human labor “You don’t want to be served by a robot, neither your food to be cooked by a robot.” (Fujimori, Brynjolfsson, Pissarides, George, & Poulsen, 2016, p. 14:08).

Therefore, skills related to communication are growingly important, being at the core of these roles. During the previous IR, the cycle of technology development followed the cycle of “creative destruction”, when technologies enabled companies to earn more money and hire more people. But this may not repeat again, and we may fall into a vicious cycle where companies earn more money through the automation. There is an uncertainty that the amount of job creation will balance the amount of job automation. “Machine will be able to do pretty much anything that human can do, and they would be better at doing that” (Fujimori, Brynjolfsson, Pissarides, George, & Poulsen, 2016, p. 25:01), this view brings again the question of the intrinsic limit of our acceptance for a service not executed by a human. It also introduces us the concept of “super-humanity”. This concept defines the state in which an AI is outperforming a human in given tasks. For example, in Checkers, Backgammon, Othello, Chess, Scrabble, Bridge, Jeopardy, FreeCell games, specially designed AI are beating the world champions, enabling the given AI to be defined as “superhuman” since they beat the most performant human at these games (Bostrom, 2014, p. 13). Human interaction is going to become a premium of services, rather than raw intellectual force. Since the distribution of tasks among humans might highly change, the definition of salary would directly impact, therefore justifying the interest for new economic paradigm such as the universal basic income.

To continue on this topic, we can question the existence of multiple scholars arguing that the economy is going to be deeply disrupted, that the 4th IR is making the actually existing economic models obsolete. The idea of basic or universal income is not new, and date from the end 18th century. The recent emergence of technologies that could reduce dramatically the required human work brings back to the table this question. In June 2016, Switzerland was questioned on this topic through a referendum. One of the candidate of the French presidential elections of 2017 – *Benoit Hamon* - proposed the universal income as the backbone of his economic program. These discussions around the computerisation in society brings questions related to what skills are going to be needed in the future and what meaning human should find in their activities, facing the final possible case of an almost complete computerisation caused by the artificial intelligence.

### The reskilling process is a solution

According to the Oxford’s dictionary, to reskill is “to teach (a person) new skills”. This process should be the logical response of companies to the computerisation of some tasks. Reskilling procedures are meant to keep the human workforce of companies through the 4th IR by endowing them with new skills. The purpose of this section is to understand what the theoretical strategies for reskilling are and how businesses are practically expected to deal with this question.

As previously described, the previous IR brought different cases where workers had to reskill themselves in order to stay relevant for the economy. It could be supported by the institution, for example, the 1st IR triggered the development of public education, in order to upgrade the workforce enabling it to accomplish more complex tasks, facing the massive rural exodus of unskilled workers.

### Fujitsu case

A case brought by the telecom branch of Fujitsu (Politt, 2012) is a further illustration on how reskilling is generally embedded with developing businesses’ value. In 2012, a team of Fujitsu in Ireland highly threatened by new technologies and the loss of an important contract. In reaction, the company implemented a strategy to develop new skills in this precise sector – the recycling of telecom hardware. Most of the targeted employees belonged to what we define as intermediary skilled staffs. In the paper of Frey and Osborne, these same intermediate positions are the most threatened by the computerisation. According to “Robots at Work” of Graetz and Michael, the average growth rate of countries increased by 0.37% thanks to the computerisation. Their findings confirm this trend of middle-skilled tasks disappearance, stating that the total number of hours worked stayed constant while the proportion of middle-skilled workers decreased (Graetz, 2015) and (Levy, 2010). The strategy decided by corporation involve a training of several months, aiming at upgrading the roles of the recycling team. They selected some employees across the teams to receive a specific training including both the new skills and how to share them with their respect. This strategy not only managed to save the jobs by implementing new skills but also brought new business to the company’s branch. This business case raises the question of challenges related to the process of reskilling. In this case, many employees didn’t receive new formation for decades and were therefore afraid and not self-confident about their learning capacities. According to the paper, the “sense of mutual ownership” and “careful monitoring” helped to achieve a successful retraining. In a less communicative speech, we can simply infer that the process of reskilling is challenging and should be decided as a part of the whole corporate strategy.

## A review of the contemporary trends in sales processes

### The emergence of new roles in sales

The World Economic Forum Skills survey synthesizes the overall opinion of industry leader about the skills they would need for their businesses in the future. The purpose of this survey what to define the opinion of the business leader towards the technologies included in the 4th IR. This paper gives a solid theoretical and practical background about how to study the phenomena of the job computerisation, bringing a view of leaders representing more than 13 million employees from a relevant panel of different industries. The panel of countries included in the research is sufficient to justify relevance, including both developed and developing economies (ranging from USA, Western Europe, India, China, Brazil). The research has a comprehensive list of surveyed industries: Basic and Infrastructure, Consumer, Energy, Financial Services & Investors, Healthcare, Information and Communication Technology, Media, Entertainment and Information, Mobility, Professional Services. There are different categories of the conclusion that the paper brought to us, enabling us to have a better comprehension of the phenomena.

The “Automation of checkout processes and smart inventory management through sensors and other applications of the Internet of Things are some of the factors expected to lead to a decrease in demand for traditional roles in the Sales and Related job family.” (World Economic Forum, 2016, p. 13). Meanwhile, “The Consumer industry is likewise reducing its Manufacturing and Production roles but anticipates at least stable overall demand for Sales and Related Jobs, as rising middle classes in emerging markets, changing consumer values and, in particular, the rising economic power of women, are significant drivers of job growth in the sector.” (World Economic Forum, 2016, p. 15). Data specialists are frequently quoted as a highly emerging new role in the company. In the second, specialized sales are likely to be more and more specialized to their market. “Specialized sales representatives (will be needed), as practically every industry will need to become skilled in commercializing and explaining their offerings to business or government clients and consumers, whether due to the innovative technical nature of the products themselves, due to their being targeted at new client types with which the company is not yet familiar or both.” Besides that, the paper predicts that the roles related to basic customer services are going to become obsolete, which is in correlation with the already mentioned rise of Chatbots. The skill’s stability is highly reduced, enhancing the importance of continued training in companies and giving governments incentive to update educational systems. During the previous industrial revolutions, the educational system spent years to adapt and start to offer newly relevant skills in their curriculums. The pace of development is now faster compared with previous IR, therefore governments and businesses should get closer to this question in order to simply survive.

### A time of transition for sales methods

The informative disruption brought by the digitalisation of the economy has deeply affected the way businesses are conducted, therefore how the salespeople are involved in value creation within the companies. The emergence of web retailing made obsolete sales practices such as door-to-door traveling, physical catalogs while making the market more transparent and liquid. While addressing the question of sales processes is vital for this paper, we make the decision to follow the approach to the subject of sales developed by (Martin, 2013), because of its interest for the salespeople, putting them on the framework’s center. While some other theories describing sales processes such as Blue Ocean are more related to strategy, we prefer to stick to the model that help us for our subject related to salespersons.

We understand that the job of the salesperson is changing, for several factors beyond the fourth industrial revolution. The digitalisation of the retail displaced the information about the product from the retail point of the internet, therefore accessible to anybody. Before the sales assistant had an informative utility, he was able to access information that was not necessarily accessible to the whole public. The emergence of new customers’ behaviors, consuming through new interfaces such as website, application, Chatbots or interface we even ignore disrupted businesses, triggering “the digital transition” across the companies. In many extents, we can consider that the adaptation of businesses is not over. There are several reasons for that. Firstly, the generational gap makes the attitude toward sales channel and product different. Elders are naturally reluctant to adopt new behaviors, forcing companies to have a differentiated strategy – multiplying the type of tasks required in these various sales models. Naturally, it forces companies to need a wider set of skills in their sales teams, for the reason that the definition of business itself is changing.

### Uberisation and new value creation paradigms

We can also mention even deeper changes in the core idea of work. The “Uberisation” is a concept that has been introduced by the apparition of Uber. This model aims at making intermediaries in business irrelevant, reducing costs for final customers. Many businesses are themselves intermediaries across businesses, therefore they are threatened by this trend. Of course, they are many legal, functional and societal barriers to the Uberisation, and the best example is what happened to Uber itself in many countries. The long-term survival and adaptation of the model is yet to be discovered. Its interactions with the 4th IR itself are pretty hard to determine, but we can safely say that they both go in the same direction of disruption of a system.

In the previously quoted pool of opinion of the Pew Research Centre, several new trends of approach toward sales are proposed to keep relevant the value creation by the companies. Several interviewed experts argue that the 4th IR would lead to “and explosion in new types of production: small-scale, artisanal, hand-made, barter-based”. This argument is supported by the visible emergence of bio-labelled, fair trade food. This idea is similarly explained by the emergence of millennials, a cross-national class of customer variably but highly motivated by the ethical consideration of their products. Millennials are defined as customer born between 1985 and 1999 with their own way of consumption (Bucic, Harris, & Arli, 2012).

### Sales cycle and human resources use

We understood that during the last decades, until the end of the third industrial revolution, the roles operating in sales processes have remained largely unchanged. They were basically deployed across two main teams. Field salespeople, making face-to-face sales with prospective and current clients, and “inside sales representative” who supported them, providing data, materials, etc. (Martin, 2013). According to the framework developed by Martin, “there are three different key factors that determine whether a sales organization will utilize a field or inside sales model.”.

The first factor is defined as the “Sales Organization Development Stage” refers to the different stage of development of a given organization in a given market. It is somewhat similar to a life cycle, with the first step illustrating growth “Build, Compete”, the intermediary “Maintain” step, concluded by “Extend” or “Cull” stages, depending on the organization ability to pursue its success in business. “The challenges sales organizations face is dependent upon the stage of their development. The top sales challenge in the Build stage is creating sufficient sales coverage to push the product into the market. The Compete stage challenge revolves around quickly scaling the sales organization so it can compete effectively against larger established competitors. The focus shifts to maximizing sales productivity by lowering the cost of sale and increasing the average sales price in the Maintain stage. The Extend stage challenge is to attain widespread customer adoption so their solution becomes the de facto standard. The Cull stage challenge is to revitalize a demoralized and marginalized sales force. These challenges directly influence the sales organization’s structure and whether a field or inside sales model will be deployed.” (Martin, 2013). This factor implies that in each of these stages, the need for salespeople are going to be different simply because the sales’ strategy changes. Concretely, the first steps are embedded with aggressive sales strategy, aiming at creating a base of clients, while the following steps are involving the management of internal process in order to keep it functioning. From our perspective of skills change, these scenarios are interesting because they show how diverse skills might be needed to address different management cases across the sales lifecycle. The last case, “Cull” encompasses coaching, change management, basically skills that are not necessary related to sales itself, while it probably involves people with the title of “sales management”.

The second factor defined by Martin is the “Sales Cycle Complexity”. It is simply the “number of individuals involved in the selection process, the size of purchase, and the sophisticated nature of the solution offered”.

The third factor of this model is more related to internal organization, “Sales Leader Perception of Field and Inside Sales Models” it refers to the duality between “Intern Sales” and “Outside Sales”. There is a biased perception of Outside sales that are believed to have better relation skills than Intern ones. The author also underline how the change in the nature of information implied changes in the relationship between clients and sales.

The companies experimenting delay in their very understanding of the fourth industrial revolution, or simply ignoring it might suffer the Darwinian rule and disappear. Some companies, notably in private transportation (taxis) suffered it. The emergence of cross-disciplinary teaching and approach, such as design thinking is the evidence that educational actors are naturally shifting toward this direction.

## A Comparison of salespeople classification methods

In order to understand how the computerisation will impact the sales jobs, we have to understand the different existing roles related to sales. As we saw in the dedicated part of this paper, the definition of sales have been already impacted by the Third IR, and the 4th IR – even not fully deployed – has already consequences. One basic difficulty will be to find a way to organize the different jobs positions in order to fit them both into our primary data research and computerisation models previously told. Each company, each framework, is using his own classification for job description,

### International Standard Classification of Occupations

The International Standard Classification of Occupations – or ISCO has been developed by the International Labour Office from Geneva. It offers a practical way to classify any imaginable job through a codification, whose additional each figure adds a layer of precision, considering up to 4 level of definition of a job.

Table - ISCO8

|  |  |  |
| --- | --- | --- |
| Group | ISCO Code | Denomination |
| Major Group | 3 | Technicians and Associate Professionals |
| Sub-major group | 31 | Science and Engineering Associate Professionals |
| Minor Group | 312 | Mining, Manufacturing and Construction Supervisors |
| Unit Groups | 3121 | Mining Supervisor |

*Developed by the author using ISCO8*

The system also proposes an embryo of skills classification related to the ISCO code, defining four categories of skills, ranging from 1 to 4 subjectively associated with the intellectual and physical difficulty of the job. This denomination is universal, the only identified equivalent is the codification used by the 0\*NET dataset.

### Review of classical sales classification - McMurray, Newton and Derek, Moncrief and William

According to the managerial literature, there are three classical but outdated classifications of sales positions from (McMurray, 1961), (Newton & Derek, 1973) and (Moncrief & William, 1986). Then we will investigate two contemporary models, (Darmon, 1998) and (Moncrief, Marshall, & Lassk, 2006). The goal of this part is to understand how to differentiate the different roles involved in sales. The first three models are pretty outdated. They are antecedent to the 3rd IR, while the 2 other models are not updated to the 4th IR. While the goal of this paper is not to propose a new way to classify salespersons, we experiment the need to at least approach this problematic in order to answer our questions.

In order to stain synthetic, we detail the 3models in a single tab.

Table - Classical Sales Role Classification

|  |  |  |  |
| --- | --- | --- | --- |
| - | McMurry (1961) | Newton (1973) | Moncrief (1986) |
| Universe | Sales positions | Sales Positions | Industrial tangible product sales positions |
| Classification  | Nature of selling activates | Nature of selling activates | Task-based classification |

*Developed by the author*

The Moncrief classification has the obvious advantage to be based on salesperson’s task, making it compatible with the computerisation model of (Arntz, Gregory, & Zierahn, 2016). But before of the lack of primary data related to tasks, the model would not be relevant. Most of these models consider salespeople within sales context that are no longer existent (door to door selling…).

### Rene Darmon “A Conceptual Scheme and Procedure for Classifying Sales Positions”

“A Conceptual Scheme and Procedure for Classifying Sales Positions”, 1998 by René Darmon brings us a simple framework to classify jobs. Here the original version of the model:

Table - Salespeople classification

|  |  |  |
| --- | --- | --- |
| - | Complex Information Processing | Simple Information Processing |
| Heavy Information Load | Light Information Load | Heavy Information Load | Light Information Load |
| Little Time Management | PARTNERSHIP BUILDERSSales positions implying highly technical selling of rather undiversified product lines/services to a few accounts. | ADAPTIVE SELLERS Sales positions implying elaborate long-purchase cycle selling processes (e.g., durables) to a diverse, self-selected clientele. | SEDENTARY INFORMERS Sedentary sales positions implying simple selling processes and extensive information provision on a standard product line to prospective customers. | SEDENTARY SERVICERS Sedentary sales positions implying simple selling processes, but the provision of basic services to customers.  |
|  | Hi-tech industrial selling (few accounts) National Account Managers | Internal advisors salespersons (furniture, appliance | Telemarketing salespersons | Internal order take (sales clerks) |
| Extensive Time Management | RELATIONSHIP BUILDERSSales positions implying highly technical selling of highly diversified product lines/services to a large number of accounts | ADAPTIVE PLANNERS Sales positions implying elaborate selling processes for a wide variety of long-purchase-cycle product lines to diverse (and not pre-identified) customers.  | MOBILE INFORMERS Field sales positions implying simple selling processes, but the provision of information on a wide variety of product lines to a large number of prospective clients.  | MOBILE SERVICERS Field sales positions implying simple selling processes, but the provision of basic services to customers. |
|  | Industrial selling (large number of accounts)International negotiator | Door-to-door selling (encyclopaedias, life insurance, etc.) | Medical detailers External order takers | Delivery salespersons Store demonstrators Merchandisers |

*Developed by Rene Darmom*

This model includes three dimensions that are useful in our context of computerisation analysis. In this model, the division of jobs is based on the load of information, the management of time and the complexity of information processing. These categories are relatable to the factor of automation developed later, but as explained before the nature of sales roles changed dramatically since the last years, making obsolete a part of this approach. Let’s investigate the different criteria of discrimination developed by Darmon, and confront them with the actual reality of sales roles and tasks.

* “The Size of the information load required by the sales person.” It refers to the amount of information related to the products (such as technical specifications), the clients (positions, type) and procedures (supply chain, provisions…). Most of these tasks are now computerised thanks to simple tool such as Office, SAP… Therefore this discrimination is not relevant anymore.
* “Extent/Complexity of information processing required by the sales position” This is simply the data mining/analysis required to understand the quantity if existing information. More than statistical skills, Darmon includes them with the strategic conclusion that workers are expected to produce from the analysis of data.
* “Time Management.” Refers to the plan of daily routine, preparation of presentations and travel itself. In many regards, this category encompasses all the related tasks to the data analysis itself.

While the approach of Darmon was relevant to understand the salesperson of the 20th century, it is not focusing on the salesperson’s relationship with the customer, which is one of the most important trends in sales.

### Moncrief, Marshall & Lassk “A contemporary taxonomy of sales positions”

In “A contemporary Taxonomy of Sales positions”, Moncrief, Marshall, and Lassk tried to bring a new way to classify sales jobs. For this purpose they used an occupational survey of different tasks, trying to infer from the answer of 1200 industrial salespeople different recurrent roles in sales. Thanks to a factor analysis of 12 different factors meant to be related to sales tasks, they found 6 different roles of salespersons. The paper was motivated by the tremendous changes in the mix of tasks operated by sales.

Here a list of the different factors used in the analysis.

* Relationship Selling, Promotional Activities and Sales Service, Entertaining, Prospecting, Computer, Travel, Training/Recruiting, Delivery, Product Support, Educational Activities, Office, Channel Support

Each of this factor is related to some tasks, for example, the factor “Travel” is related to the task “Spend Night on the Road”. From this analysis, 6 distinctive roles emerged for salespersons. Let’s show this model through a convenient tab:

Table - Salespeople classification according to Moncrief, Marshall, and Lassk

|  |  |  |  |
| --- | --- | --- | --- |
| Role | Proportion of respondents | Main occupational factors | Factorial score (only positive showed) |
| Consultative Seller | 34.2% | Relationship Selling | 0.437 |
| Promotional/Service | 0.408 |
| Product Support | 0.368 |
| Prospecting | 0.085 |
| Channel Support | 0.049 |
| Delivery | 0.01 |
| New Business Development Seller | 24.7% | Computer | 0.838 |
| Entertaining | 0.828 |
| Training/Recruiting | 0.770 |
| Travel | 0.683 |
| Prospecting | 0.606 |
| Channel support | 0.473 |
| Education | 0.473 |
| Office | 0.320 |
| Relationship Selling | 0.281 |
| Product Support | 0.259 |
| Promotion/Service | 0.169 |
| Missionary Seller  | 15.1% | Training/Recruiting | 0.681 |
| Travel | 0.505 |
| Delivery | 0.477 |
| Education | 0.314 |
| Promotion/Service | 0.263 |
| Relationship selling | 0.117 |
| Delivery Seller | 9.1% | Delivery | 0.778 |
| Prospecting | 0.288 |
| Sales Support | 8.6% | Office | 0.430 |
| Training/Recruiting | 0.210 |
| Channel Support | 0.777 |
| Key Account Seller  | 8.3% | Product Support | 0.879 |
| Travel | 0.766 |
| Office | 0.678 |
| Channel Support | 0.401 |
| Computer | 0.389 |
| Entertaining | 0.229 |
| Education | 0.073 |

*Extracted from* (Moncrief, Marshall, & Lassk, 2006)

This framework brings the modern notion of consultative salespeople, which was before ignored. As well, functions such as sales support are indirectly related to sales but are vital for its operation. The study brought a study relevant to understand the existing jobs descriptions in well-defined industries.

### Our Conclusion regarding which model to use

We will use the model developed by Moncrief, Marshall, and Lassk for different reasons. It is based on occupational factors, making it compatible with the other occupational data set of this model, the data from 0\*NET which contain information about the daily task. Moreover, the model is oriented around quite precise tasks, making it easy for a company to integrate it with their own job descriptions. Besides the argument of compatibility, the others models are pretty obsolete. The model developed by Darmon is issued from a period anterior to the emergence of digital selling techniques, which totally disrupted the relation of clients toward the information, therefore redefining the goals of salespeople.

## Research Gap and Questions

“Retraining and skill-raising programs will be important to support workers shifting to new roles and taking on new activities. It will also be critical for corporate leaders to ensure that the organizational elements of their companies are adapting to the advent of automation.” (Bughin, Manyka, & Weetzel, 2017, p. 17). Business leaders are conscious of the incoming industrial revolution, they will growingly need information about this proves in order to be the more prepared.

Businesses are going to naturally replace the tasks that are computerisable when the costs of the move will permit it. Following the O-Ring logic, the implementation of the digital tool in the salesperson environment increases the importance his/her specific skills. The fourth industrial revolution is an actual phenomenon whose possible outcomes are yet to be understood. So far, description about of this process were pretty restrained to macroeconomics, making hard for businesses to understand how the phenomena could directly impact them. The management literature took a very generalist point of view toward this question.

In conclusion, we can say that the existing managerial literature acknowledges the fourth industrial revolution but it usually fails to bring empirical conclusion for businesses. The economic literature describes it as a macro phenomenon but does aim at providing precise recommendations.

Through this analysis, we aim to import the economic approach toward the industrial revolution into clear recommendation about the future of skills in sales, which will be relevant for the human resources management. The existing literature either have an extremely macro focus, considering the whole potential impact of computerisation on the economist, either have a case-based approach failing to apprehend things outside very practical questions, describing the precise usage of a technology in a given business context.

Estimations of Automation Impact

*Evaluation of the Global Impact on the job market*

Business Cases

*Technological Description of*

*a single task/workplace impact*

**Research Gap**

*Industry-wise description of the 4th* IR effects

Future of Sales

*Technological Description of*

*a single task/workplace impact*

Human resources management

*Reskilling management*

Macro-level

Specific-level

Figure - Knowledge Gap Illustration

We develop several research questions for this paper:

* How can managers avoid the potential obsolescence of their salesperson’s skills?
* Is the concept of O-Rubber (that the automation of jobs pushes jobs to be increasingly specialized) confirmable by observations?

## Summary of Chapter 1

Industrial Revolution is phenomena which shaped the three last centuries, creating the basis of our modern society. Companies are naturally moving along these changes, evolving or disappearing because their structure, business plan or people did not match anymore the reality. The fourth industrial revolution is bringing tremendous changes, whose velocity is higher than the previous ones. Business should prepare their people to stay relevant, and the process of reskilling will happen naturally, because of the very adaptive nature of business, what economists call the “market’s invisible hands”.

Table - Review of the impact of the previous Industrial Revolutions

|  |  |  |  |
| --- | --- | --- | --- |
| **Industrial revolution** | **Period** | **Emblematic Technology** | **Consequent Reskilling processes** |
| First | 18th Century | Steam power | From Fields to manufactories |
| Second | End of 19th century – beginning of the 20th century | Ford cars, First Domestic Appliances | From manufactories to assembly lineFirst services |
| Third | End of 20th century | “A computer on every desk and in every home” *Bill Gates in 1980* | Disappearance of clerksO-Rubber phenomena |
| Fourth | Beginning of 21st century | *Doctor Watson – A complex cognitive task automated* | *Disappearance of middle-skilled position* |

Economists, Polices Makers and Businesses deciders are confused because of the extreme nature of the fourth industrial revolution. Its possible scope goes beyond the traditional borders of industry or business. It might redefine deeply the society and question the place of a human. The fourth industrial revolution is opening a “Pandora box” of new technologies, that are going to disrupt even deeper the actual economy. The existing literature fails to provide relevant advice for businesses, and how they should relocate their manpower usage in order to stay efficient.

 Meanwhile, methods and process and sales are changing and adapting to a new and changing environment, requirement salespeople to change their approach, through a process of “reskilling”.

# METHODOLOGY TO CORRELATE COMPUTERISATION OF TASKS WITH JOB-WISE INFORMATION

## Our research approach

### Regarding our overall research strategy and the decision use secondary data

David Autor is one of the most modern, prolific and successful authors about the evolution of work. His vision was central in the research approach we have selected. The differentiation between jobs, skills, and tasks is hard to address by scholars since compiling all the data related to such problems would involve an incredible workload… Therefore “a researcher who wants to identify task commonalities that cross-occupational boundaries is forced to make additional subjective judgment” (Autor, 2013, p. 13) which is undesirable for the scientific approach, but it has the advantage to be an easy, transparent and fast way to classify important dataset. The purpose of this paper is to understand the underlying effect of the automation of tasks, rather than estimate this effect. The selection of data for research related to tasks and job evolution is a real difficulty caused by an intrinsic macro aspect of jobs and work. There is the possibility to conduct task interview in the working population, directly in the workplace. These surveys bring better data, closer to the reality of task mixes. Unfortunately, they are country-wise and they might lack time constancy and purpose scopes. These approaches are challenging from the very inconstant nature of work and tasks. For example, for the scope of computerisation study, there is a need to classify between repetitive and non-repetitive tasks. It is particularly complex and subjective even for the worker themselves to have a clear answer whether the tasks they accomplish daily are repetitive or not. The incidence of tasks on the wages shows how the task-wise approach is preferable. The development of our question requires a diverse mix of information, merging different job-wise data, some related to computerisation others to skills and the knowledge (Autor, The Task Approach to Labor Markets: An Overview, 2013).

Moreover, the secondary data have the advantage to be already formatted in SAS, SPSS, SATA files, facilitating its analysis. Nevertheless, the use of secondary data has some drawbacks that should be developed. The use of secondary data creates a gap between the researcher and the data, making him/her dependent on the definition the theoretical framework used to compose these secondary data (Vartanian, 2011).

Our conclusion regarding the approach we should select is:

* The usage of secondary data is preferable over a laborious primary data acquisition
* The Task-based estimation of computerisation should be privileged

### Detailed plan of study

Table - Research Plan

|  |  |  |
| --- | --- | --- |
| Phase | Statistical information | Detail |
| 0 | Scope of variables definition | Using the classification of sales of Moncrief, Marshall and Lassk *(detailed in 1.5)* we identify 25 positions *(detailed in 2.4)* related to sales in the universal ISCO8 denomination.  |
| 1 | Independent Variable | We extract from O\*Net *(detailed in 2.2)* a list of jobs belonging to the category “Sales and Related”, to which we add jobs also related to sales but belonging to “Management” or “Office and Administrative” categories. For each of the job, we add the expected “Knowledge”, “Skills” and “Technology Skills” (Basically software whose use is associated with the given position). We also include the average salary for this job in the USA and the estimated growth of volume in these jobs.  |
| 2 | Dependent Variable | We associate each role to its probability of computerisation, extracted from the findings of McKinsey Company *(detailed in 2.3)*. |
| 3 | Statistical Test | We make a factorial analysis to determine what skills, knowledge or software usages are a factor to a jobs computerisation or non-computerisation *(detailed in 2.4)*.  |

### Research Hypothesises

Table – Table of Hypothesises

|  |
| --- |
| H0 There is no correlation between any “knowledge”, “skills” or “software usage” and the proportion of task computerisable |
| H1 A cluster of “knowledge variable” is positively correlated with less computerization of tasks |
| H2 A cluster of “skills variable” is positively correlated with less computerization of tasks |
| H3 A cluster of “software usage” is positively correlated with less computerization of tasks |
| H4 A cluster of “knowledge”, “skills” or “software” is positively correlated with more computerization of tasks |

## Comparison of the existing sources of data related to jobs – Independent Variable selection

### O\*NET – secondary database developed by the US Ministry of Labour

There is a different dataset that fit a position with a given set of skills. We are using an occupational survey developed by the US ministry of labor to have a fit between the job title and the information related to the skills, the knowledge and the software involved in these.

The data set includes 800 jobs, with several, precise and public information related to the requirement and information around these jobs. They base their sampling strategy on a theoretical framework they developed to organize the information related to the fit between one job, the worker, and their environment.

Table - O\*NET theoretical framework

|  |  |  |
| --- | --- | --- |
| - | Worker Oriented | - |
| Cross Occupation | Worker Characteristics  | Worker Requirements | Experience Requirements | Occupation Specific |
| *Abilities**Occupational Interests**Work Values**Work Styles* | *Skills**Knowledge**Education* | *Experience and Training**Skills-Entry Requirement**Licensing* |
| Occupational Requirement  | Workforce Characteristics | Occupational-Specific Information |
| *Work Activates**Organizational Context**Work Context* | *Labour Market Information**Occupational Outlook* | *Title-Description**Alternate Titles**Tasks**Tools and Technology* |
| - | Job-oriented | - |

*Extracted from 0\*NET documentation*

 Regarding the functional and human resources centered scope of our paper, we decided to focus on information related to the “Worker-Requirements”.

Skills” is divided in different sub-content.

* Basic skills
* Cross-Functional Skills “Developed capacities that facilitate performance of activities that occur across jobs”
* Technical Skills “Developed capacities used to design, set-up, operate and correct malfunctions involving application of machines or technological systems”
* System Skills “Developed capacities used to understand, monitor and improve socio-technical systems”
* Resource Management Skills “Developed capacities used to allocate resources efficiently”

“Knowledge” refers to the “Organised set of principles and facts applying in general domains”

(National Center for O\*NET Development for USDOL, p. 9).

We found that theses two axes, both assessing “cold” knowledge and “practical” skills are several relevant approaches to the problem, considering the correct questions and bringing enough information.

 The data acquisition methods are supported by the US Department of Labor, using two steps for data collection:

* “Firstly: a statistically random sample of businesses expected to employ workers in the targeted occupations will be identified
* Secondly: a random sample of workers in those occupations within that business will be selected. New data will be collected…” (O\*NET, 2016).

 The management of the database follows precise statistical procedure, detailed in the “O\*NET Data Collection Program – Part B: Statistical Methods”. During each yearly survey, new jobs are identified and previous elements are updated. For each of the position, a given relevant industry is identified and a relevant number of companies within this relevant industry is sampled.

### The Programme for the International Assessment of Adult Competencies (PIAAC) – secondary database developed by the OECD

The European equivalent for the O\*Net database is the PIAAC. It covers most of the countries of the OECD, aiming at using 5000 individuals per countries. It aims also at being cross-nationally valid and similarly to the O\*NET it has the ambition to help the development of political decision, providing material for decision-related to gender bias, the inclusion of young people in the economy, the management of illiteracy, the link between demographics, background data. The interest of this database is to compare worker skills in different economies rather than analyzing a precise sector.

### LinkedIn or internet-based acquisition of primary data

We also contemplated the use of the professional social network LinkedIn which provides a constantly updated match between skills needed for the position, company name and job position. As an evidence of the relevance of this method, in its report “The Future of Jobs: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution”, 2016 the World Economic Forum used analytics from LinkedIn to map the skills related to different occupations. This approach takes the assumption that people on this social website are showing the most relevant skills for their actual position (which is not necessary the skills they do actually have☺), permitting us to fit positions with precise skills. On a wider extent, scholar used LinkedIn data to assess other economic behaviors such as migration of skilled people from the south to northern countries (State, Rodriguez, Helbing, & Zagheni, 2014). Unfortunately, this method has two big disadvantages. Firstly, we can assume that there is a bias between what actually people express on the social network and what the actual scientific data we need are. Secondly, the use of data from LinkedIn – even for scientific uses – is an infringement to the site’s user’s terms and condition. It seems that the company has already suited scholars that used the site for their research.

### Occupational Survey – classical acquisition of primary data

 In a similar way to the LinkedIn-based approach, we could have conducted an occupational survey to get relevant information about the 25 ISCO positions or 6 Moncrief (…) roles identified as related to sales. This approach would have permitted some advantages, we could have designed a survey closer to our question of computerisation.

Using the right sampling methods, it could have reach statistical viability. The main issue for this approach is the difficulty and the resources need inherent to the occupational survey.

### Our decision to use O\*NET dataset

We could have designed a survey by ourselves or try to scrap data, but it might have created many issues. First to sample correctly required to follow different statistical rules, and it might actually be challenging to achieve to deliver a correctly unbiased outcome. What is why this way to gather data have been eliminated, we choose to use an already existing set of data.

 There are two known and reliable sets of data that have been used in similar research (that we will discuss later). O\*NET for the USA, and PIAAC for the OECD. Our decision to choose O\*NET dataset over the PIAAC one is motivated by different factors. In this research, we value the most modernity of approach and model over the regional scope. The pace and volume of the update seem way better in the O\*Net database that in the PIAAC. The main challenge for the PIAAC is the important scope of countries within the OECD, threating their assumption that the questionnaire is biases-free. Moreover, the dataset is uploaded following a calendar of different “rounds” in different countries. For example, while the information related to Australia have been collected in the 2008-2013 period, the information related to Greece have been collected in the 2012-2016 period. In contrast, the O\*NET database fills the requirements for scientific users, with a database which is yearly updated and exists since 2000.

Secondly, the quality and structure of data are better in O\*NET. Some information such as software use does not exist in the PIAAC. Moreover, the O\*NET theoretical framework helps to consider which data to use for a research purpose. The ultimate reason to use O\*NET is that the framework is compatible with the findings of the McKinsey group, we detail in the very next part why we use it.

 In conclusion, our decision is based on the idea that we should avoid “to reinventing the wheel” when the already existing tools would be probably superior in term of quality. The ultimate trade-off of our decision, between Secondary and Primary type of data relied in the fact that home-made occupational survey would have permitted to obtain information of better relevance, requiring the usual cost for such high-volume survey (in order to design their framework, Moncrief, Marshall and Lassk used the answers from 1200 salespeople professional).

Table - Comparison of different occupational datasets

|  |  |  |  |
| --- | --- | --- | --- |
| Data Base  | Data type | Advantages | Drawbacks |
| O\*NET | Secondary | Yearly updated | US-Specific |
| PIAAC | Secondary | International | Not yearly updated, macroeconomic scope |
| LinkedIn | Primary | Business centred | Illegal, costly in time, potentially biased |
| Occupational Survey | Primary | Business centered, Flexible  | Extremely costly in resources, potentially biased  |

*Developed by the author*

## The existing approaches for jobs automation estimation

Different ways have been constructed in the last years to describe and estimate the process of jobs computerisation for a given group of people. They are mainly economically driven approaches.

### Frey and Osborne - The Future of Employment: How susceptible are jobs to Computerisation?

As a reminder, in his paper “The Task Approach to Labor Markets: An Overview” David Autor defined that jobs with repetitive tasks are the ones likely to be interchangeable. This assumption that original and not formalized tasks are not computerisable is questioned by the emergence of artificial intelligence. Frey and Osborne, therefore, revamped the model of Autor, considering that the conversion of labor to capital is no longer restrained to already repetitive and precisely measured tasks. The purpose of the work of Frey and Osborne is based on the precedent tremendous evolution in the scope of possibility unlocked by machine learning and robotics, what we define in this paper as the 4th IR. In order to define the degree of computerisation of each position, the authors based their research on the occupational O\*NET list from the US government. To achieve this they also investigate the literature of offshoring jobs transition – phenomena of job substitution comparable with the computerisation. They, therefore, were inspired by a previous work about the chance of jobs to be moved offshore. These papers consisted in mating each O\*Net occupation with a degree of offshoring, using the information coupled in the O\*Net dataset. The comprehension of jobs computerisation is based on two main features of the 4th IR, the Machine Learning, and the Mobile Robotics. They use a previous approach of Autor which compared jobs following two axes, non-routine vs routines jobs and manual vs cognitive tasks. In order to get to their results, Frey and Osborne firstly extracted the O\*Net list of the US Department of Labor. They decided to fit each O\*Net occupation to its corresponding six-digit SOC (another more detailed method of jobs classification). Excluding non-relevant data, they brought a preliminary list of 702 occupations. The next step was to assess the impact of Machine Learning and Mobile Robotics on these jobs. The strategy of the authors avoided to use Autor’s model of job computerisation and preferred another approach. Analyzing the drawback of the previously work done about offshoring movement, they started to focus on 70 occupations. With the help of the Oxford University Engineering Sciences Department, they labeled each of these positions as binary, either computerisable or not computerisable. The goal was to only label the occupation which the researcher considered as doubtless either computerisable or not-computerisable. Secondly, they used the O\*Net variable related to the computerisation. They considered three “computerisation bottleneck” that are “Perception and Manipulation”, “Creative Intelligence” and “Social Intelligence”, our subject mainly focusing on the two later ones. Taken individually, a low level of skill needed for one of these bottlenecks involves a high degree of computerisation of the task. Oppositely, high skills in one of these bottlenecks involve a relatively low chance of computerisation. They associated these computerisation bottlenecks with their corresponding O\*Net variables. The findings are interesting from a different perspective. They show how the position’s industry has an incidence on its probability of computerisation. For example, position in “Sales and Related”, “Office and Administrative Support” (therefore confirming the opinion expressed in the World Economic Forum skills survey) or “Transport and Material Moving” would be more impacted than jobs in Education, Management or Healthcare.

### Arntz, Gregory, and Zierhan - The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis.

As quoted in the introduction (Arntz, Gregory, & Zierahn, 2016) shifted the approach positions-based approach used by Frey and Osborne to a task-wise exercise. There are several practical reasons for that. The most obvious one is also shared by Autor in his model of task comprehension, arguing that the task is the real unit of labor rather than skills or even the one’s whole occupation. The paper bases his research on occupational survey-based the mix of daily tasks executed by the answering professionals - “The Survey of Adults Skills”, conducted by the Programme for the International Assessment of Adult Competencies (PIAAC). This approach of using occupational survey in order to analysis the possibility of computerisation have been discussed by Frey and Osborne. Arntz, Gregory, and Zierhan basically translated the findings or Frey and Osborne into a task-based paper. Their main point was to critic the findings that 47% of jobs are under the threat of computerisation and to turn it into a prevision based on what jobs are actually consisting in. For example, accountants would be theoretically mainly doing accounting. According to Fray and Osborne, the probability of their computerisation is 94%, which is consistent with the repetitive nature of numbers processing. But the reality is different, accountants need social skills to obtain their raw numbers and to share their refined financial statements. In some case, they have to proceeds to a wide range of tasks involving to have judgment, these tasks are not related at all to simple numbers proceeding. Why not imagining more precise cases, when an accountant is needed to know how to build an efficient tax evasion strategy or how to deal with an administrative official when required. It goes without saying that these tasks, from their informal nature, are not simply computerisable, at least until the development of a general artificial intelligence.

### Bughin, Manyka, & Weetzel - A Future that Works - McKinsey Global Institute.

Using a similar method to the two precedent ones, the consulting company McKinsey concluded that 49% of paid tasks are susceptible to automation and that 60% of overall tasks are computerisable.

In order to assess the degree of automation of tasks, they also used a list of jobs provided by the US government. From each occupation, they extracted the “Activities” (for example to greet the customer). Then they matched each of this activity with a precise “capability requirement”, When in their paper Osborne and Fray divided it between three elements that are Social, Cognitive and Physical requirements, McKinsey got a more factual approach. For each of the identified professional activities, they estimate what are the technical requirements needed to automate the given task. The database from which they import the primary data contains more than 2000 activities, on which they analysis the technical requirements through 5 axes. (Bughin, Manyka, & Weetzel, 2017, p. 4)

Table - Capability Requirement for Activity Automation according to McKinsey

|  |  |
| --- | --- |
| Axis of Capability Requirement  | Precise Capability Requirement |
| Sensory perception | Sensory perception |
| Cognitive capabilities | Retrieving informationRecognizing known patterns/categories (supervised learning)Generating novel patterns/categoriesLogical reasoning/problem solvingOptimizing and planningCreativityArticulating/display outputCoordination with multiple agents |
| Natural language processing  | Natural language generationNatural language understanding |
| Social and emotional capabilities | Social and emotional sensingSocial and emotional reasoningSocial and emotional output |
| Physical capabilities | Fine motor skills/dexterityGross motor skillsNavigationMobility |

*Extracted from* (Bughin, Manyka, & Weetzel, 2017)

While being similar to the others work in term of goals, this work shows two main quality. First, they make a difference between tasks (here activities), jobs and skills. Secondly, they have a more practical way to assess the technologies required to computerize each of the tasks. Their study – on the contrary of the others – has an international range, considering that costs of computerisation can vary across countries, because of the facility of access to the technologies. This very precise element has interesting consequences. The total amount of tasks automatable varies across countries, reaching a pick of 55% with Japan for example, which may be explained by the unique demographic, economic and political situation of the country which encourages the Robotisation as a viable solution to immigration.

The discussion integrated into the paper are interesting. The study also addresses the question of labor market dynamics, considering – as Autor did – the question of supply and demands of skills and the convertibility of people with a machine. They cite the example that even if cooks are highly exposed to the computerisation – 75% of the tasks they operate are automatable – they are not likely to be replaced by robots, simply because they are cheap, removing the incentive to invest in new technologies. On the contrary, manufacturing is likely to adopt computerisation as fast as possible, following a logic which is old as the Industrial Revolutions, reminding the Luddites of the 18th centuries.

Linking some other ideas previously exposed, we can perfectly acknowledge the existence of an incoming wave of computerization. Predicting the exact variable of this change is absolutely impossible. Countries, companies, science involve thousands of different stakeholders, and rather than limiting ourselves to passive actors of the change, we all are going to act around this change. McKinsey developed a different scenario to weight the impact of computerisation. Providing a graph which is not without recalling the model of global warming prediction, the consulting company define both phenomena of technology for automation development and its adoption, marking between them a time gap of several decades. They consider that “Even as it causes shifts in employment, automation can give a strong boost to productivity and global GDP growth” (Bughin, Manyka, & Weetzel, 2017, p. 14), reminding the questions raised in the literature review of this paper about the future of society. Three groups of countries are considered when estimating the impact of automation. Advanced countries (Rich OECD basically) will deal with the automation as a solution in an aging context. Emerging countries with aging population can also benefit from the automation. Emerging countries with young population are expected to face difficulties. Again the question of demographics shows how the automation brings all the questions of the economy back.

Their empirical model also differs from the previous ones. In order to estimate the computerisable part of the economy, they inferred from the previously quoted list of technology a tab of requirement (ranging from “Basic to Execute” to “High human”). They used precise metrics, for example, “Natural language understanding is broke down into 4 steps, with precise metrics. They used a machine learning model based on how basic data bout work tasks inferred from an occupational survey would trigger the keyword contained in the previously described matrix. Using a machine learning algorithm and human assisted correction, they determined their findings. Their estimation of computerisation is based on the case where the existing technologies would be fully deployed in the economy.

In continuation with the main finding of their paper, McKinsey modeled adoption timelines of technology for 46 countries. For that, they broke down the question of computerisation implementation into three distinct sub-questions. First, they consider how the technical feasibility, questioning whether the science “exists”. Secondly, they estimated the solution development. For that they reviewed 100 cases of automation, being interested in efficient metrics such as the time and resources required to implement the automation, Thirdly, they checked the economic feasibility, confirming the idea of David Autor that at the end, the tasks are interchangeable between people following the trend of the cheapest task deliver. To estimate its impact on the whole economy, they estimated the hourly wage of the automated job and the hourly cost of the automated version of the job.

### Our decision to use the McKinsey’s study

Following the deeper comparison discussed in our literature review, our choice to choose the results of McKinsey rather the other findings of different works about the computerisation is motivated by practical reasons.

* The study represents the state of the art on this question (published in 2017)
* It follows the theory developed by David Autor that the task-based approach is the most realistic.

Table – Review of the different Automation Estimations

|  |  |  |  |
| --- | --- | --- | --- |
| Work | Date | Unit of Analysis | Main findings |
| Frey and Osborne | September 2013 | Jobs/Occupation | 47% of the US jobs are subject to automation |
| OECD –Arntz, Gregory and Zierahn | June 2016 | Tasks | 9% of the OECD jobs (…) |
| McKinsey – A future that works | January 2017 | Tasks | Almost half of tasks are automatable |

*Developed by the author*

* The findings of Osborne and Fray are not obtained task-wisely, which has been criticized enough.
* Arntz, Gregory, and Zierhan use the PIAAC (an occupational survey about the tasks proceeded per occupation) data set to translate the results of Osborne and Fray, which is extremely disputable since the model of Osborne and Fray is itself based on another occupational survey. Moreover, the aim of their study is extremely motivated by the need to have macroeconomic findings, making the research extremely difficult to translate into an industry case.
* The model of McKinsey is also based on an occupational survey which includes the different tasks proceeded in each job but has the advantage to be more accurate in term of their estimation of resources needed for computerisation.

 Table E is a good illustration that McKinsey research is more usable in a research context than the findings of their Oxford’s counterparts, is more nuanced and less binary. Anyway, it is important to underline that Fray and Osborne’s research is an important milestone in this field, their work inspired and permitted the later development of this question.

## Empirical Approach

Our goal consisted in determining what variable are correlated with the computerisation of work. We end up with a set of “independent” variable to compare with the core independent variable, the “dependent” probability of computerisation. We followed two guides to efficiently deal with our secondary dataset (Koziol & Arthur, 2011) and (Vartanian, 2011). Therefore, our goal was to determine which variable are related, and which ones are foreign to the movement.

### Sample size of the secondary data

Table - Sample Size and Jobs extracted from the 0\*NET

|  |  |  |
| --- | --- | --- |
| **Job Title** | **Category** | **Sample Size** |
| Marketing Managers | Management | 37 |
| Demonstrators and product promoters | Sales and related | 18 |
| Advertising Sales Agents | Sales and related | 23 |
| First-Line Supervisors of non-retail sales workers | Sales and related | 29 |
| Sales representatives, wholesale and manufacturing, except technical and scientific products | Sales and related | 40 |
| Real estate sales agents | Sales and related | 21 |
| First-Line Supervisors of Retail Sales workers | Sales and related | 40 |
| Sales Engineers | Sales and related | 20 |
| Financial Managers | Management | 31 |
| Energy brokers | Sales and related | 25 |
| Purchasing Managers | Management | 24 |
| Sales representatives, wholesale and manufacturing, technical and scientific products | Sales and related | 31 |
| Door to Door sales worker | Sales and related | 20 |
| Securities, Commodities and Financial Services Sales | Sales and related | 28 |
| Retail salespersons | Sales and related | 45 |
| Cashiers | Sales and related | 43 |
| Telemarketers | Sales and related | 28 |
| Gaming Change Persons and Booth Cashiers | Sales and related | 35 |
| Real Estate Brokers | Sales and related | 21 |
| Counter and rental clerks | Sales and related | 22 |
| Insurance sales agent | Sales and related | 30 |
| Sales Managers | Management | 23 |
| Travel agent | Sales and related | 21 |
| Loan Interviewers and Clerks | Office and Administrative | 46 |
| Parts Salesperson | Sales and related | 31 |

We selected a total of 25 positions that would fit with the framework developed by Moncrief, Marshall, and Lassk. For that purpose, we extracted all the position in the 0\*NET labeled to belong to the “Sales and related” category (20). To that, we added 4 Management positions related to sales, and the specific position of “Loan Interviewers and Clerks”. As the precedent literature suggested, this very precise position has been transformed into a position more related to sales through the 3rd IR.

Regarding the high number of independent variable, we silo the research in 3 distinct sets.

### Data acquisition methods

 In order to develop their dataset, the O\*NET office proceeded with the U.S. Department of Labor to a national survey which started in 2001. The database is yearly updated and the acquisition follows strict rules to keep its statistical relevance:

* The use of a clustered approach. Targeting a random sample of actual businesses for each existing position, then targeting a random sample of workers within these jobs.
* The use of standardized questionnaires.
* The removal or “flagging” of non-statistically relevant data, excluding data with high (higher than 0.51) standard error.

### Set A - variables related to knowledge.

1. Data overview

This set included originally a total of 32 Variables. Each of the background results from the occupational survey conducted on the sample was transformed into a score ranging between 0 to 100 variable. Each of this variable was inferred from the questionnaire questions structure deployed by the 0\*NET office. In the questionnaire, two axes were assessed: The level of the skills required and its importance for the same job. The consideration of these two things permits to reduce balance the skills input of the respondent with the reality of the jobs, none of this dimension should be undermined to consider the reality of a given position.

1. Primary data retreatment

Some knowledge variables are removed because insignificant in the panel of data: Therapy and Counselling.

 Some knowledge variable is absolutely not related to sales but can have an importance because they might be related to the knowledge about the product/the industry which is sold. (Biology, Building, and Construction, Chemistry, Fine Arts, Food Production, History and Archaeology, Mechanical, Medicine and Dentistry, Philosophy and Theology, Physics).

We created a new variable “Product knowledge” being a mean of these variable. We decided to not eliminate these variables,

* After the pre-treatment, the dataset includes a total of 23 Variables
1. Variables description
* Product Knowledge – Variable created for this study by grouping the knowledge axis we considered to be not relevant for this study (O\*NET, 2016).
* Category “Business and Management Knowledge”
	+ Administration and Management – Knowledge of business and management main principles used in strategic planning, human resources management, resource allocation and coordination using leadership.
	+ Clerical – Knowledge of administrative and clerical procedure and systems, such as managing files, documents or the basic files management procedures such as stenography or terminologies management.
	+ Economics and Accounting – Knowledge of economics and accounting theory. Usable in diverse contexts such as financial markets, banking and the reporting of financial data.
	+ Sales and Marketing – Knowledge of principle and strategies for promoting, selling and communication about products or services. It includes marketing strategy, methods, best practices and sales techniques.
	+ Customer and Personal Service – Knowledge related to the management of processing services for customers. It also includes needs estimation, quality standard definition, and customer satisfaction estimation.
	+ Personnel and Human Resources – Knowledge of principles required to efficiently select, recruit, train and pay personnel. It may also include some tools such as the usage of specialized personnel information systems
* Manufacturing and Production
	+ Production and Processing – Knowledge of production processes, quality control, costs control and underlying techniques aiming at improving the efficient creation and distribution of goods.
* Technology
	+ Computers and Electronics – Theoretical knowledge of hardware functioning, including its sub content and programming.
	+ Engineering and Technology – Knowledge of the practical application of engineering science and technology.
	+ Design – Knowledge of Design techniques, principles and concepts. It also involves the tools, best practices required to create precision plans, blueprints, drawings, and models. As well, it considers the knowledge of aesthetical principles.
* Mathematics and Science
	+ Mathematics – Knowledge of arithmetic, algebra, geometry, calculus, statistics and other related mathematical fields.
	+ Psychology – Knowledge of the human behavior. Comprehension of the individual differences in term of ability, personality, and interests. The understanding of required psychological research methods, the assessment and solving proposition of behavioral and affective disorders.
	+ Sociology and Anthropology – the Knowledge of human group’s behaviors, trends, ethnicities, cultures, and history.
	+ Geography – Knowledge of principles describing the earth’s features.
* Education and Training – Knowledge of principles and methods for training design, teaching methods and the measurement of its effects.
* Law and Public Safety
	+ Law and Government – Knowledge of laws, legal principles, courts organization, government regulations, political processes.
	+ Public Safety and Security – Knowledge of relevant equipment, policies required to organize public events. It is relevant for sales because of the recurrence of such events.
* Communication
	+ Communications and Media – Knowledge of media production, communication and using channels to inform or entertain.
	+ Telecommunications – Knowledge of network, data emission and reception using the relevant technologies
* English Language – Knowledge of the structure and content of the English language, rules, grammar, etc.
* Foreign Language - Knowledge of the structure and content of a foreign language, rules, grammar, etc.
* Transportation – Knowledge of principles and methods for moving people or goods

### Set B - variable related to skills.

1. Data overview

The set included a total of 34 variable, retreated using the same method as the one described for *knowledge* variable.

1. Primary data retreatment

Some skills variable are removed because they are not related to sales. (Installation, Equipment Maintenance, Equipment Selection, Repairing, Science).

1. Variables description

After retreatment and elimination of irrelevant skills, we have a total of 29 variable that we are going to use for the statistical analysis.

* Content comprehension skills
	+ Reading Comprehension – To understand written sentences
	+ Active Listening – Basic ability to listening to what people are saying
	+ Writing – To communicate efficiently using the written form.
	+ Speaking – To talk and share information efficiently
	+ Mathematics – To use math knowledge to solve issues
* Processing of knowledge
	+ Critical Thinking – Ability to find the strengths and the weaknesses of a given process, the capacity to infer and original alternative or approach to a problem.
	+ Active Learning – Basic ability to process information and turn it into a usable knowledge.
	+ Learning Strategies – the more advanced capacity to develop different approach when teaching new things
	+ Monitoring – To assess oneself/colleagues/organizational performance, imagining potential correctives.
* Social Skills
	+ Social Perceptiveness – To be aware of others’ reactions and understand why, how they react in a given way.
	+ Coordination – Management of other’s actions and tasks.
	+ Persuasion – To persuade other to consider things differently
	+ Negotiation – To bring others to agree on oneself position
	+ Instructing – Teaching the others how to do something
	+ Service Orientation – To actively look for ways to help people.
* Technical Skills
	+ Operations Analysis - To analyze products, equipment, resources requirements in order to trigger the need for a new design.
	+ Technology Design – to generate or adapt equipment and technology.
	+ Operation and Control – To control operations of equipment or systems.
	+ Operation Monitoring – Watching indicators and diagram in order to judge whether it is correctly functioning.
	+ Programming – To write computer programs for various purpose
	+ Quality Control Analysis – To conduct tests and inspections of products, services and evaluate the overall performance
* Systems skills
	+ Judgment and Decision Making – Considering the precise costs and advantages of actions, choose the most relevant approach.
	+ Systems Analysis – To analyze needs and products requirement to create a design
	+ Systems Evaluation – To look at a high number of indicators of system performance, taking into account their individual relevance and their importance for the work realization.
* Resource Management Skills
	+ Time Management – Managing one's own time and the time of others.
	+ Management of Financial Resources – Determining the financial cost of a work and organizing its accounting.
	+ Management of Material Resources – To obtain and evaluate the required equipment, facilities required to do a given work.
	+ Management of Personnel Resources – To motivate, develop and direct working people, fitting them to the most relevant work.
* Complex Problem Solving
	+ Complex Problem-Solving Skills, The advanced capacity to find a solution for the newly created problem, with few definition of the problem’s setting in a real-world situation.

### Set C - variable related to software ability

1. Data overview

Before retreatment, the set C included a total of 47 binary variables, representing 47 types

of software. Software variables were encoded in a binary style: 1 = software is used by the profession, 0 = not used by the profession.

1. Primary data retreatment

Basic office software are removed from the sample because they assumed to be widely used by sales: “Office Suite Software”, “Presentation Software”, “Document Management Software”, “Electronic Mail Software”, “Internet Browser Software”, “Spreadsheet software”, “Word processing software”.

Similarly, “Customer relationship management CRM software” is reportedly used by almost all the jobs included in our sample.

Some software are removed from the sample because they are specific to a given task “Expert system software”, “Interactive voice response software”, Computer aided design CAD software”, “Administration software”, “Information retrieval or search software”

Then we created several clusters to organize the software skills activity-wisely. In aims as improving the relevance of the observation provided by the O\*NET database.

* “Web page creation and editing software”, “Web platform development software”, “Webpage creation and editing software” were summed in a new variable “Web management”
* “Voice recognition software”, “Video creation and editing software”
* “Business intelligence and data analysis software”, “Analytical or scientific software”, “Database management system software”, “Data base user interface and query software”, “Database user management software”, “Data Mining” and “Medical Software” are summed in new variable “Data”

### Regarding the treatment of Secondary Data

 As specified before, our work is based for practical reasons on an analysis of secondary data. For this study, it was necessary to look for an economy of scale for data processing, regarding the high diversity of both the information (various skills) and sources (various industries and companies) involved in our research question.

### Spearman Rank Correlation test (A, B and C)

1. Correlation test

We are looking for a correlation between one independent variable (the percentage of computerisation) and several dependent data. We want to eliminate the variable that is not connected with the proportion of tasks computerisable.

We are going to proceed through a repeated paired statistical test, testing individually each of the variables to assess the existence or the absence of statistical correlation. The data we are using belong to the non-parametric type, while the assumption of normality is present is the statistical sample we use, we cannot confirm the other parametric assumptions that are the linearity of data. Therefore we use the Spearman Rank Correlation test to assess the correlation between the percentage of computerisable tasks and the given knowledge level. The test is indicated to be relevant to test the correlation between an independent and a dependent variable in a non-parametric context (Hauke & Kossowski, 2011).

* Following the tradition of statistics, any result whose p-value is inferior to 0.05 is estimated to be relevant and showing the actual existence of a correlation.
* Regarding the nature of the data, we are not going to comment the curve of the logarithmic relationship (rho), since our purpose here is mainly to judge whether a correlation exists or no.

### The usage of R

 R is a programming language for statistical computing and consequent graphical representation. It belongs to the GNU projects which are open-source, free and operating systems whose most famous project is Linux.

 In order to run our statistical tests, we used the free software R. There are reasons for that. Firstly, it permits to be closer to the data, because it is a language designed exclusively for statistical maths. We also contemplated the usage of Matlab, but the free and open source aspect or R made it more relevant for our needs. The research-oriented software such as SPSS, STATA was also contemplated, but they create a distance between the practitioner and its dataset and therefore the operations conducted on it. While it requires some basic coding skills, it permits more flexibility in the operations conducted. We used the main guide for R to proceed to the statistical tests, “An Introduction to R” (Venables, 2004).

For practical reasons, we used the widely curated “RStudio” interface which is an improved a more user-friendly computing interface than the “raw” R program. This interface has multiple advantages, removing the complexity inherent to a free program such as R, it makes easier the usage of different datasets, statistical functions, and help.

## Summary of chapter 2

This chapter brings us different insights about the strategy required to assess properly the correlation between skills, knowledge, and automation of tasks. For each of these steps, please refers to the corresponding subchapter for detailed information.

Following the ideas of Autor, we consider that the most relevant approach for this research would consist of using secondary data, since the cost of obtaining primary data is overwhelming, and risks to face relevance issues. Our set of Independent Data is extracted from an occupational survey produced by the US government Department of Labor (0\*NET database), and it covers the knowledge, skills, and software uses the 25 jobs description selected.

Then we discuss the use of McKinsey as a source of jobs’ estimation of computerisation from the fourth industrial revolution – our dependent variable. Three main studies – representing the state of the art in this field – are compared. We take the decision to choose the most modern findings, and the one respecting the idea that the correct approach to evaluating the job market is to operate through task-based model rather than job-based ones.

Finally we describe the statistical test we implement in order to find correlated variable, and which software we use to conduct it.

# THE EXPECTED CHANGES OF SALESPERSON SKILLS

## Hypothesises Validation or rejection

From the empirical approach detailed in the previous chapter, we obtained the following results expressing the different presence or absence of results.

Table - Hypothesis results

|  |  |
| --- | --- |
| Hypothesises | Result |
| H0 There is no correlation between any “knowledge”, “skills” or “software usage” and the proportion of task computerisable | Rejected |
| H1 A cluster of “knowledge variable” is positively correlated with less computerization of tasks | Confirmed for 4 variables |
| H2 A cluster of “skills variable” is positively correlated with less computerization of tasks | Confirmed for 6 variables |
| H3 A cluster of “software usage” is positively correlated with less computerization of tasks | Confirmed for 1 variables |
| H4 A cluster of “knowledge”, “skills” or “software” is positively correlated with more computerization of tasks | Rejected |

 The results of our statistical test are detailed in the corresponding annexes (A, B & C) which describes the precise results of the statistical test conducted between the independent variables – the different knowledge, skills and software usages – and the dependent variable – the proportion of tasks automatable for the corresponding job. Following the classical approach of statistics, the statistical results that triggered a *p-value* inferior to 0.05 are considered to be relevant, expressing the existence of a statistical correlation in the pairs of variables.

Table - Detailed Hypothesis Results

|  |  |  |
| --- | --- | --- |
| Hypothesis | Variable sub-category | Variable Name |
| H1 | Customized variable | Product Knowledge |
| H1 | Technology | Design |
| H1 | Science | Psychology |
| H1 | Science | Sociology and Anthropology |
| H2 | Social Skills | Coordination |
| H2 | Process management | Learning Strategies |
| H2 | Resources Management | Management of Financial Resources |
| H2 | Resources Management | Management of Personnel Resources |
| H2 | Technical Analysis | Operations Analysis |
| H2 | System Evaluation | System Evaluation |
| H3 | Software Management | Web and Media Management |

*For further detail about these variable, please consult the chapter 2*

 The three research hypothesizes which support the idea that some of the *work requirements* are positively correlated with less share of task automatable are accepted. The managerial implications of these results are going to be discussed in the very next subchapter.

 *The precise variable-wise results are exposed in both annexes*

## Visual Representation of the salespeople’s requirement shift



|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Business | Communication | Education | Legal | Manufacturing | Product Knowledge | Science | Technology | Transportation |

Figure – H1- Description of variables – Developed by the author



|  |  |
| --- | --- |
| Variable Correlated with less automation | Variable non correlated |

Figure - H1- Findings – Developed by the author



|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Complex Problem Solving | Content Comprehension | Process of Knowledge | Resource Management | Social Skills | Systems Skills  | Technical Skills | Technology Skills |

Figure - H2 – Description of variables – Developed by the author

|  |  |
| --- | --- |
| Variable Correlated with less automation | Variable non correlated |



Figure - H2 - Findings– Developed by the author

## Knowledge and Skills associated with automation

### Knowledge: Product Knowledge

Rather than simply negotiating or addressing issues related to the supply chain, salespeople are expected to deploy their culture of the products and the environment to bring the full potential of their added values.

In many sales cases, we are talking about the emergence of job entitled as “customer’s expert” that actually are rather managing the relationship with clientele than anything else. In the salespeople classification proposed by Moncrief, Marshall, and Lassk, the “Key account sellers” are likely to be involved in deep relational negotiation which requires cultural fit.

The knowledge of the product main characteristic is no longer sufficient to justify the relevance of a salesperson. Background and environmental knowledge - which is defined by this variable we created by merging knowledge not directly related to sales practices – is going to be growingly needed. The relevance of this variable is limited for the cases where the salesperson is selling a service related to the world of sales.

### Knowledge: Design

As highlighted by our literature review, the shift from technical and simply emotional tasks (such as negotiation) is one of the outcomes expectable from the fourth industrial revolution. The technological requirement of computerisation, highly creative tasks requires more technological capital than repetitive tasks, due to the unpredictable and complex patterns involved in human creation. The development of a new pattern of sales, through a new channel of communication, marketing or sales is growingly requiring the mastering of creative tools. The evolution of sales process treated in our literature review is far from behind concluded, and the need for sales manpower able to evaluate the quality of design tasks will clearly develop. The development of courses of “Design Thinking” in business schools is supporting the idea that the mindset behind the design is a knowledge that is growingly recognized as useful for managers and salespeople.

Figure - Research Interest for "Design Thinking" - Google Trends

Salespeople and manager have been taught in the previous decades basic knowledge about computing in order to support services growingly dependent on these technologies. The next years could vector the development of knowledge related to design, and in a similar way to programming, the salespeople might not be asked to directly design materials, but hey will be required to have a basic comprehension of the underlying principles in order to efficiently communicate with specialists on this question. The emergence of UX (user experience) design teams specialized in the visual improvement of classical managerial materials such as PowerPoint presentations and data visualizations confirms this trend.

### Software usage: The Web and Media Management

 Software mastering is growingly required to apply the previously quoted knowledge related to design. The emergence of new online platforms is paired with the growing importance for internal sales for mastering the different tools of communication.

While some may consider it as an outsider to the work of salespeople themselves, the staffs working on communication and branding are growingly important for the final sales, as the purchasing act is shifted to a digital platform. The previous cases where social network rumors (viral video) highly damaged the reputation of a given brand are illustrating how the mastering of these tools is required to communicate efficiently. Following the logic of the O-Rubber, the creative content’s importance is going to justify growingly the need for a human.

### Knowledge: Sociology and Psychology

 The automation of sales procedures through website increasingly rely on science than on the experience based feelings. The sales methods developed during the 20th century are now confirmable with the use of Big Data.

 Sociology is the precise knowledge of people as a group, and their possible behave. The emergence of complex cross-cultural transactions, requiring the understanding of different emotional background are far of a reach for the actual existing artificial intelligence, which is just starting to acquire the basics of sales what. Therefore the salespeople of the future are going to require to understand theoretical ideas behind the sociology in order to be able to improve sharply the quality of their sales strategy.

 The emergence of more complex negotiations schemes is growingly getting closer to real psychology. The Neuro-Linguistic Programming uses advanced concept inferred for psychology. It is widely used to improve the quality of sales strategy deployed, and become sometimes the theoretical backbone of sales speeches.

 A discussion that somewhat questions this idea is that the most of BTC sales phase of negotiation are automated using an algorithm based on machine learning, that actually does not need the understanding of what there are actually doing to propose a relevant product to the relevant customer. For example, algorithms behind the Amazon’s platform are improving themselves using the big data. Do they use as input any sociological element to improve their proposition? Not consciously.

### Skills: Learning Strategies

 The presence of this skill is particularly interesting. It comes in correlation with the global trend for employees to get involved in self-development. The rapid changes in work environments, products sold and customer’s expectation underlines the need for salespeople to be flexible.

As previously described, the knowledge about products/services once was monopolized by the salesperson. The emergence of the digital economy debunked it, and in order to persist in existing, the salespeople should “confirm their utility” by staying ahead of trends easily accessible by the public through the internet.

This need for both employers and employees to train and be trained is helped by the development of e-learning technologies, permitting to fragment the knowledge, making the traditional educational processes redundant. Moreover, this is sometimes supported by public initiative, materialized in some countries by a legal obligation for employers to train their workforces

### Skills: Coordination

Firstly, coordination and management skills are complex to automatize, requiring to involve different actors in different interactions. The correlation of this skills with lesser computerisable tasks is rather the representation of a technical reality than a deep conceptual change in sales.

This finding could probably be exported to other industries or jobs. Coordination skills are more complex jobs requirement. While the last progress in the artificial intelligence and algorithms confirm that even the most complex individual tasks can be automated, there is still an extreme difficulty to create systems able to coordinate different applications.

Rather than forming personnel to unique tasks, companies should focus on underlying skills showing coordination and management aptitude. Because the 4th is likely to facilitate individual, the most efficient worker are going to be the ones able to flexibly switch between different tools and coordinate complex processes, without necessary getting in the detail of the operations. Logically sales is a good example of this, with the huge amount of different precise tasks that should be deployed to conduct successful sales.

Figure - Research Interest for Data Science - Google Trend

### Skills: Operation Analysis and System Evaluation

 The development of Big Data for sales brings simultaneously opportunities and difficulties. The core problem of data flow is the difficulty in extracting the relevant from the inextricable flow. Salespeople are learning how to correctly understand this new input in order to support their business decision. The development of courses of *data sciences* shows how this problematic is taken into consideration by the public.

 The knowledge of the permitting to survey, monitor and improve processes and data analysis is not a feature of the future, rather we estimated that due to the relative simplicity of the other tasks, these precise skills are going to be growingly important.

### Skills: Management of Financial Resources and Management of Personnel Resources

The underlying cause of this shift is that the automation of basic tasks related to sales highlight the importance of managerial skills and knowledge, following the O-Rubber theory the salespeople are on the overall going to be more manager than before.

While usually, jobs of management are less likely to be automated, but the research of McKinsey shows an interesting outlier in this logic. The position of *sales manager* has a proportion of 70% of its actual tasks that could be made automatic with the existing technology. This may be explained by the fact that while many of the tasks operated by sales manager are complex, there are not necessary requiring a deep level of creativity, making them still computerisable. The “survival” of the work might rather be justified by its complex mix of the task while by the individual complexity of each task.

 Anyway, skills of management are the skills related to the ability to take the final decision, to arbiter a trade-off. The best imaginable algorithm can provide the detailed big picture of a situation, but in the near future, the most crucial decisions are still going to be judged by humans.

### The absence of a group of skills or knowledge positively correlated with higher computerisation

 This absence of group showing a positive correlation between the mastering of a given skills or knowledge is explainable by one the of logic flaws in our research process. In order to statistically identify a correlation, the data had to present a value difference between jobs showing respectively high and low proportion of tasks computerisable. We can assume that the skills and knowledge associated with a higher share of computerisable tasks do exist, but are hidden because they are similarly mastered by profession with both high and low degree of computerisation. In other words, the manager is required to implement the same skills as their less prominent counterpart, making difficult to identify a positive correlation between work requirements and automation of tasks.

 Therefore, we can imagine that a future work on this question should find a way to correct this lack of data and enable to identify the skills, knowledge that are actually correlated positively with a bigger share of tasks automatable.

## Contribution to the knowledge

### O-Rubber theory supported by the findings

Our findings confirm the idea developed in the O-rubber theory - adapted to the question of computerisation of jobs by David Author - that the automation of tasks naturally leads to the shift of a profession to the skills the knowledge with bigger added value. The shift to tasks requiring creativity, complex negotiation and advanced managed confirms that the salespeople are following the logic, the importance of simple negotiation and supply chain management – the traditional skills/knowledge used by the salespeople – is reducing because it may at long term be computerized.

The O-rubber theory explains that skills before considered as secondary in a given job became the main element. Reminding the example of the 3rd Industrial Revolution when clerics became sales representatives in banks, the actual 4th IR will bring a similar transition. The sales trends of products personalisation and deeper client orientation for sales support the idea

### To suggest the idea that the polarization of job market

 The idea that the market of jobs is polarizing toward both highly and lowly specialized jobs –reducing the need for medium position – is not justified directly by our observation, but rather indirectly inferable. The appearance of specific combinations of profile naturally induces the need for highly specialized profiles, such as data scientist for sales. On the other hand, these hybrids profiles seem to similarly develop for roles requiring lesser skills complexity. The emergence of roles such as “community managers” – requiring few market-related skills and a little mastering of content creation software is confirming this idea of polarization.

## Discussion and Limitation

### Time applicability of findings

 We base our research on the findings of McKinsey which estimated the share of the tasks done in the economy that would potentially be automated if the existing technologies would be fully implemented. According to the same source, the delay between a technology’s inception and its implementation in the economy varies, being of several decades and depending on a very high number of uncorrelated and unpredictable factors.

Therefore, in the hypothetical case when the technologies implementation would be blocked for some reasons, the relevance of our findings would be limited, since our logic relies on the idea that jobs are disrupted by different factors, among them the automation of tasks.

### Geographical Extrapolation of findings

 In addition to the findings we are using here, McKinsey proposes an approach to extrapolate their figures in different countries. In order to facilitate the extrapolation of our findings, we should consider two main elements: how the technological resources vary across countries, and how the cost of labor affects the cost of task substitution by the machine.

Table – Country-wise automation potential -

|  |  |
| --- | --- |
| Country | Automation potential in % |
| Japan | 55 |
| India | 52 |
| China | 51 |
| United Sates | 46 |
| Europe (big 5) | 46 |
| Rest of world | 50 |

*McKinsey Global Institute*

 As the table 15 shows, there are not general rules that could be applied to directly estimate how findings in the US should be inferred for another one.

 Some countries are exposed to the future environment, “In Russia, where the number of employees will likely decrease by 30 percent over the next half-century as a result of a declining birth-rate, automation could compensate for the smaller workforce and revitalize growth in manufacturing sectors.” (Bughin, Manyka, & Weetzel, 2017, p. 116)

### Uncertainty of institutional moves

 As recurrently developed in our literature review, the public powers have a role to play in the implementation of technologies derived from the fourth industrial revolution. There is a delay between the inception of a technology and its assimilation by businesses. The delay of assimilation by institutions is even longer, permitting a “no-rules” period usually concluded by official and legal adjustment. The transition that affected the business model of cabs initiated by Uber was not addressed by the government before months and even years. The rules governing the national sovereignty over data on the web are not yet fully invented, the topic is just introduced.

Public regulation and the direction taken by governments about the fourth industrial revolution is impossible to predict. While some approach may consist in changing the society to reduce the impact of technologies on people (universal income solution), others imaginable approached may consist in simply forbidding a technology, or not encouraging its adoption in order to save jobs.

“Oh, I thought you were trying to build a canal. If it is jobs you want, then you should give these workers spoons, not shovels.” Milton Friedman, 1960

This quote from the famous economist shows that government meddling in technologies is not a new factor to consider.

### Importance of private players

 In sales, a single business player such as Amazon can totally disrupt whole industries, may change the human resources needs, redefining the traditional roles. Most of the type of products are represented in the platform, which could virtually impact all the industries. It happened in the past for several industries, since the practices adopter by markets’ leaders are likely to be copied by competitors.

In parallel, this single player could have an unexpected influence on the definition of sales role from its size. A simple numeric estimation can help us to figure it out. The sample used this paper is supposed to represent around 15 million people in the USA (O\*NET, 2016). Amazon employs now almost more than 120 thousands employees and planning to double in volume in the next years. Taking the inelegant assumption that they all belong to sales or related industry, it means that more than 2% of the salespeople of the USA are directly working for this single player.

### Limitation from our assumptions about technology diffusion

 One of the assumption taken to develop our reasoning is that technologies diffuse themselves linearly. Nowadays, one of the most valuable software ability is the mastering of the COBOL language (COmmon Business Oriented Language). This language was developed around the 60’s, therefore, it is quite obsolete now. It comes out that the cost for companies to switch to more recent coding language is high. In the case of sales, the automation of some services would be reduced for similar reasons. For example, an important investment in workforce’s formation would lead to consider the automation differently. Reminding the case of banks’ clerks during the 3rd Industrial Revolution, the businesses’ kinetics make difficult to implement change, even if the technology is available it can take time before it is actually understood and assimilable.

Figure – Jobwise relationship between the proportion of computerisation and expected growth

 As the graph shows, there no evident correlation between the jobs growth and the jobs exposition to the automation. It is explained by the idea that the actual market and economic trends have a direct, immediate volume impact on employer’s decision to hire or dismay.

### From the O\*NET dataset

Our analysis about the set independent variable – software usage – was limited by the fact that the 0\*NET dataset ignore the fact there are a different level of usage for the same software. The way the 0\*NET framework is constructed is solid, having the accreditation of several official institutes in the USA, reducing the chance of mistakes coming from this dataset.

### From the McKinsey findings

 Since developed in a private context, some elements of the model might be biased for some purposes that we ignore. For the reason already evoked, their estimation of computerisation is still the most accurate and holistic, making redundant the others.

 We can see on annex E a comparison between the figures of Fray and Osborne and the ones of McKinsey. While the findings of McKinsey are pretty normally distributed, the values of Fray and Osborne are rather diametrically distributed, with some jobs with extremely low chance of computerisation and some very high. It is quite normal since the two research compare different things, one the proportion of tasks automatable the other the probability of computerisation.

### From the statistical relationship

Our approach relies on the assumption that there is no correlation between the chance of computerisation and type of skills. This assumption is supported by the evidence-supported fact that the correlation between salary and computerisation proportion is not strong. There are tasks requiring very high degree level of education that are now automatable, such as legal clerics and medical scans interpretation.

### Validity Tests

 Construct validity – The research uses the most up to date secondary data, issues respectively from the US government and one of the most prestigious business consulting research institute. It follows the tradition of the previous study to use this type of secondary data to draw a general conclusion on automation processes.

 Internal Validity – The research framework we used faced the difficulty to link macro economic study with the field of management. These two different worlds do not share the same type of framework and concepts, which makes complex the development of a clear framework of research, creating weaknesses. The statistical method used was artificially reduced to the world of sales in order to get more relevance. We could have run an analysis on the whole existing dataset, but it would have been risked, opening the door to the possibility to lose the managerial scope expected for this dissertation.

 External Validity – This study could serve as a pilot for further investigation inferred from the main findings about the importance of computerization of tasks. This topic of research is quite young – as mentioned lest than five studies have been produced in the evaluation of the automation impact for the economy. Therefore, the development of secondary study commenting the effect of this technological transition are relevant and should be growingly needed in order to help the business and the public to make the best fact-based decisions. As previously quoted, the public discussion about the future of the economy is pending and growingly controversial, the development of further information to feed the debate is more than ever required.

 Reliability – Several different questions are involved in defining whether a study a reliable. The sample used in this research are public, inferred from information freely available. The simplicity of the statistical approach used is twofold regarding this question. While it permits to simply confirm our findings, the usage of a simple non-parametrical model reduces the impact of the findings.

## Summary of Chapter 3

This chapter showed the different aspects of our findings for companies, and how this paper should be interpreted to make managerial decisions.

We express here the idea that the mastering of classical skills or knowledge related to sales for salespeople is not correlated with the amount of tasks computerisable for a given job. On the contrary, the classical profile of the salesperson if shifting toward a more versatile and less specialized worker:

* The importance of the skills and knowledge related to the creation of content is explained, showing the first element of profile shift. It is explained by the digitalisation of the market, and the growing importance of creative tasks to fit it.
* Then we underline how managerial skills are going to be more important - relatively -because the other tasks are computerisable.

We also express how this research is pertinent to understand trends, but do not pretend to create a ranged conclusion. It should be interpreted as the enlightenment of the trends of formation that companies should implement in the future.

# CONCLUSION

Our findings confirm the trend that the core of skills and knowledge required to be successful in sales is shifting from the traditional negotiation/product-wise/administrative skills to a wider set, concentrated around the personal, cultural and creative added value delivered by the salespeople. Even if we cannot ensure that the computerisation will not at the end affect all the tasks, the flexibility is a value that companies should find in their salespeople, not only for its skills of negotiation or resource management.

We bring evidence supporting the theory of O-Rubber developed by David Author to describe the impact of automation of jobs. Sales skills related to negotiation, management of supply chain and classic business are not going to continue to make the different through the fourth industrial revolution. As in the O-Rubber theory, the skills that are not easily automatable by the machines are going to gain in value not only because they will be the justification to still employ humans, but also because they will be integrated into a chain of value reinforced by the machine. We defined that skills and knowledge related to the visual design of content are going to be needed to support efficiently sales operation. Naturally, the aptitude for salespeople to judge the situation and consider a trade-off is going to be more important, as the simple tasks are automated. The development of analytical tools for data triggers more time for pure strategic judgment and less need for laborious analysis. Finally, we believe that company has to encourage the flexibility and the aptitude for salespeople to continuously learn new knowledge and information.

In more general, the future of the sales is yet to be discovered, but companies should start or continue to invest in people with skills previously considered as outliers in the classical set of skills. This is supported by the recent trends is companies such as Google or Microsoft to start investigating people with unusual profiles and set of skill, privileging new hires with a diverse profile such as art, history or design. Cutting from the tradition of cold calling, companies are taking into consideration that the management of the information on the internet is their direct interface with their clients. That is why salespeople should be trained with the tools enabling them to understand and create digital contents whose importance is now basic in sales. The digitalisation increases the access to contradictory information and sources for the prospective clients, multiplying the source of contradiction against a salesperson argumentation. The impact of Fourth industrial revolution for companies is not only to automatize tasks but also to underline where and how the company should create value since this very same way how the value is created is mutating. Moving toward this trend is not only a way to keep the company’s manpower useful, but also it is a way to gain a better position in the market and develop a better understanding of the strategic environment. The early adopter of technologies usually profited from it, similarly the first to fit their staffs with the reality of the environment are likely to profit from it. By staying flexible and ready to re-educate, retrain their teams companies would not only benefit from the Fourth Industrial Revolution, but manage to disrupt their competitors.

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# DATABASES ADDRESSES

For accessing the databases, that we are using, please refer to the following links:

PIAAC: http://www.oecd.org/skills/piaac/

0\*NET: https://www.onetcenter.org/dataCollection.html

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#  SUPPLEMENTARY MATERIAL

## Appendix 1. Model A

|  |  |  |  |
| --- | --- | --- | --- |
|  | S | p-value | rho |
| Product Knowledge | 3431 | 0,0494 | -0,3196 |
| Administration and Management | 2905 | 0,5766 | -0,1173 |
| Clerical | 2260 | 0,5343 | 0,130427 |
| Communications and Media | 3348,2 | 0,1631 | -0,28775 |
| Computers and Electronics | 2560,5 | 0,9425 | 0,01521 |
| Customer and Personal Service | 2274,3 | 0,5508 | 0,125265 |
| Design | 3964,1 | 0,0071 | -0,52466 |
| Economics and Accounting | 2638,6 | 0,9439 | -0,01483 |
| Education and Training | 2576,9 | 0,9664 | 0,008873 |
| Engineering and Technology | 3383,8 | 0,1431 | -0,30145 |
| English Language | 2753,7 | 0,7789 | -0,05913 |
| Foreign Language | 1834,7 | 0,1532 | 0,294333 |
| Geography | 2743,5 | 0,7933 | -0,0552 |
| Law and Government | 2840,7 | 0,6598 | -0,09259 |
| Mathematics | 2644,6 | 0,9351 | -0,01718 |
| Personnel and Human Resources | 3015 | 0,4460 | -0,1596 |
| Production and Processing | 2920,3 | 0,5574 | -0,12319 |
| Psychology | 3645,8 | 0,0462 | -0,40224 |
| Public Safety and Security | 3033,2 | 0,4260 | -0,16663 |
| Sales and Marketing | 3435,6 | 0,1172 | -0,32139 |
| Sociology and Anthropology | 3971,3 | 0,0067 | -0,52744 |
| Telecommunications | 2841,5 | 0,6588 | -0,09287 |
| Transportation | 2766,3 | 0,7613 | -0,06396 |

## Appendix 2. Model B

|  |  |  |  |
| --- | --- | --- | --- |
|  | S | p-value | rho |
| Active Learning | 3045,7 | 0,4126 | -0,17141 |
| Active Listening | 2046,9 | 0,3072 | 0,212746 |
| Complex Problem Solving | 2959 | 0,5105 | -0,13806 |
| Coordination | 3602,3 | 0,0470 | -0,38552 |
| Critical Thinking | 3266 | 0,2159 | -0,25646 |
| Instructing | 3033,6 | 0,4256 | -0,16677 |
| Judgment and Decision Making | 3184,7 | 0,2798 | -0,22489 |
| Learning Strategies | 3642 | 0,0471 | -0,40078 |
| Management of Financial Resources | 3589,8 | 0,0495 | -0,38069 |
| Management of Material Resources | 3509,8 | 0,0864 | -0,34994 |
| Management of Personnel Resources | 3733,7 | 0,0293 | -0,43605 |
| Mathematics | 2562,1 | 0,9449 | 0,014566 |
| Monitoring | 2920 | 0,5578 | -0,12308 |
| Negotiation | 3356,8 | 0,1580 | -0,29108 |
| Operation and Control | 2484,5 | 0,8330 | 0,044412 |
| Operation Monitoring | 2470,8 | 0,8135 | 0,049711 |
| Operations Analysis | 3843,9 | 0,0164 | -0,47495 |
| Persuasion | 3380,5 | 0,1448 | -0,3002 |
| Programming | 2602 | 0,9971 | -0,00078 |
| Quality Control Analysis | 3302,5 | 0,1915 | -0,27018 |
| Reading Comprehension | 2240,6 | 0,5099 | 0,138248 |
| Service Orientation | 1853,5 | 0,1640 | 0,287129 |
| Social Perceptiveness | 3411,2 | 0,1289 | -0,31201 |
| Speaking | 2327,5 | 0,6181 | 0,104808 |
| Systems Analysis | 3468,3 | 0,1028 | -0,33398 |
| Systems Evaluation  | 3609,9 | 0,0450 | -0,38844 |
| Technology Design | 3362,5 | 0,1548 | -0,29329 |
| Time Management | 3352,9 | 0,1603 | -0,28959 |
| Writing | 2778,4 | 0,7445 | -0,06861 |

## Appendix 3. Model C

|  |  |  |  |
| --- | --- | --- | --- |
|  | S | p-value | rho |
| Web and media management | 4029,6 | 0,0044 | -0,54984 |
| Supply chain software | 2589 | 0,9840 | 0,004229 |
| Task management | 3126,9 | 0,3313 | -0,20265 |
| Development software | 3300 | 0,1931 | -0,26924 |
| Data Management | 3211,1 | 0,2581 | -0,23503 |

## Appendix 4. O\*NET selected list of jobs

|  |  |  |  |
| --- | --- | --- | --- |
| ISCO classification | Salary | Volume (in 000) | Growth |
| Marketing Managers | 57,2 | 174 | 11% |
| Demonstrators and product promoters | 14 | 77 | 11% |
| Advertising Sales Agents | 23 | 149 | -2% |
| First-Line Supervisors of non-retail sales workers | 36 | 246 | 5,50% |
| Sales representatives, wholesale and manufacturing, except technical and scientific products | 29 | 1403 | 6,50% |
| Real estate sales agents | 24 | 159 | 3% |
| First-Line Supervisors of retail sales workers | 20 | 1214 | 3% |
| Sales Engineers | 46 | 66 | 6,5% |
| Financial Managers | 54,2 | 500 | 6,5% |
| Energy brokers | 27 | 761 | 6,5% |
| Purchasing Managers | 49,7 | 70 | 0,0% |
| Sales representatives, wholesale and manufacturing, technical and scientific products | 38 | 353 | 6,5% |
| Door to Door sales worker | 12 | 6 | 0,0% |
| Securities, Commodities and Financial Services Sales | 40 | 325 | 11,0% |
| Retail salespersons | 13 | 4485 | 6,5% |
| Cashiers | 10 | 3343 | 3,0% |
| Telemarketers | 12,9 | 232 | -2,0% |
| Gaming Change Persons and Booth Cashiers | 11,5 | 19 | -2,0% |
| Real Estate Brokers | 37 | 38 | 3,0% |
| Counter and rental clerks | 13 | 431 | 3,0% |
| Insurance sales agent | 27 | 354 | 11% |
| Sales Managers | 54 | 352 | 6,5% |
| Travel agent | 17 | 64 | -2,0% |
| Loan Interviewers and Clerks | 17 | 213 | 11,0% |
| Part salesperson | 15 | 221 | 6,5% |

## Appendix 5. Computerisation estimation comparison between McKinsey and Frey and Osborne

|  |  |  |
| --- | --- | --- |
| ISCO classification | Frey and Osborne | McKinsey  |
| Marketing Managers | 0.014 | 0,13 |
| Demonstrators and product promoters | 0.51 | 0,17 |
| Advertising Sales Agents | 0.54 | 0,2 |
| First-Line Supervisors of non-retail sales workers | 0.42 | 0,2 |
| Sales representatives, wholesale and manufacturing, except technical and scientific products | 0.85 | 0,21 |
| Real estate sales agents | 0.86 | 0,27 |
| First-Line Supervisors of retail sales workers | 0.94 | 0,33 |
| Sales Engineers | 0.0041 | 0,33 |
| Financial Managers | 0.069 | 0,34 |
| Energy brokers | - | 0,36 |
| Purchasing Managers | 0.03 | 0,36 |
| Sales representatives, wholesale and manufacturing, technical and scientific products | 0.25 | 0,37 |
| Door to Door sales worker | 0.94 | 0,4 |
| Securities, Commodities and Financial Services Sales | 0.016 | 0,46 |
| Retail salespersons | 0.92 | 0,47 |
| Cashiers | 0.97 | 0,49 |
| Telemarketers | 0.99 | 0,49 |
| Gaming Change Persons and Booth Cashiers | 0.83 | 0,5 |
| Real Estate Brokers | 0.97 | 0,51 |
| Counter and rental clerks | 0.97 | 0,58 |
| Insurance sales agent | 0.92 | 0,6 |
| Sales Managers | 0.013 | 0,7 |
| Travel agent | 0.099 | 0,73 |
| Loan Interviewers and Clerks | 0.92 | 0,73 |
| Part salesperson | 0.98 | 0,85 |

## Appendix 6. Complementary occupational information from O\*NET

|  |  |  |  |
| --- | --- | --- | --- |
|  | Salary | Volume | Projected Growth |
| Marketing Managers | 57,2 | 174 | 11,0% |
| Demonstrators and product promoters | 14 | 77 | 11,0% |
| Advertising Sales Agents | 23 | 149 | -2,0% |
| First-Line Supervisors of non-retail sales workers | 36 | 246 | 5,5% |
| Sales representatives, wholesale and manufacturing, except technical and scientific products | 29 | 1403 | 6,5% |
| Real estate sales agents | 24 | 159 | 3,0% |
| First-Line Supervisors of retail sales workers | 20 | 1214 | 3,0% |
| Sales Engineers | 46 | 66 | 6,5% |
| Financial Managers | 54,2 | 500 | 6,5% |
| Energy brokers | 27 | 761 | 6,5% |
| Purchasing Managers | 49,7 | 70 | 0,0% |
| Sales representatives, wholesale and manufacturing, technical and scientific products | 38 | 353 | 6,5% |
| Door to Door sales worker | 12 | 6 | 0,0% |
| Securities, Commodities and Financial Services Sales | 40 | 325 | 11,0% |
| Retail salespersons | 13 | 4485 | 6,5% |
| Cashiers | 10 | 3343 | 3,0% |
| Telemarketers | 12,9 | 232 | -2,0% |
| Gaming Change Persons and Booth Cashiers | 11,5 | 19 | -2,0% |
| Real Estate Brokers | 37 | 38 | 3,0% |
| Counter and rental clerks | 13 | 431 | 3,0% |
| Insurance sales agent | 27 | 354 | 11,0% |
| Sales Managers | 54 | 352 | 6,5% |
| Travel agent | 17 | 64 | -2,0% |
| Loan Interviewers and Clerks | 17 | 213 | 11,0% |
| Parts salesperson | 15 | 221 | 6,5% |

1. The Galleries Lafayette during this period in 1912. [↑](#footnote-ref-1)