Università degli Studi di Padova

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HYBRID JOBS & ORGANIZATION OF WORK: SKILLS, ROLES AND MEASUREMENTS

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Firma

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INTRODUCTION & SUMMARY

THE REASON FOR MY DISSERTATION – It is unquestionable that jobs are in continuous evolution: their DNA is slowly mutating, reflecting changes in the external environment. Over the last decades, digital transformation has had a role in boosting the adoption of new digital tools and ITC systems; robots and automation both displaced labour and crated new roles and jobs at the same time, providing workers with the opportunity to do more human and challenging tasks. The complexity of jobs dictated by tech advancements and automation calls for similarly complex interdisciplinary skills. Organizations more and more often need people with unusual combinations of competences, which greatly differ from traditional skillsets: they are at the heart of hybrid jobs.

THE AIM OF THE DISSERTATION – The major purpose of this master thesis is to explore how and to which extent the mix of skills that are effectively asked in workplaces nowadays is evolving across different professional areas. This research objective can be attained by answering questions like "to which extent different job categories are hybrid?", "which non-job specific skills do diverse functional roles require to workers and which are the most important?", "how often has the workforce to perform non-technical competences and which level of knowledge is actually necessary?". The ultimate aim of this research work is to help business leaders and HR functions in the recruitment and reallocation of people by suggesting which profiles are the most suitable to develop the desired set of non-technical skills.

CHAPTER 1 – *DIGITAL TRANSFORMATION VS DIGITAL SOCIETY: A HOLISTIC APPROACH* –

This chapter is aimed at presenting different perspectives on the impact of digital transformation on society. We illustrated how the adoption of DT technologies might not be a fully profitable investment when not accompanied by a proper integration within the organizational design and internal systems and procedures. We demonstrated that DT technologies have a big potential for creating synergies also in the business environment where they are embedded, but it is pivotal that they are matched with proper skills and competences. We explained in which sense digital transformation goes beyond mere technology and reaches and permeates the society as a whole: proper mindset and sufficient readiness and adaptability are essential to effectively face the blurring of borders of industries and jobs. We highlighted how completely opposite perspectives coexist regarding the impact of digital transformation on work - forecasts of employment growth on one side and fear of labour displacement and technological unemployment on the other side– and we suggested a possibile explanation. Two points of view are then presented and dicussed concerning two different ways for firms to look at digital tranformation and to approach it.

CHAPTER 2 – *HYBRID JOBS AND NEW SKILLS ON THE LABOUR MARKET* - In this chapter we explored the concept of skills as the DNA of jobs and we illustrated three macro-categories of jobs which differ for the variety and intensity of abilities involved. The evolution of traditional jobs and the transformation of the skillsets necessary to complete tasks have an impact on the HR functions, which, as we discussed, have to select people with unusual competence mix and manage transitions of employees from a position to another. With this regard, we highlighted the importance of reskilling and upskilling of workforce to prevent firms from the obsolescence of their human resource's skills as a strategic solution to seize opportunities coming from an ever-chaning external context and to stay competitive.

CHAPTER 3 –*JOBS' HYBRIDIZATION: RESEARCH METHODOLOGY* - This chapter describes research conducted at the end of 2018 to study the hybridization phenomenon across long-established jobs. Data pre-processing phase was illustrated and major information about the sample's profiles in terms of both personal and work-related details were provided through descriptive statistics. We idenfied six professional areas where we wanted to focus our research on. Three skill domains were analysed across the sample in terms of frequency of utilization and depth of knowledge and preliminary results were shown. It emerged that: soft abilities have a pivotal role as they are intensively needed across the sample; IT skills are asked in workplaces with good levels of knowledge as well, but a larger variability exists in terms of frequency; digital competences are not very much developed and spread.

CHAPTER 4 – *EXPLORING HYBRIDIZATION ACROSS JOBS* - After having exhibited some insights on the features of the three skill domains of interest across the sample, in this chapter we offer more specific information controlling by professional areas. This allows us to provide an overall view on how hybridization differently permeates various job categories and to make comparisons between them. Interesting results came out: while soft skills seem to be a necessary element across different functional families, it appears that the frequency of utilization of IT competences is strictly dependent on the kind of job; as of digital skills, they resulted to be poorly managed across occupations. Further investigations on the features of IT, digital and soft skill domains are carried out, with a focus on knowledge dispersion measurements.

CHAPTER 5 – *SKILLS LEADING TO HYBRIDIZATION OF JOBS* - Up to this point, the analysis on hybridization features were conducted on the whole sample and on every skill domain, across jobs. In this chapter, we shift the focus and we study hybridization focusing on each professional area specifically, across the three skills domains. The object of this chapter is to explore more in depth each functional family to understand to which extent different jobs require to use and develop IT, digital and soft skills and in which combination; in other words, we pursued the purpose of finding the "hybrid shape" of jobs.

CHAPTER 6 – *MEASURING JOBS HYBRIDIZATION: THE WHEEL OF HYBRID JOBS*- This chapter has the aim of measuring the hybridization of jobs and providing proper organizational and managerial implications. To reach these goals, we explored new paths and we attained our purposes by creating an original model: we identified the Hybridization Index of jobs – or jobs categories - and we integrated it within the Hybridization Wheel, a graph devoted to displaying the status quo in terms of hybridization level and to help HR managers and business leader taking actions to move toward desired outcomes. We applied this model to study the hybridization level and the features of the six professional areas of interest and we provided suggestions about the personnel's profiles that best fit the requirements of each functional family in terms of hybridizing skills.

CHAPTER 7 – *JOB HYBRIDIZATION: MANAGERIAL IMPLICATIONS* - This chapter completes the previous one with some implications, also considering findings from the previous chapters. Its major aim is to help the identification of proper profiles in terms of hybridizing skills, based on some people's characteristics. In particular, this chapter illustrates up to which point people with different education levels, age or gender are more inclined to develop specific hybridizing skills. We showed the impact of these features on workers' performances in terms of IT, digital and soft skills in the workplaces, highlighting the aspects that could help business leaders, hiring managers and human resources managers in making decisions.

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1. CHAPTER

DIGITAL TRANSFORMATION VS DIGITAL SOCIETY: A HOLISTIC APPROACH

1.1 Introduction

An article published in the Harvard Business Review in 2019, headlined *Digital transformation is not about technology* (Tabrizi et al. 2019), stated that 70% of all digital transformation initiatives do not reach their goals and estimated that about $900 billion went to waste in 2018 with respect to the $1.3 trillion that was invested.

Most digital transformation initiatives are based on the so-called 3rd platform technologies, that are built on cloud, mobile, social and big data technologies (IDC 2013), and, more specifically, on cloud computing, mobile solutions, social media, big data analytics and Internet of Things (from now on IoT).

According to that article, a reason why many digital transformation initiatives do not pay off is that they are focused on the digital technologies taken individually rather than on a broader and clear digital strategy and vision. The risk of turning a huge investment into a big waste emerged from the same study as the number one concern for directors, CEOs and senior executives in 2019.

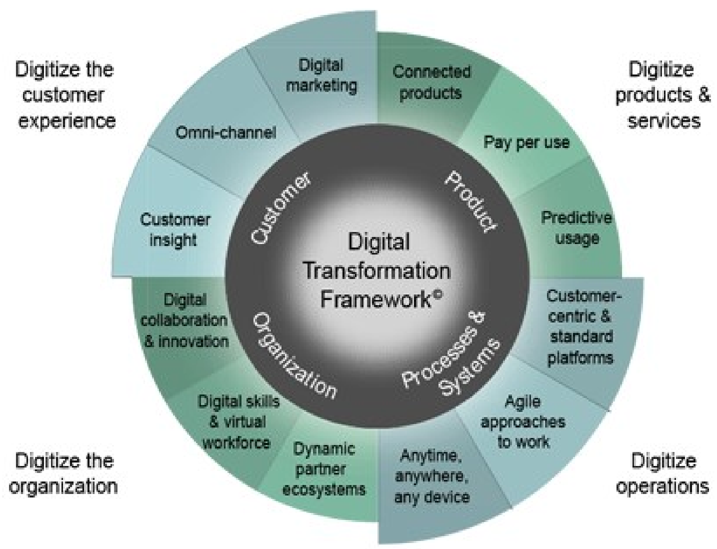
In 2015, the importance of a more comprehensive approach toward digital has been highlighted by MIT Sloan Management Review and Deloitte in the article *Strategy, Not Technology, Drives Digital Transformation* (Kane et al. 2015). This work suggests that to evolve from a non-mature digital company to a maturing digital one, it is necessary to shift the focus from solving discrete business problems with individual digital technologies (like social, mobile, analytics and cloud ones) to integrating them within the organizational design. Again, risk-taking cannot be avoided, but it may be seen as a

cultural norm for more digitally advanced companies. This leads not only to a higher competitive advantage and enhanced business performance, but also to an increase in the attraction and retention of employees across all age groups.
Consistent digital operating models are the only way to stay ahead. Also Jeff Bezos, the founder and CEO of Amazon, talked about digital transformation in these terms:

> «There is no alternative to digital transformation. Visionary companies will carve out new strategic options for themselves — those that don't adapt, will fail».

This sentence unequivocally states that having a digital strategy is no longer a possibility, but a necessity, as digital transformation (from now on DT) has now become a holistic process that undoubtedly goes further beyond mere technology; proper mindset and sufficient readiness are required to embrace change instead of being overwhelmed by it. As technology and business have become more and more intertwined, DT initiatives have started transforming industries in completely new ways, providing opportunities for efficiency, efficacy, personalization and flexibility.
According to *Cognizant*, an American a leading provider of information technology, consulting, and business process outsourcing services, DT has an impact on four different areas: operations, products and services, customer experience and the organization as a whole (Cognizant 2014).

Figure 1 Cognizant's DT Framework



Source: Cognizant, 2014

This chapter aims to provide some insights into the relationship between digital transformation and digital society, passing through implications for workers in the labour market. Paragraph 1.2 will illustrate which technologies are now leading the digital transformation process and what are their main features, as a full comprehension is essential for understanding DT implications. In paragraph 1.3 two different perspectives toward the impact of digital transformation on the society and, more specifically, on the labour market will be discussed. In paragraph 1.4 we will argue in which sense DT can represent at the same time a threat and an opportunity for firms.

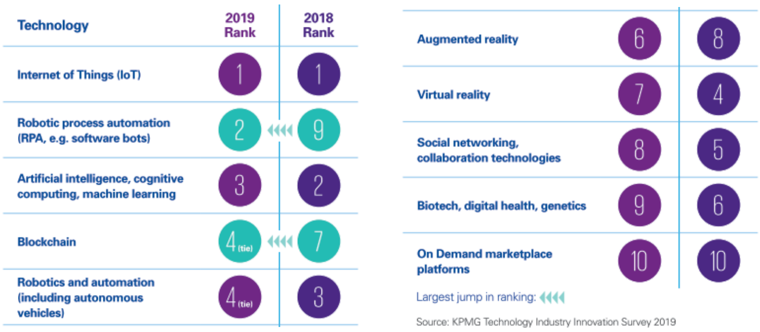
It will emerge how digital transformation has gone beyond technology, affecting both the structure of labour market and the organizational structure of the firms.

1.2 An insight toward new DT technologies

In the digital era, an increasing number of new technologies have been developed and adopted by firms, thus enabling product, process and service innovations, in addition to more comprehensive transformations in the business model.

The KPMG Technology Industry Innovation Survey 2019 found that the first three technologies that company leaders envisage to have the greatest potential for driving future business transformation and long-term value are, in order: IoT; robotic process automation; artificial intelligence (from now on AI), cognitive computing and machine learning (KPMG 2019). The results were similar in the analogous 2018 survey, with the major difference that process automation and blockchain rose through the ranks.

Figure 2 The top 10 technologies for business transformation



Source: KPMG Technology Industry Innovation Survey 2019

Technologies listed in Figure 2 may seem just buzzwords, but they have really taken the lead in transforming businesses, their processes, business models and the organization of work. Indeed, they are blurring the borders not only of industries, but also of jobs, as it will be argued throughout this master thesis.

This paragraph has the aim of investigating and shedding light on the nature and the relations among the main DT technologies that are revolutionizing the world around us. Only a sufficiently deep knowledge of what they are and which features they have enabled to understand their consequences in firms and workplaces, both in terms of competences and organizational aspects.

The whole exceeds the sum of the parts

Even though artificial intelligence, big data, cloud computing and IoT technologies were created independently and evolved on separate paths, over the last decades they have been strengthening their ties and have become increasingly interdependent (Analytics Insight 2017). The relation among technologies leading digital transformation is not, or no longer, linear or just "additive". It implies that their connection and interaction creates an overall value which is greater that the sum of the single elements considered separately.

This concept recalls that of synergy, which is at the core of IoT platforms, just to make an example. We would suggest that this effect, which also applies when DT technologies are included in the business environment, may be magnified by proper interaction with another kind of resources: the human capital. As it will be discussed in Chapter 2, workers' digital and IT competences are among the factors that enable the amplification of these synergies, as new technologies and systems call for new abilities.

DT technologies as complex and convergent systems

Literature talked about digital transformation technologies in terms of complex systems and of convergence (Park 2017)(Pietsch 2013a)(Mainzer and Mainzer 1996).

The so-called "theory of complex systems", which originates from physics, refers to situations where a multitude of elements connect and interact with each other in a non-linear way and can be applied to DT technologies like artificial intelligence, for example (Goertzel and Wang 2007). For this reason, among the others, many digital transformation systems fall within such complexity; indeed, to perform their function, these technologies have to solve a problem that cannot be worked out by breaking it down into independent blocks and it is not possible to proceed step-by-step.

The concept of "convergence" is also recalled, with particular reference to technologies like IoT, big data analytics and cloud computing: the alignment in their capabilities

"…creates a shift towards the dependence on interconnected devices and the information they generate"; we are moving the orientation from product to information-based outcome (Analytics Insight 2017).

To clarify how the concepts of complexity[1] and convergence apply to DT technologies, we will now provide an example, which considers big data and related data-intensive techniques. Before starting, let us briefly take a look at what we are talking about. The term big data has been defined in several ways, most of them pointed it out as a pure collection of informative data or as the technical or technological challenges they pose to extract value from them, as they are characterized by the so-called 3 Vs: volume, velocity, variety (Meta Group 2001). Big data can be seen as complex systems not just because of their size, but also because of their nature. In this regard, Pietsch (2013, p. 1) stated that "..Big data allow for novel ways to address complexity in science".

Let us consider, as a real-life example, a big data software: suppose we dispose of a rich database on people's sleeping habits, which is based on the information collected through their wearable devices (IoT) over a continuous flow, and that statistics are computed on those data so that new knowledge is gained for a variety of purposes.

The first aspect that emerges is the high-dimensionality of data, as they are seamlessly generated; to no surprise, big data involves many observations, parameters and combination of parameters (Pietsch 2013b). The second aspect is the need for systems that take all these data in, store them, perform operations to process them and to update computations quickly enough as new data arrive: for this reason, it is not possible to manage big data without having cloud servers, cloud computing services and sufficient computer processing power. The third point that is worth noting is that the process of analysing, processing, modeling and extracting information from big data is completely automated, allowing to somehow sidestep human cognition[2], but, at the same time, also impairing it[3]. A significant role is played by artificial intelligence to draw insights from IoT data and to enable machines to perform tasks based on that information. The last

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[1] The terms "complexity" or "complex" are used with respect to the complex systems theory, so they do not have the general meaning of "difficult" or "intricate".

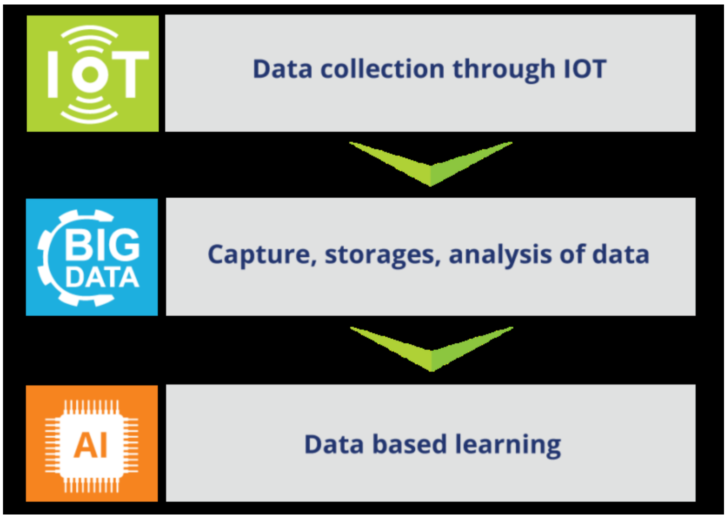
2 Big data often do not require human cognition: for example, machine learning translation works without any knowledge about grammar.

3 Automation in the whole process hinders human control of procedures like the model selection, making it more difficult to understand and interpret the results.

characteristic of big data technologies, but maybe the most important, concerns its fundamental components, i.e. the data, as their value is not addictive. Indeed, knowing the sleeping habits of each person individually has no relevance at all, but by aggregating them and computing statistics, it is possible to derive highly valuable insights on the sleep quality and sleeping times of the population. The demonstration that the overall value of integrated data is greater than their mere sum is quite easy: the value of data of each people considered individually is close to zero so that the sum of these single pieces of information is overall close to zero. However, by aggregating data, it is possible to get highly valuable insights, whose value is far away from zero.

To sum up, the high-dimensionality of data over a regular flow, the need for increasingly greater storing space and computing processing power for automated analysis, together with the non-linear value of data, make big data technologies a complex system. This is also evident if we consider the interconnection between them and the other business transformation technologies: it should not come as a surprise that while discussing big data, also AI, cloud systems, computing processing power and IoT were mentioned.

Figure 3 Synergies and convergence between technologies



Source: I-ON communications blog

Connections between certain technologies are becoming so strong that lines dividing them are increasingly blurring; this phenomenon is called technological convergence (McKinley 2020). The scope of this trend is becoming wider and wider, so that "…convergence with new technologies is expected to create new markets and jobs" (Park 2017, p. 3). When technological convergence is observed across industries, it leads to a phenomenon called the industrial convergence (Gartner 2014). Digital technologies are

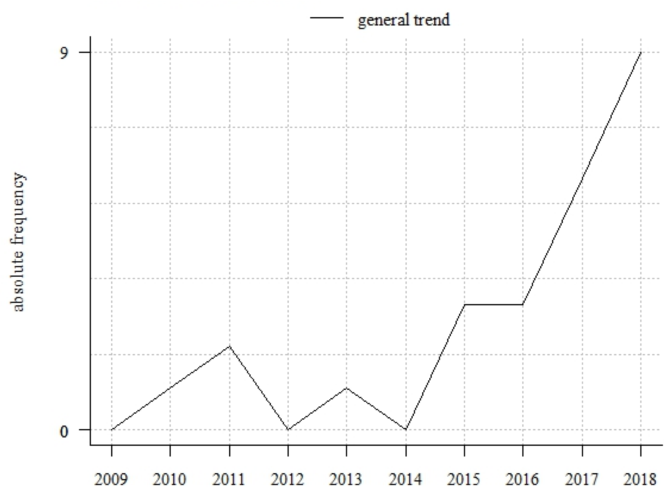
spreading capillary with important and concrete implications on the labour market as well, as firms are increasingly relying and reliant on the new DT technologies to stay competitive. However, they would not be able to achieve their goals without integrating them in their operations and processes, and in people's training as well. Workers from a variety of industries have started facing complex systems and they are required to understand them, to have a certain level of knowledge about specific software and devices and to develop informatics and digital skills, for example.
The consequences of digital transformation on firms and the labour market are discussed in the next paragraphs, while those on the workplaces and the new skills required to perform traditional jobs will be discussed in the next chapters.

1.3 Digital transformation and the labour market

1.3.1 The end of work or a promising future?

As advances in robotics, big data and artificial intelligence move forward, a growing number of human tasks are performed by technology. When machines become able to complete a certain set of activities, they replace workers. This phenomenon is referred to as technological unemployment and it occurs whenever people lose their jobs because of technological progress. Fear of technological unemployment is in the air, and in statistics as well.

Figure 4 Technological unemployment trend



Source: https://www.bigpolicycanvas.eu/community/kb/technological-unemployment

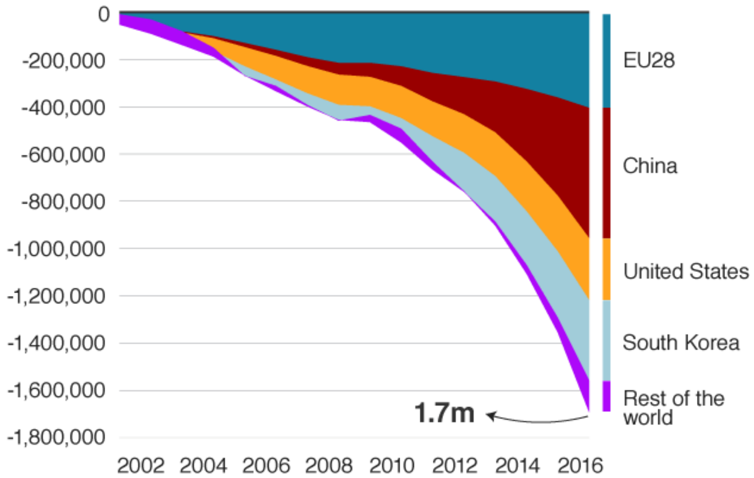
Some researchers have even forecasted that automation would lead to a future without work; for instance, Rifkin, yet in 1995, published a book titled *The End Of Work: The Decline of the Global Labor Force and the Dawn of the Post-Market Era*. Throughout his work, the author provokingly predicted a devastating impact of automation on worldwide employment with particular reference to blue-collar, retail and wholesale employees, as the increase in information technology eliminated tens of millions of jobs in the manufacturing, agricultural and service sectors.

The future of work: grey literature

In more recent years, many institutional reports, articles and papers were entitled *The Future Of Work*, as if they wanted to contrast the gloomy perspective of Rifkin and the subsequent part of literature that built on his forecasts. Recent examples come from articles of McKinsey[4], OECD[5] , Deloitte[6], World Economic Forum[7] and hundreds of scientific papers. Just to give an idea of the intensity of the utilization of such concept, when typing on the web search engine for academic resources Google Scholar the key words *The future of work*, it appears that this formula is included in the title of about thirty papers just in the first six months of 2020, with an average of more than once per week. This may convey the idea that a positive perspective toward the effect of technology on work is nowadays widely diffused, but again this conclusion would be simplistic. According to a research conducted in 2019 by the research firm Oxford Economics, up to 20 million manufacturing jobs around the world could be replaced by robots by 2030. In the same report, a retrospective and a prospective investigation are provided. On the one hand, the firm showed that displacement of labour has been a global trend and that about 1.7 million manufacturing jobs have already been replaced by automation from 2000 to 2016; in particular, 400,000 jobs were lost in Europe, 260,000 in the US and 550,000 in China (see Figure 5).

[4] The "Future of work" is among the trending topics on the McKinsey & Company website: https://www.mckinsey.com/featured-insights/future-of-work
[5] https://www.oecd.org/future-of-work/
[6]https://www2.deloitte.com/us/en/insights/focus/technology-and-the-future-of-work.html
[7] https://www.weforum.org/projects/future-of-work

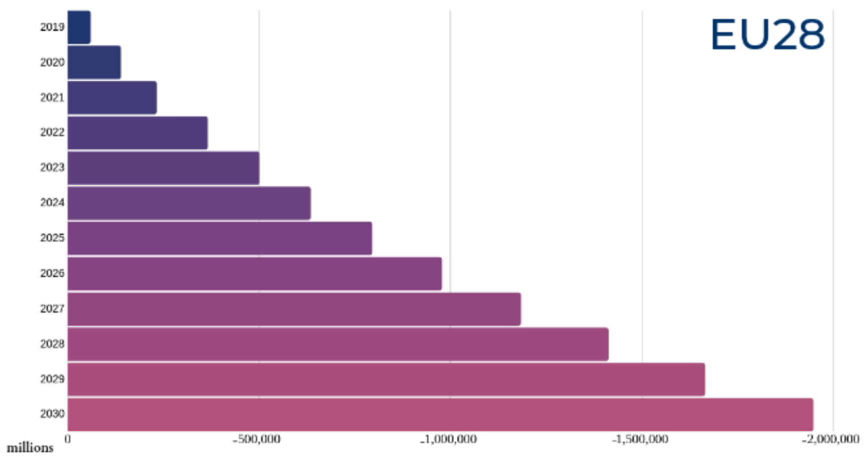
Figure 5 Cumulative job losses attributed to automation since 2000



Source: Oxford Economics, https://www.bbc.com/news/business-48760799

On the other hand, Oxford Economics forecasted that the workforce would continue to be replaced also in the next decade. With reference to Europe, Figure 6 shows the estimates of cumulative job losses; it is worth noting is that the increase in the values prospected is not constant in absolute terms, but incremental growth is expected.

Figure 6 Forecast of cumulative job losses



Source: Oxford Economics, http://resources.oxfordeconomics.com/how-robots-change-the-world

The future of work: scientific literature

Coming to academic research papers, the literature on labour displacement due to substitution with AI and robots is still nascent, but a few studies have already been conducted. For instance, a survey which examined more than 700 occupations to detect how susceptible they are to computerisation found that up to 47% of all jobs in the USA are at risk and could be automated over some unspecified number of years, perhaps a decade or two (Frey and Osborne 2017).

The OECD Employment Outlook (2019) founded that 46% of jobs are likely to disappear because of automation (14%) or to be radically transformed by it (32%). These data may be daunting as they may suggest that technological unemployment is inevitable, but they represent just one side of the story. Indeed, if innovations in robotics, artificial intelligence, process automation and big data are harnessed, job prospects for people with the right mix of skills, knowledge and abilities have never been better (Deloitte 2016, p. 1). Technology is a "great job-creating machine" and history provides significant lessons on how it interacts with employment; this was demonstrated in a study on England and Wales which found that, in the last about 140 years, technology created more jobs than it destroyed (Deloitte 2015). The authors noted that when a machine substitutes a worker, an apparent paradox occurs, as employment grows faster (with new organizational issues for managing the transition from one job to another, as it will be explained in Chpater 2). Thus, from this perspective, we may have reasons to expect that technological change will lead to an overall creation, not destruction, of work. An article of the World Economic Forum (2018) stated that machines would do a greater number of tasks than humans by 2025, but that technology advances would create 58 million net new jobs up to 2022.

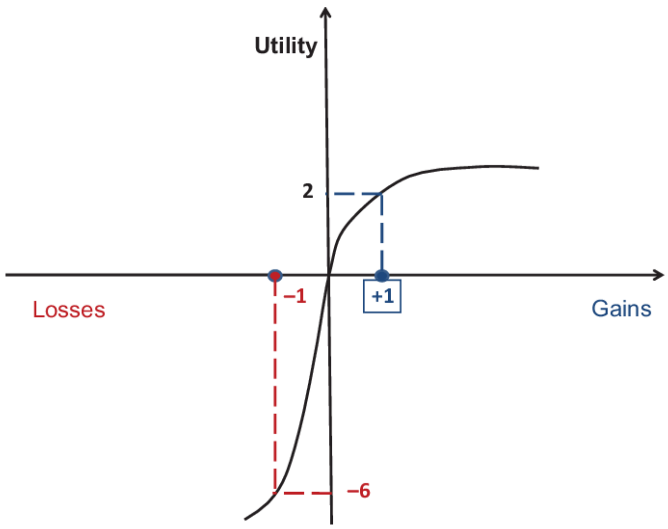
In front of these and many other studies and forecasts that provide such an optimistic outlook for the future, it is reasonable to question why a significant fear that robots would leave humans without jobs still exists. A possible interpretation is presented in the next subparagraph.

1.3.2 Technology and Workers: an application of the theory of prospect

Technological development and its application in business can be envisaged as either daunting or compelling, depending on whether the emphasis is on the job losses or on the creation of new jobs. These different prospects on work implications may be quite confounding, especially if we consider that both the forecasts are all based on objective data.

The theory of prospect, which is the founding element of behavioural economics and behavioural finance in situations of uncertainty (Kahneman and Tversky 2018) might bring us a step forward. This model relates to the way people make decisions when alternatives involve risk and uncertainty; it can be applied to many forms of behaviour and decision. The biases underlying this theory can be found in the way people look at the growing ubiquity of automation in organizational tasks, systems and processes. Basically, the prospect theory shows that people think not in terms of absolute outcomes, but they start from a reference point, that usually is the current situation, and tend to weight losses more than gains, in an asymmetric and skewed manner. Figure 7 shows that the underlying loss aversion makes S-shaped and asymmetrical the value function that passes through the reference point. The fact that the utility function is steeper for losses than for gains indicates that agents are more sensitive to the former than to the latter, so that, for example, a loss or a gain of the same amount, let us say 1, leads to a reduction in utility by 6 and in an increased satisfaction by 2, respectively (Figure 7).

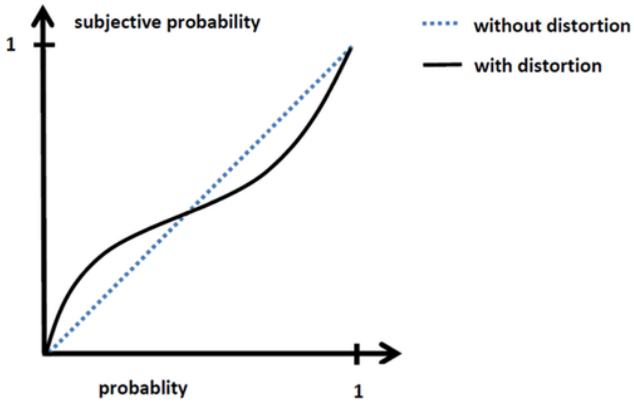
Figure 7 Loss aversion in the utility function



Source: Adapted from Kahneman and Tversky (1984)

According to the prospect theory, moreover, people think using not actual, but distorted probabilities of potential events so that subjective perceptions overcome the objectivity of the reality. Thus, small probabilities are overestimated and large ones are underestimated (Richter, Rub, and Schelling 2019), as Figure 8 shows.

Figure 8 Probability distortion



Source: Richter, Rub, and Schelling 2019

We suggest that the prospect theory might apply to the workers' perception of the role of automation in workplaces, thus explaining why the fear of technological unemployment is still a significant concern for many workers. In particular, this is the case if we consider that:

- the gains and losses might refer to an increase or decrease in employment;
- there is a large probability that technology once again will create more jobs than it has destroyed, as many studies forecast;
- there is a small probability, due to uncertainty, that this will not happen and that overall unemployment increases.

The framing is another interesting phenomenon that may help us understand why opposite approaches to automation and digitization in workplaces co-exist. It is a process that leads people to perceive a piece of information differently accordingly to the way it is presented or expressed. Tversky and Kahneman (1981) first demonstrated it with an experiment where they asked people to choose between two possible treatment methods that could be applied in case a deadly disease occurred. By rephrasing the same solution using either the positive or negative terms, they influenced people's choices. We would suggest that the same occurs to workers' perceptions about the future of their professions according to the way the future perspective is proposed. For example, highlighting that robots will replace workers in repetitive tasks or that humans will have the opportunity to do more human and complex tasks are two sides of the same story that may distort people's attitudes toward automation.

1.4 Digital transformation: a threat or an opportunity for firms?

In a world that evolves at an increasingly faster pace, organizations cannot remain stuck in their status quo and indifferent to the changes that are taking place around them if they want to stay competitive in the medium and long run. Broadly speaking, changes may represent threats to the current structures and systems but also opportunities to revamp them and give them a new guise. It is interesting to explore how firms perceive digital transformation and for which reasons.

A four-year study of Kane that involved about 16,400 responses - about 4,000 per year - and conducted in collaboration with MIT Sloan Management Review and Deloitte to investigate companies' digital maturity, found that as firms become more digitally mature, they tend to see digital technologies as an opportunity (Kane 2019). This result may indicate that the more a business enters in the depths of the digital logic, the more it is likely to understand their underlying potentials and take advantage of them.

Another relevant finding from the same study is that 25% of the firms contacted saw digital technologies as a threat, no matter what their digital maturity level was. Interestingly, the author pointed out an underneath intrinsic contradiction: "If the disruption is an opportunity for you and your competitors, then it is by definition a threat to you, as well".

However, other points of view and different perspectives can be adopted to better understand whether and to which extent digital transformation represents a threat or an opportunity for firms. For example, there are cases where firms feel threatened by digital transformation because they see it as a sort of binding force that puts new pressure for altering those routines, procedures and structures they have slowly built over time. From this perspective, it seems like DT qualifies as a breaking point with past habits and well-established ways of doing business, but this intuition does not properly match with the definition of this term. Indeed, literature separated the concept of *digital transformation* from that of *digital disruption*. The main difference is that the latter refers to the new rules of business that, due to the diffusion of digital technologies, have disrupted entire industries, while the first one denotes how firms are adapting to the situation induced by digital disruption (Kane 2019).

According to this distinction, we could say that:

> "Digital transformation represents the way change is managed, not the change itself. In a sort of parallelism with the Schumpeterian concept of creative destruction, digital disruption can be viewed as the destructive phase and digital transformation as the reconstruction process."

From this angle, it is straightforward that DT encompasses the big set of opportunities that normally arise after an upheaval. In this context, the diffusion of digital technologies is the most immediate outcome, and companies should take advantage by adopting and leveraging them. However, we cannot take for granted that these opportunities are always grasped successfully, as Bill Gates, the founder of Microsoft Corporation, clarified:

> "The first rule of any technology used in a business is that automation applied to an efficient operation will magnify the efficiency.
> The second is that automation applied to an inefficient operation will magnify the inefficiency" (Bill Gates) (cited in Krishnan 2013)

As Bill Gates suggested, the potential of digital tools can be leveraged only if adopted in a proper way, otherwise it can even end up being detrimental. From this perspective, the new technologies are a double-edged sword and firms need to accurately plan how to manage them, and this is possible if they are guided by a broader business strategy. A good example is given by the Li&Fung, a multinational firm specialized in managing supply chains, which decided to digitally transform by focusing its attention on specific areas: speed, innovation and digitalization. In particular, the company wanted to reduce production lead times, improve speed-to-market and enhance the use of data. Only after they set concrete goals, they decided which digital tools to adopt: a virtual design technology and a real-time data tracking management system (Tabrizi et al. 2019). As the researchers of this study pointed out, it does not exist a unique solution for improving speed, innovation or digitalization, but it is a matter of combination of tools that is also contingent on the organization of each firm and its vision. This validates the concept that the implementation of digital transformation can represent an opportunity, but it is true depending on the context: it can become a threat if a firm is not far-sighted enough to change together with, or even earlier than, the external environment.

Literature has widely supported the idea that firms cannot be static, but dynamic and flexible; in particular, they need to be resilient to be able to adapt and flourish in a turbulent environment (Fiksel 2015). Thus, organizations are virtually in a continuous evolution that can be seen as a relentless shift (Brown and Eisenhardt 2003). In an organization, changes can be considered a natural activity even though it is also natural resisting anything that challenges the status quo (Craine 2007). Therefore, digital transformation can be seen as a threat if firms want to stay close to their old paradigms within a past-bound logic or as an opportunity if they are willing to break with the traditional schemes to let a new and challenging system emerge.

1.5 Conclusion

In this Chapter, different perspectives on the impact of digital transformation on society were discuessed. In a world where only dynamic and forward-looking firms can stay ahead, we illustrated how the adoption of DT technologies might not be a profitable investment if it is not accompanied by a proper integration within the organizational design and internal systems and procedures. Indeed, we demonstrated that DT technologies have big a potential for creating synergies in the environment where they are embedded, but for this effect to take place in workplaces it is pivotal that new tools are matched with proper skills and competences. This explains in which sense digital transformation in firms goes far beyond mere technology: proper mindset and sufficient readiness are essential to effectively face changes. Indeed, the DT tools and systems are blurring borders not only of industries, but of jobs as well; furhermore, they are expected to create many new markets and profesions. We highlighted how completely opposite perspectives exist regarding the impact of digital transformation on work: fear of labour displacement and technological unemployment clashes with forecasts of employment growth. Despite occupational projections being reassuring, the transition from a job to a radically tranformed one or to a totally new one is likey to create anxieties and worries, as the change could undo, or in the worst cases reset, the accumulated value of human capital. On the other hand, “job prospects for people with the right mix of skills, knowledge and abilities have never been better” (Deloitte 2016). With occupations requiring new set of capabilities, it is extremely important that people are ready to take on new challenges and that firms are willing to help them leveraging their potential, as it will be discussed in the next Chapter.

2. CHAPTER

HYBRID JOBS AND NEW SKILLS ON THE LABOUR MARKET

2.1 Introduction

In January 2019, Burning Glass Technologies published an article titled *The Hybrid Job Economy: How New Skills Are Rewriting the DNA of the Job Market*. By analysing about a billion job posting and employee resumes from millions of companies, it emerged that jobs are more and more numerous, so that new sets of skills are required on the labour market.

The hybridization trend does not come as a surprise, as Burning Glass Technologies identified it yet in 2015 (Burning Glass Technologies 2015), but since then jobs have become more hybrid and complex at an increasing faster pace. Therefore, it should not surprise that, yet in 2018, a quarter occupations is the U.S were highly or very highly hybridized and only a quarter of them appeard to still have a low hybrid component (Burning Glass Technologies 2019).

This trend has relevant implications for workers, educators, employers, and society as a whole. Hybridization includes the risk of magnifying the divide among workers, making some of gaining ground in the future economy and leaving behind those who are not able to adapt to the new skill requirements. For this reason, it is of paramount importance that no workers, educators, employers, organizations, institutions nor the entire society rest on laurels, but everyone has to watch out for signs of change in the labour market and act accordingly.

This chapter is organized as follows. Paragraph 2.2 explores the concept of skills as the DNA of jobs and illustrates three macro-categories of jobs (standard jobs, hybrid jobs and superjobs) which differentiate on the basis of the variety and intensity of the abilities involved. Some considerations are then proposed with respect to the advantages of being employed in a hybridized job. Paragraph 2.3 investigates how the presence of transformed or totally new working positions affected HR managers, who are entitled to the selection of people with the right skill mix and who have to deal with the transition of employees from a job to another. Paragraph 2.4 discusses the importance of reskilling and upskilling of workforce, to equip them with the competence needed to seize strategic opportunities and to avoid losing competitiveness due to the obsolescence of their skillsets.

2.2 Hybrid jobs' genome and jobs' macro-categories

2.2.1 A DNA for jobs

The report *How New Skills Are Rewriting the DNA of the Job Market* (Burning Glass Technologies 2019) offers an original perspective, as it talks about jobs referring to their genomes. In molecular biology and genetics, a genome is the genetic material of an organism that consists of base pairs of DNA. The association between jobs and living cells may seem an odd association, but its conceptualization is brilliant. It suggests that just like a cell is characterized by the presence of DNA, which is made of several and different pairs of nitrogenous bases, likewise jobs are defined by a combination of skills. Interestingly, the report contradicts an apparent triviality:

- we usually think that jobs are the basic units of the labour market, because they are what firms ask for and what people apply for; in other words, jobs are the common language in the labour market.
- However, "…jobs themselves are simply a way of organizing tasks and the skills needed to complete them" (Burning Glass Technologies 2019, p. 8). Thus, we could argue that when people supply labour, they are supplying a set of skill.

At this point, the parallelism with biology is again highly explicative. In that field, to derive knowledge on an organism, scientists look at its cells and analyse the genome; analogously, to understand and categorize jobs, it is important to study their underlying DNA of skills and necessary abilities (Burning Glass Technologies 2019). Tasks and skills required to workers in order to perform well-established jobs are mutating due to digital transformation technologies and the hybrid trend. Traditional professions are evolving toward the inclusion of tasks requiring new skills or a new combination of them and being able to adapt to the new paradigm is key to maintain a profile with high employability.

2.2.2 Standard jobs, hybrid jobs, superjobs. From automation to augmentation

In the *2019 Deloitte Global Human Capital Trends*, three macro-categories of jobs, based on the typology and variety of skills involved, are discussed: standard jobs, hybrid jobs and superjobs.

We might say that these categories could be placed on a continuum in terms of complexity, novelty and chronological development. According to Deloitte (2019):

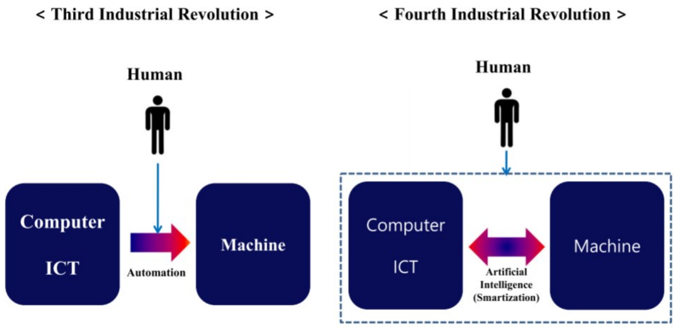
- *Standard jobs* involve a specified and narrow skillset as they relate to repeatable tasks and standardized processes; broadly speaking, they correspond to traditional professions.
- *Hybrid jobs* are defined as roles that encompass a combination of skills coming from both technical and soft competence. They are the most in-demand jobs today and those with the fastest wage growth; the abilities and capabilities they involve have never been merged in the same job before. For instance, a hybrid job might blend technical skills referred to technology operations with skills like data analysis and interpretation in addition to communication and collaboration.
- *Superjobs* are the combination of work and responsibilities from multiple traditional professions, like in the case of hybrid jobs, but they more deeply rely on technology to broaden the scope of the work. Superjobs include jobs that are more machine-powered and data-driven than in the past and they require that people work with smart machines, data and algorithms, leaving aside repeatable tasks.

While standard jobs are characterized by fixed roles and clear job description, the hybrid ones require more flexibility, not to mention superjobs. As machines automate some of the tasks previously performed by workers within their jobs, firms have to create more flexible positions and roles. Indeed, what is left to humans has to do with interpretation, creativity, teamwork and collaboration in a service-oriented perspective (Deloitte Insights 2019).

A great advantage deriving from being employed in a hybridized job (both what Deloitte calls hybrid jobs or superjobs) is that they are resistant to automation. A Burning Glass study found that about 42% of jobs could theoretically be replaced by automation; however, because hybridized jobs are more complex and heavily rely on soft competence, only 12% of them are estimated to be taken over (World Economic Forum 2019).

New technologies and the associated new skills and tasks lead to the creation of new job roles, occupations and industries. While, for example, in the Third Industrial Revolution workers had the role of linking computers to machines by applying automation, in the Fourth Industrial Revolution computers and machines can communicate interactively and independently from humans, thanks to developments in artificial intelligence (Park 2017); this is illustrated in Figure 9.

Figure 9 Comparison of the Third and Fourth Revolutions: automation and AI



Source: Park 2017

A research conducted by WEF (2018b) found that in many cases employers do not intend to make automation replace human workforce, but, on the contrary, they want it to augment them. This has been defined as an *augmentation strategy*: automation is applied on some job tasks to "complement and enhance the human workforces' comparative strengths and ultimately to enable and empower employees to extend to their full potential and competitive advantage" (World Economic Forum 2018b, p. 10). In practice, an augmentation strategy does not just focus on automation-base labour cost savings, but considers also the broader horizon of activities where human workers can create more value in complement to technology (Harvard Business Review 2015). In other words, people are freed from routinized and repetitive tasks to allow them to use their distinctively human talents.

2.3 Hybrid jobs in the labour market: a harder life for employers?

Dynamic firms, and cutting-edge ones in particular, have already experienced that finding the right employees can be very tough when unusual combinations of skills are required. Of course, changes in the labour market from the demand side cannot be immediately followed by an ad hoc renewed education system, but a certain time gap inevitably exists.

Consequently, it should not come as a surprise that is not so easy finding workers who offer their human capital with a skill set updated with the current demand. The more sophisticated the needed combination of skills is, the more employers will find it difficult to identify the profiles they are looking for. The CEO of Burning Glass, Matt Sigelman, stated that recruiters call these people *purple squirrels*, to indicate their rarity. This term is used to describe a "job candidate with precisely the right education, set of experience and range of qualifications that perfectly fits job's requirements"[8]. To snare such scarce creatures, employers are ready to pay a premium, which sometimes is very large; for instance, marketing managers with strong competence in data analysis earn 40% more than their colleagues without such ability (World Economic Forum 2019). On the other hand, employers may decide to fill job vacancies not by searching for the right people in the external labour market, but instead by training internal resources.

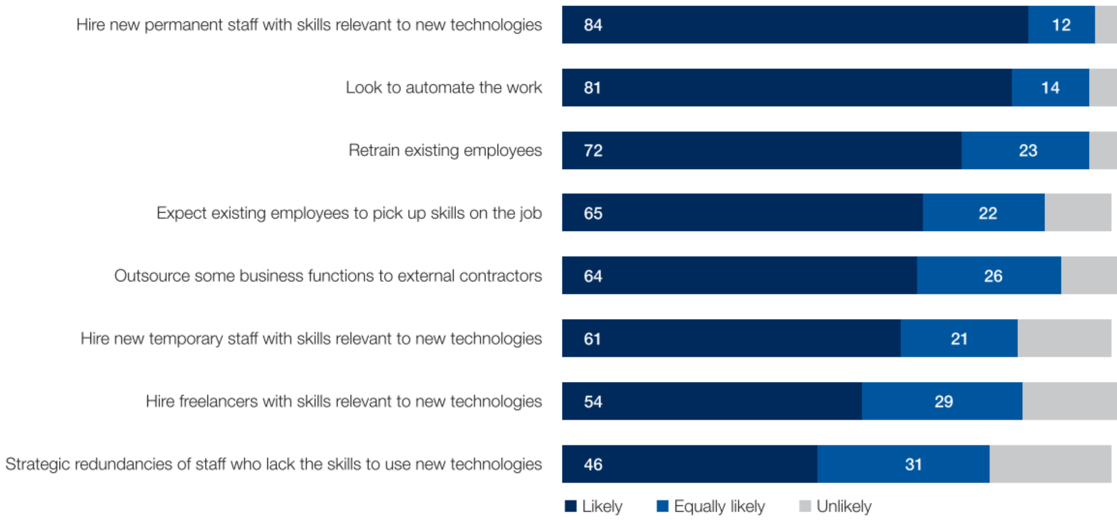
Indeed, as Figure 10 shows, companies can purse different organizational strategies to stay competitive in the face of quickly evolving workforce skills requirements. In particular, three future strategies emerge as the most important:

- hiring completely new permanent staff who already have skills relevant to new technologies;
- seeking to totally automate certain the work tasks;
- retraining current employees (World Economic Forum 2018b).

For this reason, among the others, reskilling and upskilling of the workforce is pivotal, as it will be discussed in the next paragraphs. Even after people with the most suitable mix of competences are matched with the right job, employers cannot live an easier life: traditional job design does not fit such unique resources. Good news, however, comes from an increased projected diffusion of hybridized jobs (Burning Glass Technologies 2019) and, as a consequence, of people with different skills mix: this leads us to suppose that new standards in the job design are likely to emerge. As Figure 11 shows, the rate of growth of complex and highly hybridized jobs is estimated to double with respect to all the professions overall (21% vs 10%) by 2028.

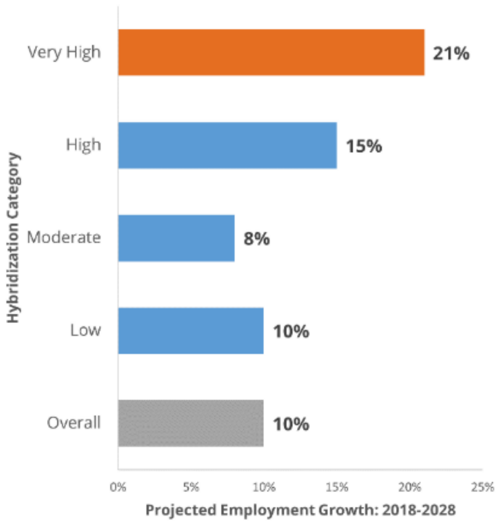
[8] Source: https://www.pbs.org/newshour/economy/purple-squirrels-and-the-reser

Figure 10 Projected (2022) strategies to address shifting skills needs, by proportion of companies (%)



Source: World Economic Forum 2018b

Figure 11 Projected growth of hybridized jobs



Source: Burning Glass Technologies 2019

This increase in the employment levels expected for highly and very highly hybridized jobs will have important consequences not only for workers, but also for employers, who need to be flexible and ready to adapt to different situations.

As firms will need to pursue a range of organizational strategies in order to stay competitive in times of rapidly changing workforce skills requirements, HR functions need to evolve as well and to find and adopt the most suitable approaches.

2.4 The importance of reskilling and upskilling to fill gaps

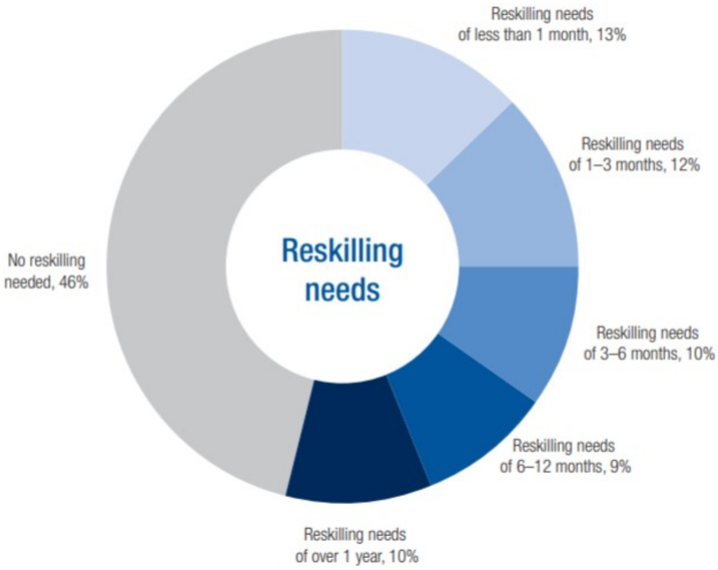
The Founder and Executive Chairman of the World Economic Forum (WEF), Klaus Schwab, stated:

> "It is critical that businesses take an active role in supporting existing workforces through reskilling and upskilling, individuals take a proactive approach to their lifelong learning, and governments create an enabling environment to facilitate this workforce transformation. This is the key challenge for our time"[9].

Reskilling might be defined as the development of significantly different skills to make someone suitable for a different role, while upskilling is the development of additional skills to help make someone more valuable in their current role[10].

The *Future of Jobs Survey 2018* of WEF found that more than half of the interviewed employers will require significant reskilling and upskilling by 2022. In particular, 25% of respondents were expected to require additional training by up to 3 months and about 20% in a timeframe between 3 and 12 months (see Figure 12).

Figure 12 Expected average reskilling needs across companies, by share of employees, 2018–2022



Source: World Economic Forum 2018b

The same report also found that employers intended to focus their reskilling and

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[9] Source: https://www.weforum.org/press/2018/09/machines-will-do-more-tasks-than-humans-by-2025-but-robot-revolution-will-still-create-58-million-net-new-jobs-in-next-five-years/

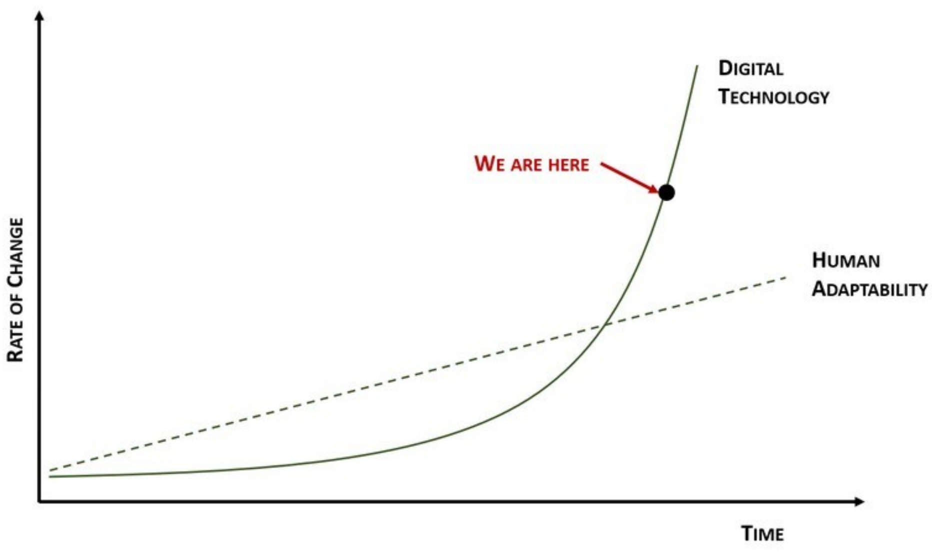
[10] *https://learn.g2.com/upskilling-and-reskilling*

upskilling interventions on employees who currently were in high-value roles, particularly those using relevant new technologies, with the final aim of improving the firm's strategic assets. It also emerged that employers were more inclined to focus their reskilling activities on already high-performing workers rather than on at-risk employees who are more likely to be affected by technological disruption.

On the other hand, also individuals themselves can take actions to stay employable and maintain desirable profiles. The article *Hybrid jobs are on the rise. This is how you can prepare* of the World Economic Forum (2019) was aimed at encouraging people keeping updated with new skills requirements and at orientating their efforts. The same institution published another article which may seem in an apparent contradiction with the one just mentioned: in *De-learning: the flipside of reskilling* (World Economic Forum 2020) workers are suggested to forget what they acquired over the past. The major point of the article is that it is necessary to put aside what once was the "best in class" if one wants to recognize and disrupt what is outdated and challenge oneself to deviate from conventional ways of doing things and working.

Indeed, according to OCSE and WEF, one of the skills of the 21st century is the adaptability (Gubitta and Gianecchini 2019). Focusing on this soft competence is particularly important, as the rate of technological change is accelerating more than that at which most people are now able to absorb it, as Figure 13 illustrates.

Figure 13 Rate of technological change



Source: Friedman 2016

Despite this gap is progressively widening, according to Deloitte (2017) individuals do and will adapt to technology very quickly. As curve 2 in Figure 14 illustrates, people are relatively fast in adopting new technologies, whose diffusion is denoted by the exponential rate shown in curve 1. We can notice this phenomenon if we just think that it is true that after more than 50 years from the statement of Moore's law[11] technologies like mobile devices, sensors, AI and robotics permeate our lives, but also that we are willing to adopt and use them. For instance, U.S. citizens look at their mobile phones about 50 times a day on average (Deloitte 2018), 68% of people uses some forms of artificial intelligence or machine learning - like predictive text, driving route suggestions and voice assistants - on their smartphones[12]. Individuals' intense use of such technologies leads companies to build digital products and services, and this is why curve 3 in Figure 14 is below curve 2. Indeed, firms are slower in adapting to new digital technologies, as business practices of corporate planning, job design, organizational structure, management and goal setting have to be updated as well. Lastly, curve 4 indicates public policy and its policies related to issues like income inequality, unemployment and trade which directly affect business through regulations and taxes; the latter adapt to technological innovations even slower.

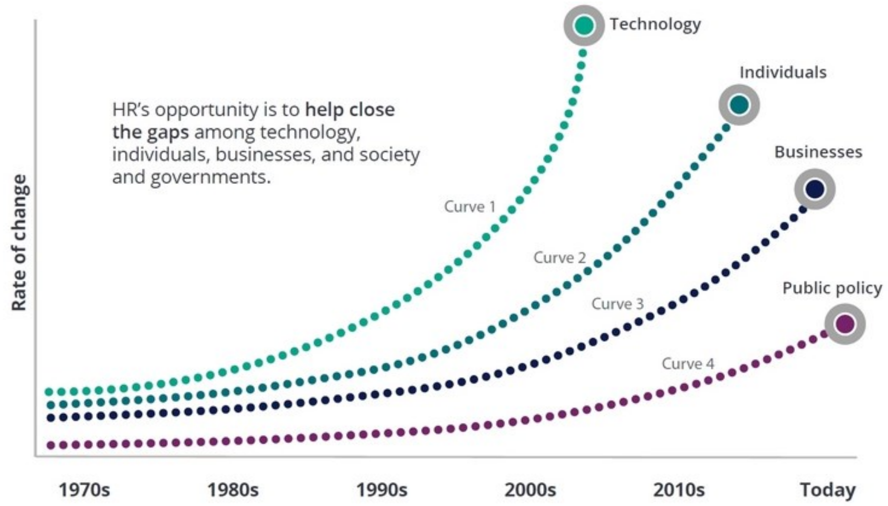
Within this context, HR functions are put in front of a challenging task, that is helping close gaps between technology advances and individual, organizational and public policies' steps forward, knowing that people have the biggest adaptation capacity and that they could be seen as a leverage to foster also companies' one (Deloitte 2017).

In this sense, workers' retrain or upskill can either be aimed at equipping a firm's workforce with the skills needed to seize strategic opportunities that arise in the external environment or at avoiding losing competitiveness due to the obsolescence of employees' actual skillsets (World Economic Forum 2018b).

[11] Moore's law dates back at 1965 and states that computing power doubles in capability every 18 months (and so it quadruplicates every 3 years).

[12] Source: https://www.prnewswire.com/news-releases/deloitte-americans-look-at-their-smartphones-more-than-12-billion-times-daily-even-as-usage-habits-mature-and-device-growth-plateaus

Figure 14 HR functions and Technology



Source: Deloitte 2017

2.5 Conclusion

More than any other factor, changes in technology, from the increasing reliance of firms on big data to the emergence of the Internet of Things, are fueling the diffusion of hybrid jobs. As technology evolves and firms try to keep pace with it and to take advantage of its advances and applications, in any job there will be a need for workers to become able to harness new tools and devices to create new value for businesses. Not only completely novel professions are emerging and deserve HR functions' attention, but also traditional jobs cannot be left aside; instead, they are urging a redesign to keep pace in the digital era (Deloitte Insights 2019). In this chapter, we observed that jobs are defined by a combination of skills, similarly to how DNA constitutes and characterizes living cells and organisms. We highlined how skills needed in workplaces are changing due to digital transformation technologies and the hybrid trend, so that different combinations have arisen, both transforming well-established jobs and creating new working positions and professional areas. Looking through the lens of skill composition, we presented three macro-categories of jobs: standard jobs (which correpond to traditional professionals), where a narrow skillset is asked; hybrid jobs, the most in-demand group, where new combinations of soft and technical competences are required; superjobs, which distinguish by the latter ones for a more intense reliance on technology. We noticed that traditional professions are evolving toward the inclusion of tasks requiring new skills or a new combination of them and being able to adapt to the new paradigm is key to maintain a profile with high employability. Workers employed in hybridized jobs are more likely to resist to technological displacement, as automation is aimed at augmenting them, instead of substituting them. In this context, we put in the shoes of HR managers, which have to deal with new challenges: from finding, hiring and retaining people with unusual combination of skills to managing internal transitions from a traditional job to a transformed one. We discussed these issues and we emphasized the importance of workers' reskilling and upskilling, but also of the so-called delearning, as a way to seize strategic opportunities and avoid losing competitiveness due to the obsolescence of employees' skillsets.

3. CHAPTER

JOBS' HYBRIDIZATION: RESEARCH METHODOLOGY

3.1 Introduction

A study of *Osservatorio delle Competenze Digitali* (2019) analysed about 106.000 online job postings addressed toward ICT profiles in the national territory throughout 2018 to investigate and measure the digitization rate of skills necessary within ICT functions. It emerged that ICT profiles are mainly demanded in the homonymous sector, followed by the services one; big data specialists, quality assurance managers and AI specialists are among the professions which exhibit the fastest growth rate. Furthermore, the study found that the increased relevance of digital skills was accompanied by a greater pervasiveness of soft competence in any ICT occupations.

At the 2020 Conference on AI, Ethics and Society (AIES) that took place in New York, the paper *Learning Occupational Task-Shares Dynamics for the Future of Work* was presented, where job postings were analysed to explore how occupational task demands have changed over the past decade in artificial intelligence innovation across high, mid and low wage occupations. Data covered about 170 million online job vacancies posted on over 40,000 different job online sites in the U.S. between 2010 and 2018. It emerged that the most frequently required tasks in that timeframe across occupations were: communication skills, computer literacy, organizational skill, writing, teamwork/collaboration, among the others. When measuring the width of jobs in terms of variety of performed activities, it emerged that 9 professions arrive to include in their postings more than 1000 tasks.

These studies were aimed at studying some hybridizing features through the analysis of job vacancies posted on the web. In other words, they are based on tasks and competences which are *formally* asked to workers and they do not keep under consideration what is *really* required to them. The underlying assumption of this master thesis is that there are some discrepancies between what people are asked to do in the recruiting phase and what they actually do after the signing of the working contract; more precisely, we believe that some differences exist between the skills people are theoretically required to have – mainly hard skills – and those they are effectively asked to perform for proper completion of day-to-day tasks. For this reason, we decided to attain the aim of our research, which is studying the hybridization level of jobs and measuring it, by adopting not an external point of observation, but rather from an internal e more truthful perspective. To do so, the voices of workers themselves were heard to assess which skills they actually perform in their workplaces, with which level of frequency they effectively use them and which level of knowledge they need to possess. Only long-establish jobs were considered, as they still represent the dominant part within the job market.

This chapter is organized as follows: the research design is illustrated and the sampling process and data collection method were explained (paragraph 3.2), then the two main dimensions for the purpose of this study, which are the job categories and the hybrid skills, are thoroughly analysed and articulated (paragraph 3.3). Some general information on the sample are provided and some preliminary insights on the three hybrid skills, namely IT, digital and soft ones, are shown (paragraph 3.4). The chapter ends with a recap of the most significant aspects that emerged from this first glance at data and introduces the next chapter.

3.2 Research design, sampling and data collection

The research was carried out in October 2018 by the *Osservatorio Professioni Digitali*, a joint research project between the University of Padova and the Veneto region which is appointed to the observation and investigation of digital and hybrid jobs for supporting the labour market and the economic and entrepreneurial system. The study was conducted in collaboration with Veneto Lavoro, a regional institution with the role of monitoring and supporting labour policies and that provides specific services to unemployed people. The research aimed to investigate and detect the phenomenon of hybridization of jobs in the labour market, by assessing which factors are more likely to trigger the development of workers' hybrid skills and the diffusion of hybrid jobs. The research focuses on long-established jobs rather than on the new ones, as they still represent the most significant component within the labour market.

Sampling and data collection method

The study was based on a sample of 300 workers who were registered in the databases of Veneto Lavoro at the time of the research, i.e. in October 2018. The sample was randomly extracted from a population of 2.864 workers. Only people who were born between 1955 and 1997 and who signed an employment contract in the 11 months before October 2018 or earlier were involved. In other words, data came from people who were 23 to 65 years old and who have been performing their current job since November 2017 or before.

The survey

A quantitative survey was delivered to the sample and two different methodologies were used for data collection, both CAWI (Computer Aided Web Interviewing) and CATI (Computer Assisted Telephone Interview).

The survey was divided into five sections, with different aims:

- in the first part, general data about the personal profile, education and work experience were asked; it included 10 questions.
- The second section had the aim of getting information on IT skills, to assess whether, how often and up to which level of knowledge workers are required to use them. In this case, 6 IT-specific questions were formulated and two types of information were derived from each: the frequency of utilization and the intensity of knowledge needed.
- The third part had the purpose of investigating the importance of digital skills in workplaces. The same structure of the previous section was adopted, meaning that for each question both the level of frequency and the level of knowledge were ascertained, with the difference that 5 questions were posed instead of 6.
- The fourth part was aimed to verify to which degree a profession is technical. 6 questions relative to the hard skills were proposed; as jobs differ from each other in terms of technical competences, a different set of questions was thought for the 9 specific work categories initially involved in the research.
- The last section is organized in a very similar way to the second one. However, its focus is on another typology of competencies: the soft skills. Again, 6 questions were

asked to workers to understand how often their job requires them to manage these skills and how their in-depth knowledge is important.

For the purpose of this research work, which is to measure if and to which extent long-established jobs are becoming hybrid through the utilization of IT, digital and soft skills, data from 283 workers instead of 300 have been considered, as it will be explained below in the Data Analysis subparagraph (§ 3.4). Analysis were conducted through the statistical software R, after some pre-processing operations on the dataset.

3.3 Two main dimensions: professional areas and hybrid skills

In this section, the creation, classification and management of variables is illustrated relative to the two core dimensions of this research, namely professional categories and hybrid skills.

Variables: professional categories

Professional areas constitute a piece of pivotal information for our objective of measuring the hybridization of jobs. Thus, it deserves to be carefully considered and categorized in the pre-processing phase of the analysis.

The survey involved 14 professional areas (production; inbound logistics and procurement; outbound logistics and distribution; administration, finance and control; commercial services and sales; marketing and communication; education and training; services to the person; ICT systems; research and development; legal affairs; services in medical, pharmaceutical, scientific area; services related to tourism, restoration and hotels; management of people, training and organization). When the survey was concluded in October 2018, in their preliminary analysis, the authors combined these professional areas to obtain nine categories that matched with organizational functions. Namely, they were: production, inbound logistics and procurement, outbound logistics and distribution, administration, finance and control, commercial services and sales, marketing and communication, human resources and training, ICT and information systems, research and development, legal affairs.

For the aim of their analysis, which was to explore the shapes of jobs by assessing their relationship with the workers' characteristics, the variable referring to professional areas was not the core one. Thus, a factor variable composed by a large number of levels, the ones listed above, was created.

For the purposes of this master thesis, where professional categories are among the key focus, however, dealing with so many levels would have been confusing. For this reason, we grouped the 14 professional areas that emerged from the survey in a different manner, to make analysis less complicated and results easier to interpret.

We created a categorical variable including information on the professional area of employment and we built 6 levels, in addition to a residual one.

The following job categories were considered for our analysis:

- *Operations*, which includes the functions of production, inbound logistics and procurement, outbound logistics and distribution;
- *Administration, finance and control*;
- *Sales and marketing*, which includes the functions of marketing and communication and of sales;
- *Information systems*, which includes the functions of ICT and research and development (R&D);
- *Organization and support services*, which includes five functions (management and training of personnel; education and training courses; services to the person; services related to tourism, restoration and hotels);
- *General services*, which includes jobs in the context of plants and equipment maintenance and jobs related to services in the medical, pharmaceutical and scientific field;
- *Other*, which is the residual category.

Variables: four types of skills

In line with the aim of studying hybridization across jobs, variables that indicate the presence and the intensity of skills related to this phenomenon are also key. These abilities have been grouped into four classes, according to their domain: technical (or hard) skills, soft skills, IT (or computer-related) skills and digital skills.

- *Technical skills* are the competence that characterizes and differentiates jobs; they are function-related and represent the technical component of work. For example, hard skills for the area *Sales and marketing* include doing market researches, defining the sales strategy and promoting sales; hard skills for the area Inbound logistics and distribution encompass managing claims on the products' quality, inventory goods and equipment and optimising transport times and costs.

- *IT skills* include: the online search of information and content storage; the comparison of different sources; the simple digital content production (like writing a text); the capability of applying formattings (e.g. to tables, notes, graphs); the capability of using advanced communications tools (like conference calls, sharing of data) and online services (like e-banking, shopping online); communication through smartphone or voice over IP technologies (like Skype, e-mail or chat).
- *Digital skills* refer to: IoT technologies, big data analysis, cloud computing, cybersecurity, augmented reality, artificial intelligence and robotics.
- *Soft skills* are related to the capability of: performing operative tasks, helping people, influencing others, managing a team toward a common objective, understanding situations, tasks and problems, challenging themselves and attain individual goals.

Table 1 The hybridization process: types of skills

IT SKILLS	DIGITAL SKILLS	SOFT SKILLS
Searching online of information and storing contents	Dealing with iot technologies	Performing operative tasks
Comparing different sources	Dealing with big data analysis	Helping people
Producing simple digital content	Dealing with cloud computing	Influencing others
Applying formatting	Dealing with cybersecurity	Managing a team toward a common objective
Using advanced communications tools	Dealing with augmented reality, artificial intelligence and robotics	Understanding situations, tasks and problems
Using advanced communications tools and online services		Challenging themselves and attain individual goals

Source: Adapted from Osservatorio Professioni Digitali (2019)

For each skill that constitute one of the four domains of competences, a multiple-choice question was asked to the interviewees to assess the frequency and the intensity of utilization of such abilities. With reference to the usage frequency, five options were provided, ranging from 1 (never) to 5 (always); other five alternatives were offered to state the level of knowledge that was required by each of them, spacing from 1 (basic) to 5 (advanced). Thus, we disposed of information on both the frequency of utilization and the level of knowledge required to workers for each of the six IT skills, the five digital skills, the six soft skills and the six technical skills investigated throughout the survey. For the study and computation of the hybridization levels, hard skills have been initially left aside. In the end, 34 numerical variables taking integer values from 1 to 5 were created relative to the levels of the three hybrid skills.

3.4 Data analysis and descriptive statistics

The original dataset was composed by information from a sample of 300 workers employed in the Veneto Region, but we have analysed the answers of 283 of them only, as 17 people did not provide complete information and too many missing values were present for them, leading to the risk of impairing results.

As outlined above, the initial part of the survey was aimed at obtaining general information on the sample and 10 questions were asked, the remaining part of the research was focused on hybrid skills utilization and level.

It will be now briefly explained how these data were processed and how the variables were constructed.

General information on the sample

With respect to personal details of workers, age, gender and education were surveyed; then data on the working function, experience, career seniority and employment contract were requested.

Age groups of respondents were created by surveying the year of birth. It ranged from 1955 to 1997, meaning that the youngest interviewee was 23 years old and the eldest was 65 years old. This wide range allows for all the generations to be represented: from the baby boomers (born between 1946 and 1964) and the X generation (born between 1965 and 1980), to the millennials (born between 1981 and 1996) and the Z generation (born in 1997 or afterward). It is worth noting that the median age is about 40, which is a significant number for us as it perfectly splits the two former generations from the latter two and enables us to draw insights on the skills level and performance of people under 40 and those over 40. To avoid dealing with 31 different years of birth, a factor variable that summarizes the age groups was created and four levels were assigned: up to 29 years old, between 30 and 39 years old, between 40 and 49 years old, from 50 years old onwards (Table 2).

As regards of the gender, the sample is well balanced, with a 45,6% male component and 54,4% female component (Table 3).

In terms of education, the sample is quite differentiated. 11% of the interviewees turned out to have low qualifications as they entered the market job right after lower secondary education; about half of the workers (51,6%) reached a medium level, as they received upper secondary general education by attending the high school. The remaining part of the sample benefitted from a high level of education and obtained a bachelor degree or a master one, and 6% of them completed the PhD or a second level master. To carry all these pieces of information, a factor variable was constructed. Despite 6 levels of education were available from the data collected, we grouped them into 4 classes by considering together bachelor and master degrees, and PhD and the II level master (Table 4).

Table 2 Age distribution

	N	%
<= 29	73	25.8
30-39	97	34.3
40-49	77	27.2
>= 50	36	12.7
Total	283	100.0

Source: my research, data from Osservatorio Professioni Digitali (2019)

Table 3 Gender distribution

	N	%
Female	154	54.4
Male	129	45.6
Total	283	100.0

Source: my research, data from Osservatorio Professioni Digitali (2019)

Table 4 Education distribution

	N	%
Secondary school diploma	32	11.3
High school diploma	146	51.6
Bachelor or Master Degree	88	31.1
PhD or II level Master	17	6.0
Total	283	100.0

Source: my research, data from Osservatorio Professioni Digitali (2019)

Coming to the professional area of employment, other important aspects were investigated. With respect to the function families, 7 classes were created (as already explained in paragraph § 3.3). According to this classification, most interviewees (29%) were employed in functions related to the provision of products or services and in the functions involved in marketing, sales and communication activities (about 26 %). A residual class, called *Other*, includes a few observations on which we had no information. Also in the case of the professional areas, a categorical variable was created which grouped some of the modes provided in the original dataset to limit the number of levels and simplify both the analysis process and the interpretation of results.

Table 5 Professional area distribution

	N	%
Operations	82	29
Administration, finance and control	39	13.8
Sales and marketing	73	25.8
Information systems	22	7.8
Organization and support services	36	12.7
General services	25	8.8
Other	6	2.1
Total	283	100

Source: my research, data from Osservatorio Professioni Digitali (2019)

The contractual form was another available information. Seven alternatives were provided to workers in the survey to indicate which working contract they had in place. A factor variable was created to convey this information and, for simplicity, some modes were grouped and only five levels were built instead of seven. It emerged that the majority of the sample was employed with a fixed-term contract (41,3%) or with an open-ended contract (40,3%), while a minor share of them was engaged on an apprenticeship contract (7,8%) or was self-employed (3,2%). The mode called *Other* includes work arrangements for jobs on call and internships.

Table 6 Working contract distribution

	N	%
Fixed-term contract	117	41.3
Open-ended contract	114	40.3
Apprenticeship contract	22	7.8
Self-employment	9	3.2
Other	21	7.4
Total	283	100.0

Source: my research, data from Osservatorio Professioni Digitali (2019)

The sector where interviewees were employed was also investigated. They could choose between nineteen different alternatives, which ranged from agriculture to financial activities, from warehousing to ICT services, from manufacturing to provision of public services and to retail. Despite the large number of levels, a factor variable was created without aggregating them, as it is not key for the aim of this master thesis. It emerged that the most popular sector is manufacturing, with 28% of the sample involved, followed by retail (11%), healthcare and social assistance (11%), transport and warehousing (7,8%)

and wholesale (6,4%). The class named *Other* includes the remaining sectors, which all have a share smaller than 9%.

Table 7 Sector distribution

	N	%
Manufacturing	80	28.3
Distribution	49	17.3
Services to the firm	35	12.4
Services to the person	28	9.9
Other	60	21.2

Source: my research, data from Osservatorio Professioni Digitali (2019)

With respect to the sample's company size, it emerged that half of workers are employed in firms with less than 50 employees. Company distribution is thus skewed toward small enterprises. It did not come as a surprise, as small and medium firms constitute the backbone of the Italian economic system. Again, a factor variable was created with 6 levels for company size.

Table 8 Company size distribution: number of employees (N=268)

	N	%
< 10	74	27.6
10 - 49	64	23.9
50 - 249	49	18.3
> 250	81	30.2
Total	268	100.0

Source: my research, data from Osservatorio Professioni Digitali (2019)

The survey also detected how long interviewed people had worked till the time of the survey, in order to assess their seniority level. It emerged that the sample was quite well balanced, with about one third of workers having less than 10 years of working experience, about one third with 11 to 20 years and about one third with 21 years of experience or more. A variable factor for seniority was created that distinguished between four groups: people with less than 5 years of working experience, with 6 to 10 years, with 11 to 20 years and with 21 or more years of expertise.

Up to now, we have seen some descriptive statistics deriving from information collected throughout the first part of the survey, which was focused on the features of the sample. Other four sections relative to the skills domains were completed by respondents and in the next comma we are going to show preliminary results.

Table 9 Career seniority distribution

	N	%
<= 5	44	15.5
6 – 10	54	19.1
11 - 20	106	37.5
>= 21	79	27.9
Total	283	100.0

Source: my research, data from Osservatorio Professioni Digitali (2019)

General information on skill levels

Four skills domains were considered and each of them was identified through 5 to 6 specific abilities. As hard skills are job-specific and represent the non-hybrid component of work, they will be initially left aside.

It will now be now graphically illustrated how the three hybrid skills are characterized across the sample in terms of frequency of utilization (on the x-axis) and depth of knowledge (on the y-axis).

In each of the three graphs, 283 points corresponding to the observations within the dataset are plotted. Each of them represents the centroid for IT, digital and soft skills, respectively. This explains why the plotted points assume continuous values between 1 and 5 even though interviewees were asked to indicate an integer number from 1 to 5 to define their skill level. For the sake of clarity, we will go through each step which led to the computation of the plotted points.

Box 1 Centroid definition and computation

> The centroid is "the multivariate equivalent of the mean. Just like the mean, the centroid of a cloud of points minimizes the sum of the squared distances from the points of the cloud to a point in the space". In a cloud of points, the centroid is the most representative point. It is computed as the mean of the values of all the points in the graph (or of each group of points, in the case of a cluster analysis).
> Let us see an example of computation. Given a cloud made by four points whose coordinates are (35, 11), (72, 47), (48, 70), (5, 12), the sum of these values would be (160, 140). By dividing such numbers by the number of points considered when computing the sum, i.e. four, we get a centroid whose coordinates are (40, 35).

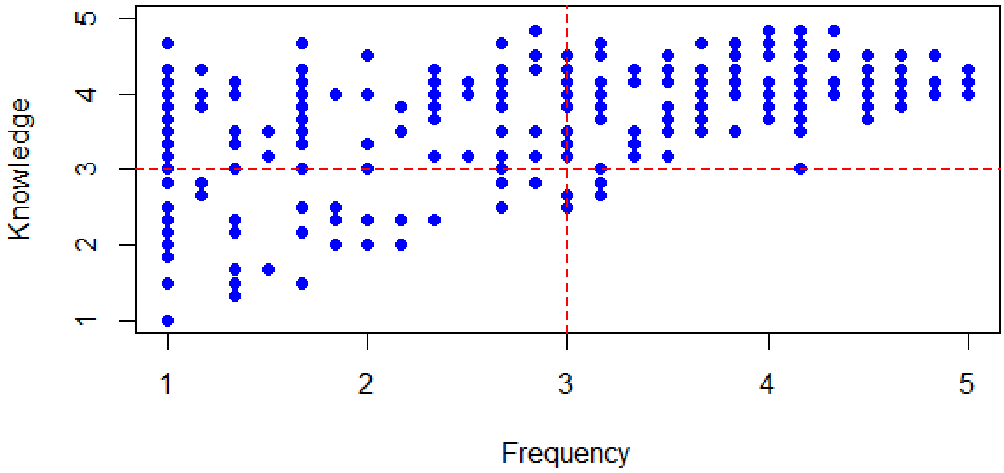
Let us take into consideration the IT skills domain, for example. It was surveyed by asking information relative to six IT abilities: the online search for information and content storage; comparison of different sources; production of simple digital content; capability of applying formatting; capability of using advanced communications tools and online services; communication through smartphone or voice over IP technologies. Each ability was investigated over two levels, namely the frequency of utilization and the depth of knowledge required. Thus, for each respondent, six values were available regarding how often they were asked to use IT skills and six regarding how difficult those activities were. These data were averaged for each worker, preserving the distinction between the two dimensions. We ended up with two values for each interviewee, one representing their frequency of utilization of IT skills and the other one indicating the intensity of knowledge required. These two numbers provided the coordinates to plot a synthetic point for each worker within the scatterplot of IT skills. The same procedure applied to digital and soft skills.

In the following graphs, four quadrants are built for an easier interpretation of results. For simplicity and in consistency with plane geometry, the quadrant on the top right will be considered the first one and the enumeration of the others goes counter-clockwise; it implies that the quadrant on the top left will be considered the second one, the one on the bottom left will be the third one and the one on the bottom left the fourth one.

In Graph 1, the 283 workers constituting our sample are plotted considering their IT skills levels in terms of frequency of utilization (on the x-axis) and level of knowledge required (on the y-axis).

As the graphic shows, a positive relationship between the two dimensions represented on the axis emerges, as they appear to grow together. This implies that tasks that need basic IT knowledge are not much frequent, while advanced activities face also high demand. Interestingly, in the second quadrant frequency has low values and knowledge performances are high, while in the fourth quadrant the opposite situation occurs. The difference in points distribution within these two areas of the graph is curious: the second includes many points, while the fourth one has almost no observations. In broad terms, it means that IT skills which are quite easy to perform are only asked occasionally. This result is in line with expectations: people are more and more likely to be substituted by robots in simple and repetitive tasks, where human intervention does not add much value. On the contrary, workers are quite often asked to perform tasks that require depth knowledge in the IT field. We can also observe that most points are positioned mainly above the horizontal line that split the graph into two parts, meaning that thorough and in-depth IT abilities are very important in workplaces.

Graph 1 IT Skills: plot

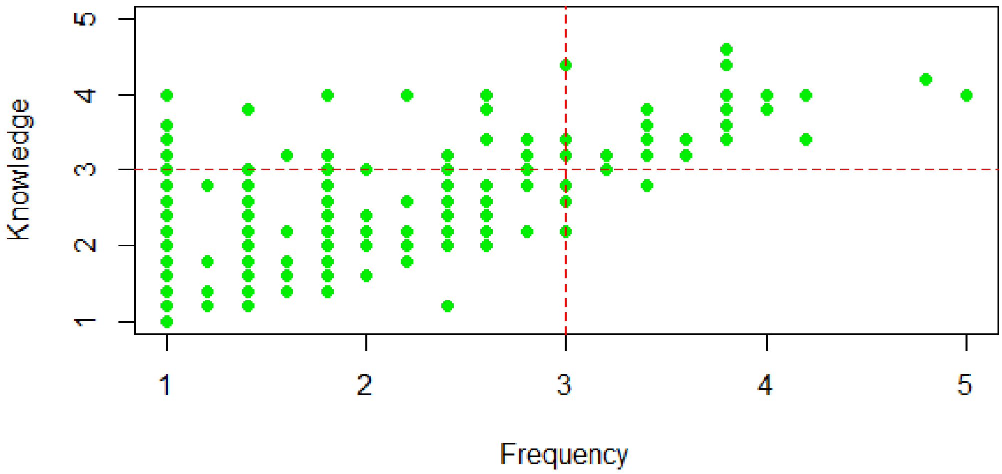


Source: my research, data from Osservatorio Professioni Digitali (2019)

Completely different considerations are to be made with respect to digital skills (see Graph 2). Even though the scatterplot shows a positive trend between the two dimensions of frequency and knowledge, the points distribution has varied a lot. The great majority of observations are plotted within the third quadrant, few are present in the first and second one, the fourth one is almost empty. Compared to the already described IT skills, it emerges that digital skills are less frequently demanded and a lower level of knowledge is sufficient for performing tasks. It also appears that is that no one of the 283 respondents was asked to use digital competences in the everyday working life. The fact that digital skills utilization hardly ever reaches elevated knowledge levels might imply that, as we expected, such abilities are quite complex to develop and they take a lot of effort and time to be managed, so that it is not reasonable to demand people to performe digital skills with high confidence and expertise. Consquently, our finding that these competences are required at most in a simplified way and at low level should not come as a surprise. We suggest that when digital skills are very well managed, it is because we are dealing with professional workers and, in that case, these abilites become part of the technical competences.

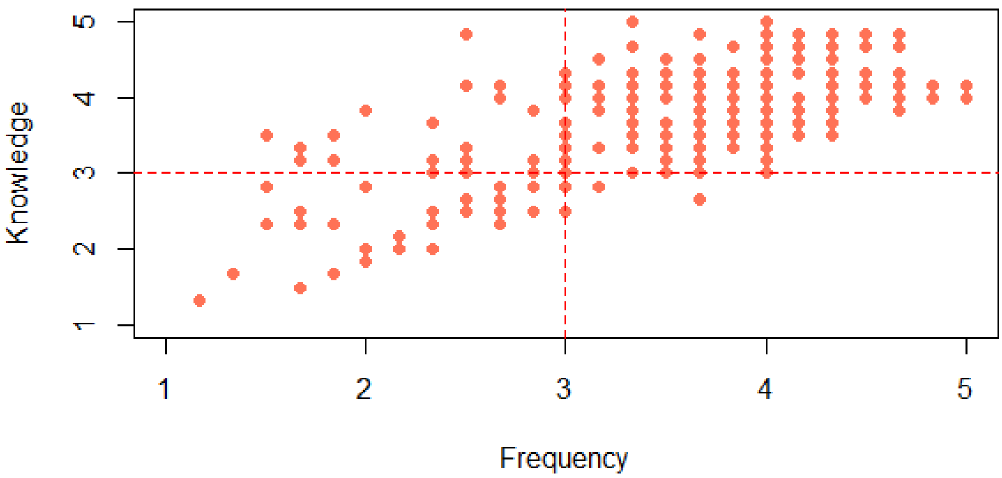
The distribution of soft skills shown in Graph 3 highlights once again a positive relationship between their frequency of utilization and the intensity of knowledge that they require. In this case, however, points are mainly concentrated in the first quadrant: most of the time, soft competence is required on a regular basis and certain expertise is expected. We can infer that workers are frequently involved in tricky circumstances that require to master soft skills quite well, while it is rarely the case that they face easy-to-solve situations with a high frequency.

Graph 2 Digital skills: plot



Source: my research, data from Osservatorio Professioni Digitali (2019)

Graph 3 Soft Skills: plot

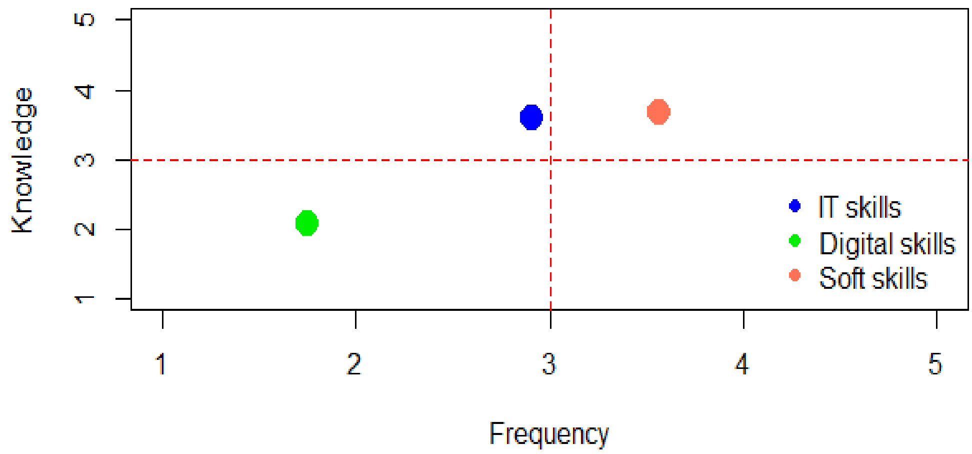


Source: my research, data from Osservatorio Professioni Digitali (2019)

To allow for comparisons, a centroid was computed for each of the previous graphs. The three centroids obtained were then plotted one against each other in Graph 4. Again, the graphic was divided into four quadrants. It resulted that the centroids summarizing the three skill domains lie in three different quadrants. With respect to the x-axis, it emerges that the skills which are most frequently asked in workplaces are soft skills, followed by IT and digital skills. Looking at the level of knowledge required (y-axis), it appears that workers need to show a deep familiarity with both soft and IT skills, while less intense efforts are necessary to perform digital tasks.

As concern the position of the three centroids within the graph, some interesting insights may be drawn. Regarding IT skills, it results that workers are asked to use their IT skills with a medium frequency (the average value is 2.9 on a scale from 1 to 5) and with a level of knowledge above the mean (a knowledge of 3.6 points on a scale from 1 to 5 was declared). For digital skills, the situation is quite different, as digital competences are not usually required and when it happens, basic knowledge is needed. The opposite case occurs for soft skills, because they are highly demanded in terms of frequency and an advanced level of expertise is expected. Such differences in the diffusion of the three skill families emerging from Graph 4 is quite interesting, as it tells us that they are in three diverse phasis of their life-cycle: soft skills are already widespread across most jobs, also IT competences represent a significant threshold for performing tasks and thay are becoming increasingly important, while digital abilities are still poorly developed.

Graph 4 IT, digital and soft skills centroids



Source: my research, data from Osservatorio Professioni Digitali (2019)

3.5 Conclusion

Throughout this chapter, we offered an overall view of data on which the research has been built. We illustrated the aim of the study and the methodology adopted for data collection and pre-processing. In particular, we have outlined how statistical observations were sampled and the main features of the sample, we have also provided a preliminary look at skills performances in workplaces. Throughout the whole chapter, we illustrated step-by-step how data were managed and how calculations and computations were made. We started from a dataset constituted by the answers of 300 workers employed in the Veneto region. Only surveys from 283 of them were taken under consideration for the purpose of this analysis, the others were left aside due to missing values. We have seen that gender distribution across the sample is well balanced and that half of the respondents terminated their education path after the completion of the high school, while about one third reached the bachelor or master degree. Coming to working aspects, six professional areas were created by aggregating similar functional units. About a third of the sample is involved in manufacturing, while lower shares are attributed to the other sectors. The great majority of respondents are employed with a fixed-term contract or an open-ended contract. As concerns the distribution of surveyed skills, the analysis of the three categories of IT, digital and soft skills brought to light completely different scenarios. By plotting in the same graph the three centroids of the three competence domains over the considered sample, we surprisingly discovered that they lie on three different quadrants. Indeed, soft skills are demanded in workplaces with high frequency and high knowledge prerequisites, the precise opposite situation occurs for digital skills, while IT skills are needed with low frequency, but high knowledge. These aspects are very interesting and deserve to be further explored; having these data in aggregate form, however, does not tell us anything in terms of hybridization across jobs. Consequently, the next chapter has the aim of going deeper within each professional area, to explore if and how different jobs are becoming hybrid.

4. CHAPTER

EXPLORING HYBRIDIZATION ACROSS JOBS

4.1 Introduction

Demand for individual skills, knowledge and abilities is changing due to technology shifts. The report *Talent for survival - Essential skills for humans working in the machine age* (Deloitte 2016) stated:

> "…we believe that, although Science, Technology, Engineering and Mathematics (STEM) skills and knowledge are important in an increasingly digital economy, the UK will benefit most from a workforce that has a balance of technical skills and more general purpose skills, such as problem-solving skills, creativity, social skills and emotional intelligence."
> (Deloitte 2016, p. 1)

Provided that this might apply also to countries other than the UK, where the research was conducted, an important question could arise: which jobs would need skills like problem-solving, creativity or social and emotional intelligence the most? Provided that such skills are important across all jobs, are they equally important?

In this chapter and in Chapter 5 we tried to answer these questions. For the purpose of this master thesis, by hybridization we mean a mix of three skills domains (IT, digital and soft ones). We will only consider the jobs aggregated into the six professional areas indicated in Chapter 3, paragraph 3.

This chapter has the aim of illustrating how each of the three skills areas is important for various professional areas. Before analysing whether, how and to which extent such abilities are important constituent elements for proper completion of tasks in different jobs, the concept of hybridization is clarified (paragraph 4.2). Then, we will assess where the six working categories place themselves in terms of development and deployment of

IT competence, digital competence and soft competence, respectively (paragraph 4.3). We will then focus on the knowledge intensity that workers actually need to perform when deploying their IT, digital and soft abilities. Three boxplots will be provided to investigate this dimension across different professional areas for each of the three skills domains individually. Insights on the measure of the spread of the knowledge dimension will be offered and comparisons between groups of jobs will be made (paragraph 4.4).

4.2 Hybridization features within job categories

Hybridization is spreading capillary across the job market at a faster and faster pace. Skills other than the technical ones have been developing in more and more jobs and advantages are visible from various points of view, providing benefits from the firm's competitiveness and internal organization to people's employability, personal and professional growth. However, jobs are not equally hybrid.
We state that:

> Hybridization does not just mean developing a non-job-specific ability and implementing it in the workplace, but it refers to the creation of a unique bundle of technical and non-technical - or hybrid - skills. Such a blend is indivisible, as the overall value from the combination of job-specific skills and non-job-specific ones is greater than the sum of each of them considered separately.

This point has to be carefully addressed, as it will be discussed in the next Chapter, as some activities that increase the hybrid component within certain jobs are mere professional skills when included in other ones. For example, digital competences are job-specific in the IT function, but not within the logistics area; therefore, they increase hybridization of the latter unit, but not that of the former. For the purpose of this research, skills leading to hybridization of work have been classified into three areas and have been named:

- IT skills;
- digital skills;
- soft skills.

We will now investigate whether and in which terms these three competence domains distribute within and characterize the six working categories identified in paragraph 3.3. In the next three graphs, each skill family will be plotted separately, distinguishing by professional area to allow comparisons.

In the next three graphs and in those shown in the next chapter, we applied the following graphical conventions:

- *points* represent centroids relative either to individual functional families (in this Chapter) or to the single skill domains (in Chapter 5);
- the *colour* of the points indicates the professional area to which they refer;
- the *shape* of the plotted points allows us to distinguish among IT skills (the triangle), digital skills (the square) and soft skills (the circle).

Centroids have been computed for each job class individually by calculating the mean level of the frequency of utilization and of the intensity of knowledge of a specific competence domain, filtering every time for the professional area of interest. The resulting points for the six functional families were plotted together in the same graph, according to the skill area under consideration; thus, three graphics were created in the end. Throughout computational steps, the two features related to each skill, i.e. the frequency of utilization and the intensity of knowledge, have been considered individually and have been kept separated to preserve the information necessary for maintaining a bidimensional structure; indeed, they were used as the variables to be placed on the axis and they provide the coordinates necessary to the graphical representation of points. The results from the three graphs will be now analysed.

4.3 IT, digital and soft skills across professional areas

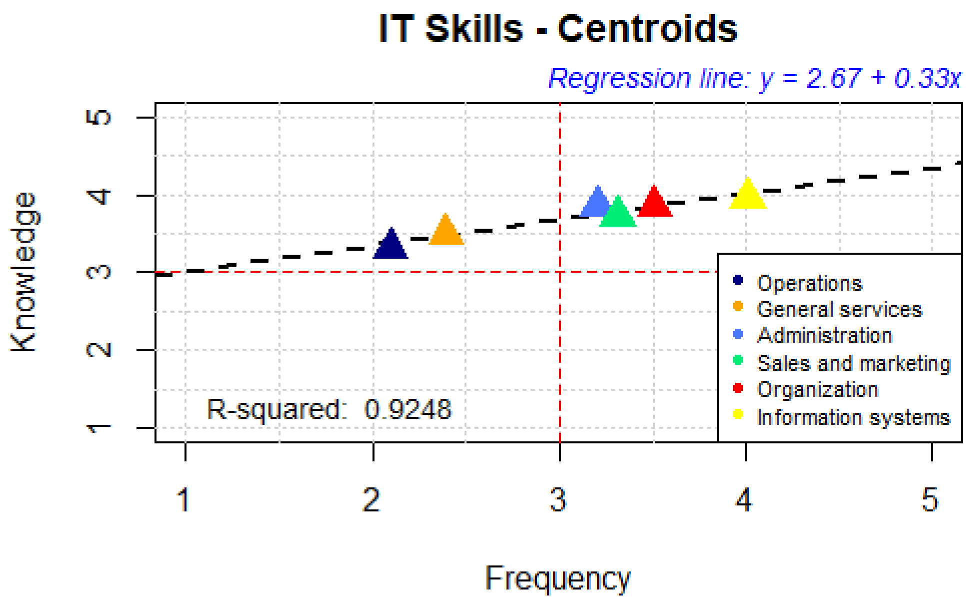
4.3.1 IT skills across professional areas

We are now going to explore whether and to which extent job classes and relative tasks are characterized by the presence of IT competences. As there still is not an agreed threshold above which jobs can be considered hybrid, an approach based on relative comparisons will be adopted for now[13].

By plotting IT skills levels required to our sample in their workplace, distinguishing by professional area, some considerations might be drawn.

[13] Throughout this master thesis, however, a path to compute hybridization level of functional areas will be provided.

Graph 5 IT Skills centroids of professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019)

The centroids of IT abilities for every working category lie in the two top quadrants of Graph 5, namely the fourth and first ones. Let us make some overall consideration on the level of knowledge and the frequency of utilization of IT skills. This graphic shows that by aggregating data according to the professional area of employment intense knowledge of IT skills is required to workers regardless of the job they do. If we shift the focus from the average knowledge level of IT abilities to the mean frequency of their utilization, however, we could notice that professional area has a role. Indeed, the frequency of utilization of IT skills strongly depends on the functional family: for example, tasks within the *Operations* or *General services* categories rarely require to use computer skills, while in the *Information systems* area their implementation might be considered an ordinary activity.

Graph 5 shows that IT skills are overall demanded with medium to high levels of knowledge and that the latter variable increases together with the frequency of utilization. The dashed line, that visually represents the regression line, has a positive slope and indicates that the two variables on the axis vary together, but with frequency growing faster when IT skills are needed in tricky situations that require careful interventions.

The focal point this graphic concerns the distribution of professional areas, which is illustrated in greater detail in Table 10.

The most hybrid jobs, in terms of IT competences, are undoubtedly those dealing with information systems and research and development (the yellow triangle in Graph 5). They perform a score of about 4 out of 5 in terms both of frequency and knowledge[14].

The second more hybrid job category in terms of IT skills intensity is the *Organization and support services*; this implies that jobs dealing with people management, training, organization, education, and other services to the person require to use computer skills quite often and with a remarkable depth of knowledge.

This category is followed, for the intensity of computer skills, by *Sales and marketing* and *Administration, finance and control*, which display quite similar values.

The least hybrid professional area in terms of IT competences is the *Operations* one, where computer skills are asked with a frequency of 2.1 out of 5 and with a depth of knowledge of about 3.31 out of 5. This indicates that in functions like production, inbound logistics, procurement, outbound logistics and distribution, despite people being expected to have an operative knowledge, they are seldom asked to use it.

Table 10 IT Skills centroids

IT Skills Centroids	Frequency	Knowledge
Operations	2.10	3.31
Administration, f., c.	3.21	3.85
Sales and Marketing	3.31	3.72
Information systems	4.01	3.96
General services	2.39	3.50
Organization and s. s.	3.51	3.84

Source: my research, data from Osservatorio Professioni Digitali (2019)

Our findings that jobs where it is most important to possess IT skills and deploy them are those related to information and communication systems are in line with expectations, as professions in this area usually require to deal with networks of hardware and software to collect, process and distribute data. Thus, workers have to perform their IT competencies very often and with specific and profound knowledge.

By analysing gaps between the frequency and knowledge levels displayed in Table 10, we might notice that the only working area where the two dimensions almost perfectly

[14] The maximum score was 5, but the minimum one was 1, not 0. So, 4 out of 5 is not 80%, but 0,75%, as the right computation is 3/4 and not 4/5.

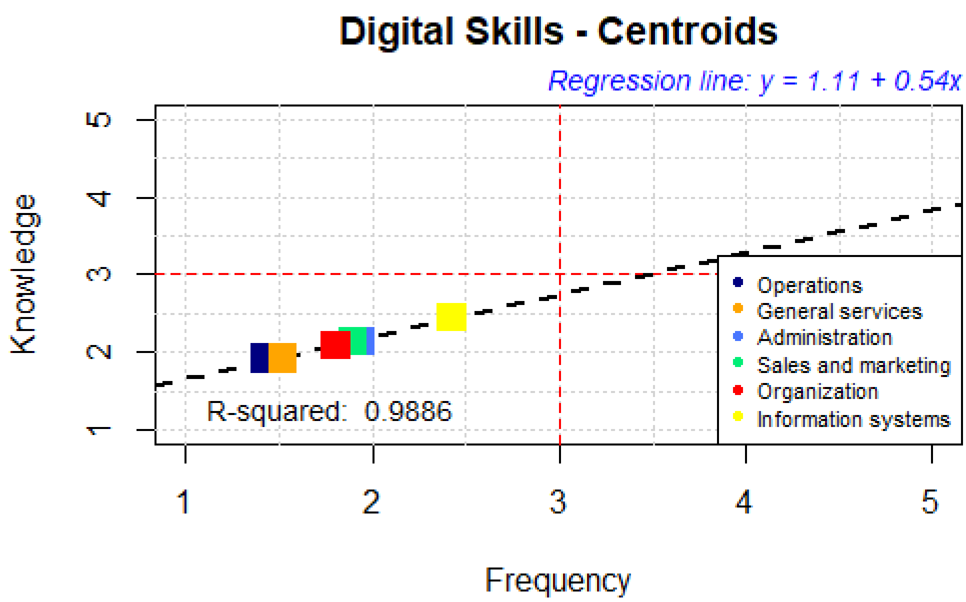
match is the *Information systems* one; furthermore, it presents the highest scores. Leaving aside this exception, gaps between frequency and knowledge average scores exist in all the other cases, with the former dimension always displaying lower values than the second one. The professional areas presenting the widest gaps are the *Operations* and the *General services* ones. This suggests that most jobs, particularly those related with production, inbound logistics, procurement, outbound logistics, distribution, and services like plant maintenance and healthcare assistance, require that workers possess a good knowledge of IT skills even when they are not that important for ordinary activities and, consequently, they are necessary with a moderate frequency. This is also confirmed by the fact that the depth of knowledge that workers declared to use concerning computer skills has little variability. On the contrary, frequency average scores presented greater variations, with a consequent increase in the gap with knowledge levels, depending on the type of job.

We may also observe that there is not a perfect match between how frequently a skill is actually used and how deeply its implementation is required. From an organizational point of view, it means that there are cases where human resources have to use IT competences with consolidated knowledge despite they are actually required to deploy them only once in a while. One could argue that these people are not put in the conditions of working at their full potential, as they have abilities that they are required to perform just occasionally. By observing this same phenomenon from another perspective, however, another interesting consideration may be made. The fact that workers have higher levels of knowledge and confidence in the use of IT skills with respect to what it is actually required should prompt some reflections. It might signal that there is a relevant threshold level for IT abilities, below which it is more difficult for people to enter and remain in the labour market.

4.3.2 Digital skills across professional areas

As regards digital skills, centroids for each professional area were computed to study in which sense and to which degree these competences characterize different jobs. Their graphical representation is provided by Graph 6, where we could observe that all points are concentrated in the same quadrant, the third one. It indicates that dealing with digital technologies, i.e. those related to artificial intelligence, big data, cybersecurity and so on, is not so frequently required across different jobs and, when it is the case, a basic level of knowledge is expected.

Graph 6 Digital Skills centroids of professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019)

Most squares are concentrated in the central area of the third quadrant, except for the *Information systems* professional category, which might be defined the most hybrid in terms of digital skills, in addition to its primacy for IT competences utilization and depth of knowledge, as Graph 5 illustrated.

From Table 11 we may notice that, with the exception of the *Information systems* functional area, where values for both frequency and knowledge levels are closed to 2.5, no other job classes exceed the score of 2 out of 5 with regard to how often digital skills are to be used and, as concern the second dimension, the highest values go a little over 2. Professional areas where digital skills are asked with the least relative frequency are *Operations* (1.43) and *General services* (1.52); in these cases, this competence is very rarely required (let us remember that a frequency of 1 means "never" and 2 means "seldom"). They are also the last job categories when looking at the level of knowledge required, as, when digital skills are required to workers employed in these areas, just very basic knowledge is required (1.92). This implies that, generally speaking, human resources within the professional classes we took under consideration do not generally need to know and to use digital skills.

Table 11 Digital skills centroids

Digital Skills Centroids	Frequency	Knowledge
Operations	1.43	1.92
Administration, f., c.	1.94	2.14
Sales and Marketing	1.90	2.13
Information systems	2.43	2.45
General services	1.52	1.92
Organization and s. s.	1.81	2.09

Source: my research, data from Osservatorio Professioni Digitali (2019)

Such low values are quite curious and unforeseen. Looking at the reports and articles of many important institutions (KPMG 2020; McKinsey Global Institute 2018; LinkedIn 2020), it seems that the future trend is all about these kinds of digital technologies and related skills. However, our findings do not show they are much significant or, at least, much developed. One may wonder whether the importance of these skills is generally overestimated or whether firms are struggling to improve and boost their development and this is just the initial phase.

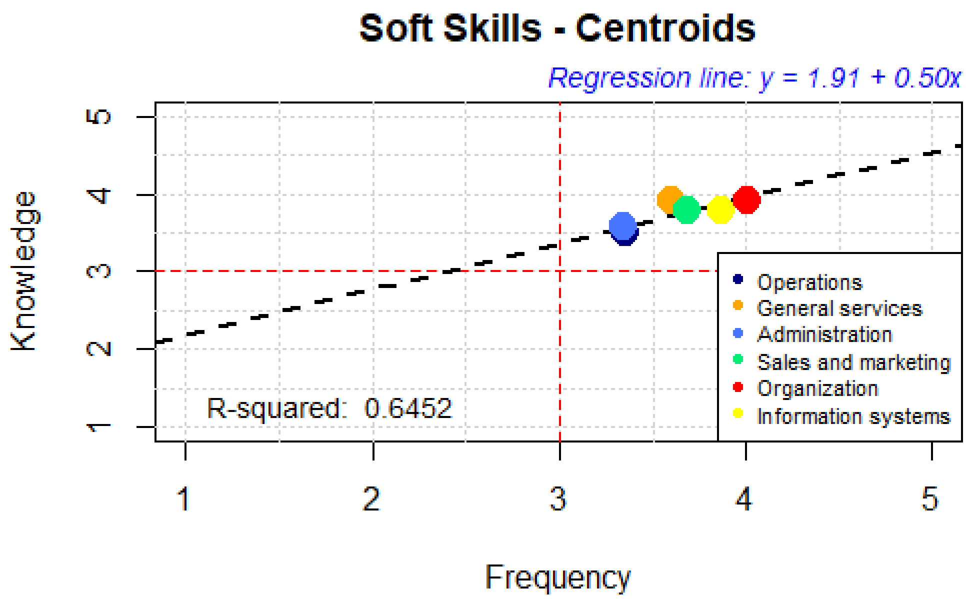
4.3.3 Soft skills across professional areas

Also in the case of soft skills, a centroid was computed for each professional area to identify the mean level of such competence for workers employed in different functions. Centroids of aggregated job categories with respect to soft competences were plotted in Graph 7. It shows that all centroids lie in the first quadrant, meaning that soft skills are generally required across jobs with medium to high frequency and with medium to high depth of knowledge.

It emerges that soft skills are an important asset for organizations, as they are very often needed and carefulness is expected from workers when it comes to acting for helping others, managing teams, challenging themselves, attaining personal and team goals, completing tasks and implementing their analytic abilities.

As concerns soft skills, there is no professional area that remarkably stands out from the others, as their values of utilization and knowledge only slightly differ. In other words, these abilities are wherever important and their development is commonly held in high regard, without regard to the kind of job. In particular, all professional areas display frequency values that fall in a small interval [3.34, 4] and knowledge ones being comprised in an even smaller range [3.53, 3.91]. This means that soft skills are generally needed quite often and with quite strong knowledge across jobs.

Graph 7 Soft Skills centroids of professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019)

Working positions that are a little bit more intense in soft skills with respect to the others are those related to people management, training, education, organization and services to the person (within the professional area called *Organization*); workers employed in these occupations are asked to use their soft skills very often and in delicate situations that require to perform them at high levels, based on a consolidated experience.

The second more hybrid professional area is the *Information systems* one.

The least hybrid ones in terms of soft skills are *Operations* and *Administration, finance and control*; however, their soft skills scores do not differ too much from those of the *Organization* area (the delta is 0.65 for frequency levels and about 0.40 for knowledge ones).

Also in the case of soft skills, the two variables plotted are positively correlated, with frequency increasing faster than knowledge, as the regression line shows: for a unitary addition of 1 in the level of frequency, the other dimension augments by 0.5 only.

Table 12 Soft skills centroids

Soft Skills Centroids	Frequency	Knowledge
Operations	3.35	3.51
Administration, f., c.	3.34	3.57
Sales and Marketing	3.68	3.77
Information systems	3.87	3.79
General services	3.60	3.91
Organization and s. s.	4.00	3.90

Source: my research, data from Osservatorio Professioni Digitali (2019)

Table 12 shows that soft skills, compared to IT and digital ones (in Table 10 and Table 11, respectively) display the highest perimeters for both the frequency and the knowledge and very tiny gaps exist between them for each professional area. It emerged that soft skills are an important asset that workers need to possess, as such abilities are generally very valuable for completing tasks in whichever functional family. Organizations have to foster the development of soft skills, as their implementation might be considered an integral part of daily tasks.

4.3.4 Insights from the regressions on the three skill domains

So far, we have analysed the three graphs about the average levels of IT, digital and soft skills across professional categories and we have explored the information they conveyed; however, little was said on the relation between the two variables that characterize each skill domain. We only stated that, by looking at graphics on IT, digital and soft centroids per professional area (Graph 5, Graph 6, Graph 7), a positive association always appears between the frequency of utilization and the knowledge level, as they vary together (they co-vary). It is important to notice that nothing can be inferred on the causality of this relation, given these data. We cannot state a priori whether it is the increase in the frequency of utilization that fosters the boost in knowledge levels or vice versa. In other words, we cannot say if workers are expected to perform skills at higher levels because they have become confident in their utilization or if it is the other way round, i.e. the stronger the knowledge that people possess, the more intense the frequency they are asked to perform. Broadly speaking, we do not have information on which dimension drives the other one.

When creating a regression model, however, some assumptions have to be made. We then

supposed that knowledge about a skill is dependant on the frequency of utilization.
In practice, for the creation of the three linear regression models applied to each skills areas individually, the level of knowledge was considered the dependent variable and the frequency of utilization the independent one. We adopted a simple linear regression model assuming the relation between the output and the explanatory variable to be linear, as the previous graphical representations suggest. Indeed, in each of the three plots (Graph 5, Graph 6, Graph 7), a dashed line was drawn to linearly describe the behavior of data, the corresponding equation was outlined in the top-right position above the graphic.
The values of R^2, the coefficient of determination, of the three regression models created on the centroids are very for both IT and digital skills, and for soft skills as well: the frequency levels explain 93%, 99% and 65% of the variability inside their respective models. Such extremely high values are explained by the fact that regressions were computed on already aggregated data, namely on the centroids of the six professional areas. The same regression computed on the sample data, however, still shows a relevant fit to the data, with R^2 of 0.33, 0.55 and 0.47 respectively, as illustrated in the Appendix (Figure 16, Figure 17, Figure 18).
The regression outputs are:

- $y = 2.67 + 0.33x$ for IT skills,
- $y = 1.11 + 0.54x$ for digital skills and
- $y = 1.91 + 0.50x$ for soft skills.

The x variable indicates the frequency and the y value the level of knowledge.
By comparing the resulting regression lines which best fit centroids of professional areas, we might notice they all have a positive slope (the angular coefficient is above 0). It indicates that it always happens that when one of the two dimensions increases, the other one follows; in particular, the more often a skill is performed, the higher the level of knowledge workers are expected to have.
We wondered whether a rise of a unit in frequency matches with a unitary increase in knowledge and a closer look at the regression coefficient provided the answer. In all the three linear regression equations, the angular coefficient was smaller than 1 in absolute value, meaning that their increase is not proportional. In particular, the slopes were 0.33, 0.54 and 0.50 for IT, digital and soft skills respectively. This implies that whenever the frequency of whichever skills increase by 1, the knowledge level is found to increase by

were 0.33, 0.54 and 0.50 respectively.

In concrete, it implies that when digital and soft competences are twice as often, workers do not face a drastically higher need for knowledge; in other words, they are left some times to internalize what they learn on the job. This is even more true in the case of IT skills; this might imply that computer abilities are a little harder to acquire than skills falling in the other two domains. From another point of view, we could suggest a different interpretation: a sharp increase in the use of IT skills does not make firms proportionately more demanding, but their expectations toward workers' computer skills in terms of intensity of knowledge are lower than they could have been, given the increment in their utilization. This issue will be discussed in Chapter 7.

Having taken a look at the slopes of the regression lines for each of the skills domains, a glance should be given to their intercepts, as well. IT, digital and soft skills data presented a constant – or intercept value – of 2.67, 1.11 and 1.91, respectively. These coordinate indicates the expected mean of y when x is equal to zero and, in our case, the expected level of the knowledge that firms assume workers have even when they are rarely asked to use such competences in the workplaces. It emerges that when each of the three skills is never or very rarely asked within specific tasks, workers are expected to have good knowledge of computer skills (2.67), moderate soft skills (1.59) and minimal digital skills (0.77).

To get more information on the regression models created on the whole sample rather than on professional areas centroids and to make some comparisons between them, always controlling by three skill domains one at a time, see the Appendix (Figure 16, Figure 17, Figure 18).

4.4 The intensity of knowledge of hybridizing skills

To provide insights on the features of knowledge dimension relative to IT, digital and soft skills respectively across different professional areas, three boxplots were created and will be now analysed.

The boxplot representation was chosen because it is a tool for data distribution visualization that enables to identify actual measures of spread directly from the scatters of boxes and whiskers; in addition, it facilitates comparisons between data sets (in our case, between groups of people employed in the same professional area). Each box represents a working category and is characterized by three horizontal lines, two vertical ones and some points. The line which splits boxes in two parts indicates the median, the one at the bottom of each rectangle represents the first quartile (Q1, the 25^{th} percentile), the one on the top identifies the third quartile (Q3, the 75^{th} percentile). The two vertical lines (whiskers) below and above the boxes represent the dispersion, as well; their length depends on how far values are from the median one. Overall, four sections of the boxplot are defined: from the minimum value to Q1, from Q1 to the median, from the median to Q3, from Q3 to the maximum; single points are the outliers, which are considered apart as they could distort statistics. Each section contains 25% of the data. When one of them is longer than another, it means that data are more spread out (and not that they have bigger dimensionality); on the contrary, a smaller section of the boxplot indicates that data are closer to each other and condensed in a smaller range. The interquartile range (IQR) describes the variability in the central half of observations in the data set and can be computed as the difference between Q3 and Q1; it is a measure of dispersion and indicates how the middle 50% values deviate from the median. Higher values of IQR indicates a wider variability.

As before, knowledge scores vary between 1 and 5 and take continuous values because they were computed, for each of the 283 workers under consideration, as the mean of the knowledge levels they have to perform for the six IT skills surveyed.

4.4.1 Some assumptions

We chose to focus on the dimension of the *knowledge* to assess the *intensity of the cognitive effort* required to perform non-job-specific tasks because we assumed that in the medium and long run knowledge level matches or, in the worst case, underestimates people capabilities. Indeed, we stated that when a worker is asked to use a specific hybridizing skill with a certain depth of knowledge in the short run, it might happen that he is not able at all to complete some tasks so that his managers will probably assign to him other ones where his potential could be better leveraged.

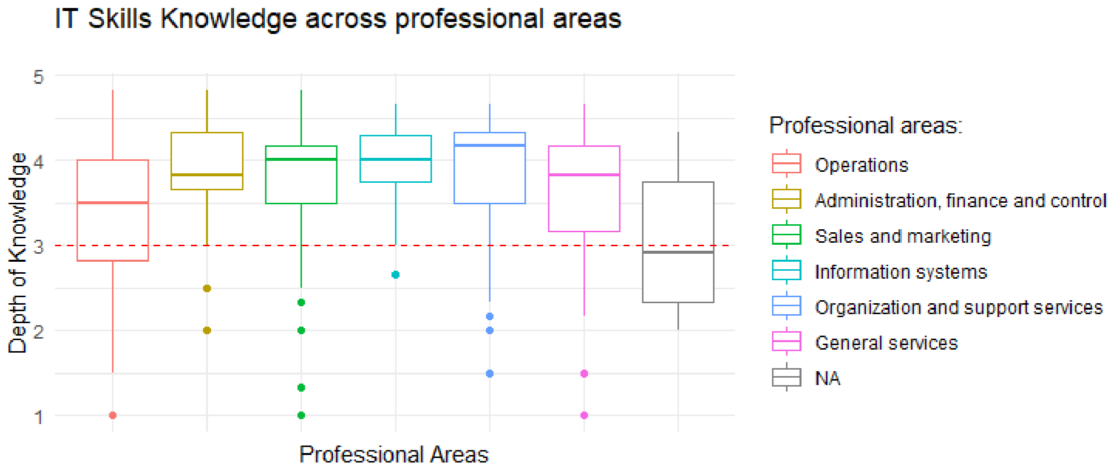
Of course, training can fill some knowledge gaps between the required level and the one actually possessed, but if such difference is too large, it is more convenient for a firm to allocate resources in a different manner. Therefore, we expect that in the short run reallocations take place – and this is among the reasons why, as a selection criterion for this research sampling, workers employed in a certain job since less than 11 months were excluded; this way, in the long run, the knowledge level required on the workplace relative to some hybridizing skills matches what a worker can actually do with the proper depth. Asking people to perform their abilities at a level below their capabilities means that their knowledge is underestimated or, at least, it is not fully exploited. This might lead to motivational issues, as people who feel having some potential are not challenged enough and they will probably end up being bored and disengaged. From an organizational viewpoint, this situation is no less unfavorable, as talented people who are not offered the opportunity to put to use their qualities and knowledge are likely to arise retention issues.

4.4.2 IT Skills Knowledge

This subparagraph investigates the IT skills distribution in terms of knowledge intensity among workers employed in different professional areas. For a closer observation of how deeply IT competences are used across job categories, a specific boxplot is provided (Graph 8). By looking at that graphic, we can notice that:

- the *medians* for all the aggregated functional categories are always above the dashed red line, which indicates an operative knowledge level, that corresponds to the central layer (3) on the aforementioned scale ranging from 1 to 5. This could have been expected by recalling Graph 5, where IT skills centroids were plotted. In that graphic, all the professional areas presented average scores for knowledge that were above the central value (3), meaning that a more than operative level was generally required, independently on the job. Even though in Graph 5 the mean was considered instead of the median, we could have anticipated these results by relying on the fact that these two measures are never too far.
- The *length of boxes* changes quite a lot across professional areas, indicating that there are functional categories where gaps between workers exist in terms of development and knowledge of IT skills.
- All the *outliers* are positioned in the lower part of the graph and are present for all the professional categories, indicating that there always are workers who, for different reasons, are not at the same level as their colleagues, from this perspective.

Graph 8 IT Skills Knowledge across professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019)

Let us now extract some information from each professional area by analysing them one at a time starting from the left; some organizational implications are discussed after the illustration of descriptive statistics emerging from the boxes. Through this analysis, comparisons among functional families and other considerations will be made.

Operations

Workers employed in *Operations* present the biggest differences in terms of knowledge of IT skills. Indeed, the length of the red box, indicating the interquartile range, is the greatest. The fact that data relative to *Operations* are quite dispersed is corroborated when looking at the two most external quartiles. Their vertical lines display once again the greatest length and they almost cover the whole set of knowledge values possible, starting from 1.5 and almost reaching the level of 5. However, the median is above the central value, despite it appears to be the lowest compared to that of the other categories.
From an organizational point of view, human resources working in the functions of production, inbound logistics, procurement, outbound logistics and distribution have big gaps with respect to each other in their knowledge of computer skills.

Administration, finance and control

The *Administration, finance and control* professional area shows a moderate variability in terms of depth of knowledge; the box corresponding to this category has a length that is about half of that of *Operations*. The median is fairly in line with the other classes and, precisely, it is just a little below them. In Table 10, which illustrated the mean values of frequency and knowledge of IT skills across professional areas, we saw that *Administration, control and finance* had the second-highest average score in terms of depth of knowledge; therefore, we may state that its median is below its mean. We could have noticed that even without having taken a look to Table 10. Indeed, yet in Graph 8 the area between the median and the upper quartile (Q3) is bigger than the area between the first quartile and the median indicates that the distribution is skewed. The longer part is above the median, therefore a quarter of observations are condensed underneath that line, precisely around a score of knowledge of 3.7, which is a considerable level. As concerns the external quartiles, those that are left outside the IQR, they present low variability and the one below does not reach the central value; only two outliers exceed that threshold.

From an organizational point of view, the boxplot relative to IT skills knowledge in *Administration, finance and control* suggests that all workers use them quite deeply and not too big gaps among colleagues appear in this sense, with most of them having discrete expertise in this sense.

Sales and marketing

The green box, relative to the *Sales and marketing* professional area, is similar to that of *Administration, finance and control* in some ways and different from it in other respects. The dimension of the box is almost the same, also their position with respect to the y-axis is not too different. What differentiates them is where the median is placed, the length of the external quartiles and the number and distribution of outliers. They show that 50% of workers in this field use IT skills with a medium to high level of knowledge (ranging from scores of 3.5 to about 4.2); among them, a half is condensed within values from 4 to 4.2, that indicate that they possess and deploy a consolidate knowledge. The remaining 50% of the workers are quite disperse and declared to have very disparate levels, from a bit over the basic one to the advanced one. *Sales and marketing* are the functions with the greatest number of outliers, which are far away from the median level.

From an organizational point of view, we might say that when workers from *Sales and marketing* professional area perform IT skills, they need significant knowledge, with half of them having consolidated expertise or above. Again, moderate differences exist among colleagues in these terms.

Information systems

The box representing the *Information systems* professional area is the shortest one, indicating that it is the function where IT skills knowledge presents the lower variability. This box is also the most even in size: the median splits the box into two almost identical parts, whiskers are not too long and, in particular, the upper one has almost the same vertical extension of the areas between Q1 and the median and between Q3 and the median. Only one outlier is present, which is not so far from the smallest value of the distribution.

What this box suggests is that values of knowledge of IT skills for workers in ICT and R&D functions can be approximated to a normal distribution, meaning that there is a great number of people deploying such competences at a median level or close to it and that a smaller group of them has abilities that are below or above the standards.

Organization and support services

The *Organization and support services* professional area praises/claims the highest median score (around 4.3) in the knowledge of IT skills in workplaces. It did not have this primacy according to Graph 5, which considered the mean of professional areas instead of their median. This incongruity is highlighted by the box relative to the working category under consideration: the box is split into two unequal parts, implying that the distribution of knowledge levels across workers employed in these fields is strongly skewed. Variability is very limited above the median, with 50% of workers using IT skills with a profound depth of knowledge (values from 4.3 to 4.7), while it is very spread below it, with the remaining 50% declaring lower levels. In particular, the lower whisker is quite long and indicates that the last 25% of workers within the distribution has a depth of knowledge below the operative level, diminishing almost up to the basic understanding.

From an organizational point of view, the box representing the *Organization and support services* area indicates that in these professions the highest levels of knowledge are required to a limited number of people, while the others still performing IT skills with a remarkable depth and a minority having just an operative knowledge or lower.

General services

The last box, the pink one, relates to the *General services* professional area. In this case, the box is quite large, meaning a significant IQR and thus a relevant variability; actually, it is the second-longest after that of Operations. Differences in IT knowledge levels among workers are also visible on the two whiskers, which have an overall balanced extension between them; this is in contrast to professional areas like *Information systems* or *Organization and support services*, where the upper vertical lines were really short. The distribution is a little skewed as the median line is shifted upwards, implying that, within the IQR area (50% of workers), most people have a consolidated knowledge about IT skills.

From an organizational point of view, jobs included in the *General services* professional category require a lower median level of IT knowledge that is in line or a little below that of the other classes. Furthermore, quite wide knowledge gaps in terms of computer skills emerged among colleagues, with a consolidated level being the most required.

4.4.3 Digital Skills Knowledge

The distribution of digital skills in terms of knowledge intensity among workers employed in the six professional areas under our consideration will be now analysed. A specific boxplot for observing how knowledge of digital skills is spread out is provided (Graph 9). By looking at that graphic, we can underline some issues.

Medians

The *medians* for all the aggregated functional categories are always pretty much below the dashed red line, implying that workers employed in whichever job use digital skills knowing only some essential elements.

From a general glimpse, it emerges that the professional areas where digital skills are most deeply deployed is *Information systems*, while the second-highest median characterizes both the *Administration, finance and control* function and the *Organization and support services* class. The latter two, however, present a significant difference in terms of variability, with the *Administration, finance and control* box being longer, actually it is the biggest among all the others.

Length of boxes

The *length of boxes* is remarkable across functional families, indicating that digital skills knowledge is present with quite big gaps between colleagues in the same professional area, with no exception; in other words, digital competences are quite dispersed in any jobs. The shortest boxes are those relate to *Organization and support services* and *General services,* which have similar interquartile ranges; again, other aspects distinguished between them: they both represent skewed data, but the former professional area is slightly distorted toward values above the median, while the opposite is true for the latter one and to a larger extent.

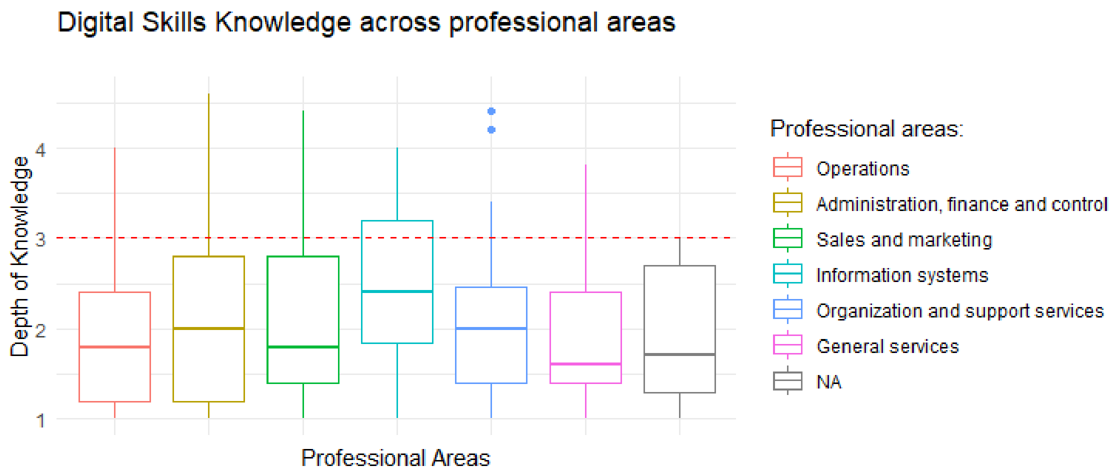
Outliers

Considering *outliers*, a minimal number of them appear and only in one area, *Organization and support services*.

In sum

In sum, we can state that workers usually have limited knowledge about digital skills, making an exception for those working in ICT and R&D functions and that consistent differences in such levels exist for every job category. This indicates that some people are more expert in digital skills than others; however, at best, no more than 50% of them possess basic knowledge.

Graph 9 Digital Skills Knowledge across Professional Areas



Source: my research, data from Osservatorio Professioni Digitali (2019)

Below, a closer look at each professional area is given and comparisons between them are placed throughout the analysis; we need to remember that digital competences are generally used with moderate frequency and low knowledge level, both in general terms (Graph 4) and by controlling for professional areas (Graph 6).

Distribution of digital skills knowledge in *Operations* presents a quite low median and a remarkable variability, in line with the other professional areas. Data in the IQR are well balanced, whit the box being split into two identical parts. What is worth noting is that the upper whisker is very long, even more than the box itself, meaning that knowledge is more dispersed among colleagues employed in this functional family when higher levels of expertise are needed.

Also the *Administration, finance and control function* reflects the general features outlined above with respect to the median and the length of boxes. What marks this professional area with respect to the other ones is that its distribution of digital skills exhibits the longest box, with an interquartile range spacing from about 1 to about 3, indicating an impressive variability in the knowledge of digital skills. In other words, and from an organizational point of view, huge gaps are present between colleagues of this function.

In *Sales and marketing* professional area the distribution of knowledge in digital competences is remarkably skewed and IQT is wide, as well. Data are differently dispersed even outside the box; the upper whisker is longer than the height of the green rectangle, while the one at the bottom is quite short. It means that half of the workers in *Sales and marketing* have an almost null knowledge of digital skills (the second quartile, the median, is below the level defined in the survey as “basic”). On the contrary, the other 50% use such competences with an intensity that varies between scores of roughly 2 to 4.5, indicating that a very small number of people perform digital skills with a depth of knowledge that goes beyond the superficial layer.

Information sytems professional area stands out for the position of its box, the level of its median and the overall balance in the distribution over the four quartiles. In practice, by looking at it we can derive that workers in this functional category are the most expert with digital technologies overall and that there is an overall homogeneous distribution among them. This professional ara is the only one where the upper area of the box exceeds the threshold we have set on the central value (3) of the ladder; it means that more than 25% of workers use digital skills with a depth of knowledge above the operative level.

Organization and support services presents one of the two shortest boxes, together with that of *General services*, indicating that a significant share of workers is concentrated around the same knowledge levels of digital skills. The median value of depth of knowledge used in these professional areas is in line with the general features outlined above; it cuts the box in two similar pieces, where the upper one is just slightly bigger than the other one. This means that the middle 50% of workers have, more or less, a basic ability in terms of digital skills. *Organization and support services* is the only professional area characterized by outliers, which indicate that there are people with extremely advanced knowledge about digital competences; their ability is much far from usual and it would be interesting to investigate why. This may support the hypothesis that certain digital skills, in the context of ICT function, are at the border with hard skills and therefore an intense and specific knowledge is required.

As concerns the *General services* professional area, it displays the lowest median value. We have already outlined that the small length of its box is explained by a relatively intense concentration of workers within the interquartile range. However, the fact that the median creates very different areas indicates that data are skewed toward smaller values. In practice, such position of the median line denotes that half of the workers have very low knowledge about digital skills (below a score of 1.6). People with higher preparation in these terms are present, as we can see by observing where lines for the fourth and the third quartile are, but they are not so many.

4.4.4 Soft Skills Knowledge

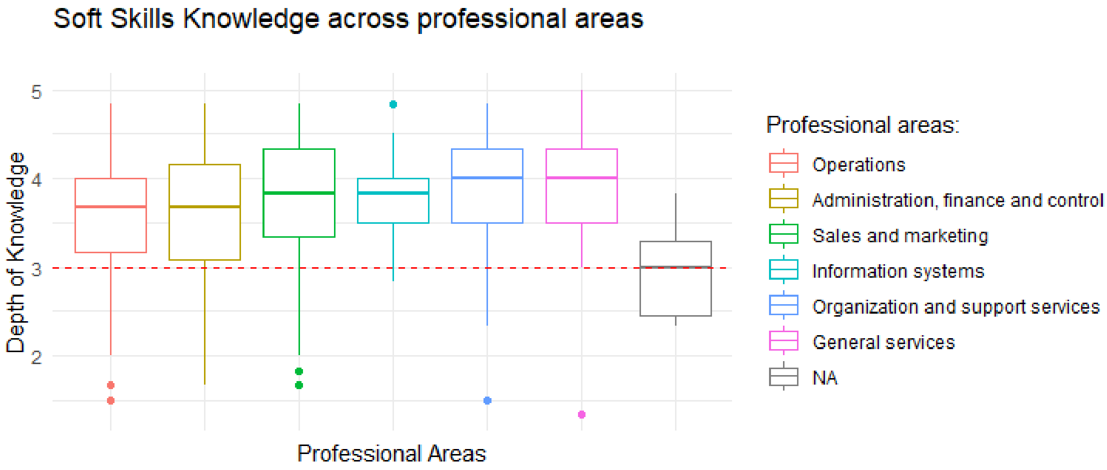
The depth of knowledge about soft skills within single professional areas will be now investigated. A boxplot representation (Graph 10) is created to graphically illustrate how knowledge in soft skills is spread out and to allow for immediate comprehension.

By looking at Graph 10, we can notice that all the boxes lie above the red dotted line corresponding to an operative level of knowledge. The *median* level of knowledge does not vary so much across functional families and displays values between 3.7 and 4. This indicates that consolidated expertise in the utilization of soft skills is generally important in whichever jobs.

The *length of boxes* differs across job categories, with the shortest one referring to the *Information systems* class and the longest one belonging to the *Administration, finance and control* function. It emerged that.

Some *outliers* are present below boxes for almost all the professional areas, except for the *Information systems* one, which is characterized by one outlier positioned above the upper whisker. This means that, generally speaking, it is not unusual to find workers who have quite low abilities in terms of soft skills, regardless their profession.

Graph 10 Soft Skills Knowledge across Professional Areas



Source: my research, data from Osservatorio Professioni Digitali (2019)

We will now analyse how the depth of knowledge about soft skills is distributed on workers employed within the same professional area.

The *Operations* boxplot shows that workers employed in functions like production, inbound logistics, procurement, outbound logistics distribution deploy soft skills with notable differences in depth of knowledge. Indeed, scores space from a basic level (2) to an advanced one (almost 5). The IQR includes knowledge levels from the operative to consolidate. To be precise, the distribution of values relative to such intensity is a bit skewed upwards. Two outliers are found below the lower whisker.

In the *Administration, finance and control* function the median value is similar to that found in *Operations*, which indicates a discrete knowledge level. This professional area displays the highest variability in terms of knowledge about soft skills; this is true both considering the IQR only and looking at the distribution over the four quartiles. Such dispersion suggests that jobs involving administrative and financial tasks do not always require profound knowledge or, in other words, that only certain activities necessitate a high-level implementation of soft skills.

In *Sales and marketing* professional area, the median level of soft skills knowledge perfectly falls into the general range outlined above (3.7 – 4). The length of the box (IQR variability) and the overall dispersion of data is not too different from the two previous functional categories. In this case, however, data are between Q1 and Q3 are not skewed, as the median line divides the box into even pieces.

The *Information systems* professional category is the most interesting one in this framework, as it stands out among the others for several aspects. Despite its median still falling in the general interval outlined above, its low variability is surprising: its box is by far the shortest. Not only the middle 50% of workers in the distribution are condensed between knowledge values between 3.5 and 4, but also the whiskers highlight a very small variability. From an organizational point of view, all the human resources employed in ICT or R&D functions use soft skills with high remarkable intensity. It might suggest that tasks within these functions presuppose the possess of notable soft abilities or they foster their development and acquisition.

The professional areas of *Organization and support services* and *General services* present quite similar situations. Their median distribution of soft skills has the highest values and it indicates that a consolidated knowledge is required and deployed by workers. Their IQR, which has the same length, does not show excessive dispersion. Furthermore, in both the professional areas values are slightly more concentrated in the upper part of the box and an outlier comes out in correspondence of very low knowledge levels. The only aspect that distinguishes them is the variability outside the interquartile range: in the case of *Organization and support services*, a long lower whisker points out a widespread in terms of soft skills knowledge and it goes below the threshold of 3; when looking at *General services*, on the other hand, the longer whisker is that on the top, which gets close to the knowledge of depth 5.

From an organizational point of view, we can say that people employed in both the professional areas deploy their soft competences at significant levels. Overall, a bigger gap in terms of knowledge intensity exists between colleagues in the *Organization and support services* professional area compared to those employed in the *General services* category. In particular, workers in the latter class never use soft skills with knowledge below the operative level, in contrast to the former category.

4.5 Conclusion

Too often, it is taken for granted that all professions are going in the same direction at the same pace. Instead, paths toward hybridization can be more or less long and more or less straightforward according to the functional area considered. In a sense, jobs are at different points of the hybrid evolution. In this chapter, we demonstrated how different functional families are differently permeated by the hybridization phenomenon. We did so by: I) finding out and comparing the centroids (average values) of different professional areas with respect to IT, digital and soft skills; II) computing and analysing regression models for each of the competence domains; III) investigating the intensity of knowledge of hybridizing skills through the creation of specific boxplots.

Our major findings are described below.

With respect to IT skills, it emerged that while a good level of knowledge is required to workers from whichever jobs, the frequency of their utilization strongly depends on the functional family. For example, professional areas of *Operations* or *General services* rarely require workers to use computer skills, while in the *Information systems* area their implementation might be considered an ordinary activity.

Regarding digital skills, we found that, broadly speaking, human resources within none of the professional classes we took under consideration need to deeply know nor intensively use digital skills. The only functional family which stands out from the others for its higher values is the *Information systems* one: workers involved in ICT and R&D activities sometimes use digital skills in the workplace and moderate depth of knowledge is required.

As concerns soft skills, we found that almost all the jobs require workers to frequently use them and a remarkable mastery is necessary. Differences among professional areas exist, but they are very tiny; the ones displaying slightly higher average scores in terms of frequency and knowledge *are Organization and support services* and *Information systems*.

For all the skill domains, the association between the two dimensions of frequency and knowledge is positive, with the former growing faster than the latter. It emerged that even when such skills are very rarely asked, a certain level of knowledge is expected. In particular, the IT threshold is quite high, followed by a moderate one for soft abilities and some low expectations in terms of digital competences. It implies that to stay in the labour market, hybridizing skills are an imperative prerequisite.

In terms of the intensity distribution of knowledge, some boxplot analysis showed that IT, digital and soft skills present different behaviours both between them and across professional areas. Considering IT skills, it resulted that median workers from every job have at least an operative knowledge, with those from the professional area *Organization and support services* exceeding the consolidated level. Variability across functional families is relevant, with the *Information systems* one having the lowest differences between colleagues in terms of knowledge, while the *Operations* one exhibits the widest gaps.

With respect to the knowledge distribution of digital skills, digital competences are quite dispersed within any jobs we considered. We found that people usually have limited knowledge about digital skills, making an exception for those working in ICT and R&D functions (*Information* systems area) and that consistent variability in such levels exists among workers in every job category. This indicates that some people are more expert in digital skills than others; however, at best, no more than 50% of them possess basic knowledge.

As regards soft skills, it emerged that consolidated expertise in their utilization is generally important in whichever jobs, despite different levels of variability in the distribution of soft skills existing among professional areas, also in this case. The professional area where knowledge dispersion is less pronounced is *Information systems*, while the one where the largest differences are present among colleagues is the *Administration, finance and control*.

5. CHAPTER

SKILLS LEADING TO HYBRIDIZATION OF JOBS

5.1 Introduction

Jobs are made of tasks and they are carried out by performing skills. What distinguishes professions are the technical competences they require to perform assigned tasks, but for their proper completion other skills need to be developed and deployed. For example, a professor has to be very competent on certain subjects, but to perform their jobs and related tasks conveniently and effectively, they also need to possess other general skills, like being able to plan lessons, create slides, be able to speak in public, know how to use a video-projector or a voice over IP services like Zoom.

These skills, who are not technical or job-specific, but are highly important as well, are what we will call from now on "hybridizing skills" or, more generally, "hybridization skills". Actually, this denomination may lead to some misunderstanding, so it is important to make it clear some points. There is any univocal and sharp distinction between competences that increase job hybridization and those who are just technical. The same ability might be job-specific for one professional area and, at the same time, it could be included among the hybridizing skills of another functional category; it depends on the context. For example, the public speaking competences is not job-specific for professors and teachers, but it is so for television presenters. Similarly, the ability to perform data analysis is a core technical competence for data scientists, while it is a non-job-specific skill for people engaged in management activities. For this reason, different professional areas require diverse combinations of non-job-specific competences to support and foster the implementation of technical (or hard) skills, with the final aim of putting workers in the best position to perform the set of assigned tasks optimally.

This chapter has the aim to explore every professional area within its “hybridizing” component to get some contextualized insights. In particular, it will be examined whether and in which terms non-job-specific skills are important, according to the functional area under consideration. Professional areas will be analysed one at a time in this order: operations; administration, finance and control; sales and marketing; information systems; general services; organization and support services. For each of them, a centroid for the three skills domains (IT, digital and soft ones) is computed, graphically represented and analysed at first. Then, each centroid will be further investigated by splitting it into its constituent elements to catch which specific skills are the most important among the IT, digital and soft ones. In other words, in the second phase analysis, three graphs will be provided, one for each skill domain and they show where the centroids of the 6 skills (or 5, in the case of digital skills) are positioned in terms of frequency of utilization and depth of knowledge necessary.

5.2 Professional areas across IT, digital and soft skills

Up to now, we have analysed hybridization skills controlling by job category. We mined valuable information from data to get some insights about the three skills domains composition and professional areas hybridization features. However, we still do not know so much about how hybridization is shaped within each job. In this paragraph, the focus will be shifted from the characteristics of the three competence domains to the hybrid structure of each professional area. Of course, keeping separated IT, digital and soft skills and controlling by them will be pivotal for an exhaustive study.

Points in the following graphics represent the centroids for the three skill domains and they are labeled with their frequency and knowledge average level. In particular, values of the former dimension will be plotted below the points themselves (or above, in case of overlaps), while those referring to the depth of knowledge will be displayed on the right (or on the left, in case of overlappings).

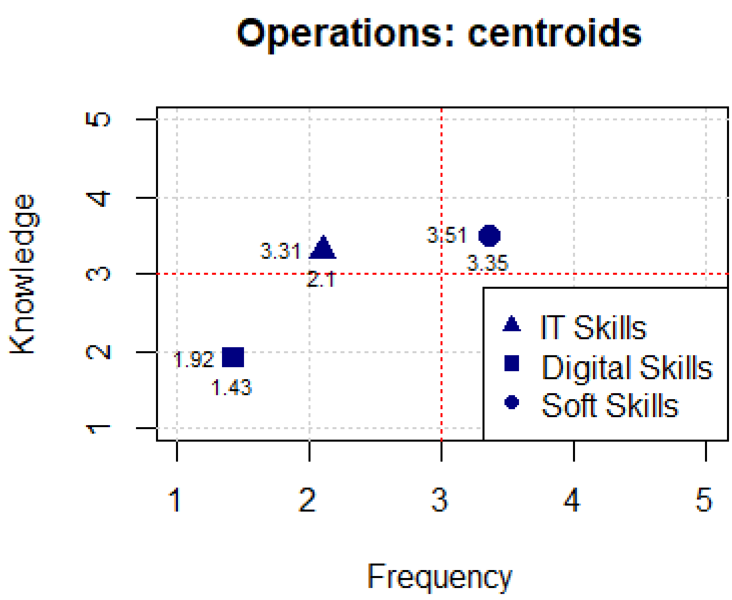
We will see in the next subparagraphs how hybridizing skills characterize each professional area and where their centroids locate in terms of frequency of utilization and intensity of knowldeg required.

5.3 Professional area: Operations

The professional area Operations comprises jobs in the functions of production, inbound logistics, procurement, outbound logistics, distribution. People working in production are mainly employed in the sectors of manufacturing (about 60%) and transportation and storage (about 20%). By looking at gender distribution, interesting data emerged: about 70% of people employed in Operations are male.

We are now going to dive into this professional area to explore its hybridization features. Graph 11 shows that hybridization in Operations does not come from an equal contribution from IT, digital and soft skills, instead their relative importance is quite different.

Graph 11 Centroids in the professional area: Operations



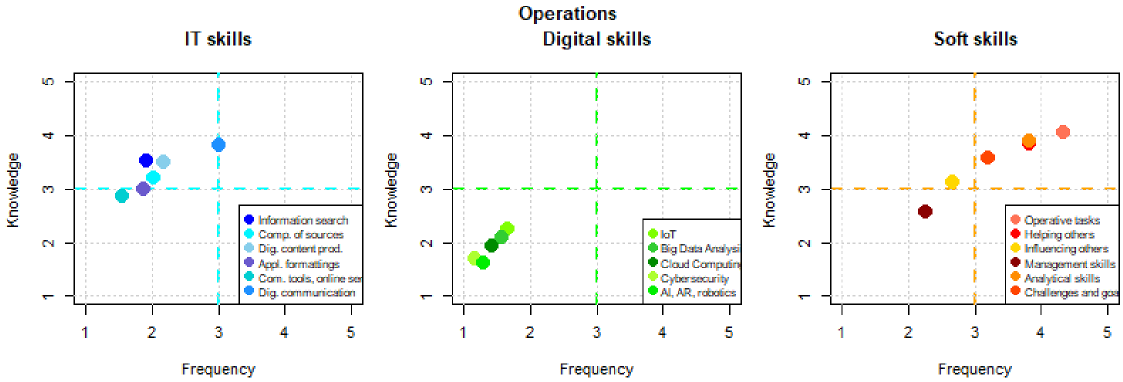
Source: my research, data from Osservatorio Professioni Digitali (2019)

The plot shows that the main constituent in the hybridization framework of these professional areas is the soft skills domain, as its centroid presents medium-high values for both frequency and knowledge dimensions (respectively, 3.35 and 3.51).

Also IT skills are actually required to workers with a mean level of expertise above the central one (knowledge of 3.31), but it does not happen so often (frequency of 2.1).

Digital skills are very rarely required (frequency of 1.43 where the lower value is 1) and only basic understanding is needed (knowledge of 1.92).

Graph 12 Skills distribution in Operations



Source: my research, data from Osservatorio Professioni Digitali (2019)

Results show in which terms the professional area Operations may be considered hybrid. To perform tasks like controlling and managing the correct implementation of safety regulations, assessing the attainment of production objectives, analysing data on production and produce reports, distributing oneself and other's workload, evaluating the efficacy of product and process innovations adopted and monitor product quality or manufacturing process, a high variety of *softs skills* is clearly required. It does not come as a surprise that, leaving aside technical competences, skills like completing operative tasks, attaining goals, analysing situations and helping others are pivotal.

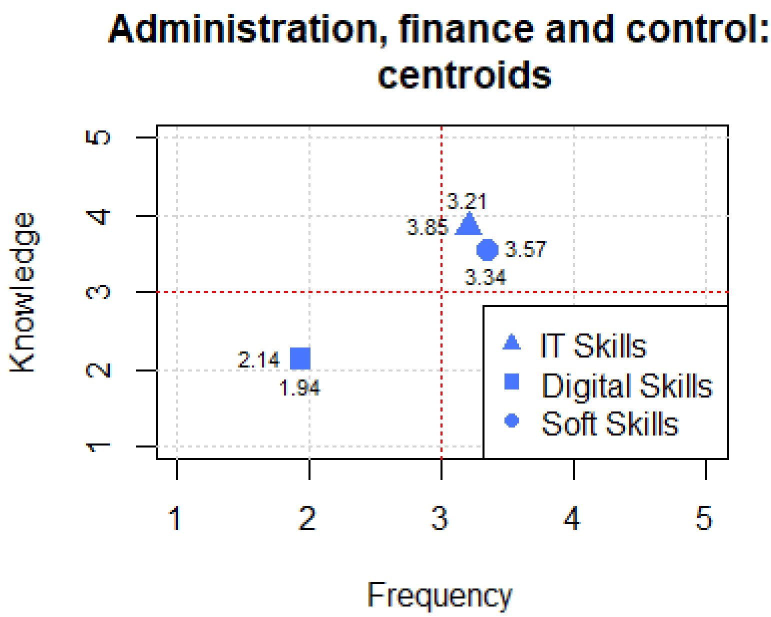
As regard *IT skills*, these competences are generally performed with low to medium frequency and with a good level of knowledge. In particular, it is very important for workers employed in Operations to develop digital communication abilities not only through the telephone or by e-mail, but also through voice over IP applications, like Skype. Such skills have to be performed occasionally, but quite high confidence is required. As concerns the other IT skills, they are seldom needed, although medium to high levels of knowledge are expected. The position of the centroids relative to the six survey information and communication skills (in the first graph on the left) reveals that information technologies competences are not exactly at the core of production and logistics tasks, which, on the contrary, are not too dependent from the computer and similar devices.

Considering *digital skills*, Graph 11 shows they are not relevant competences for the *Operations* professional area. They all lie in the third quadrant and are actually required with a frequency that workers overall defined between "never" and "rarely"; the expected confidence with such digital technologies is also low. The digital competences with values slightly over the others are, in order, those concerning IoT, big data analysis and cloud computing.

5.4 Professional area: Administration, finance and control

The professional area Administration, finance and control is a traditional functional unit that, according to our research, employs far more women than men: about 80% of workers from this filed are female. This is quite curious and further explorations will be made and discussed in Chapter 7.

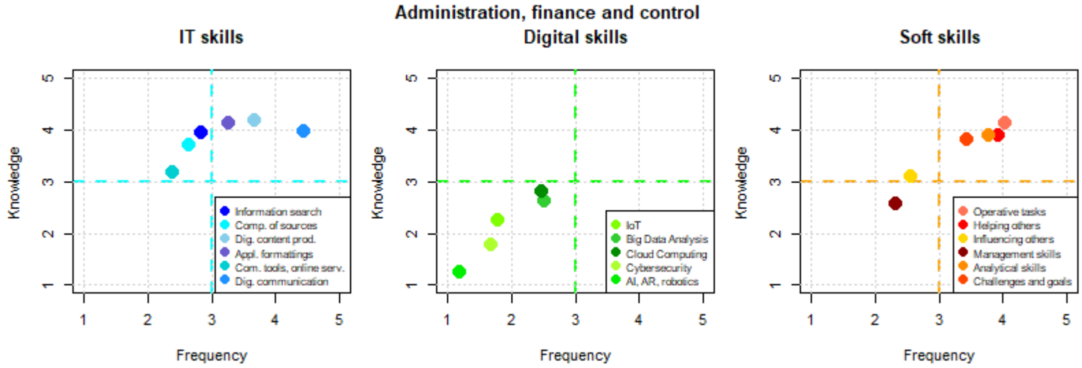
Graph 13 Centroids in the professional area: Administration, finance and control



Source: my research, data from Osservatorio Professioni Digitali (2019)

As of the three competences domains, in the Administration, finance and control functional area, both IT and soft skills are needed quite often (with mean scores of 3.21 and 3.34, respectively), with an operative depth of knowledge required for soft skills (3.34) and consolidate ability asked for IT skills (3.85). With respect to digital skills, their utilization is low (1.94) and basic (2.14).

Graph 14 Skills distribution in Administration, finance and control



Source: my research, data from Osservatorio Professioni Digitali (2019)

Figures in Graph 14 help us understand what brought centroids of Graph 13 to end up in that position. Very interestingly, each centroid represented a range of IT, digital and soft abilities that actually were quite disperse; we will now zoom into each competence domain to find which skills are pivotal for the completion of tasks within the administration, finance and control function and which, on the contrary, are just marginal.
As concerns the *IT domain*, it results that being able to effectively communicate through several channels (telephone, voice over IP, e-mail…) is part of routine tasks; indeed, their score in terms of frequency is next to 5 out of 5, meaning that workers always have use this kind of skill. Also competences like producing digital contents and applying proper formattings to documents, tables, graphics, notes are used quite often. For all the IT skills we have just mentioned and for others like searching for online information and comparing different sources to assess the reliability of the information, the level of knowledge required is not to be given for granted: they all display values around 4.
Considering *digital competences*, a wide variety is again found. It emerged that the two most important digital skills, cloud computing and big data analysis, do not exceed the value of 3, nor they go beyond this threshold in terms of depth of knowledge; this means that they are just occasionally required to workers and less than medium level of competence is accepted. The ability to deal with artificial intelligence, augmented reality or robotics is never asked within this function.
As regards *soft skills*, they are very important for workers in Administration, finance and control. Even though their overall centroid in Graph 13 presented scores of 3.34 for the frequency dimension and 3.57 for the knowledge one, which are relevant values, but not excessively high, by breaking down this syntetic information interesting insights can be

discovered. Some specific skills within the soft competences domain present very high scores in both frequency of utilization and depth of knowledge required. Namely, they are: the abilities to complete operative tasks, to help others, to understand and evaluate situations, to challenge oneself and achieve desired goals. On the contrary, skills like influencing others or especially managing people, are not as important as the aforementioned ones. This finding, however, should not surprise us, as the function of *Administration, finance and control* is based on tasks involving precision, responsibility, collaboration, assess and evaluate different cases and scenarios.

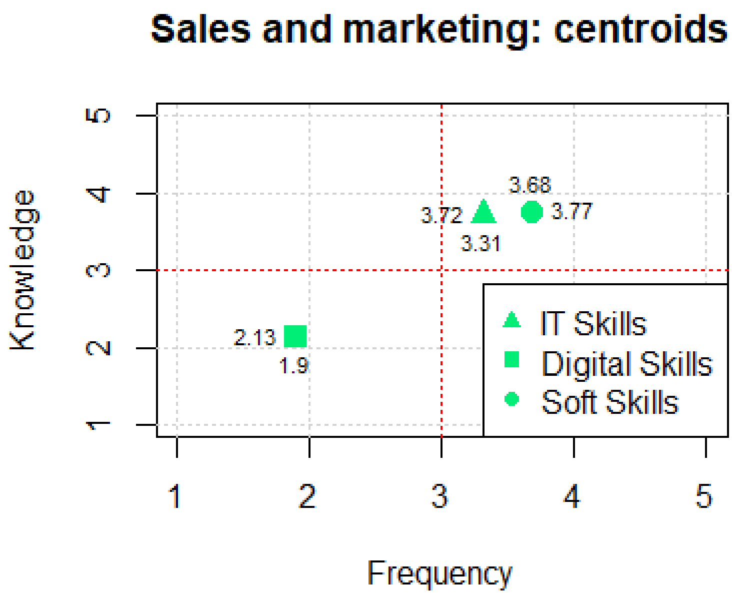
5.5 Professional area: Sales and marketing

The *Sales and marketing* professional area includes jobs dealing with sales, marketing and communication. The graphic showing the centroids of IT, digital and soft skills for this working category, Graph 15, is quite similar to that for *Administration, finance and control*. Also in this case, centroids for IT and soft skills present similar; they both lie in the first quadrant. It means that these competences are overall needed more than occasionally and with a consolidated level of knowledge values (about 3.5 in terms of frequency and about 3.75 in terms of effort and carefulness). The centroid of digital skills is again in the third quadrant, as workers employed in this functional area are required to deal with digital transformation technologies rarely (1.9) and with basic knowledge (2.13).

Despite centroids of Graph 15 being so similar to those of Administration, finance and control functions, their breaking up into specific skills shows some differences with respect to them.

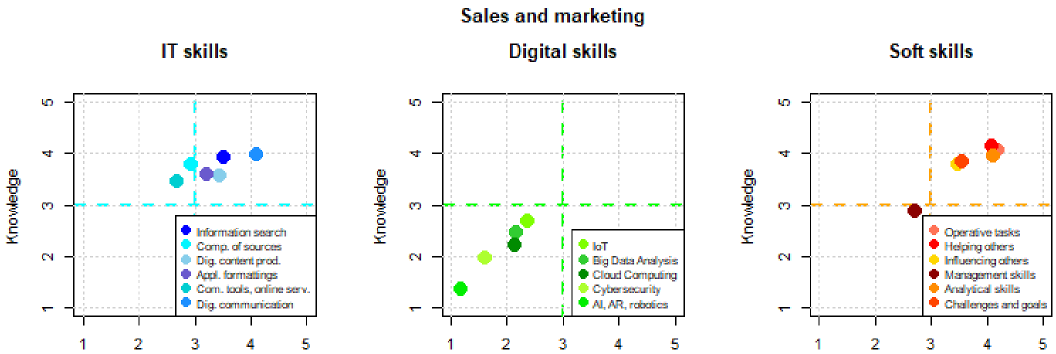
IT skills are not too disperse, indicating that they are quite important on the whole. More specifically, workers dealing with sales, marketing and communications tasks are often required to perform digital communication abilities through different channels (from the telephone and the e-mail to the voice over IP). This was highly predictable, as for people working in the communication field, being able to effectively convey contents and information is undoubtedly essential. The second more important skills for the Sales and marketing area is the search for online information, which is a competence regularly needed and for which expertise is expected.

Graph 15 Centroids in the professional area: Sales and marketing



Source: my research, data from Osservatorio Professioni Digitali (2019)

Graph 16 Skills distribution in Sales and marketing



Source: my research, data from Osservatorio Professioni Digitali (2019)

As of *digital skills*, a few of them are used by workers more than the squared centroid of Graph 15 revealed. The ability to manage IoT devices and technologies is amazingly important, considering that we are talking about sales, marketing and communication functions. In particular, it emerged that this skill with almost medium frequency and and operative knowledge. Also being able to implement big data analysis is sometimes required and sufficient confidence is asked; this is in line with our expectations, as dealing with marketing and sales also involves collecting data, processing and analyse them. Cloud computing competences are another digital skill occasionally used in this professional area, but just a basic understanding is sufficient; also this result might make sense, as data management is often supported computing services including servers, storage, analytics, databases, software, intelligence, ect over the internet (cloud). Also in this case, digital competences relate to artificial intelligence, augmented reality and robotics are never used.

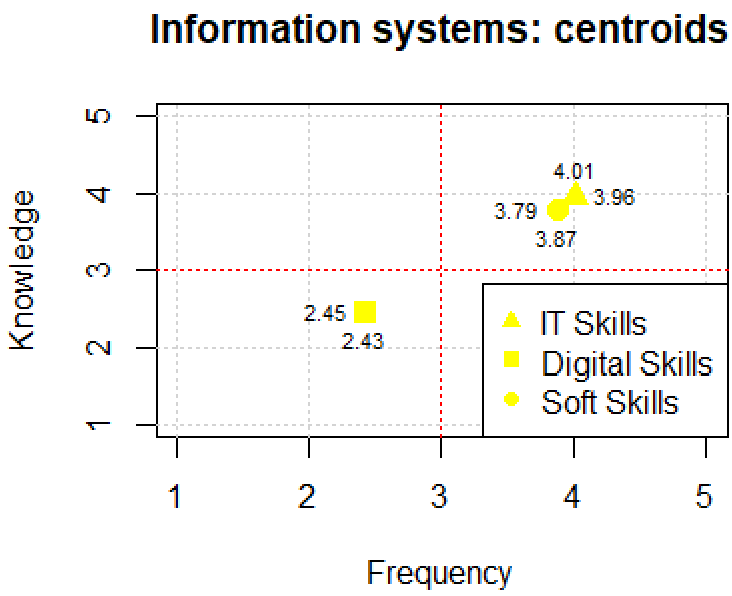
Soft skills are pretty important also in Sales and marketing functions. Their centroid in Graph 15 is highly representative, with just one exception (management skills are less important). In particular, three soft skills are remarkable for people employed in this professional area: helping others, completing operative tasks and comprehending situations and problems. Workers in this field have to use such competences with very high frequency (more than 4) and knowledge (more than 4). Lower scores, even though still important in absolute terms, are displayed by skills like influencing others, challenging oneself and reaching individual objectives; their levels of frequency is around 3.5 and those for knowledge are a little below 4.

These results on soft skills allow us to make some interesting considerations. *Sales and marketing* are the functions in charge of supporting clients or potential ones in satisfying their needs or in finding exactly what there were looking for; it should not come as a surprise that the capability to help others, trying to understand their interests and needs is a pivotal soft competence for people working in sales, marketing and communication functions. Also, as concern analytical capabilities, it is clear that it cannot miss when conducting market researches, organizing marketing campaigns or setting sales objectives, for example. The ability to influence others is also easily ascribable to tasks involving marketing, communicating and selling goods and services.

5.6 Professional area: Information systems

The *Information systems* professional area comprises jobs within the functions of ICT (information and communication systems) and R&D. People working in this fields have high or medium education, indeed about 14% of them attended a master or a Ph.D. and 45% attained a bachelor or master degree, the remaining part has a high school diploma, while no one has a low-level qualification. Interestingly, 36% of workers within this professional area is very young (up to 29 years).

Graph 17 Centroids in the professional area: Information systems

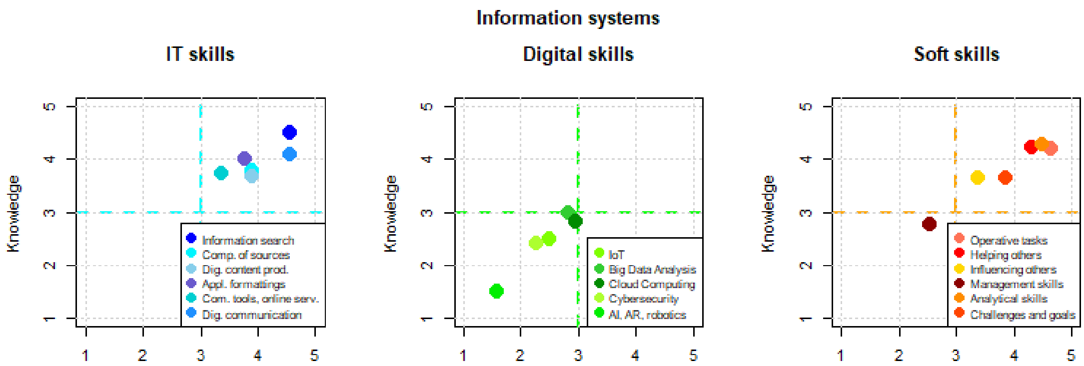


Source: my research, data from Osservatorio Professioni Digitali (2019)

Graph 17 shows that *Information systems* professional area claims among the highest values for the centroids of all the three skill domains when compared with whichever functional category.

As regards *IT skills*, their average values are remarkable (about 4), meaning that such competences are overall essential for working effectively. About the same could be said about soft skills, which are required with a frequence and knowledge level of about 3.8. The centroid for digital competences still lies in the third quadrant, but it is positioned in the top-right side, where no other digital centroids arrived.

Graph 18 Skills distribution in Information systems



Source: my research, data from Osservatorio Professioni Digitali (2019)

Graph 18 helps us understanding which skills are the most important within the relative competence domains.

Looking at *IT skills*, we can notice that there are two of them that workers always have to use (the mean level of frequency is close to 5, the maximum one); they are the online search for information and the ability to digitally communicate. The former has to be performed with the deepest possible level of knowledge, also the latter is required with high performances, specifically with consolidated expertise. It may seem curious that these skills are asked at such high levels of knowledge, especially considering that workers in this field are quite young on average, with one third being below 30 years. This aspect and related ones will be discussed in Chapter 7. The other four IT skills surveyed displayed quite high values in both dimensions, having all scores for frequency and knowledge around 4, with one exception (about 3.5).

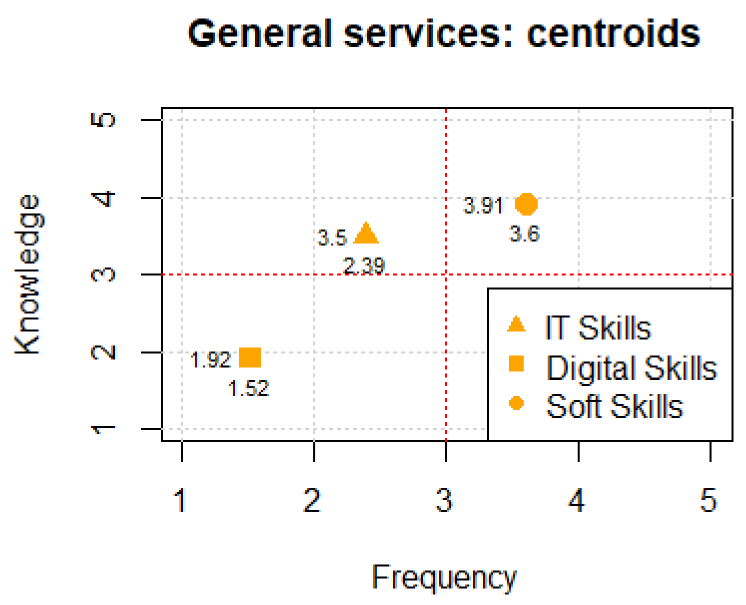
Also in the case of the *digital domain* results stand out with respect to the other professional areas, with two digital skills almost going outside the third quadrant, where we have found such competences up to now. They are the capability to implement big data analysis and to understanding and managing cloud computing services; their scores on both dimensions are around 3, meaning that workers occasionally have to use these competences and with an operative level of knowledge. Also skills related to IoT and cybersecurity are sometimes useful and a more than basic understanding is required.

Soft skills are an essential component as well for workers employed in ICT and R&D functions. In particular, there is a group of such competences that workers perform with a high level of knowledge (scoring a little more than 4) and with intense frequency (ranging from less than 5 to more than 4); in order, they are: the ability to act and complete operative tasks, the capability to understand tasks, problems, situations and the disposition to help others. If we think of the professional area we are dealing with, we may easily realize why soft skills, and the one just mentioned in particular, are so important. Tasks like providing technical advice, installing information systems, finding out and developing IT solutions and procedures, making researches and developing projects necessitate such softer skills.

5.7 Professional area: General services

The *General services* professional area includes jobs in the context of plants and equipment maintenance, in addition to services in the medical, pharmaceutical and scientific field. Because of their wide range, they have been called “general” and can be considered a sort of residual category.

Graph 19 Centroids in the professional area: General services



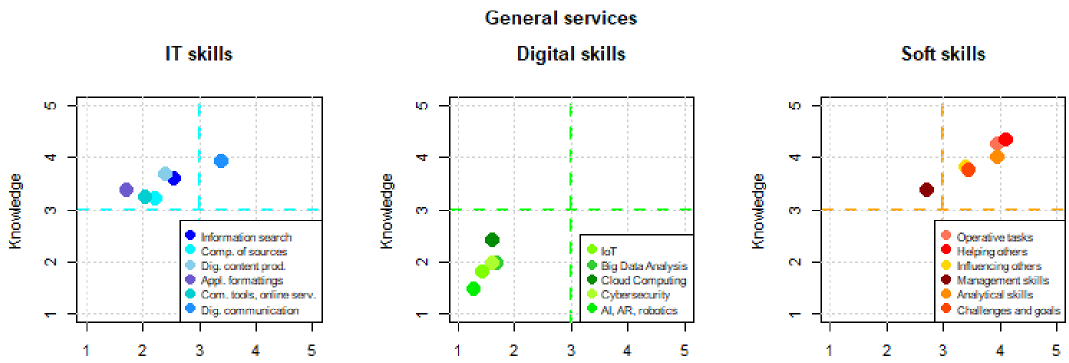
Source: my research, data from Osservatorio Professioni Digitali (2019)

Graph 19 illustrates how centroids for IT, digital and soft skills distribute. At first glance, it seems like nothing remarkable emerges: IT skills are sometimes used and with good knowledge, soft skills are quite frequently asked and with consolidated knowledge and digital skills are almost never used and, in case, vary basic understanding is sufficient.

IT and digital centroids for *General services* are the second-lowest ones among the professional areas, after those for *Operations*.

Let us take a look at Graph 20, which breaks centroids into their constituent skills, to explore whether there are some specific skills at the core of general services tasks.

Graph 20 Skills distribution in General services



Source: my research, data from Osservatorio Professioni Digitali (2019)

As the *IT* centroid suggested, skills related to computer abilities and similar are not frequently asked within General services, despite the level of knowledge needed is not that basic. Just one IT skill stands out from the others for its higher values: the ability to communicate via different digital channels is more than occasionally required and confidence in doing so is expected.

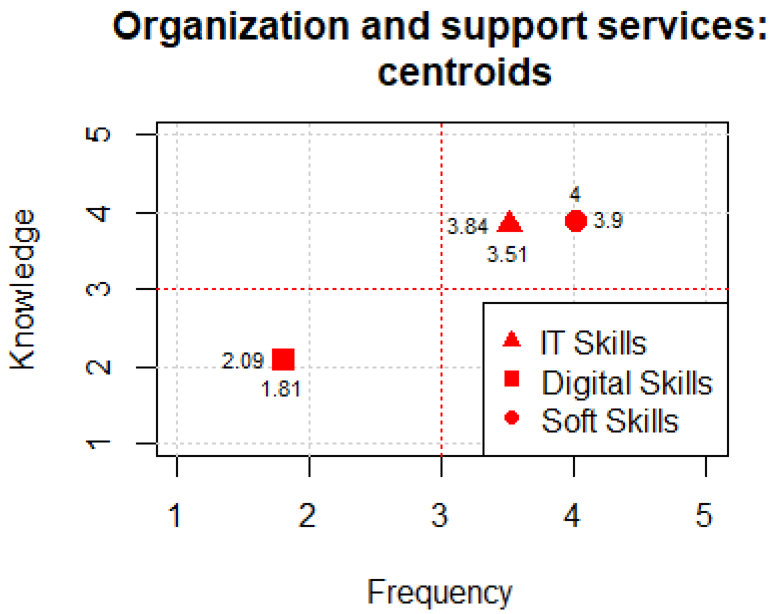
The positioning of *digital skills* is quite singular, as no centroids in the central figure of Graph 20 reach the frequency of 2, meaning that these competences are almost never used. Interestingly, despite such low demand, values for the knowledge dimension are wider, with the ability referring to cloud computing requiring a level that cannot be taken for granted.

Centroids for *soft skills*, in the figure on the right in Graph 20, are in the first quadrant, as for the other professional areas; just one skill provides an exception. The most important soft competence in General services in terms of both the dimensions is the disposition to help others by understanding their interests and needs; this is something we could expect, as this kind of service requires to be in direct and close contact with people. The second most important soft skills has values very similar to the first one and it is the ability to act and complete operative tasks; this result makes sense, especially in the case of plant maintenance, where it is pivotal to take actions and effectively intervene. The third one still has high absolute scores for frequency and knowledge (about 3) and concerns comprehending situations and problems; again, it was predictable that when dealing with people in need, workers employed in such general services jobs are expected to be bright, sharp and solicitous.

5.8 Professional area: Organization and support services

The professional area *Organization and support services* includes a set of jobs devoted to managing, educating and assisting people. More specifically, this category involves role positions related to: management and training of personnel, education and training courses, services to the person, services related to tourism, restoration and hotels. We will see that this professional area stands out among the others from different points of view. For example, as regards the level of education, here the highest rate of people with a master or PhD certification are employed, about 17%.

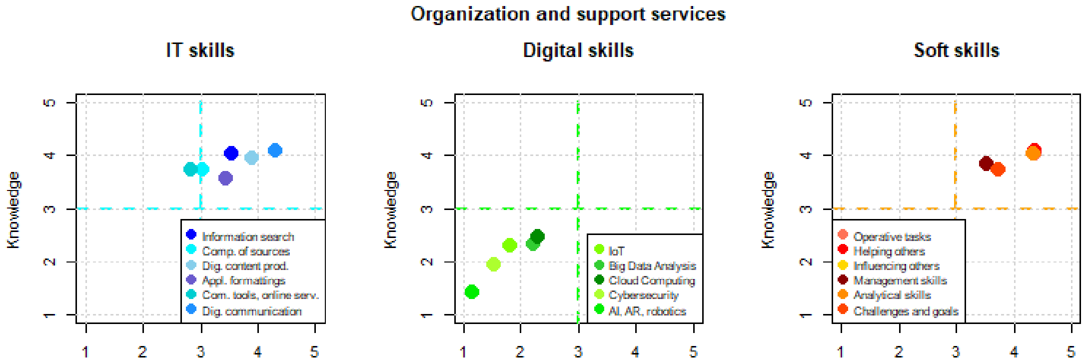
Graph 21 Centroids in the professional area: Organization and support services



Source: my research, data from Osservatorio Professioni Digitali (2019)

Average levels of IT and soft skills make this professional category stand out among the others, as well, and Graph 21 helps us understanding in which terms. Indeed, as Graph 5 already showed, centroid for IT competences is the second-highest for both frequency and knowledge, with scores of 3.51 and 3.84 respectively. It implies that people working in *Organization and support services* regularly need to deploy their computer skills and consolidated expertise is required. What makes this professional area excel with respect to the other ones is its centroid for soft skills, which has very high values both in absolute terms (4 for frequency and 3.9 for knowledge) and from the comparison with those of the other classes, as Graph 7 clearly illustrated. In other words, no other working areas deploy soft skills with such an intensity of utilization and knowledge as this one, on average. The centroid of digital skills, on the contrary, has quite low values, but it is more or less in line with those of the functions we have analysed so far.

Graph 22 Skills distribution in Organization and support services



Source: my research, data from Osservatorio Professioni Digitali (2019)

The breaking up of the centroid of IT, digital and soft skills seen in Graph 21 is shown in Graph 22. Once again, splitting global averages into their main constituent elements helps us deepen our comprehension about the hybridization of jobs phenomenon.

The six *IT skills* surveyed are not too much disperse in terms of depth of knowledge required, as their values range from about 3.5 to about 4; they are a bit more disperse if we look at the frequency of utilization, as they space from a little less than 3 to a bit more than 4. Provided that their values do not differ that much overall, the most important IT competences in Organization and support services are, in order: the ability to digitally communicate via various channels; the production of digital contents and the online information search of information and content storage. These results are meaningful, despite predictable, as we are considering a set of jobs where the contact with others is key, so that being able to effectively communicate via different channels and to provide accurate and reliable contents is relevant as well. It is worth noting that the competence of producing simple digital contents was never found among the most significant IT skills before; it might be due to the fact that jobs involving education and training require to implement this ability more than usual. Further explorations will be conducted in Chapter 6, which is devoted to the implications.

As concerns *digital skills*, it is interesting to observe that some of them are quite important, both in absolute values and by considering scores from the other professional areas. The most important digital competence concerns cloud computing and people employed in this field are asked to deploy their ability to use such systems with a frequency and depth of knowledge of about 2.5, indicating an occasional utilization and a more than basic understanding. The second and third most important digital skills are the capability to deal with big data analysis and IoT technologies. Again, results make sense: managing people implies managing their data as well, and when databases are too large and rich of information, it is important to get proper digital competences to adopt and take advantage of cloud computing services or, at least, to make some analysis autonomously. Something that was not expected, however, regards IoT competences: some workers declared they need to use them, even though rarely; this is quite curious.

Regarding the *soft skills*, also in this case, the centroids of the six competences surveyed are particularly close to each other, with the centroids of three of them lying in almost the same position and the other two presenting a perfect overlapping. Several considerations deserve to be made here. First of all, the three just mentioned points have very high levels of frequency (about 4.5) and of knowledge (a little more than 4); they are the ability to help others, to analyse and understand situations and problems and to carry out operative tasks. Other soft skills that are often used by people employed in jobs within this professional area and that require sufficient confidence levels consists in challenging themselves, influencing others and managing people, leading them toward the achievement of specific objectives. Centroids of the latter two competences overlap. The last skill mentioned is strictly related to management and organization, so it does not come as a surprise that the professional area Organization and support services is the only one when it reaches such high scores for frequency and knowledge required.

5.9 Conclusion

In this chapter, the "hybrid shape" of the six professional areas we are considering was brought to light. Many interesting findings emerged from this chapter that will be now summed up passing by each professional area.

As regards the *Operations* professional area, the analysis showed that to carry out tasks in jobs related to production, inbound logistics, procurement, outbound logistics and distribution is very important that workers possess, first of all, soft skills like the ability to complete operative assignments, to attain goals, to understand situations and problems and to help others (particularly clients) in the fulfillment of their needs. Secondly, workers within this professional area mainly use one IT skill, which concerns communication through several channels, from telephone and e-mail to voice over IP technologies. Digital competences are almost never required for tasks in these fields.

For jobs in the *Administration, finance and control* function, the most important skills in terms of both frequency of utilization and intensity of knowledge required are the IT skills to digitally communicate and to produce simple digital contents (in the form of reports, we suppose), and the soft skills of completing operative tasks, understanding and helping others, being able to challenge oneself and reach individual objectives. Digital skills in this professional area are more used than in the other ones – with an exception of the *Information systems* category; in particular, it emerged that people working with financial data and administrative systems and procedures have to occasionally use their competences in cloud computing platforms and big data analysis.

Similar results appear for people employed in *Sales and marketing* professional area, with the main differences that the IT competence of searching online information added to the most important ones and that the first digital skilled used concerns IoT technologies.

The *Information systems* area stands out among all the others for its high average levels of hybridizing skills: it is the most intense professional category for IT and digital skills and the second one in terms of soft skills, after Organization and support services.

Workers employed in the *General services* professional area are mainly asked to deploy soft skills; in particular, they are required to have the right disposition to help others, the ability to complete operative tasks and to seize challenges to reach individual goals. As of IT skills, they are only occasionally asked, however a good level of knowledge is required. Digital skills, on the contrary, are almost never asked and, in case, a basic understanding is overall sufficient.

The last professional area analysed is *Organization and support services*, which is the most intense among the others for its utilization and level of soft skills needed, while it is the second more important for its IT competences average scores.

Having found these and other features, one might wonder why jobs present different levels of such non-job-specific skills, whether there are any drivers. This issue will be mainly addressed in Chapter 7.

6. CHAPTER

MEASURING JOBS HYBRIDIZATION: THE *WHEEL OF HYBRID JOBS*

6.1 Introduction

An article of the World Economic Forum (2019), headlined "Hybrid jobs are on the rise", stated:

> "Jobs are going hybrid, and the trend is only set to continue".

It is well-known that the hybridization phenomenon is spreading across professions and industries and that it is not bound to be just temporary nor reversible.The point is:

> How is it possible to measure at which step jobs are along the path toward hybridization? Are all professional categories equally hybrid?

This chapter addresses these questions. In particular, we will present an original model to measure the hybridization of jobs. It has to assess the intensity of hybridization of jobs and at the same time to provide organizational and managerial implications tailored to the hybrid features that emerge. In practice, we wanted to find a way to convey these pieces of information by identifying a number which indicates the level of hybridization and by making it univocal.

This chapter is organized as follows: paragraph 2 explains the methodology adopted for the construction of the model, paragraph 3 outlines results and paragraph 4 provides interpretations and discussions about the findings.

This model is applied to the six professional areas of interest, but it might be applied to whatever jobs or job categories.

6.2 Methodology

In this paragraph, we will explain how we measured hybridization through the creation of an original model. After taking a look at data processing, we illustrated the three main steps we followed for building the model. As we will see, two dimensions are needed to identify univocally the hybridization level of jobs: the hybridization intensity and the type of effort. Their combination is pivotal for measuring the hybridization of jobs and for deriving managerial and organizational implications.

In the following paragraphs the main steps are presented. Computations and Demonstrations are extensively illustrated in the *Appendix – Chapter 6*.

6.2.1 Data processing

We started from a database of 300 observations (rows) and 44 variables (columns), corresponding to the information collected through the survey:

- 10 questions concerned respondents' profile and, in particular, some personal data and working information (section 1 of the survey);
- 12 questions were referred to the frequency of utilization and the level of knowledge of 6 IT skills (section 2 of the survey);
- 10 questions concerned the sample's frequency and knowledge about 5 digital skills (section 3 of the survey);
- 12 questions investigated the levels of frequency and knowledge of 6 soft skills (section 4 of the survey).

Because of missing data, only responses from 283 workers were considered.

Other 9 columns (vectors) were computed from the 44 already provided by the survey and they conveyed information, for each worker, on:

- The mean frequency of utilization of the 6 IT skills (let us identify it as column a);
- The mean knowledge for performing the 6 IT skill (column b);
- The mean frequency of utilization of the 5 digital skills (column c);
- The mean knowledge for performing the 5 digital skill (column d);
- The mean frequency of utilization of the 6 soft skills (column e);
- The mean knowledge for performing the 6 soft skill (column f);
- Then mean of the frequency means of: IT, digital and soft skills (the mean of columns a, c, e; let us call it column g);

- Then mean of the knowledge means of: IT, digital and soft skills (the mean of columns b, d, f; let us call it column h);
- The overall mean of frequency and knowledge of the three skill families (the mean of the columns g and h; let us call it column i).

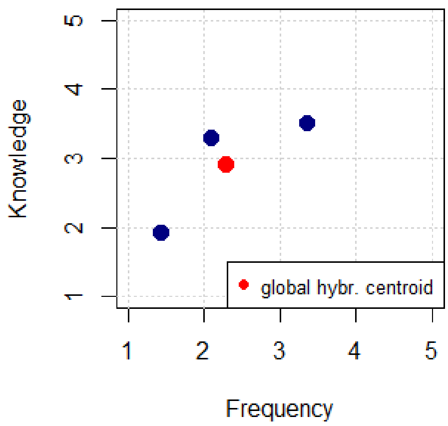
While in columns comprised in sections 2, 3 and 4 of the survey values attributed to frequency and knowledge were integers ranging from 1 to 5, in columns a) to i) they assumed continue values, as they resulted from the computation of the mean.

6.2.2 The global hybridization centroid

Our initial purpose was to find a value that could indicate, for every professional area, its hybridization level. For this reason, we considered one functional category at a time and we computed the average levels of frequency and knowledge for each of the three hybridizing skills; by plotting them in a graph we obtained three centroids. Each of them says which frequency of utilization and depth of knowledge are actually needed from workers in terms of IT, digital and soft skills in a specific workplace.

To condense these three points into one, we computed their centroid, which we called of "global hybridization" or "global hybridization centroid". It reveals, for every professional area, the average level of frequency and knowledge of the hybridizing skills taken together. It means that the average worker employed in a certain field actually needs to use hybridizing skills with the frequency and depth of knowledge that emerged from the computation of the global centroid of hybridization (graphical illustration is exhibited in Graph 23).

Graph 23 Global hybridization centroid: the case of Operations area



Source: my research, data from Osservatorio Professioni Digitali (2019)
The centroids for the three skills characterizing the Operations area are represented by the blue points, while the red one represents its global hybridization centroid

6.2.3 First variable: *Hybridization Intensity*

Having obtained these pieces of information through a pair of coordinates, namely those of the global hybridization centroid, we wanted to convey them into just one number. For this reason, we needed to aggregate values of frequency and knowledge in every functional family.

The first issue we faced concerned how to aggregate such dimensions and how to weight them, as literature did not say anything about which of them dominate on the other. Therefore, not to be hindered by this possible obstacle, we had to make an assumption:

ASSUMPTION: the dimensions of frequency and knowledge have the same weight in the computation of the hybridization coefficient and it is equal to 0.5.

Based on it, we computed the hybridization coefficient for each professional area by calculating a weighted average of the levels of frequency and knowledge. As they both vary between 1 and 5, it resulted that the hybridization coefficient, which consists of their mean, also takes continuous values between 1 and 5.

The *hybridization intensity* for every job category was a rate computed by normalizing the hybridization coefficient on a scale 0 – 1.

The *hybridization intensity* of each professional area tells us at what point jobs are in this evolution process (from 0 to 1)

In particular, in jobs with an *hybridization intensity* close to 1 workers are required to perform IT, digital and soft skills at the maximum level possible, namely very frequently and harnessing strong knowledge. On the contrary, workers displaying the lowest *hybridization intensity*, 0, never use hybridizing skills. Following this method, any job is associated to a number between 0 and 1.

Box 2 Clarification of the hybridization intensity

We need to be careful in the interpretation of the hybridization intensity: the corresponding rate has not been computed to weigh the hybrid component of a job against the utilization of technical skills. For its construction, this number identifies the magnitude of hybrid skills pervasiveness or, in other words, the actual relevance of such competences in a workplace with respect to the theoretical maximum utilization, measured as the mean of frequency and knowledge levels.

6.2.4 Moving to the second variable

The *hybridization intensity* is not sufficient to give a whole information on job's hybridization.The reason is that the same rate of hybridization intensity could derive from many different combinations of frequency and knowledge levels. For instance, 0.4 might result from:

- A high frequency score and a low knowledge one, for example 0.2 and 0.6;
- A low frequency score and a high knowledge one, for example 0.6 and 0.2 or 0.7 and 0.1;
- the same scores of frequency and knowledge, for example 0.4 and 0.4.

These three scenarios have the same *hybridization intensity*, so that they are all represented by a rate of 0.4, but have different organizational implications. This rose the need for considering a second dimension, which enables us to distinguish between jobs – or, in our case, job categories - with the same overall hybridization intensity, but diverse internal features.

6.2.5 Second variable: *Type of Effort*

We found that despite the *hybridization intensity* was significant for determining the overall position of a professional area within the hybrid trend, it exhibited a relevant weakness. Indeed, because it was computed assuming that the frequency and knowledge dimensions had the same weight, we could no longer distinguish whether these two dimensions were somehow balanced or if one dominated on the other. Having this information is pretty important in order to derive concrete implications. For this reason, we run a second step within the procedure for constructing our model and we created a second dimension, which we called-*type of effort*.

The efforts are named:

- *organizational effort* refers to changes of *operative processes* the role holder follows for effectively and efficiently performing the required tasks: layout of the workstation, work tools and methods, sequence of activities, organizational routines, social interactions;
- *cognitive effort* refers to changes of *conceptual patterns and mental pathways* the role holder is required to follow for framing the emerging circumstances, mobilizing the necessary skills, acting in an appropriate way, behaving in an appropriate manner.

The *extent* (and the *type*) of the effort the workers put in depends on the combination between *level of knowledge* and *frequency*:

- A *level of knowledge* that is *equal to frequency* leads to a *balance* between *organizational effort* and *cognitive effort* (both are low, medium or high): the number of times the role holder is required to harness non-technical skills (IT, digital and soft ones) *varies together* with the depth of required knowledge.
- the more frequency levels are higher with respect to the depth of knowledge needed, the more a worker has to make an organizational effort and his job is skewed toward organizational tasks;
- on the contrary, the lower the frequency level with respect to the performed level of knowledge, the more tasks require cognitive effort;

We measured the type of effort as explained in detail in *Appendix – Measuring the type of effort* and we made the resulting values range between -1 and 1. The interpretation is the following:

- effort equals to 0 indicates that the role holder experiences both organizational (*operative processes*) and cognitive (*conceptual patterns and mental pathways*) efforts at the same level (efforts are balanced);
- the more the value is distant from 0, the wider is the unbalance between tasks. In particular, negative values point out a preponderance of *organizational effort*, while positive ones show the major relevance of *cognitive effort*.

Box 3 Clarification on the type of effort

> We need to pay attention to correctly interpret the coefficient referring to the type of effort. A negative number does not indicate an undesired or suboptimal situation. We just set, by convention, that values between -1 and 0 denote tasks where organizational effort dominates and that values between 0 and 1 identify tasks with more intense cognitive exertion. The farther from 0 the number is in absolute value, the stronger the unbalance.

Implications from the direction of effort have an impact on the personality traits of the workforce which best suit specific functional roles.

For example, tasks which require to perform non-technical skills with elevate frequency call for people with organizational abilities, enough patience and ease in frequently switching between the deployment of different competences. On the contrary, tasks where profound knowledge of hybridizing skills is asked imply that people perform tricky activities that require some degree of expertise, an overall carefulness and an intense cognitive effort.

6.2.6 *Hybridization Index*: Hybridization Intensity and Type of Effort

The *hybridization index* is the indicator which univocally identifies the *hybridization level* and the *features* of a job or a job category. It is constituted by two dimensions:

Hybridization Index (Hybridization Intensity; Type of Effort)

which are shown in Graph 24:

- the *hybridization intensity* is represented as isoquants;
- the *type of effort* is indicated on the x-axis.

All the points lying on the same isoquant represent jobs with the same overall *hybridization intensity*, but a different mix of *frequency* and *level of knowledge*:

- these lines are called "isoquant I_n";
- where "I" refers to the *hybridization intensity* of rate "n";
- therefore it ranges between 0 and 1.

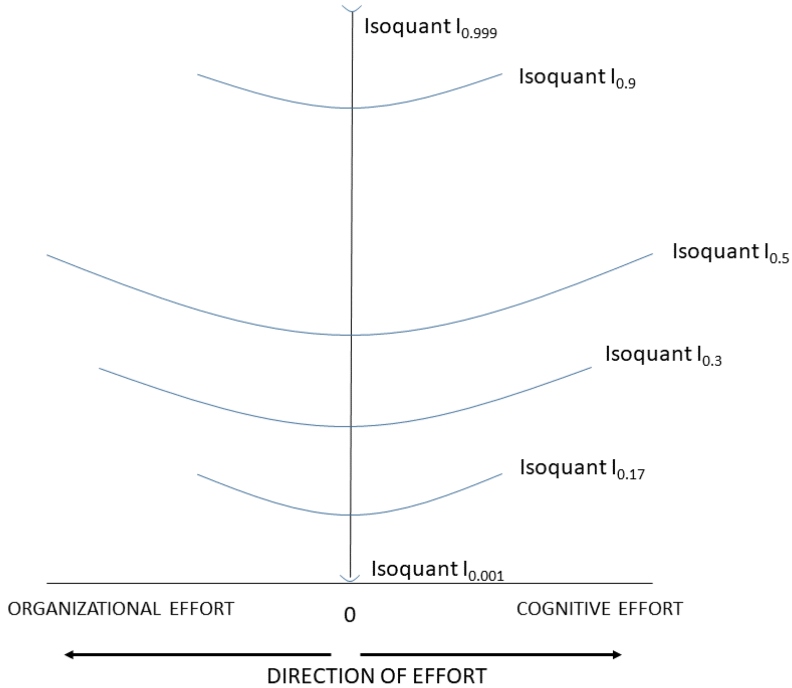
We can notice from Graph 24 that the length of isoquants differ so that the more isoquants get closer to extreme levels of intensity (namely, 0 and 1), the shorter they become; on the contrary, the longest isoquant is in correspondence of a hybridization rate of 0.5 (only in this case the extreme points of the Isoquant reach the maximum unbalance possible in the type of tasks, namely -1 and 1). The underlying reason is analytically illustrated in *Appendix – Measuring the type of effort*.

In brief, we can explain that by looking at the number of possible combinations of *cognitive* and *organizational efforts*:

- Jobs with an extreme *hybridization intensity* (with a value close to 0 or 1) have similar values for frequency and knowledge (respectively, both very low or very high scores). It follows that even when skewness between these two dimensions is maximum, they still do not differ too much. In other words, even in the extreme case where a dimension is deployed at maximum and the other one at minimum, their unbalance remains small.
- Jobs characterized by a medium *hybridization intensity* might present a wide range of combinations between cognitive and organizational tasks; the number of possible mixes increases the closer the hybridization intensity is to 0.5. In correspondence of the latter value, the greatest variety of scenarios occur.

Everything we have illustrated in this paragraph, any computation we made or demonstration and procedure we followed is extensively illustrated and explained in the Appendix – Chapter 6.

Graph 24 Isoquants for hybridization intensity



Source: my research

6.3 The *Hybridization Wheel*

In the previous paragraph, we observed that isoquants in Graph 24 are longer in correspondence of central values of intensity (0.5) and shorter when the hybridization intensity gets closer to 0 or 1. We noticed that if we drew all the isoquants for every possible level of intensity, we obtained a full circle, which is depicted in Graph 25.

Axis

On the *x-axis*, the dimension related to the type of effort is represented and values range from -1 to 1.

On the y-axis, the *hybridization intensity* is shown and values range from 0 to 1.

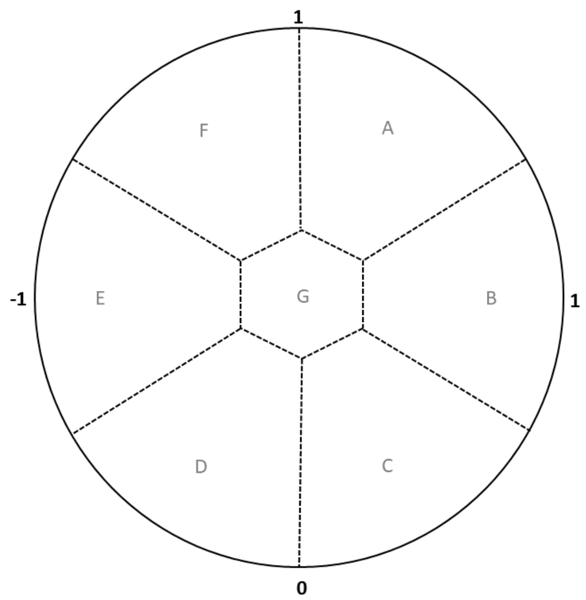
Hybridization Index

Every point within the circle can be identified by a pair of coordinates (hybridization index [x,y]) and indicates a professional area with specific features: depending on which scores of hybridization intensity and of type of effort a job (or a category of them) displays, a point can be positioned inside the graph.

No points could be plotted outside the circle, as they represent non-plausible situations (for further details see Appendix – Chapter 6).

Different positions within different areas unequivocally indicate different scenarios and diverse managerial and organizational implications.

Graph 25 The hybridization wheel



Source: my research

In order to foster immediate understanding and to make this model as much useful as possible to HR managers and business leaders, we divided the circle into seven macro-areas, which we named with letters from A to G (see Graph 25). Each slice on the graph is the locus of jobs with different features and lead to different implications.

In terms of *Type of Effort,* the *Hybridization Wheel* shows that:

- slices from A, B and C indicate jobs where *cognitive effort* dominates;
- slices from D, E and F point out jobs where *organizational effort* prevails;
- slice G identifies a balance between the two efforts (differences are negligible).

In terms of *Hybridization Intensity*, the *Hybridization Wheel* shows that:

- slices A and F reveal a high *hybridization intensity*;
- slices E, G, B present a medium *hybridization intensity*;
- slices C and D display a low *hybridization intensity*.

6.4 Results

We will now show the findings that emerged from the application of our model to the six professional areas of interest. After having taken a look at the positions of their global hybridization centroids, we will focus on the two dimensions that are necessary to univocally determine the hybridization of jobs.

We combined the information provided by the hybridization intensity and by the direction of effort to obtain the *hybridization index*, which fulfills our aim of univocally determining the hybridization of jobs and providing useful insights in terms of organizational implications.

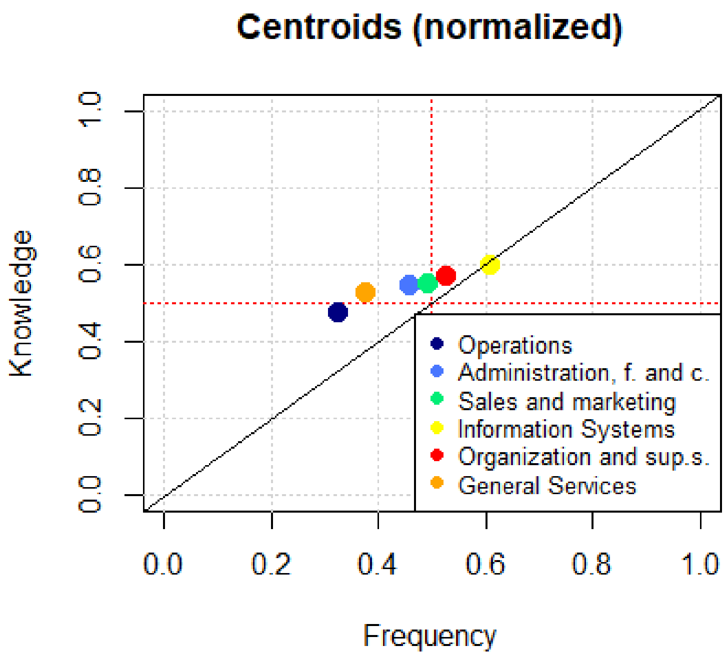
Global hybridization centroid of the six professional areas

For each of the six professional areas of interest, centroids of global hybridization are shown in Graph 26 and their average level of frequency and knowledge of hybridizing skills, which are their coordinates, are exhibited in Table 13.

It emerged that all centroids are positioned in the central area of the graph. The overall level of utilization of hybridizing skills is quite diverse across functional categories, while differences in terms of depth of knowledge are less pronounced. Values for utilization varies between about 0.3 and 0.6, indicating that hybridizing skills are effectively required in workplaces and, in some cases, workers are asked to use them more than occasionally. Scores for knowledge, which present central values as well, vary within a more narrow interval, from about 0.5 to about 0.6. It implies that it is not sufficient that workers have a basic knowledge of hybridizing skills; on the contrary, they need to possess them at an operative level, no matter their job category .

Looking at the single professional areas, it is worth noting that while the *Information systems* one stands out for the highest values in both frequency and knowledge, the *Operations* job category distinguishes from the others for the opposite reason.

Graph 26 Global hybridization centroid of the six professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019)

Table 13 Global hybridization centroid of the six professional areas

	Frequency	Knowledge
Operations	0.32	0.48
Administration, f. and c.	0.46	0.55
Sales and marketing	0.49	0.55
Information systems	0.61	0.60
Organization and supp. s.	0.53	0.57
General services	0.38	0.53

Source: my research, data from Osservatorio Professioni Digitali (2019)

The first dimension: the hybridization intensity *of the six professional areas*

From the global centroids of hybridization, we computed the hybridization intensity for every functional family (see Table 14); this was the first dimension we need for obtaining the hybridization index and a pivotal element for the implementation of our model.

It emerged that the number that summarizes the hybrdiziation level of jobs ranges from 0.4 to 0.6 (on a normalized scale 0-1). This indicates that important differences exist between functional areas: deploying the hybrid component of work at 40% with respect to the theoretical maximum or at 60% have relevant implications, as we will see.

We want to clarify that it is not always the case that the highest the hybridizing rate, the better; on the contrary, a certain degree of frequency and knowledge might be considered optimal depending on the professional area under consideration.

Table 14 Hybridizing rates of intensity of the six professional areas

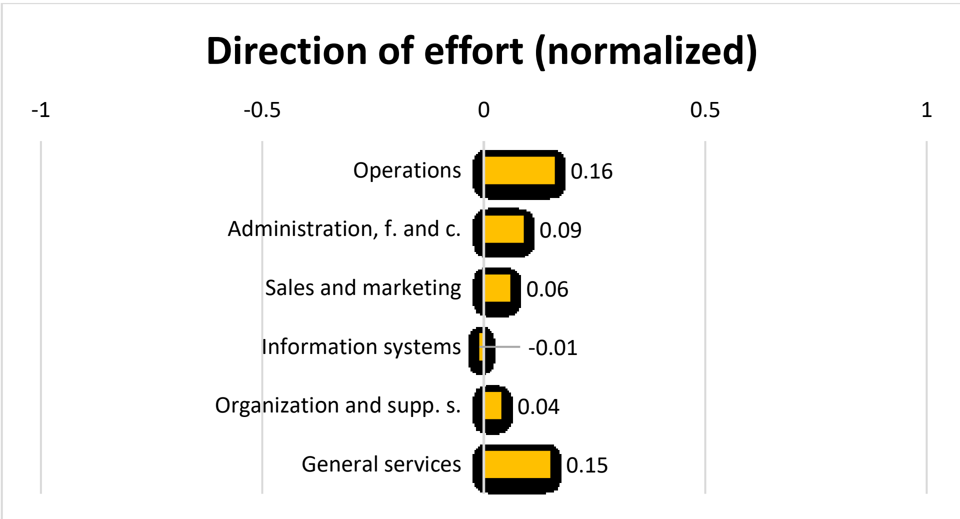
Operations	0.40
Administration, f. and c.	0.50
Sales and marketing	0.52
Information systems	0.60
Organization and supp. s.	0.55
General services	0.45

Source: my research, data from Osservatorio Professioni Digitali (2019

The second dimension: the type of effort of the six professional areas

As regards the second dimension, we computed the degree of unbalance in the nature of tasks to find the main direction of effort required in the workplace. Results are illustrated in Graph 27, where numbers on the right of the bars indicate the (normalized) distance of the global centroid of hybridization from the corresponding point in case of a perfect balance between the efforts. As previously seen, values with a positive sign indicate a preponderance of cognitive tasks, those with a negative sign refer to a predominance of organizational ones.

Graph 27 Type of effort of the six professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019

It emerged that all job categories are slightly skewed toward cognitive tasks, with the exception of the *Information systems* area. In the *Operations* and *General services* functional categories, the preponderance of cognitive tasks is higher than in the other ones, indicating that the knowledge levels that emerged are higher than expected if compared to those that the other professional areas usually require, given a certain frequency level. Despite two functional families present the highest skewness with respect to the others, if we look at their values we realize that the preponderance of cognitive effort is not particularly significant: it means that a gap of 16% and 15%, respectively, exists, between the two types of effort.

It also emerged that the only functional category whose value presents a negative sign, indicating a skewness toward organizational tasks, is the *Information systems* one; however, its value is so small (-0.01) that we could say that a sound balance between tasks occurs.

The Hybridization Index and the Hybridization Wheel

Having computed for each professional area the two dimensions and having analyzed their results separately, we are now able to find their *hybridization index* and to get a clearer picture of their hybrid features and implications by implementing the *Hybridization Wheel* model.

The *Hybridization Index* enables to univocally identify a job or job category, so that having this information, one can know not only the overall hybridization level, which can encompass different situations in terms of frequency and knowledge (as explained in paragraph 6.2.4), but also some internal characteristics.

Table 15 shows the hybridization index (from now on HI) of the six professional areas of interest.

Table 15 Hybridization indexes of the six professional areas

$HI_{Operations}$ (0.40; 0.16)
$HI_{Administration}$ (0.50; 0.09)
$HI_{SalesMarketing}$ (0.52; 0.06)
$HI_{InformationSystems}$ (0.60; -0.01)
$HI_{Organization}$ (0.55 0.04)
$HI_{GeneralServices}$ (0.45; 0.15)

Source: my research, data from Osservatorio Professioni Digitali (2019

Let us remember that the first number indicates the hybridization intensity and ranges in an interval [0,1], while the second one provides information on the type of effort and ranges in an interval of [-1,1], taking positive values in case the cognitive effort dominates, negative ones when organizational tasks prevail.

The dimensions that determine the HI can be used as coordinates to graphically visualize the positions of the corresponding jobs. We plotted the hybridization intensity on the y-axis and the second one on the x-axis; preliminary scatter on the positioning of the six job categories in terms of hybridization are exhibited in Graph 28.

It emerged that a kind of negative relationship exists between the direction of effort and the hybridization intensity: professional areas with the highest intensity of hybridization are those with a minor unbalance between cognitive and organizational tasks; the bigger the gap between them, the lower the overall intensity.

To make the interpretation of results easier and to facilitate the identification of proper organizational implications, we plotted the same points in the *Hybridization Wheel*, where 7 different areas are outlined (see Graph 29).

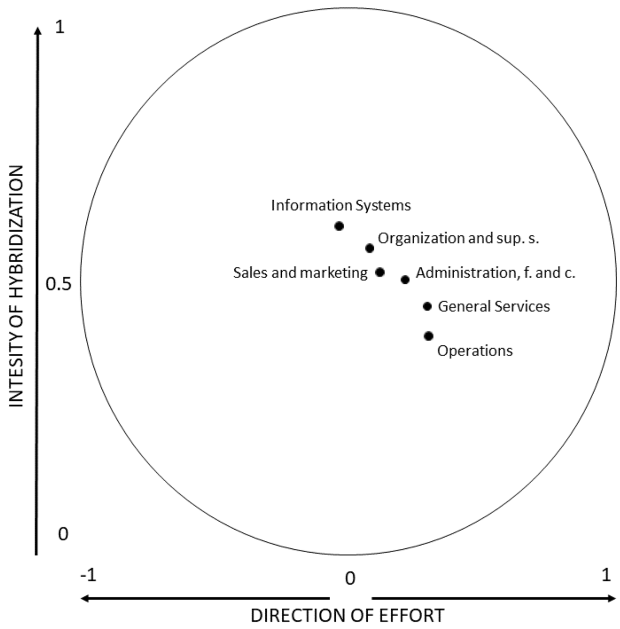
Points indicating the hybridization level of job categories have different positions withing the wheel, despite they all are located close in the central part of the graph.

> The seven areas into which the graph is divided have the purpose of helping the interpretation and discussion of results and must not be understood as neatly separated categories.

Organization and support services, Sales and marketing, Administration, finance and control professional areas are located in slice G, which indicates an intermediate intensity of hybridization and a quite balanced nature of tasks. This implies that workers employed in these functional families have to use hybridizing skills occasionally and with a good level of knowledge, while fairly alternating efforts of organizational and cognitive nature, with the latter being a little more important than the former. These functional families need people who are able to perform hybridizing skills at sufficiently good levels.

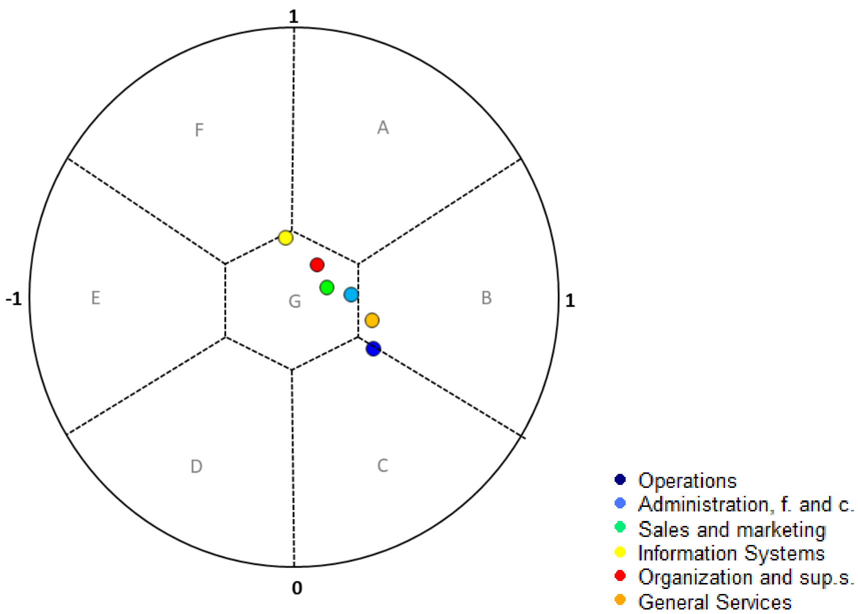
As concerns the *Information systems* category, it is still in the central area, but it is close to slice F. Area F includes all the jobs with elevated intensity of hybridization and skewness toward organizational tasks. Despite this functional category has an almost irrelevant preponderance of organizational efforts (the value for the type of effort is -0.01), some of the considerations that apply to area F in terms of intensity can be taken under consideration, with softer tones.

Graph 28 Preliminary scatters



Source: my research, data from Osservatorio Professioni Digitali (2019

Graph 29 The hybridization wheel: results from the six professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019

The implications we might derive are that workers employed in this functional area are asked to make organizational and cognitive efforts in the same proportion. If we take into account that the Information systems category stands out from the other for its elevated intensity of hybridization (0.6), we can derive that workers often use hybridizing skills and that a quite consolidated knowledge is necessary. Thus, this functional area will need to hire or invest in training for people who are more inclined at quickly developing and properly deploying hybridizing skills (we will see their profiles in Chapter 7).

The *General service* professional area lies in slice B. This part of the graph encompasses all the jobs with an intermediate intensity of hybridization; as regards the type of effort, tasks are more directed toward cognitive exertion. It implies that workers in this job category have to use hybridizing skills with moderate intensity (0.45) and that behind this result a larger relevance is attributed to the depth of knowledge rather than to the frequency level. Indeed, a type of effort equal to 0.15 indicates that for performing tasks these workers need to be ready to use hybridizing skills with quite profound knowledge with respect to the number of times they have to deploy them. We might suggest that proper training is necessary on a regular basis to put people in the condition of performing hybridizing skills at desired level when asked.

The *Operations* job category is at the border between slice B, which we have just illustrated, and slice C. The latter distinguishes from the former for its lower intensity of hybridization. This functional category has a similar type of effort with respect to General service, as also in this case a value of 0.16 indicates that cognitive tasks are relatively more important than organizational ones. However, Operations distinguishes from the previously seen professional area for a lower score of hybridization intensity (0.4). Considerations made for General service professional area might apply, but considering that the overall level of hybridization is lower. It means that also people which are a little less inclined to acquire and perform hybridizing skills might be suitable for roles in the Operations job category.

6.5 Conclusion

In this chapter, we measured the hybridization of jobs with an original model. We arrived at a solution to indicate in a univocal manner the hybridization level of professional areas while at the same time providing coordinates to derive useful organizational and managerial implications.

We conveyed these pieces of information by creating what we called the *Hybridization Index*. It combines the information provided by the hybridization intensity, which indicates the overall intensity of hybridizing skills, and by the direction of effort, which identifies the magnitude of the unbalance in the type of efforts required in a specific workplace.

To make the Hybridization Index a useful practical tool for hiring managers, HR managers and business leaders, we integrated it in a model we created, that we called the Hybridization Wheel. It appears as a graph with a circular shape and encompasses all the possible situations that might occur in terms of hybridization. To foster its concrete adoption, we sketched some areas, or *slices*, which are the locus of jobs presenting similar situations and for which similar managerial and organizational implications apply.

We used this model to study the six professional areas of interest but this tool has been thought for a universal application, so that it can be used to find the hybridization level of single jobs or individual workers.

After having analyzed and interpreted the hybridization indexes of the six functional families, some directions and recommendations are provided by looking at their position on the Hybridization Wheel. Suggestions mainly relate to the personnel’s profiles that best fit the requirements of the different professional areas in terms of hybridizing skills.

The next chapter continue in this direction and helps move forward in practical terms, by illustrating up to which point people with different education levels, age or gender are more inclined to develop specific hybridizing skills.

7. CHAPTER

THE *HYBRIDIZATION WHEEL*: MANAGERIAL IMPLICATIONS

7.1 Introduction

Having seen and measured IT, digital and soft skills across the sample and across jobs in Chapters 3, 4 and 5, we need now to consider them in light of results from Chapter 6 and to move forward, in an even more concrete perspective, so that our findings are eligible to fall into real life and to provide social utility.

This chapter is aimed at illustrating the major implications for hiring and human resource manager, for business leaders, but also for people involved in organization, training, career development and education.

In this chapter, implications on education, age and gender were outlined.

Paragraph 2 is devoted to exploring whether education has a role in determining IT, digital and soft skills performance in the workplace. In particular, four different educational levels were identified and their impact on each of the three hybridizing skills was investigated, keeping separated the dimension of frequency from that of knowledge, to get richer insights. It emerged that some educational qualifications have an impact, either positive or negative, on non-job specific (or hybridizing) skills. To broaden knowledge on hybrid jobs, we also explored how people with different education levels are employed in diverse professional areas; also in this case, peculiar features of specific functional families emerged.

In paragraph 3, we outlined the importance of the workforce's age as a determinant of IT, digital and soft competences required on the job. We compared results for people aged under-40 and over-40 and, to go into details, we distinguished among four generations: the Z, Y, X ones and the baby boomers.

Paragraph 4 was aimed at analysing whether and in which direction gender affects frequency and knowledge levels of the three hybridizing skills.

Analysis, considerations, interpretations and implications are proposed throughout the whole chapter.

7.2 Implications on Education

We are interested in finding out whether and to which extent the education level of people have an impact on their actual utilization of IT, digital and soft skills and on the level of knowledge they are required to possess and deploy.

In this paragraph, we will show how IT, digital and soft skills distribute through the sampled workforce, controlling by their education. For this purpose, three comprehensive graphs will be exhibited. Four levels of education were considered, based on workers' qualifications, which could be: secondary school diploma, high school diploma, bachelor or master's degree, PhD or a II level master. Points from each category were fitted by a smoothing spline, a line that interpolates and describes the relationship between two variables by minimizing curvatures to smooth noisy data.

7.2.1 Education and hybridizing skills

IT skills grow with education

People's level of education has a strong impact on the intensity of utilization and knowledge of IT skills. Graph 30 help us to explore how different qualifications lead to various combinations of utilization and knowledge of IT competences required in the workplace; it also enables us to make comparisons between groups of workers with diverse educational level. It shows that the four lines interpolating data have about the same linear trend, but different slopes and lengths.

The smooth blue line, the one referring to workers with *secondary school diploma* only, is placed below the other ones in the graph and it never reaches the top-right area. It means that people who stopped their education path before high school, perform the lowest levels of both IT skills frequency of utilization and depth of knowledge in workplaces. In other words, people with low education levels are asked to perform computer skills fewer times and with a lower knowledge with respect to the other workers.

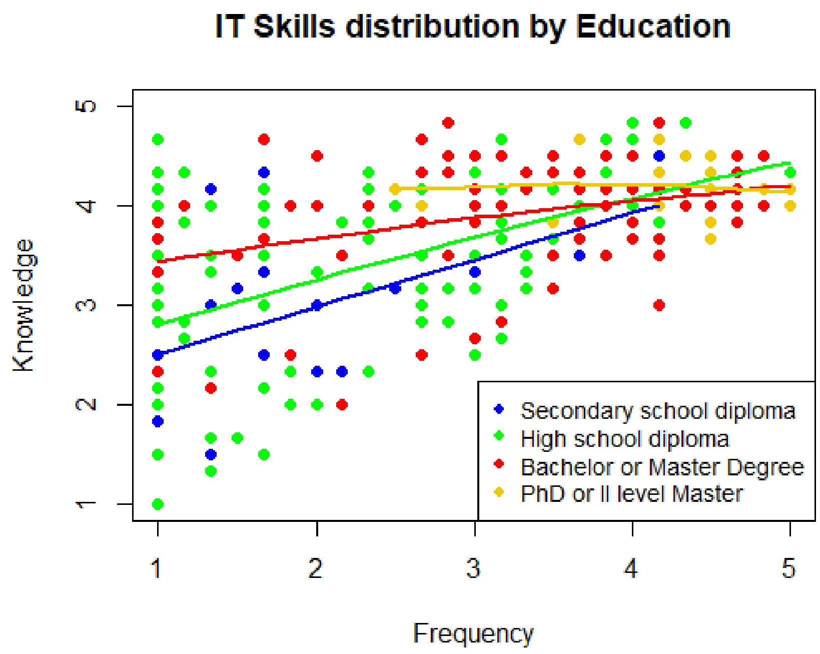
The green line is a little above the blue one and represents workers with a *high school* diploma (secondary education). It has about the same slope of the previous one, meaning that in both cases when the frequency of utilization increases by one, the required knowledge level increases as well, but at a smaller rate. The green line is the one that gets closest to the top-right angle of the graph, meaning that workers of medium educational level not only are expected to acquire a deeper knowledge of IT tools as their use increases, but they might even be asked the highest expertise compared to their colleagues.

Coming to high educational levels, the *red and the gold lines* represent people with a bachelor's or master's degree and with a Ph.D. or II level master, respectively. In both cases, the slope of the lines is far flatter than the blu and green ones, indicating that the greater the qualifications, the less an increase in the utilization of IT skills leads to higher knowledge levels. Even when such competences are rarely asked (in correspondence of frequency equal to 1), values of the red and the gold lines are higher with respect to the other two, indicating that people with higher education levels are expected to have a more profound knowledge of IT skills with respect to the other workers, no matter the frequency of their actual utilization.

In particular, the *gold line*, which refers to people with very high qualifications, is almost horizontal and it starts in correspondence of sufficiently high levels of frequency; this implies that people with a brilliant education path are asked to deal with computer programs, advanced communication tools (like video conferencing or data sharing ones) and online services always with medium to high frequency, never just occasionally.

To sum up, IT skills are asked to workers with low and medium education levels with increasing knowledge as their frequency of utilization grows. This is also true for people who obtained a university degree, but the relationship between the two dimensions of frequency and knowledge is weaker. For workers with very high qualifications like a Ph.D. or a II level master, frequency of utilization is remarkable and knowledge levels are elevated. The fact that the latter workers are never asked to use their IT competences just rarely or occasionally, means that they are required to use some of their endowments at the utmost; in other words, their high abilities are fully exploited.

Graph 30 IT Skills distribution by Education



Source: my research, data from Osservatorio Professioni Digitali (2019

Digital skills and education

The relation between digital skills and education is quite peculiar. A linear association between utilization and deployment of digital competences seems to exists in workplaces for people with medium and high education, but not for workers with low or very high qualifications.

Graph 31 helps us understand this curious situation. Again, four smooth lines interpolate the aforementioned education categories we are considering. It emerged that lines representing workers who attained a high school diploma, a bachelor's degree or a master's degree are not curved at all and their slope is relatively steep, as they almost reach an inclination of 45°. This means that for workers with medium or high education, knowledge increases almost at the same pace of frequency: the more one gets used to dealing with digital technologies like cloud computing, cybersecurity, big data, artificial intelligence and so on, the more they are asked to perform such skills with depth of knowledge. This could seem obvious, but the blue line and the gold one show it is not always the case. Indeed, the two smooth lines which fit points corresponding to workers with the highest and the lowest qualifications (namely, a secondary school diploma and the Ph.D. o II level master), are very sharp. It makes evident that this kind of data distribution is not the standard one as the curvature of the relationship is far from what one usually expects.

We will now illustrate some findings and suggest some considerations and possible interpretations.

People with *low education*, namely those who stopped their education immediately after secondary school, generally use IT skills very rarely and with a low depth of knowledge. Indeed, their digital performance is represented by a line (the blue one in Graph 31) which stops when low frequency and medium knowledge levels are reached. It is also singular that the spline is not linear at all and, on the contrary, it presents sharp changes of direction.

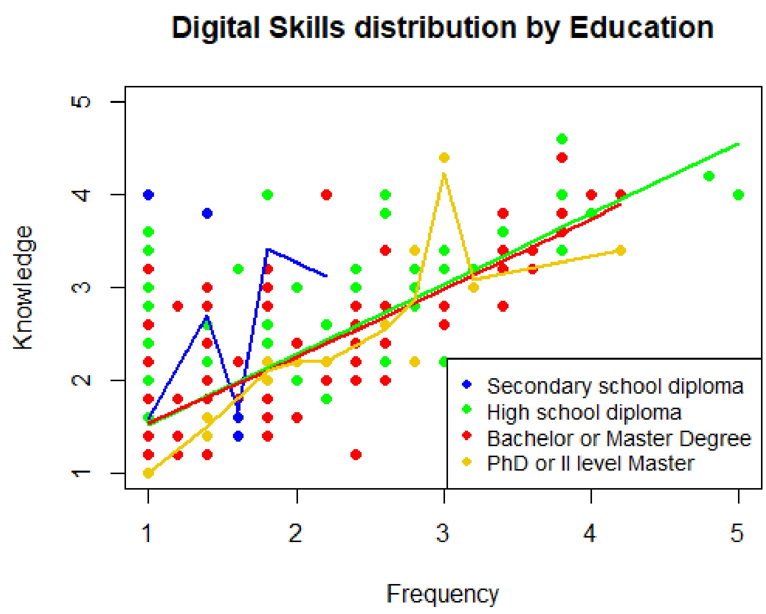
In practice, it indicates that workers with *low education* are seldom aked to perform digital tasks and, according to a possible interpretation, it might explain why they have not developed profound digital competences.

By analysing the opposite case, where people got very *high qualifications*, interesting considerations could be drawn, as well. Indeed, the gold line starts with a steeper slope than the green and red ones already observed, indicating that these workers are asked to perform digital skills with deeper knowledge the more frequently they use them. We must notice that this is true only up the frequency level reaches level 3 of the layer, which is the central value. We can thus state that people with *high education* are expected to become familiar and confident whit digital technologies at a very fast rate, which goes hand by hand with the frequency of their utilization; in other words, they are asked to learn fast and perform well from the beginning. This implies that their high qualifications signal to their employers that they have a big potential and that they are somehow authorized to demand a lot of them. If we look at the second part of the gold line, from frequency equal to 3 on, we can notice a peculiar trend: it decreases at first and then continues increasing at a lower slope with respect to the green and red lines. It might indicate that when a certain level of frequency (and the corresponding intensity of knowledge) is reached, most of the competences have been acquired with sufficient depth, according to the tasks to be performed. Therefore, when the frequency exceeds a certain threshold, the increase in knowledge is smaller, as the residual digital competences to learn are fewer and fewer.

Also people with *medium education* are represented by a smoothing spline which is not linear; furthermore, it is the only one which gets to the maximum frequency of utilization and an almost maximum depth of knowledge. It means that concluding the educational path with the completion of high school brings people to develop higher skills related to IoT, big data analysis, cloud computing, cybersecurity, artificial intelligence, augmented reality and robotics.

One possible interpretation could be that while people with low education are not sufficiently prepared to be taught – and effectively learn – digital abilities, those who received very high education are expected to be able to quickly catch novel things and to promptly develop digital skills, when they do not already possess them. Interestingly, such workers are the only ones who are not demanded to possess any digital skills when frequency is 1, indicating that having received an high education does not imply having developed these competences, on the contrary to workers with lower qualifications.

Graph 31 Digital Skills distribution by Education



Source: my research, data from Osservatorio Professioni Digitali (2019

To sum up, Graph 31 tells us that people with a medium or high education level, namely those with an high school diploma and a bachelor or master degree, present a positive linear trend in the relation between utilization of digital competences and depth of their knowledge. This does not apply to people with low or too high qualifications: the former are rarely asked to use digital skills in the workplace and their needed knowledge never exceeds a relatively low level; the latter are put in front of high expectations (also) in terms of learning digital competences. In particular, workers with a PhD or a II level master are not expected to possess digital skills at the beginning, but they are asked to perform them with a depth of knowledge that increases together with the frequency of utilization; this occurs up to when certain levels are reached, then the relation between the two dimensions comes back to a flatter trend.

Soft skills distribution by education

The relation between soft skills and education is again not regular, as graph Graph 32 illustrates.

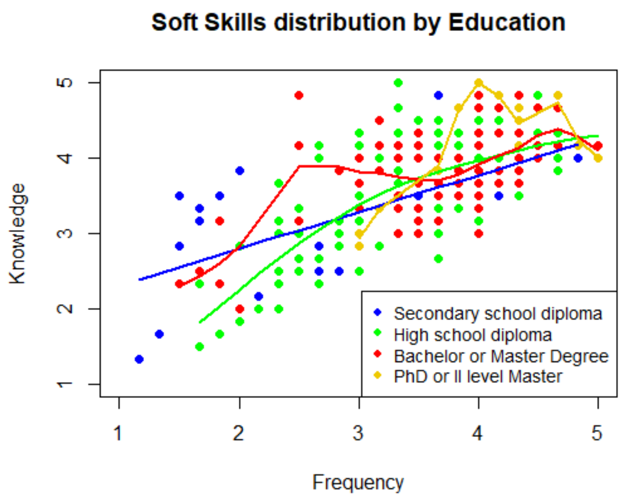
A linear reltionship exists only for workers with low education (see the *blue line*). Its positive slope and the fact that the angular coefficient is rather smaller than 1 imply that people who stops studying after the secondary school are actually required to deploy their soft abilities at lower levels with respect to the corresponding growth in the frequency of their utilization.

A faster increase in knowledge, relative to the frequency level, appears for workers who received a *medium education*. In this case, the green line which represent their situation, is a curve with a gentle downward concavity, indicating that the two dimensions grow together almost proportionally at the beginning and then the knowlege levels slow down relative to frequency ones. It implies that people with a high school diploma boost their soft abilities more rapidly than those with lower education at the beginning, but their knowledge grows less quickly when frequecy exceeds a certain level.

Some downwards concavities characterizes also the smoothing splines relative to workers with *high and very high qualifications*, but important differences occur. Indeed, the red line, indicating *graduated people*, presents two concavities, with the first one being more pronounced than the second one, which is still more relevant than that of the green line. This line indicate that *people with a bachelor or a master degree* have consolidated soft competences even when such skills are rarely required. However, when frequency of utilization increases, a lower extent of expertise is needed, despite still at good levels. Then, the relation between the two dimensions returns to be positive up to when soft skills really become an integral part of ordinary tasks (and frequency has the maximum score or values close to it); indeed, the final part of the red line has again a negative inclination.

A similar situation occurs for people with a *PhD or a II level master* (see the gold line in Graph 32), but in this case the line starts when frequency is already at a medium level and the two downward convexities are even more emphasized. This means that workers with very high education always have to perform soft skills in their workplaces with high frequency. Furthermore, they are required to deploy soft abilities with the maxium depth of knowledge very soon, as the slope of the gold line when frequency goes from level 3 to level 4 (out of 5) is even steeper than 1. Then, a second minor downward convexity appear. This behaviour of the gold line might indicate that workers who received a very high education need to perform their soft competences often and they are expected to improve themselves in this sense quite quickly. However, when deploying soft skills enter in the routine activities, the depth of their use decreases (but still remains high): this result should be further investigated.

Graph 32 Soft Skill Distribution by Education



Source: my research, data from Osservatorio Professioni Digitali (2019

To sum up, when controlling by the education level of the workers, lines of different shapes are needed to represent the relationship between their utilization of soft skills and the necessary depth of knowledge.

Provided that all the smooth lines which fit data have an overall positive trend, only the one referring to people with the lowest education is linear; all the others present some curves that make them, with different intensity, downward concavity. It implies that the former workers actually perform more and more complex soft competences as they become more used in their implementation; this is only partially true for all the other orkers, as this applies just up to a certain level of frequency.

We saw from Graph 32 that soft skills are asked to people with low education with a growing depth of knowledge as frequency increases, but the increment of the former dimension is less than proportional. These two variables rise together also in the case of workers with medium education, but after frequency level arrives at a certain point, its relation with knowledge returns to be less than proportional. We observed that for workers with high education the rise in depth of knowledge is very steep relative to increase in frequency of utilization and it is also steeper for those with very high qualifications, indicating that such workers are expected to rapidly develop soft skills in the workplaces. However, also in these cases, after a certain frequency has been reached, knolwedge levels decrease at certain intervals, indicating that when people with high or very high education are asked to constantly use soft skills, they do not have to perform them at the maximum intensity of knowledge, but they probably have to stay focus also on other issues at the same time. All in all, it emerged that tasks where soft skills are fundamental, both for their frequent utilization and their complexity, are allocated to workers with the greatest education, namely those with a PhD or a II level master.

The effects of education on hybridizing skills

We are now going to detect the relation between the level of education received by workers and their actual utilization and knowledge of IT, digital and soft skills.

Figure 15 shows the relationship between education and each of the three hybridizing skills, distinguishing by their two dimensions of frequency of utilization and depth of knwoledge. The two boxplots on the top refer to IT competences, those in the middle to digital abilities and those at the bottom to soft competences; graphs on the left (letters b, d, f) are relative to the frequecy variable, those on the right (letters a, c, e) to the knowlede intensity actually deployed.

We can observe that within each graph there is a significant variability both in the median level, in the boxes dimensions and in their position; this indicates that education is an highly significative variable affecting the hybridizing skills level, as the output of regressions in Figure 15 of the Appendix suggested. We will now outline our major findings and implications.

By looking at Figure 15, we can observe that, in all the cases, the higher the education level, the greater the actual level of IT, digital and soft skills actually performed on the workplace, both in terms of frequency and knowledge. Indeed, in all the six boxplots shown in Figure 15, the *medians* of workers with a secondary school diploma (represented by the red boxes) are always the lowest and those of their colleagues with a PhD or a II level master (denoted by the purple boxes) are always the highest; between them, medians of people with a bachelor or master degree (indicated by the light blue boxes) are always above those referred to workers with an high school diploma (see the green boxes).

If we consider the *length of the boxes*, we can notice that the purple ones have the smaller interquantile range, as workers with very high qualifications are strongly condensed aroung their medians. Such considerations lead us stating that receiving a very high education leads to using IT, digital and soft skills with the highest intensity with respect to the other colleagues and this applies with very few exceptions. Also graduated people (high education) are represented by quite short boxes, but only in the cases of IT and soft skills knowledge: it implies that having a bachelor or master degree always leads to extensively developing computer skills and soft skills.

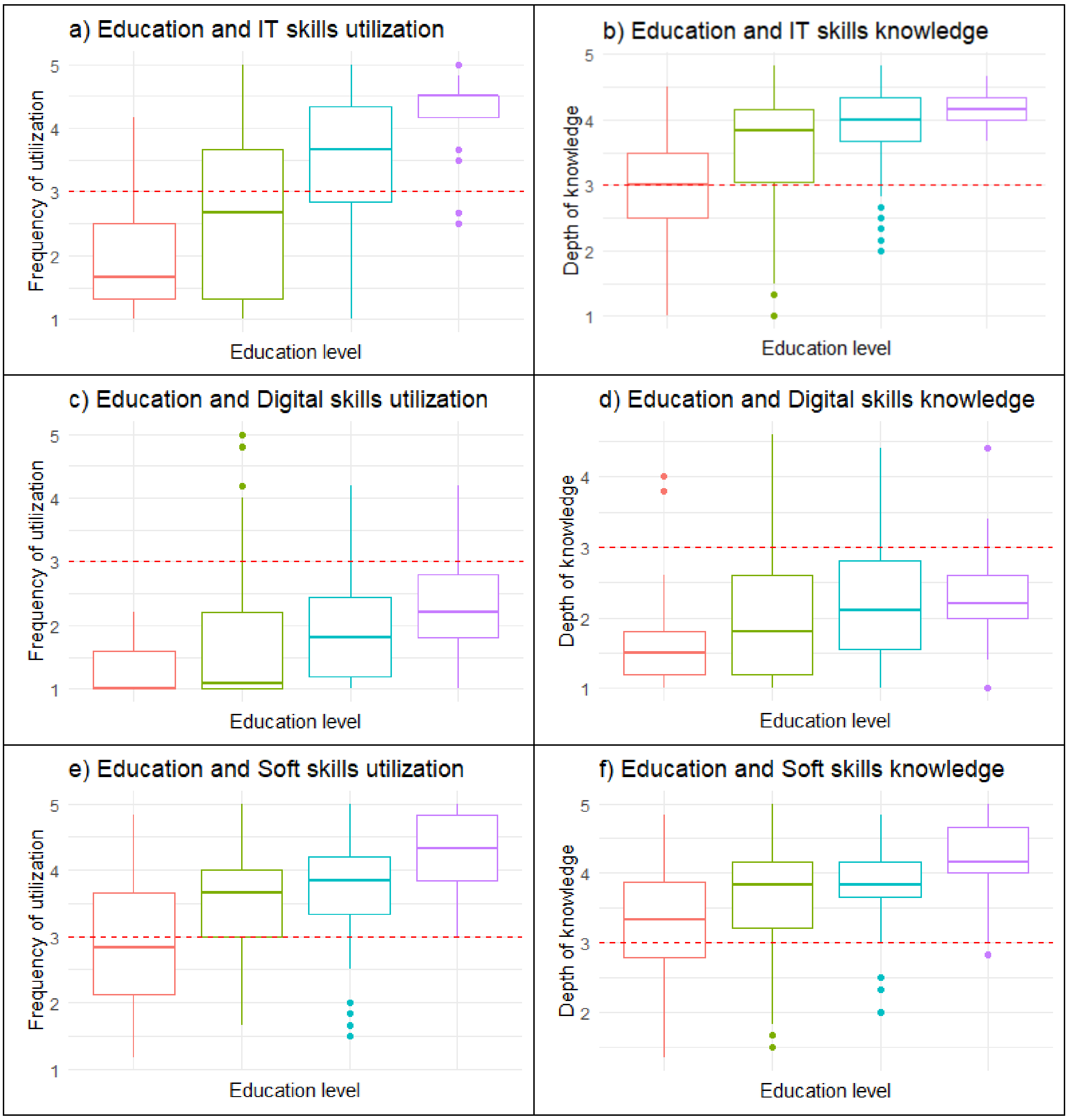
The focus on each skill domain also suggest interesting considerations.

With respect to the utilization of *IT abilites* (graph a), we can notice that medians for the four education categories are spread from about the lowest to about the highest values; this indicates that the level of the qualifications that workers possess is incredibly significant in determining their allocation to tasks which require a frequent utilization of IT skills.

With respect to the frequency of use of digital skills, it is worth noting that the medians relative to people with a secondary school diploma or a high school diploma are at the lowest levels (graph c); also looking at their level of knwoledge (graph d) we can understand that such competences are not necessary at all for tasks assigned to them. In other words, people with low and medium education are never allocated to tasks involving the utilization and development of digital skills.

Considering *soft skills*, also in this case, as in the two before, the highest median scores of utilization and knowledge are attributed to people with the highest education.

Figure 15 Education and IT Skill



Source: my research, data from Osservatorio Professioni Digitali (2019
Legend: red, Licenza Media, green: Diploma Scuola Superiore; blue: Laurea; purple: Master o PhD

7.2.2 Education and professional areas

In the previous section, we analysed how education affects frequency of utilization and depth of knowledge of the hybridizing skills. As our focus is not just on hybridization in itself, but rather on hybrid jobs, we are now going to detect how functional families are affected by education level.

A mosaic plot (Graph 33) graphically represents the distribution of the four education levels across the six professional areas. It shows that people with different qualifications are not equally present across functional categories; this suggests that a significant relationship between education and professional areas exists. Table 16 provides further details on the distribution of education levels across aggregated job classes.

Major findings from Graph 33 and Table 16 are outlined hereafter.

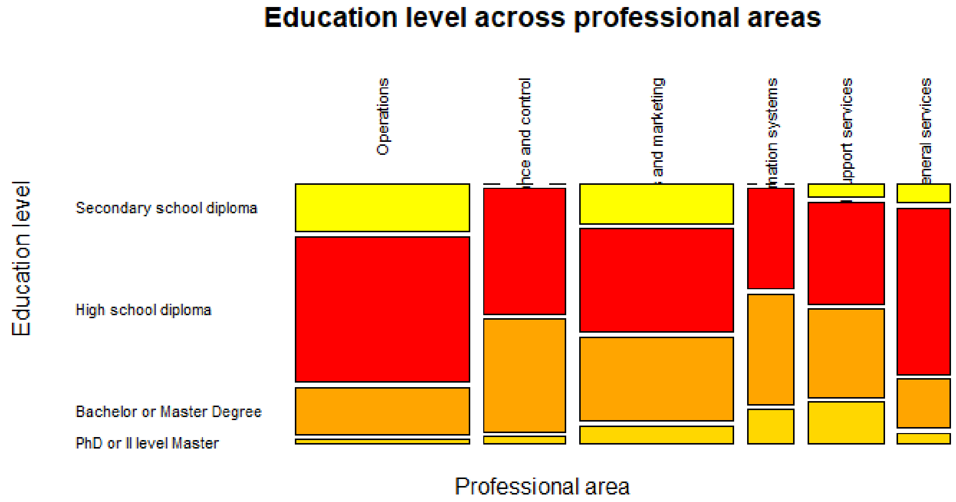
There are some professional areas where nobody with a low education level (namely the secondary school diploma) is employed: it is the case of *Administration, finance and control* and the *Information systems* ones. This fact suggests that these two job categories discriminate workers based on their education. This also makes us suppose that tasks for jobs in these areas are quite complex and require a certain school preparation or academic attendance.

The *Information systems* professional area and the *Organization and support services* one employ the biggest share of people with very high-level qualifications. It implies that having a strong academic background is recognized as an important factor/element for roles in R&D, ICT and management.

The *Operations* and *General services* areas, on the contrary, appear to prefer by far workers with medium education. We might think that jobs included in these categories require a certain school preparation (so that workers with low education are less preferred), but, on the other hand, having an academic background is likey to make people overskilled. In other words, people with a qualification higher than the high school diploma might have greater skills than what is necessary for these jobs, so that they are likely to look for more interesting and challenging works for their future.

By comparing the dimensions of the orange rectangles (high education) and the red ones (medium education) across professions, we could notice that they all have about the same dimension, with the exception of the *Operations* and *General services* areas we have just discussed about. This shows that having attained a bachelor or master degree paradoxically does not guarantee to be preferred with respect to people with a high school diploma, [in front of the HR managers].

Graph 33 Education levels across professional areas



Source: my research, data from Osservatorio Professioni Digitali (2019

Table 16 Education vs professional areas

Education vs professional areas	Operations	Administration, finance and control	Sales and marketing	Information systems	Organization and support services	General services
Secondary school diploma	19.5	0	16.4	0	5.6	8
High School diploma	59.8	51.3	42.5	40.9	41.7	68
Bachelor or Master Degree	19.5	46.2	34.2	45.5	36.1	20
PhD or II level Master	1.2	2.6	6.8	13.6	16.7	4
Total	100	100	100	100	100	100

Source: my research, data from Osservatorio Professioni Digitali (2019

7.3 Implications on Age: does age matters?

We are now interested in ascertaining whether age is a significant determinant for the utilization in the workplaces of the three skill domains leading to hybridization of jobs, as implications could be highly relevant. Regressions summarised in Appendix - Figure 19suggest that the belonging to a certain generation might have an impact on the level of workforce's hybridizing competences, in particular on IT skills knowledge and the frequency of utilization of soft skills. We want now to further investigate whether the demographic cohort or, more generally, being under or over 40 affects IT, digital and soft skills deployement in the workplace. We chose the age of 40 as a threshold because it enables us to distiguish the Z and Y generation, which include people who were born after 1980, from the X generation and baby boomers, which encompass those born before 1980.

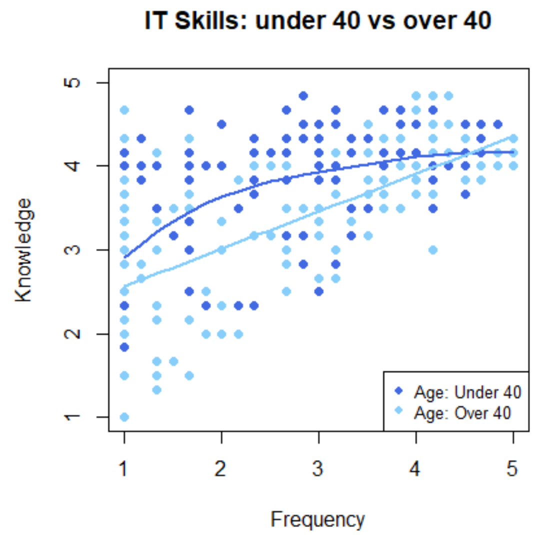
In this paragraph, for all the three skill domains, we will illustrate findings at first and we will provide some interpretations and discussions right after.

7.3.1 IT Skills: under 40 vs over 40

As Graph 34 shows, age seems to be significant in the frequency of utilization and depth of knowledge of IT skills in workplaces. In broad terms, workers who are less than 40 years old are more intensively asked to perform their computer abilities. In particular, we found that:

- For every level of frequency of utilization required in a workplace, younger employees (up to 39) regularly have a deeper knowledge; the only exception is made when IT skills are asked to be performed with extremely high frequency.
- If we keep constant the level of required knowledge, we might observe that younger workers generally deploy IT skills with a lower frequency than their over-40 colleagues.
- While in the case of workers who are over-40 the depth of knowledge of IT skills increases with the frequency of utilization at a steady pace (the light-blue smoothing spline in Graph 34 is linear), the situation for younger emplyees is quite different. This appears from the fact that the two smoothing splines have different behaviours: the one referring to people over-40 is pretty linear, whereas the one indicating younger workers shows a slight downward concavity.
- For younger people, the level of knowledge in terms of computer abilities is required to increase very fast – and quicker than for their older colleagues - at the beginning (the initial slope of the blue spline is steeper), when the frequency level is low, and at a lower pace – even slowly than the over-40 workers - afterwards.

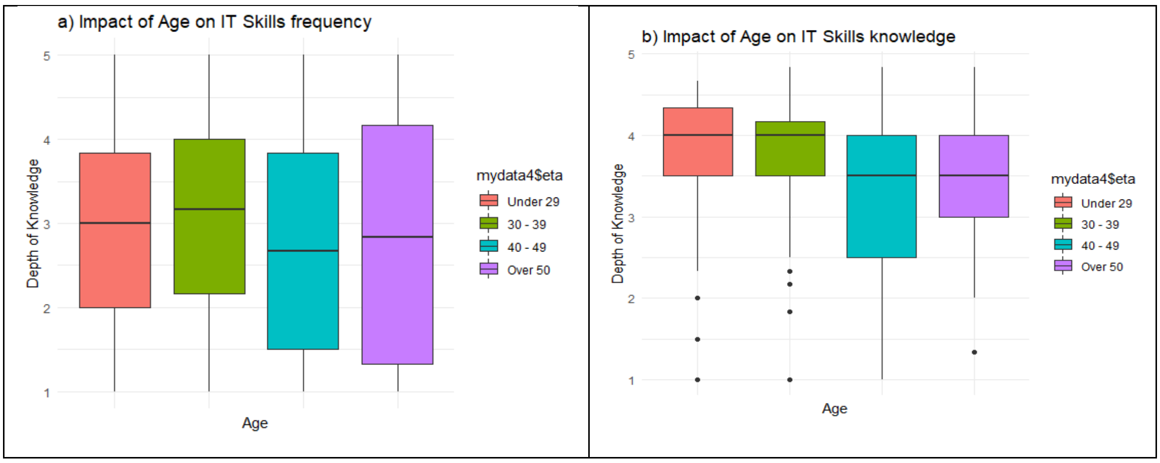
Graph 34 IT Skills: under-40 vs over-40



Source: my research, data from Osservatorio Professioni Digitali (2019

By looking at Graph 35, we can notice that the level of knowledge of IT skills is negatively affected by beloning to a certin age group. It emerged that knowledge median scores of boxes relative to people over-40 are show large differences with respect to the other ones. In paticular, workers age 40 – 49 years old show not only a low median value, but also a high downward dispersion. It appears that, in this case, age negatively affect IT skills knwoledge. It implies that workers belonging to the X generation or which are baby boomers have more difficulties in learning and developing IT skills compared to the Z or Y generations.

Graph 35 Impact of Age on IT Skills



Source: my research, data from Osservatorio Professioni Digitali (2019

Interpretation and discussion | Younger workers are expected to acquire IT skills faster than they older counterparts and they quickly become confident with information and communication technologies. When their IT skills utilization increases in frequency, their marginal increment in knowledge is small, as they already got to manage them at good levels. On the contrary, older workers more slowly acquire IT skills and steadily continue to learn them over time, as frequency of utilization increases. We showed that being aged over-40 negatively affects the IT knowledge level.

Our findind that, with knowledge level being equal, younger workers usually perform IT skills less frequently than their older counterparts, was quite unexpected. Indeed, we foresaw that, being people under-40 generally smarter in developing IT skills, tasks involving intense utilization of these competences would be allocated preferably to them rather than to older workers. We would argue that younger workers should more often put in the position to exploit and leverage their computer abilities, where they show better performance. Furhtermore, we suggest that, in the meantime, in order to foster older workers' acquisition and development of such competences, they are allocated in activies where the younger colleagues have the possibility to share their IT attitudes and practices (reverse mentoring). Therefore, we might advise/hint that organizational policies/actions are put in place in this direction.

7.3.2 Digital Skills: under 40 vs over 40

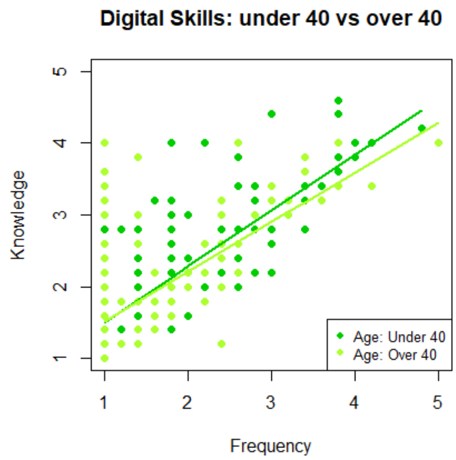
Age does not seem to be have a relevant role in determining the frequency of utilization and depth of knowledge of digital skills in workplaces. As Graph 36 shows, only small differences appear between workers belonging to the generations Y or Z and those of the X genaration or before. In other words, workers who are less than 40 years old are not more intensively asked to perform their digital skills then their older colleagues. In particular, we found that:

For a given level of frequency, younger employees (up to 39) and the older ones have about the same knowledge.

Similar scores among the two groups appear also if we control by knowledge level and we observe the frequency one.

Both the smoothing splines representing workers under-40 and the over-40 are pretty linear and close to each other. The only differences, despite slight, is provided by their slope: the light-green line of Graph 36 is a little flatter.

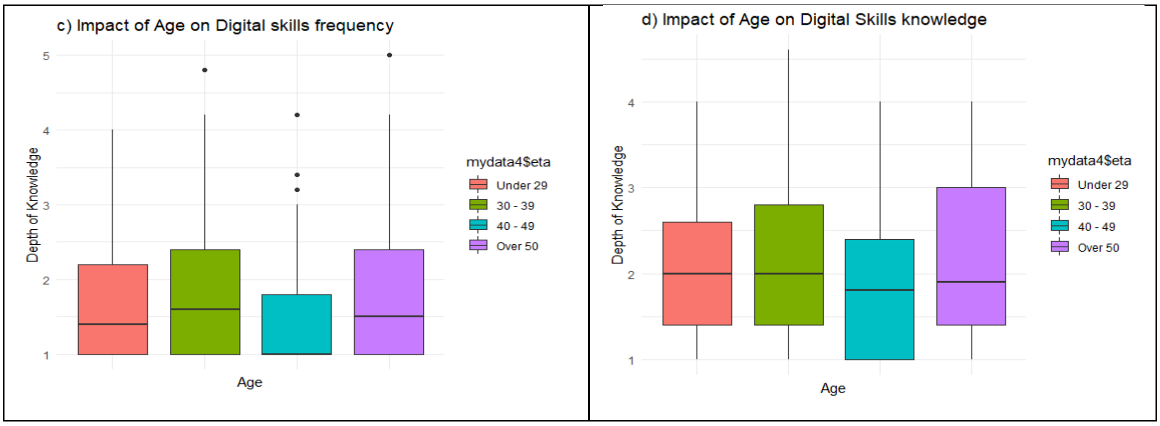
Graph 36 Digital Skills: under-40 vs over-40



Source: my research, data from Osservatorio Professioni Digitali (2019

By looking at Graph 37, we can state that no relevant differences appear across age groups in terms of digital skills. Workers who are 40 to 49 years old stand out for low scores especially in the frequency of utilization of digital skills (the median is null), but anything relevant could be said as values for the other age classes are close to the minimum, as well.

Graph 37 Impact of Age on Digital Skills



Source: my research, data from Osservatorio Professioni Digitali (2019

Interpretation and discussion | The level of digital abilities required to workers is not affected by age. Both workers under-40 and those over-40 are asked to have a deeper knowledge about digital skills when their frequency of utilization increases and no significant differences seem to exist in learning speed. This means that these groups are equally likely to develop digital competences after proper training.

7.3.3 Soft Skills: under 40 vs over 40

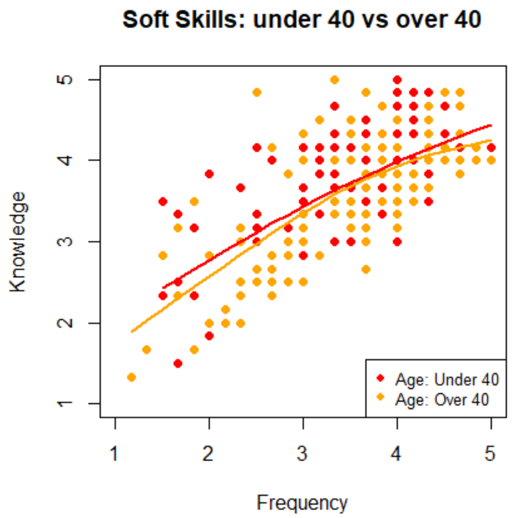
As Graph 38 shows, age is not a derminant of the workforce's overall frequency of utilization and depth of knowledge of soft skills. Considering the two aforementioned age groups that differentiate for being under or over the theshold of 40, it emerged that workers belonging to any of them are not more intensively asked to perform their soft competences just because of their age. If we further investigate, we could notice that:

For every level of frequency of utilization required in a workplace, younger employees (up to 39) always have a slightly deeper knowledge. This gap expand for low and for high levels of frequency, but still remains small.

If we keep constant the level of knowledge required, we might observe that younger workers generally deploy soft skills with a lower frequency than their over-40 colleagues. Again, differences are negligible.

The smoothing spline representing workers under-40 (the red one in Graph 38) is a bit above the other one: the range of soft skills knolwedge levels for younger people starts from larger values and reaches bigger scores with respect to their older counterparts.

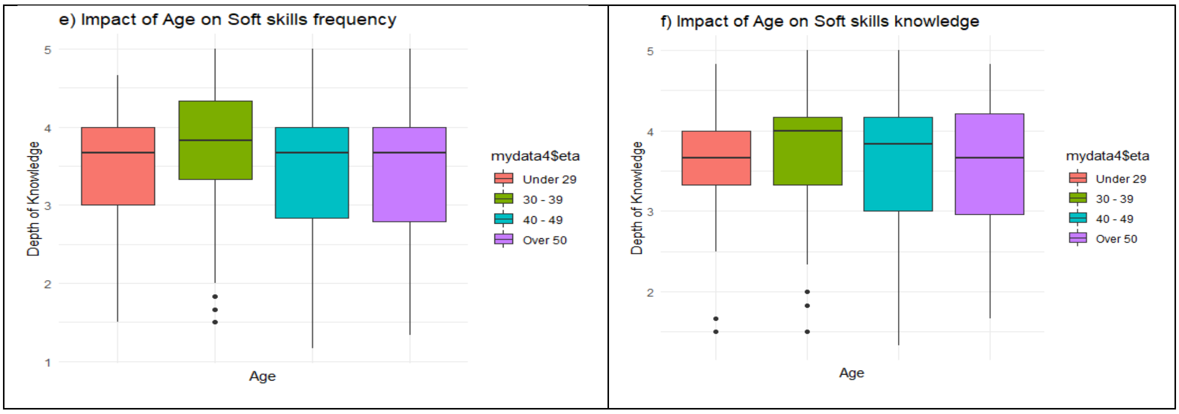
Graph 38 Soft Skills: under-40 vs over-40



Source: my research, data from Osservatorio Professioni Digitali (2019

By looking at Graph 39, we could confirm what we already noticed, but an interesting particular emerged: in terms of soft skills frequency, being in the age group 30 – 39 is significant. Indeed, the green box is shifted upwards with respct to the others. This implies that being a millennial or, more precisely, belonging to the first part of the Y generation, determines a more frequent utilization of soft skills.

Graph 39 Impact of Age on Soft Skills



Source: my research, data from Osservatorio Professioni Digitali (2019

Interpretation and discussion | Having seen that workers who are less than 40 years old do not generally use soft skills more than their over-40 colleagues or with remarkable deeper knowledge, one might think that these competences are not related to age. This, however, is only partially true. More specific analysis showed that being aged between 30 and 39 drives the frequency of utilizaiton of soft skills a little up.

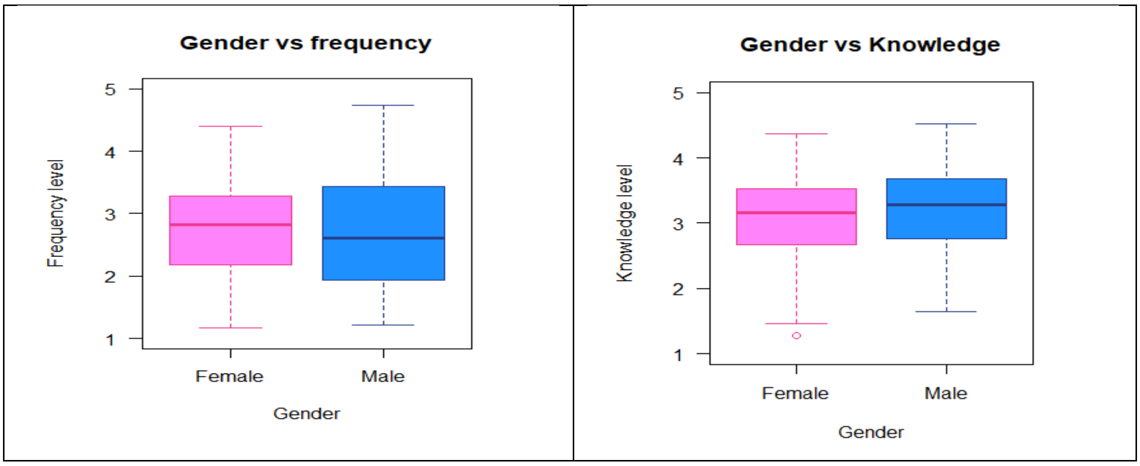
We expected that the older the worker, the more the accumulated experience in performing soft skills, ceteris paribus. However, our finding that people aged below 40 have a depth of knowledge non only similar to their older counterparts, but even slightly higher prompted some interesting considerations. Indeed, it seems that the lack of accrued expertise in workplace for younger workers is plently filled by proper training courses. It is also possible that these people also have acquired soft skills during their education. Therefore, we would suggest that human resources managers and people involved in organization, career development training planning and education recognize not only the strategic importance of soft skills development, but especially the actual usefulness of related training courses, which should always be guaranteed for supporting both good performance of young workers since the beginning and workforce's life-long learning and personal growth.

7.4 Implications on Gender

The regressions in Appendix - Figure 19 tell us that gender has an impact on some hybridizing skills.

Graph 40 shows the relation between gender and the frequency of utilization (on the left) and the depth of knowledge (on the right) of hybridizing skills, namely the average values per worker of IT, digital and soft competences. By looking at the boxplots, it appears that gender has a role in both frequency and knowledge levels of hybridizing skills on the whole. Women seem to use hybridizing skills slightly more frequently, while men show little higher scores in terms of knowledge.

Graph 40 Gender vs frequency and knowledge of hybridizing skills



Source: my research, data from Osservatorio Professioni Digitali (2019

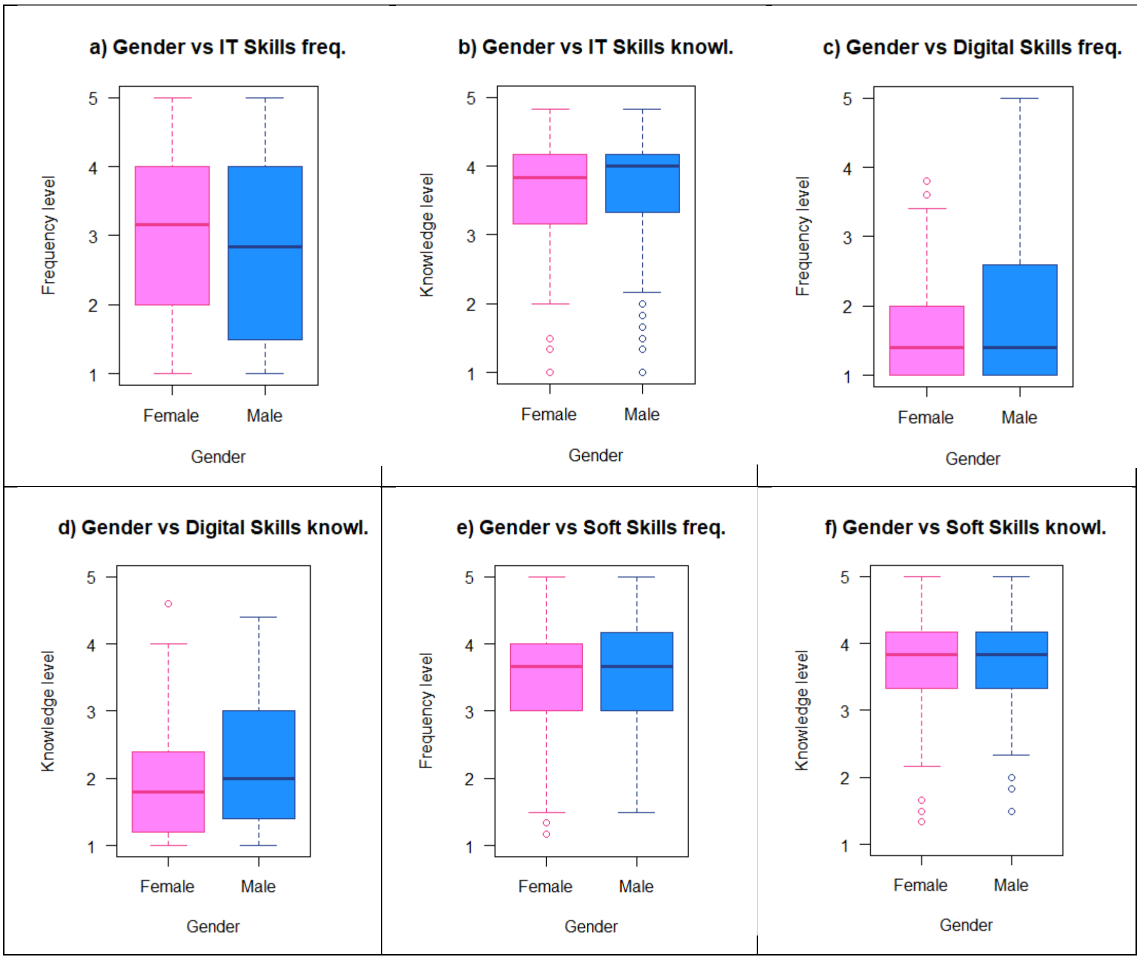
It is interesting to analyze if the situation displayed in Graph 40 is found also with respect to each skill domain individually or whether it summarizes highly different scenarios. Graph 41 enables us to go into detail in this sense, considering IT, digital and soft skills one at a time and also distinguishing between their two dimensions: frequency and knowledge.

As concernes *IT competences* (graphs a) and b)), we can see that, on average, woman use computer skills more often than men, but with a lower knowledge. Furthermore, the blu box in graph b) is shorter. We can derive that being a male generally lead to develop a little wider knowledge in terms of IT skills.

Regarding *digital competences* (graphs c) and d)), gender seems to play a role. Despite famale and male using these skills with the same median frequency, variability for men si very large and some of them are even requird to deploy them with the highest level of intensity possible (5), while women show a moderate variability. Gender is significant also with respect to digital knowledge, with females regularly exhibiting lower confidence and expertise than males. In sum, it seems that the masculine gender drives digital skill performance.

The situation is quite different in the case of *soft competences*, as graphs e) and f) show almost identical boxes and whiskers. It means that gender is not a determinant for soft skills utilization and knowledge.

Graph 41 Gender vs IT, Digital and Soft Skills



Source: my research, data from Osservatorio Professioni Digitali (2019

Interpretation and discussion | It emerged that gender does not have a role in all the hybridizing skills, but just in some of them. We found that being a male or a female does not have an impact on how often soft skills are required in a worplace nor on the level of knwoledge involved. On the contrary, gender determines the allocation of workers to tasks demanding digital performance. In particular, it emerged that men have higher level of digital knowledge with respect to their feminine counterparts. Furhtermore, a significant share of men is asked to use their digital skills very frequently, while women rarly reach a medium score of frequency.

Gender has an impact, despite moderate, on IT skills performance, as well.Women appears to be a little more used than men to deploy IT skills, but they general have a bit less profound knowledge with respect to their masculine counterparts. This implies that women are allocated to tasks involving more frequent interaction with information and communication technologies, while, broadly speaking, men are asked to use them with deeper knwoledge.

On the basis of which hybrid components prevail within a specific job, HR mangers should take these findings into consideration when selecting candidates or when re-allocate human resources because of the introduction of new roles.

7.5 Conclusion

In this chapter, implications on education, age and gender were outlined. We found that education has a role in IT, digital and soft performance of workforce. In particular, it emerged that people with the highest education stand out among the others because they always deploy IT skills with elevated depth of knowledge and high frequency. With respect to digital competences, the largest values in both dimensions are attributed to workers with medium education, suggesting that an academic background is not strictly necessary to properly deal with systems like IoT, artificial intelligence, cloud computing, ect, because suitable training courses and on-the-job learning seem to plently support the development of digital competences. However, this appears to be true only when a certain school preparation was received, as people with low education hardly reach medium levels of frequency and knowledge. As concerns soft skills, they are more intensively used and deeply performed by workers with high or very high education.

In order to further focus on hybrid jobs' features, we explored how people with different education levels compose professional areas and significant relationships emerged. For instance, we found that *Administration, finance and control* and the *Information systems* functional families discriminate workers on the base of their education, so that no one with low qualifications is employed. A strong academic background is particularly important in areas like *Information systems* and *Organization and support services*. On the contrary, highly educated workers seem to be overskilled in jobs included in *Operations* and *General services* categories.

Also anlysis on age led to many important considerations and consequent implications. We first of all investigated whether being under or over 40 affects IT, digital and soft skills deployement in the workplaces, then we went more in detail by distinguishing by four generations: Z, Y, X generations and baby boomers. It emerged that age is significant for the frequency and knowledge of IT skills, as workers under-40 are more intensively asked to perform their computer abilities; in particular, knowledge of IT skills is negatively affected by belonging to the age group 40 – 49 or over, as older workers more slowly acquire such competences. We suggest that policies of revers mentoring should be put in place to fill gaps between generations. Age does not result to be deteminant with respect to digital skills, meaning that no age groups are more intesively asked to performe them nor have developed higher knowledge or diverse learning speed. Also in the case of soft skills, age does not generally drive significant differences in terms of frequency or knowledge, with the exception that being aged 30 – 39 determnes a more frequent utilization of these competences. Our expectations that more senior workers would have developed deeper soft skills were not met, meaning that also younger people are able to use them with large confidence: this might suggest that suitable courses are effective in filling the experience they have never accrued.

Analysis on gender showed that it has a role in both frequency and knowledge levels of some hybridizing skills. In particular, it is relevant for the allocation of workers to tasks demanding digital performance: men usually develop deeper digital knowledge and when such skills have to be deployed with high frequency, the masculine gender is favoured. From a different viewpoint, this result might suggest that men are more inclined than women to develop digital abilities. We found that gender has an impact, despite moderate, also on IT skill: female workers more frequently deploy these competences, while their male counterparts are asked a deeper knowledge. No role is played by gender with respect to soft skills, meaning that men and woman are equally likely to develop and use them.

Findings from this chapter can be very useful to HR managers who are in charge of selecting candidates or re-allocating workers due to internal job transitions or to the introduction of new roles.

We also suggest that, for the purpose of an optimal allocation of human resources to tasks, the Hybridization Wheel model is applied to assess single workers' hybridization level performed at work and that results are compared with personnel's skill mapping; in this way, gaps can be identified and properly filled.

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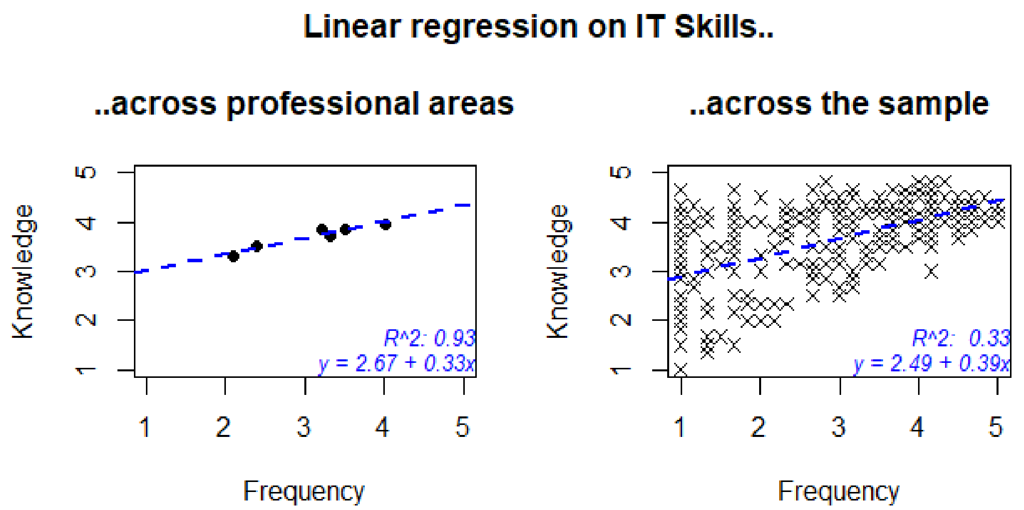
APPENDIX

Chapter 4 – Regressions on the three skill domains: graphical representation

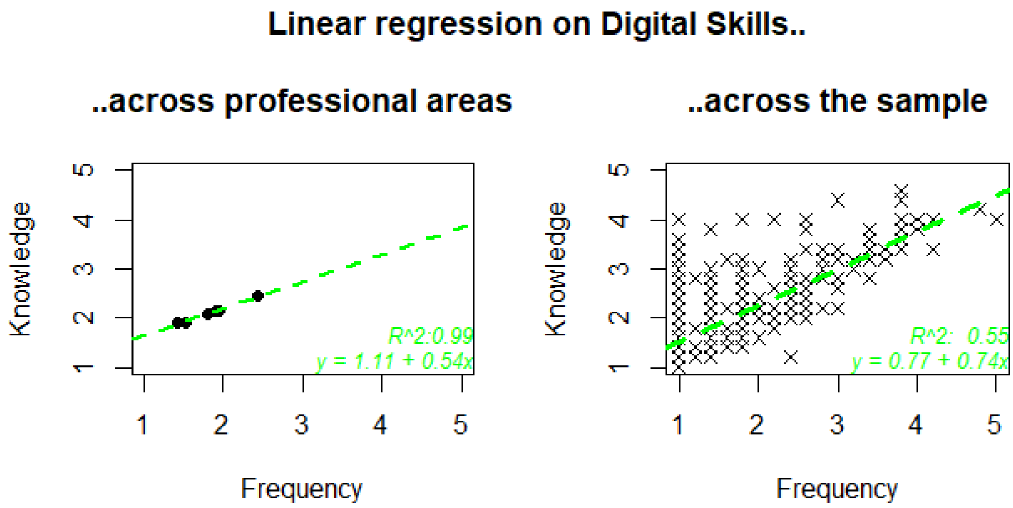
Graphs in Figure 16, Figure 17, Figure 18 compare the regression lines on regressions analysis done on the same dendent variables (namely, the three hybridizing skills) but over two different sets of observations: on the one hand estimates on the whole sample of 283 workers are conducted, on the other hand only the centroids of the six professional areas of interest are considered.

Figure 16 Linear regressions on IT Skills



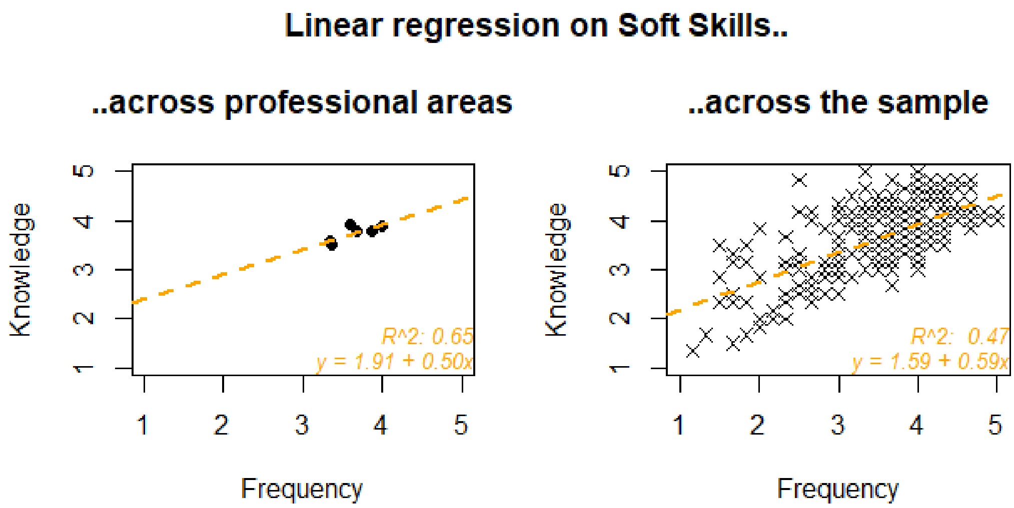
Source: my research, data from Osservatorio Professioni Digitali (2019

Figure 17 Linear regressions on digital Skills



Source: my research, data from Osservatorio Professioni Digitali (2019

Figure 18 Linear regressions on Soft Skills



Source: my research, data from Osservatorio Professioni Digitali (2019

Chapter 6 – Detailed steps for measuring hybridization of jobs

Finding the global hybridization centroid

Our initial purpose was to find an index that could indicate, for every professional area, its hybridization level; for this reason, we worked on each functional family individually. To do so, we grouped people according to their functional family; in practice, we created six sub-datasets by applying a filter on the variable related to the professional area. In actual facts, we selected workers (rows) on the base of their job, while keeping untouched the 53 columns that we disposed of.

As the adopted procedure was the same for every job category, we will now only illustrate how the centroid of one of them is computed. Let us take into consideration the *Operations* professional area. The corresponding dataset included a precise selection of workers, namely those employed in the functions aggregated in this working category. We then computed the average values of IT skills utilization, IT skills knowledge, digital skills utilization, digital skill knowledge, soft skills utilization, soft skills knowledge to get the average value of each of them within *Operations*. From an operative point of view, we computed the average means for (filtered) columns a) to f) and we obtained 6 values, which represent the coordinates for the identification of three points on a graph where frequency scores are on the x-axis and knowledge ones are on the y-axis. The three points we found are the centroids for IT, digital and soft abilities within this professional area. Starting from these points, we derived the centroid of "global hybridization", which is the point that minimizes their distance. From an operative point of view, we computed the average of the three frequency values and the average of the three knowledge ones; values of 2.29 and 2.91 resulted, respectively (let us remember that both dimensions ranged from 1 to 5).

Computing the hybridization intensity

For the computation of the hybridization coefficient we proceeded like follows:

hybridization rate of intensity (*Operations*) = average frequency (*Operations*) * 0.5 + average knowledge (*Operations*) * 0.5.

In numbers: 2.29 * 0.5 + 2.91*0.5 = 2.6. This implies that, on a scale of 1-5, the professional area under consideration has a hybridization coefficient of 2.6. To make this value fall between 0 and 1, we normalized it. The normalization formula we used was:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

In our case, the minimum value possible was 1 and the maximum was 5, so we normalized hybridization coefficients by using this formula:

$(x - 1)/5\text{-}1$

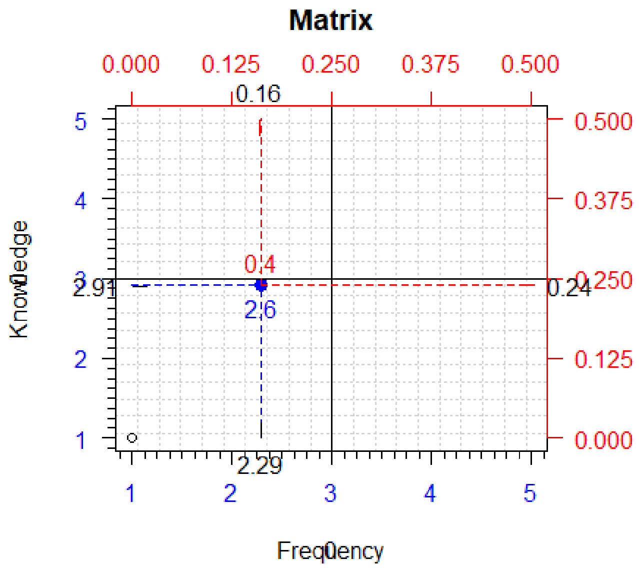
Coming back to the *Operations* professional area, it resulted that the rate of hybridization intensity was:

hybridization rate of intensity (*Operations*) = (hybridization coefficient (*Operations*) – min_hybcoeff)/max_hybcoeff – min_hybcoeff;

Where *min_hybcoeff* is the minimum hybridization coefficient possible, namely 1, and *max_hybcoeff* is the maximum one, namely 5.

In numbers, (2.6 – 1)/4 = 0.4. It emerged that this professional category has a rate of hybridization intensity of 0.4 on a scale of 0-1, as illustrated by Graph 42 by considering the red axis on the top and on the right.

Graph 42 Scale transformation



Source: my research

In Graph 42, four axes were drawn: the usual x-axis (representing the frequency dimension) and the traditional y-axis (indicating the knowledge dimension) have limit values of 1-5 and are blue-coloured, while axes on the right and on the top range from 0 to 0.5 and are red-coloured. The global hybridization centroid of the *Operations* professional area (with coordinates 2.29 and 2.91) was plotted with respect to the standard axis. Its rate of hybridization intensity was reported in blue below the centroid and it was computed, as the average of frequency and knowledge values; in practice, it derived from the mean of their coordinates. Its hybridization rate was reported in red above the global hybridization centroid and its value could be found even by just looking at the graph: it is sufficient to identify coordinates of the centroid on the red scale and to sum them. In the case of *Operations*, we got 0.16 + 0.24 = 0.4.

One may wonder why the red scale ranges from 0 to 0.5 rather than from 0 to 1, considering that we wanted a normalized hybridization rate. The reason is that if we used a red scale 0 – 1, we would not be able to detect the hybridization rate directly from the graph. Indeed, in the case of *Operations* seen below, to let the rate of 0.4 emerge, we would have not only summed the corresponding values on the red axis, but also divided them by two; in other words, we would have computed their mean. We believe that the chosen graphical representation allows for a more easy and immediate interpretation.

Measuring the type of effort

We could notice from Graph 42Graph 42 that the more a point (in our case, a centroid) is close to the bottom-left angle, the more its overall hybridization level is low; on the contrary, the more it moves towards the top-right, the more the hybrid level grows. The extremes cases are found when the centroids lie in (1,1) or in (5,5); these are the only cases where the hybridization rate (measured on the red scale of Graph 42) is equal to 0 and to 1, respectively. In other words, in correspondence of the bottom-left angle of the graph the hybridization rate is exactly equal to 0, while it takes value 1 in the top-right angle. We might state that the hybridization rate identifies the intensity of hybridization of each professional area and tells us at what point jobs are in this evolution process, assuming that the path starts in 0 and finishes in 1.

To make it clear, a segment could be drawn, where points that lie on it take continuous values between 0 to 1 (see the gold line in Graph 43).

A second issue arose at this point, as the hybridization rate (or the corresponding hybridization coefficient) did not give complete information about the context. For example, it did not tell us whether a professional area having a hybridization rate of intensity of 0.4 derives from:

- coordinates of (2.29, 2.91), as in the case of *Operations*, where the frequency is moderate and knowledge at an operative level is usually required;
- coordinates (4, 1.2), which represent a random situation where hybridizing skills are asked very frequently and minimal knowledge is required;
- coordinates (1.6, 3.6), which identify a hypothetical profession where hybridizing skills are very rarely used, but when it is required people have to deploy them with good knowledge;

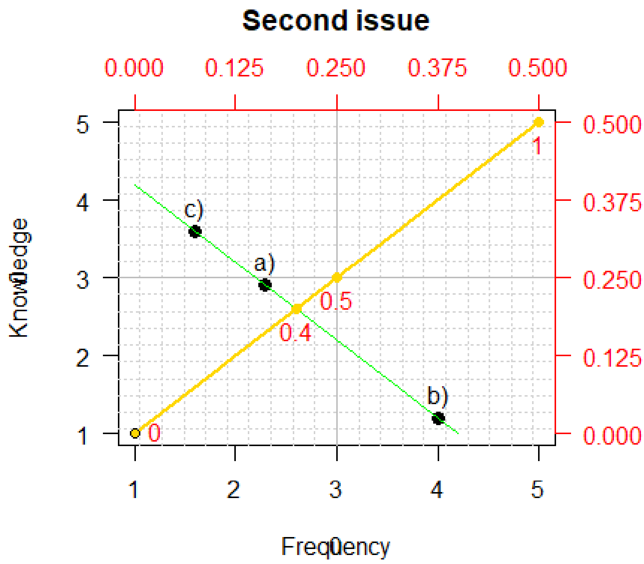
- all the other combinations of average frequency and knowledge levels whose mean is equal to 2.6 in a range 1-5 (or a normalized value of 0.4).

In other words, the second issue consisted in having a hybridizing coefficient which indicated the intensity and pervasiveness of the hybridizing component within a job, but which did not tell anything about the features of hybridizing skills and the nature of corresponding hybrid tasks which that job requires.

In the example above, the situation in a), b) and c) correspond to three different phenotypes: although they have the same hybridizing coefficient (2.6 on a scale of 1-5, or 0.4 on a normalized scale of 0-1), they lead to completely different organizational implications. Indeed, in the first scenario, people use hybridizing skills with moderate frequency and knowledge, in the second one, they perform them very often and with low knowledge and in the third one they deploy them quite rarely, but with a high knowledge level. Organizational implications in these three situations are highly diverse as, for instance, these workers need extremely different training.

From a graphical point of view, the second issue could be explained through Graph 43, were points a), b), c) correpond to the three illustrative cases mentioned above.

Graph 43 The second issue and the line of perfect balance



Source: my research

Graph 43 highlights that the same hybridization rate might represent functional families characterized by a similar hybrid intensity, but who lie in different areas of the graphic.

In our example, points a), b) and c) even lie in three different quadrants. This makes it clear that another important dimension exists, in addition to that conveyed by the hybridization rate. While the latter is measured along the gold line shown in Graph 43, the second dimension we need to consider expands in the opposite direction, from the top-left angle to the bottom-right one (see the green line of the same graphic). In particular, the more a point is close to the top-left angle, the more a professional area requires hybridizing skills with low frequency, but elevated depth of knowledge; on the contrary, the more a point is near to the bottom-right angle, the more a job asks such competences with high frequency but little knowledge. In practice, this second dimension provides us information on the type of effort needed to perform hybridizing skills:

- the more the points are close to the top-left angle, the more the cognitive type of effort is intense, as such abilities are asked rarely but with a high knowledge. This implies that hybridizing skills need to be optimally performed every time it is required, regardless of the fact that people are not used to deploying them.
- the more points are close to the bottom-right angle, the more the organizational type of effort dominates, as these skills are frequently deployed with a low level of knowledge involved. This might indicate that workers employed in these jobs are frequently asked to perform hybridizing skills that are easy in itself or whose deployment, in that context, do not necessitate wide accumulated knowledge. Because of the elevated average frequency of utilization of such hybridizing skills, however, workers need to be able to switch between several simple activities quite often.

Three ways of computing the direction of effort

To enrich the information conveyed by the hybridization rate with some insights on the organizational implications, we realized that it was not sufficient to identify whether the two abovementioned typologies of effort were balanced or whether one dominated on the other and, in case, which one prevailed. We needed to find a way to analytically measure them and to individuate a number which alone explains how the two efforts relate. Again, the graphical illustration from Graph 43 is useful to clarify it.

Provided that points on the line of perfect balance represent situations where the organizational and the cognitive effort are well balanced, it is possible to notice that the more a point is distant from that segment, the larger the unbalance between the frequency and the knowledge dimensions, with different organizational implications depending on their position along the line perpendicular to the one of perfect balance.

The distance of a point from a line could be measured in different ways, either relying on:

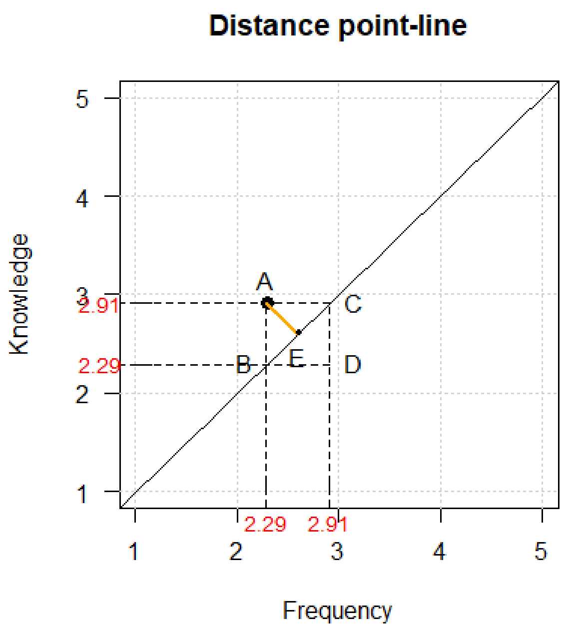
- analytic geometry or
- the theorem of Pythagoras or
- a specific formula.

We will now illustrate the mathematical passages for all the alternative methods, continuing to take as an example the case of the *Operations* professional area, which was represented by point a) in Graph 43.

Method I: analytic geometry

A way to compute the distance of our centroids from the line of perfect balance is to reason in terms of triangles.

Graph 44 Distance of a centroid from the line of perfect balance



Source: my research

As appears in Graph 44, the distance of the scattered point (called A) from the 45° line might be seen as the height of the right-angled triangle ABC. Knowing that the coordinates of point A - the centroid of the *Operations* professional area - are (2.29, 2.91), we can apply the formula:

Height of a right triangle = (catheter1 * catheter1)/hypotenuse

In our case, the catheters have the same dimension and are equal to: 2.91 – 2.29 = 0.62. The value of the hypotenuse can be computed as the diagonal of the square ABCD, where each side measures 0.62; the formula is:

Diagonal of the square = side length * sqrt(2)

In numbers, we got: BC = 0.62 * sqrt(2) = 0.876812.
Therefore, the perpendicular distance of A from the 45° line is: (0.62*0.62) / 0.876812 = 0.4384.
It means that the centroids of the *Operations* professional area has a distance of about 0.44 from the line of perfect balance. Every time a positive value is found, it indicates that the point under consideration lies above the 45° lines, implying that tasks are skewed toward the cognitive effort. The higher the resulting value in absolute terms, the larger the gap between frequency and knowledge levels. Further interpretations will be provided in the next paragraph, which is devoted to show and analyse results.

Method II: the theorem of Pythagoras

The second way to compute the perpendicular distance of the centroid from the 45° line is to rely on the theorem of Pythagoras. It states that: "In a right-angled triangle, the square of the hypotenuse side is equal to the sum of squares of the other two sides". Knowing that AB = AC = 0.62, we may apply this theorem to compute the length of the hypotenuse BC; then, for construction, we can derive that the height of the triangle is AE = BC/2.
The calculation is the following: (AB)^2 + (AC)^2 = (BC)^2.
In numbers: sqrt(0.3844 + 0.3844) = 0.876812; so that: AE = 0.876812 / 2 = 0.4384.
This confirms our previous foundings: the distance we are looking for is about 0.44.

Method III: a specific formula

The third possibility to get a point-line distance is to apply a specific formula. Given the equation line in its explicitly form:

$$y = mx + q\ ,$$

the following calculation has to be made:

$$d(P,r) = \frac{|y_P - (mx_P + q)|}{\sqrt{1+m^2}}\ .$$

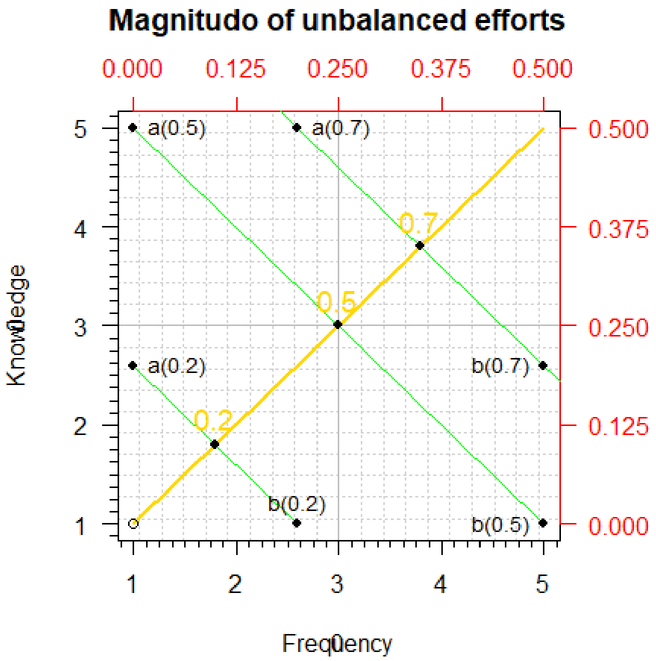
In our case, the equation of the 45° line is: y = x, meaning that m=1 and q=0. Values or Xp and Yp correspond to the coordinates of the point (centroid) under consideration. In numbers, we got: |2.91 – 2.29| / sqrt(1+1) = 0.62 / sqrt(2) = 0.4384.
Again, this result is in line with those found through the previous methods.

Skewness in the efforts

One might wonder whether a deviation of 0.44 from the line of perfect balance is an elevated value or a negligible one. This question may raise a significant issue, namely what was the maximum offset possible from the 45° line. By looking at Graph 45, we can observe that three green lines were drawn perpendicularly to the line of perfect balance and they are in correspondence of a rate of hybridization intensity of 0.2, 0.5 and 0.7 (on the golden line). From this graphic, we could see that they have different lengths. It clearly emerges that the maximum distance is reached when the intensity of hybridization is 0.5 and the direction of effort is completely skewed toward cognitive tasks only (point "a(0.5)") or organizational ones only (point "b(0.5)"). For this reason, we computed the maximum distance possible of these points, which are symmetrical, from the line of perfect balance.
In this specific case, to compute such distance, it was sufficient to calculate the diagonal of the graph (namely, the length of the golden line), and to divide by two the result. By using Pitagoras' theorem, we got: (5-1)^2 + (5-1)^2 = sqrt(32) = 5.65685; by dividing this value by two, it turned out that point "a(0.5)" is far 2.83 from the line. In other words, the maximum distance possible of a point (centroid) from the line of perfect balance is 2.83; the same is true for point "b(0.5)", but a negative sign would appear to indicate that it lies under the line, where organizational tasks prevail. In other words, we may now substitute the previously unknown values in "a(0.5)" and "b(0.5)" with, respectively, 2.83 and -2.83. The same procedure could be used to compute distances of points "a(0.2)", "b(0.2)", "a(0.7)", "b(0.7)", ect, from the line of perfect balance. To make it easier to interpret the values indicating the distance from the line, we normalized them.
Let us come back to the question of whether the distance of 0.44 of the centroid of *Operations* from the line of perfect balance is elevated or rather small. A score of 0.44 out of a maximum of 2.83 can be normalized and transformed into a range [0,1] with a simple equation: 0.44 : 2.83 = x : 1. It emerged that 0.44/2.83 = 0.16, so that the distance of a centroid with an intensity of hybridization equal to 0.4 from the line of perfect balance

is 0.16 in relative terms (16%). Again, the positive sign indicates that the point lies above the 45° line.

Graph 45 Magnitudo of unbalanced efforts



Source: my data

Two types of effort

The *cognitive effort* characterizes tasks where the implementation of hybridizing skills requires a significant depth of knowledge, indicating that a certain degree of expertise is necessary. The *organizational effort* distinguishes tasks where hybridizing skills are overall asked with elevated frequency so that workers need to be able to perform different non-technical abilities quite often and to switch among them comfortably.

These two types of effort co-exist in any jobs and, more specifically, in any tasks. Furthermore, they assume complementary values of frequency and knowledge along the same line perpendicular to that of perfect balance; in our example, the sum of the red coordinates of every point on the green line in Graph 43 was equal to 0.4.

Therefore, it might be hard to justify the creation of different categories based on the types of effort, as thresholds would be arguable. However, to overcome this point and to enrich the hybridization rate with information about organizational implications, we proceeded as followed.

We realized that one of these cases always occurred:

- the frequency and knowledge dimensions have exactly the same scores (for example: 3.45; 3.45);
- the frequency score is higher than the knowledge one;
- the frequency score is lower than the knowledge one.

Such scenarios may apply with respect to both professional areas and individual workers, but we continued to focus on job categories. These three abovementioned cases indicate a different balance of the nature of tasks:

- jobs where these dimensions have the same (or similar) values imply a tuned balance between organizational and cognitive tasks;
- in professional areas where hybridizing skills are performed with an elevated frequency with respect to knowledge, the organizational effort dominates;
- in occupations where these abilities are used with a profound depth of knowledge with respect to their frequency of utilization, the cognitive effort dominates.

From a graphical point of view (Graph 43), we can notice that the golden line has a pivotal role in distinguishing among this three scenarios: points which lie exactly on it represent jobs under I); all the points below it indicate jobs presenting the situation described in II); on the contrary, points above it indicate jobs where a preponderance of cognitive efforts occurs (case III).

Because this 45° line matches with all the points where an even equilibrium between cognitive and organizational tasks exists, from now on we will refer to it as to the "line of perfect balance". In practice, it is the locus of points where no effort dominates on the other: when hybridizing skills are only rarely needed, a low cognitive effort is required, while a more intense utilization is accompanied by a higher level of knowledge. We need to specify that the term "perfect" does not indicate that it represents the optimal situation, but it limits to ascertain that to perform the hybridizing skills required by certain professional areas, the two types of effort are equally important or, in other words, they are perfectly balanced.

Chapter 7 – Regression on the three skill domains: outputs

Figure 19 illustrates the ouput of the six regressions on, respectively: IT skills frequency, IT skills knowledge, digital skills frequency, digital skills knwoledge, soft skills frequency and soft skills knowledge. It emerged that the variables with the overall major impact on the frequency and knowledge of the three hybridizing skills are the professional area and the education level, followed by age and gender.

Results were the starting point for further analysis conducted in Chapter 7 regarding managerial and organizational implications.

Figure 19 Regressions on the three skill domains

	IT skills FREQUENZA		IT skills CONOSCENZA		digital skills FREQUENZA		digital skills CONOSCENZA		soft skills FREQUENZA		soft skills CONOSCENZA	
Coefficients:	Estimate		Estimate		Estimate		Estimate		Estimate		Estimate	
(Intercept)	*1.23649*	*	*2.83557*	***	*0.49599*		*1.05589*	.	*2.14926*	***	*3.19544*	***
area.professionaleAdministration, finance and control	0.80998	***	0.490324	*	0.391308	*	0.22825		-0.32607	.	-0.09533	
area.professionaleSales and marketing	1.1399	***	0.396837	*	0.387889	*	0.165255		0.12302		0.15679	
area.professionaleInformation systems	1.29468	***	0.385988	.	0.800989	***	0.380237		0.43206	.	0.19869	
area.professionaleOrganization and support services	0.90577	**	0.429472	.	0.291943		0.174195		0.17971		0.14094	
area.professionaleGeneral services	-0.33533		0.116593		-0.16403		0.010058		0.04118		0.48091	*
area.professionaleOther	-0.04372		-0.1846		0.042164		0.232832		-0.50267		-0.31896	
forma.contrattualeApprendistato	-0.23421		0.13489		-0.00138		0.352522		0.35064		-0.13772	
forma.contrattualeDipendente Det	-0.34135		0.077129		-0.07291		0.118876		0.2339		-0.07642	
forma.contrattualeDipendente Indet	0.01865		0.157692		0.064907		0.137195		0.08543		-0.13721	
forma.contrattualeLavoratore autonomo	-0.63713		0.30054		-0.26857		-0.0947		0.27826		-0.18476	
settoreAltro	0.05029		-0.13068		0.047785		-0.1362		0.32719		-0.40948	
settoreAmministrazione pubblica e difesa	-0.1432		-0.31792		-0.04236		-0.64683		-0.1027		-0.50732	
settoreAttività artistiche, sportive e di intrattenimento	0.86077		-0.31057		0.277445		-0.20872		0.73343		0.03023	
settoreAttività finanziarie e assicurative	0.61964		0.042216		1.619683	*	0.661514		0.59123		0.08096	
settoreAttività immobiliari	0.12342		-0.25116		0.500557		-0.03659		0.16041		-0.49477	
settoreAttività minerarie, estrazione di minerali, petrolio e gas	0.55477		0.068099		0.739074		-0.45216		0.54023		0.48909	
settoreAttività professionali, scientifiche e tecniche	1.00117	.	0.062221		1.376873	**	0.702131		0.60833		0.07074	
settoreCommercio al dettaglio	0.01516		-0.19247		0.244703		-0.00856		0.32765		-0.16723	
settoreCommercio all'ingrosso	0.19579		-0.05368		0.450738		0.077276		0.35163		-0.15243	
settoreCostruzioni	0.887		0.33989		0.875832	.	0.397753		0.13868		-0.16066	
settoreFornitura di servizi pubblici (gas, acqua, energia elettrica etc.)	2.5442	*	1.398418		1.377131		0.285618		1.64015	.	1.12568	
settoreIstruzione	0.7419		0.12843		0.277369		0.002392		0.37121		-0.1891	
settoreManifattura	0.34405		-0.02304		0.347425		-0.06239		0.30507		-0.18256	
settoreSanità e assistenza sociale	1.03176	.	0.107461		0.693022		0.070506		0.3271		-0.38467	
settoreServizi di informazione e comunicazione	1.1557	.	0.406557		0.627069		0.22151		0.03452		-0.26246	
settoreServizi di supporto alle imprese (es amministrativi, pulizia, rifi	0.87194		0.021857		0.410952		-0.05367		0.33932		-0.12703	
settoreSettore alberghiero e ristorazione	0.67216		0.291166		0.490146		0.18791		0.79566	.	0.3488	
settoreTrasporto e magazzinaggio	0.22382		0.145066		0.127689		-0.04934		-0.25223		-0.46291	
addettiTra 10 e 49 addetti	-0.1277		0.008833		-0.08369		-0.00461		-0.04608		-0.11933	
addettiTra 50 e 249 addetti	-0.35961	.	-0.1342		-0.13825		-0.05914		0.03641		-0.14708	
addettiOltre 250 addetti	0.22096		0.213477		0.026131		0.156563		0.07705		-0.03076	
etaDa 30 a 39 anni	0.1978		-0.05182		0.194824		0.117032		0.40826	**	0.16786	
etaDa 40 a 49 anni	-0.18291		-0.5392	**	-0.12673		-0.26908		0.23681		-0.06714	
etaDa 50 anni in su	-0.3181		-0.39606	.	0.07507		-0.09392		0.03057		-0.13185	
genereUomo	0.102		0.141346		0.262571	*	0.375705	**	0.03289		0.16198	.
fasce.anni.lavoroDa 6 a 10 anni	-0.17251		-0.02865		0.065616		0.060713		-0.01608		0.2253	
fasce.anni.lavoroDa 11 a 20 anni	0.09358		-0.01245		0.103296		0.115816		-0.06766		0.07786	
fasce.anni.lavoroDa 21 anni in su	0.41089		0.211429		0.256203		0.496704	.	0.17257		0.36024	.
titolo.studioDiploma I.S.Superiore	0.51927	*	0.370099	*	0.351267	*	0.338041	.	0.69345	***	0.41565	**
titolo.studioLaurea	1.01915	***	0.648735	**	0.420412	*	0.492583	*	0.82564	***	0.68465	***
titolo.studioMaster o Dottorato	1.51359	***	0.942259	***	0.743843	*	0.703557	*	1.33729	***	1.07917	***

Source: my research, data from Osservatorio Professioni Digitali (2019)