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# Automation and its Employment Effects

## A Literature Review of Automotive and Garment Sectors

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# Automation and its Employment Effects
# A Literature Review of Automotive and Garment Sectors

Guendalina Anzolin (King's College London, United Kingdom)

## Abstract

Over the past decade, the interest around automation and digitalisation processes gained considerable attention both due to industrial and productivity related dynamics that stem from such processes and for their effects on employment. A better understanding of such dynamics, away from futuristic and apocalyptic views and closer to what happens at the shopfloor level are crucial to disentangle the effects of automation on labour and to provide insights both at the research and policy making levels. This paper attempts to dig into this subject looking at technological change as an incremental – rather than disruptive – type of process, like the slow and incremental process that characterised previous waves of technological change. Digital and automated technologies are then defined as bundles of innovations, which are selectively integrated into existing systems and for specific objectives. Against this background, this paper contributes to the existing literature in two aspects: it critically engages in a literature review of the recent studies on the effects that automation technologies have on two manufacturing sectors - i.e., automotive and labour – with a focus on the gender dimension that try to emphasise the effects on female workers. Secondly, it presents an in-depth review of the technologies that are widely discussed under the 4.0 label, addressing their degree of automation and their level of disruptiveness of existing systems.

**Keywords**: Automation, Employment, Manufacturing, Industry 4.0

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# Contents

# 1. Introduction

During the past two decades, the interest in automation and digital technologies and their effects on our societies has increased substantially. The invention of new technologies, and the increasing accessibility to some of them, led to questioning – once they are adopted - their impact on different elements of productive structures; on the one hand, the impact is on production processes and GVCs' restructuring, while on the other interrelated hand, the attention has been shifting towards quantitative and qualitative effects on work organisation and, more broadly, working conditions.

The general label under which new technologies are discussed is the fourth industrial revolution, or Industry 4.0, a new concept that was part of various policy packages after the Great Recession. Sometimes these two concepts are incorrectly confused; according to Sung (2018), the fourth industrial revolution is a broader concept related to changes that will affect society as a whole (political systems, culture, ways of communicating and living). Rather, Industry 4.0 is a narrower concept, which exclusively relates to the manufacturing realm. Such concepts stem from policy programs adopted around the world – like Industry 4.0 in Germany and Made in China 2025 (Li, 2018) - that are deeply shaping how we see and forecast these technologies' adoption (Pardi et al., 2020). It is interesting to note how the policy and academic hype exceed the technical and scientific side; the fourth industrial revolution was announced way before its advent… while the first was assessed 70 years later!

In this report, we will refer to challenges related to Industry 4.0, with a specific focus on automation processes and their effects on the two manufacturing sectors of automotive and garments. The perspective here undertaken asserts that we are likely to experience an incremental type of technological change, as it has been occurring in the past with previous technologies. Industry 4.0 technologies are bundles of selectively innovations integrated into existing systems and for specific objectives (Andreoni and Anzolin, 2019; Butollo et al., 2019; Dosi and Virgillito, 2019). Against this backdrop, it is hard to define the boundaries of this wave of technological innovations, and this is especially due to the high degree of heterogeneity that countries, sectors and firms present in the level of technologies' adoption and the type of technologies' deployment. In addition, data are difficult to find as the object at study is a recent and little diffused phenomenon. However, if we take the example of the only systematic source of data available on a recent technology such as industrial robots, e.g., the International Federation of Robotics dataset, we can observe a high geographical concentration, with the top ten countries capturing 85.87% of total industrial robots worldwide, and the top five countries deploying 74.85% of the total (Andreoni and Anzolin, 2019; IFR, 2017). Sectoral concentration is also particularly high, as automotive and electronics are the two sectors that make up more than 60% of the total industrial robots in the manufacturing sector.

On a similar line of argument, preliminary studies at the firm level find that new technologies are highly concentrated in big multinational companies or in niche firms that upgraded their strategy in order to remain in the market; differently, SMEs struggle to adopt new technologies even in advanced countries such as Germany (Sommer, 2015) and South Korea (Yu, 2018). Other studies on emerging technologies such as 3D Printing (3DP), artificial intelligence and virtual reality confirm that these are at a very initial stage, often adopted in the form of pivotal stand-alone projects within the firm (Quevedo et al., 2017). A correct and careful consideration of diffusion dynamics is important because it gives a more grounded perspective to analyse and discuss the possible impacts of new technologies. On the contrary, it is relevant to discuss why despite technical feasibility, technology is not adopted across a variety of socio-economic structures. Rosenberg (1976) used to distinguish between economically relevant technologies – e.g., those that are diffused enough in the productive systems – to those that are not diffused due to impediments of different types, such as demand constraints, supply bottlenecks, machine tools' lack of complementarities, and so on (Rosenberg, 1976).

Despite the incrementality that characterises technological change, there has been pressing attention on a seeming strong trend of automation, as if robots would replace human labour within the near future. A more careful analysis would consider that automation - and possible labour displacement - is only one aspect and not even the most recent nor the most pressing one that is taking place within businesses that are rather focusing on digitalisation and connectivity challenges (Cirillo et al., 2021). If we take a look at the past, labour saving automation started with mechanization processes during the second industrial revolution, and it has been slowly evolving for decades (Staccioli and Virgillito, 2021). Such processes still present a series of challenges in terms of basic and intermediate capabilities that are necessary to engage in the structural change that automation implies (Andreoni et al., 2021); the complexity of such processes is so high that many firms in developed and developing countries are not fully automated yet. A different, although complementary, aspect of this new trend is digitalisation, intended as the use of digital technologies and digitised data, which is a characteristic feature of Industry 4.0 technologies. Both automation and digitisation have been attracting high interest and an increasing number of contributions, which unduly focus on labour displacement effects (Acemoglu and Restrepo, 2019; Autor et al., 2003); still, very often, the more recent type of automation and especially digitalisation are much more about connectivity, integration and reorganisation of production processes, rather than about automating manual tasks, and with a number of different effects that go beyond displacement.

In this report, automation and digitalisation effects on employment are reviewed and discussed in two manufacturing sectors – i.e., automotive and garments - to the extent that they produce a degree of change in labour activities, and how these activities are organised (i.e., difference between tasks and organisation of tasks). In doing so, the report explores the nexus between work and organisation, as well as the structural dimension of tasks, both in terms of the type of tasks and the way in which such tasks are performed. The two sectors are characterised by long and fragmented GVCs where automation technologies' adoption is driven by different reasons, it is deployed with different degrees of intensity, and it produced heterogenous effects on the employment structure, impacting labour and production organisations. The automotive sector is highly automated, while the garment sector still relies mainly on manual operations due to the low cost labour coming mainly from developing countries where these activities have been outsourced (Vashisht and Rani, 2020; Minian et al., 2017; Parschau and Hauge, 2020). In addition, we review the literature focusing on whether different automation trends and technologies have a different impact on gender across these two sectors. Recent trends of automation may change the gender composition of employment in both automotive – a man dominated sector – and garment – a female-dominated sector.

The rest of the paper is organised as follows. Section 2 discusses the different concepts of mechanisation, automation and digitalisation. Section 3 analytically reviews the main contributions on the impact of new automation technologies on employment, bringing in also considerations on the gender dimension. Section 4 reviews existing literature on employment effects of automation in automotive (4.1) and garment (4.2) sectors. Section 5 concludes.

## 2. Automation and digitalisation: between the past and the future

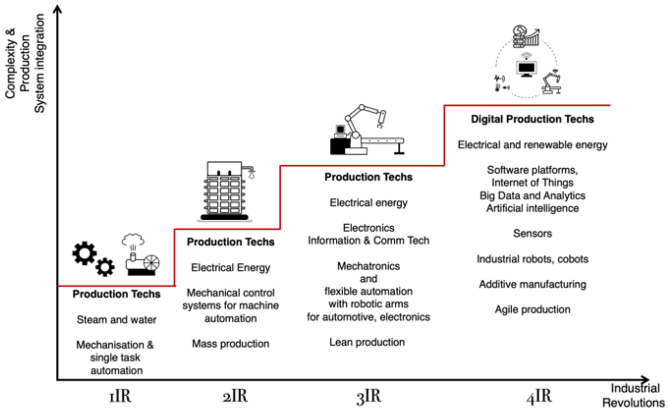
Mechanisation and automation trends are not something new; they have been evolving for decades and especially in advanced manufacturing sectors. This section reviews these different facets of technological change while proposing a categorisation of these slightly different concepts. Mechanisation is to be intended as the replacement of human labour by machine labour, and it is a process started between the first and the second industrial revolution. During that time, the steam engine and machine's electrification replaced physical effort, often complementing human work (Landes, 2003). Differently, the more intelligent and sophisticated form of mechanisation where the machine replaces human mental processes is called automation1, and it represents a situation where – within certain limits – the machine selects its own program, and it is able to reprogramme itself (Bliek, 1974).

Although the two concepts are similar, they are to be intended in sequential order, with automation as a further step that started to replace human "thinking" with machines (Kamaruddin et al., 2013).

[1] The word automation was coined in 1946 within the automotive sector to describe the automatic handling of parts in metalworking processes.

In other words, mechanisation stands for the replacement of human labour by ‘dumb’ machine labour, such as a programmed task given to the machine that will remain the same for its entire life cycle. When tasks performed by machines are more intelligent and the machine is reprogrammable, then we have automation. The latter concept has been evolving, and more recently, during the so-called second machine age, it is intended as both machines’ ability to direct physical work and to undertake cognitive tasks, while learning to use neural networks with large data sets through AI technologies (Brynjolfsson and McAfee, 2014; Harteis, 2018; Arslan et al., 2021).

*Figure 1. Industrial and technological revolutions*

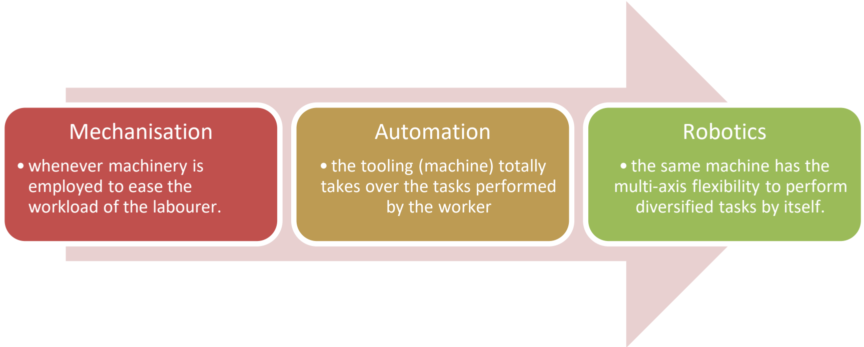



Source: Andreoni and Anzolin, 2019

Automation dates back to the last century when the first robotic arms were deployed in industrial production in the 1960s, and it has been an ongoing process characterised by small incremental changes. In the 1960s, the evolution into computerized numerical control (CNC) allowed production technologies to rely increasingly on electronics for automation and robotization – the latter is intended as machines’ ability to be more flexible in terms of tasks’ execution2. In 1965 General Motors and IBM launched the first computer-controlled production line, which later gave rise to computer integrated manufacturing (CIM) and computer-aided design (CAD) systems (Andreoni and Anzolin, 2019), which represented the initial phases of digitisation and digitalisation – see below. A further, more recent, step of automation-related technological change is robotics, which added an extra layer of complexity in tasks’ execution with machines becoming flexible enough to perform different tasks: once it is programmed, it manages to change the type and intensity of tasks, with increasing ability of self-regulating (Richard, 2005; Kamaruddin et al., 2013).

[2] CNC machines and robots became spread into production systems between the 1950s and the 1960s. CNC machine are very accurate, but they normally perform one task, through a movable tool or jig, or both. Such machines are controlled by a computer which makes them very precise. The difference with robots, although it has been narrowing down significantly, is that the latter is characterized by high flexibility in terms of tasks execution and the variety of these tasks.

*Figure 2. Graphical representation of the trajectory between mechanisation, automation and robotics.*




Source: Author based on (Kamaruddin et al., 2013)

One of the latest phases of this technological process has dealt with the digital realm. Here, two interrelated processes have emerged: digitisation and digitalisation. The former refers to the conversion of analogue information into digital; in other words, the process of converting physical space into digital information (i.e., bits, bytes), taking advantage of the enhanced possibilities of data creation, processing and storage (Fernandez-Macias, 2017). The latter, digitalisation, is a broader phenomenon (Peruffo et al., 2017) that starts from digitisation as a precondition for businesses to convert their processes over the use of digital technologies. When applied to the manufacturing sector, digitalisation is intended as the establishment of networks between machines and the use of software systems and digital databases for monitoring, controlling and optimising interconnected work processes (Hirsch-Kreinsen and Hompel, 2017) 3. Digitalisation, although progressing slowly, is already reshaping a world where data are increasingly becoming goods of extreme value (Baldwin, 2018). It is important to note that even data collection mechanisms – similar to what discussed above in relation to automation - have been part of an incremental process that started from the developments of Information and Communication Technologies (ICTs) and related data infrastructures, which diffused across the globe in the form of the internet (Dosi and Virgillito, 2019; Sturgeon et al., 2017; Cetrulo and Nuvolari, 2019). Recently, the volume of data has grown exponentially, and it potentially revolutionises the ways in which people work and live. In the words of Brennen and Kreiss (2014), "digitalization serves both as an organizing mode across social domains and as a destabilizing force".

During the past decade, there has been an accelerating trend of digitalisation, which is entrenched with increasing connectivity (De Propris and Bailey, 2020)4; although the latter concepts have been less dominant in the empirical literature, they are the most relevant processes in terms of value-creating mechanisms for businesses (Cirillo et al., 2021). Despite being an essential pre-requisite of Industry 4.0, digitalisation is not the newest element of recent technological change; rather, the novelty is, in fact, the fusion and interconnection between these different technologies across the physical and digital domains, which aim to create cyber-physical systems5 (Andreoni et al., 2021;

[3] https://insights.sap.com/digitization-vs-digitalization/

[4] Industry 4.0 is considered: "as a cluster of technologies characterized by high levels of connectivity that allow data and information integration in the production and consumption activities" (De Propis and Bailey, 2020: 113).

[5] Cyber-Physical Systems (CPS) are defined as collaborating computational entities which are in intensive connection with the surrounding physical world and its on-going processes, providing and using – at the same time – data accessing and data processing services available on the internet. Within these processes, the interaction between physical and cyber elements of key importance. (CIRP Encyclopedia of Production Engineering, available at:

Kodama, 1986). Such combination of different technologies is not something new; technologies always evolved in systems, often with technologies coming from different realms of productive systems. However, in comparison to previous waves of technological change, Industry 4.0 systems are characterised by a higher level of complexity and interdependency between traditionally separate fields of knowledge. The challenge is the building up of 'ecosystems' of actors working in networks and digital platforms, rather than chains (Andreoni et al., 2021). The tendency – and the ultimate aim - of such ecosystems is to be highly flexible in terms of production models of personalized and digital products and services, with real-time interactions between people, products and devices during the production process (Zhou et al., 2015).

The concepts mentioned above embed a large set of analytical blocks, which have been often neglected in favour of the static 'machine substituting labour' argument that is overrepresented in the academic literature. If it is true that (some) machines tend to substitute labour, it is also true that they often substitute some tasks/activities and seldom entire jobs. Even more often, jobs are modified by such technologies, both in terms of physical effort and of work autonomy and flexibility's degrees. Some other technologies do not substitute tasks, they make it possible to do things that were unthinkable before, such as collecting the huge amount of data allowed by Industry 4.0 technologies. For the scope of this review, we consider mechanisation, automation and digitalisation when these processes create a modification of the tasks performed by workers or the ways in which these tasks are performed. Specifically, we consider some technologies that may (or already have) influence task substitution – through automation – and/or task modification – through higher control over production time and execution procedures. The Appendix presents a detailed overview of these technologies.

# 3. Impact of automation on employment and gender

Based on the technologies described in the Appendix, the report reviews existing evidence on how these automation technologies may impact workers. A high portion of the risk embedded in the use of new technologies is still difficult to assess. Aspects such as flexibility in hours and locations, casual contracts, longer working shifts, low payment and inexistent legal protection are all potential risks that impact working relations beyond the impact on tasks and activities that are discussed below (Balliester and Elsheikhi, 2018). Within these aspects, workers are also likely to lose their capacity to organise and get organised due to a lack of relations with colleagues and the disappearance of a fixed working space (Tran and Sokas, 2017). The ways in which these elements disentangle is difficult to forecast, as it depends on many and heterogenous aspects; among them institutional factors have a strong role in shaping the effects of technologies' adoption and potential impact on working conditions, employment, and labour process. For example, high unionization could favour the decision-making process of technological change and avoid workers resistance. On the contrary, less unionization could pave the way for technology adoption aimed at undermining worker's space and opportunity to organise. Section 3.1 discusses the different theoretical frameworks that have been developed to study the impact of automation technologies on labour, with their main findings, while 3.2. focusses on the gender dimension and reviews existing evidence of a gender bias effect on automation technologies.

https://link.springer.com/referenceworkentry/10.1007%2F978-3-642-35950-7_16790-1#:~:text=Definition,services%20available%20on%20the%20internet.)

## 3.1 Automation and labour

Automation and its effects on labour and on society have been of great interest in economics and more generally, in social sciences. Different disciplines and different strands within the same discipline contributed to theoretical frameworks and sound empirical contributions to better understand these dynamics. The first theoretical strands focus on production processes taking the firm as the main unit of analysis. Such approaches – namely the capability theory of the firm and the labour process theory - derive from the classical political economy: the Smithian intuition that the division of labour – and the consequent deskilling – was a key enabler of technical change and economic productivity was followed by Marx's studies on the dynamism as well as the power dynamics that characterise capitalist development. Marx developed a detailed and rich study on the nexus between technological and organisational changes, where the latter is functionally arranged to fully exploit the former (Greenan, 2003).

The legacy from classical contributions was elaborated by the capability theory of the firm and the labour process theory; both theories embraced methodological variety, framing research questions starting from theory to grounded issues and to data gathering. On the one hand, capability and evolutionary economics focus on how technology diffuse, the determinants behind it, and the different forms of codified and tacit knowledge; they also consider different levels of capabilities that need to be part of firm's human resources to enable such process of technological change (Penrose, 1959; Richardson, 1972; Nelson and Winter, 1982). On the other hand, the literature on labour process emphasises elements that contribute to increasing control of capital over labour, focusing on surplus-value increasingly extracted and augmented by management with the use of more sophisticated technologies and the reduction of manual workers' autonomy (Braverman, 1974; Edwards, 1982). This literature made important contributions in our understanding of technological change processes as embedded into political choices and power distribution dynamics. Labour process theory acknowledges different forms of control that are exercised over workers, such as personal, bureaucratic and social controls (Orlikowski, 1991). Such controls have been changing as a result of technological change; for example, ICT technologies allowed managers to overcome physical supervision with systemic control, recently augmented with real-time dimension. However, recent developments challenge the direction of such change. While between the 1970s and 1990s, the literature converged around the fact that new technologies compressed workforce's skills and autonomy, the situation is different with more recent types of technologies. Despite a general agreement that digital technologies increase standardisation and control of work in lean production systems, there is no consensus on the effects of digitalisation over autonomy and control (Krzywdzinski, 2017), i.e., if technology continues to develop as a form of control (Noble, 1986), or not.

A second widespread theoretical framework comes from a more static observation of production and labour relations. Theoretical bottlenecks from the past, such as the marginalist revolution with the mantra of decreasing marginal returns and the neglected role that technology and organisation assumed in economic theory contributed to characterise a debate with scarce attention over technological progress. Technology has been observed as a part of a process that is subjected to decreasing marginal returns; a process that it is conceived as as part of an economic and social development already determined, and detached by social and political choices. As such, the focus has become almost exclusive on tasks and occupational changes while completely neglecting the other implications of technical change for work, such as conditions of work, conditions of employment and industrial relations (Fernandez-Macias, 2017).

Within this deterministic view of production process and technological advances, technology will unanimously tend to substitute labour. This, in addition to the availability of data at the sectoral – much more than at the firm – level contributed to a flourishing number of studies that focused almost exclusively on job destruction and how this is likely to accelerate due to technological change (Frey and Osborne, 2017; Arntz et al., 2016; Brynjolfsson and McAfee, 2014; Sung, 2018; Manyika et al., 2017), often overlooking the important analysis at the technological and organisational level. The rest of the section reviews empirical contribution on the effects that new technologies have on employment.

One of the most famous contributions is Frey and Osborne (2013), who forecasted a high number of job losses. They assess the degree of automation of different occupations, assuming that automation will happen and once it happens the correspondent job will be destroyed. Despite the ground-breaking effect of this contribution, the reality seems to be different at least due to the fact that automation happens to be about specific tasks and that most of the times, jobs are impacted by automation, but they seldom disappear. Such approach does not consider that the automation process is much more incremental because technical feasibility does not automatically imply economic feasibility, which vary across sectors and firms (Acemoğlu and Restrepo, 2016; Staccioli and Virgillito, 2021).

Along these lines, jobs are to be intended as bundles of different tasks (Cohen, 2016) - among which some are automated, and others are not. There have been two main conceptual frameworks to discuss technological change and employment, and these are: skill-biased technological change (SBTC) and routine biased technological change (RBTC). A third more recent framework departs from RBTC, bringing into the social and organisational dimension (Fernández-Macías and Hurley, 2016). Table 1 briefly presents these approaches.

| Taxonomies | Meaning | Authors |
|---|---|---|
| *Skill-biased technological change* | High skilled workers are complementary to the process of technological change; differently, low skilled workers tend to be substituted with demand shifting in favour of more educated workers. | *Pioneering work of (Tinbergen, 1974)(Katz and Autor, 1999); (Goldin and Katz, 2008); (Acemoglu and Autor, 2010b)* |
| *Routine biased technological change* *(or task-based technological change)* | Work tasks are defined by their routine, i.e., abstract and manual content. The more routine a job involves the more likely it is to be fully automated because technologies tend to go for routine types of activities. | *(Autor and Handel, 2013; Goos et al., 2014; Goos et al., 2009; Autor and Dorn, 2010; Autor and Dorn, 2013)* |

| | | |
|---|---|---|
| *Task-based technological change – revisited -* | Taxonomy that considers:<br>i) what people do at work – the physical and intellectual activities (content of tasks)<br>ii) how do they perform such activities, in the sense of the organisational structure (methods and tools for tasks activities) | *(Fernández-Macías and Hurley, 2016; Macias and Bisello, 2020)* |

Table 1. Source: Author

The SBTC approach is problematic because it does not explain job polarisation, as it does not give sufficient attention to the role of tasks, imposing a one-to-one mapping between skills and tasks (Acemoglu and Autor, 2010a). Nonetheless, there is a crucial difference between tasks, which are units of workers' activities, and skills, which are workers' endowments of individual and collective capabilities. Workers deploy their skills to perform specific tasks; this difference is crucial since workers can perform a variety of tasks with their given set of skills, adapting them in response to technological and organisational changes.

A further elaboration on this topic has been the task-based technological change, which sees a technological bias for routine-based activities. This approach divides tasks into routine and non-routine tasks and cognitive and manual tasks; the problem with this approach is that routine and cognitive tasks are strongly associated and correlated (Macias and Bisello, 2020). Such framework maintains the process of substitution/complementarity between human labour and machine – the higher the routine, the higher the probability of substitution, while overlooking the heterogeneity of tasks automation both at the sectoral and technological level (Fana et al., 2021). Thus, the problem with the task-based technological change approach is that it omits two important aspects, which are: i) consideration of human agency as a key factor shaping tasks at the workplace level; ii) proper account of the social and organisational aspects of production and service provision. A revisited task-based technological change approach by Fernandez Macias and Bisello (2020) brings into the analysis the social and organisational dimensions, such as further specifications on what people do at work and how do they do it. This framework is better in line with the evolution of organisational and technological changes and the capability theory of the firm discussed above (Dosi, 1982; Penrose, 1959), where resources, capabilities and power distribution play a central role. A complementary approach is the one introduced by Cetrulo et al. (2020), with reference to the Italian occupational structure; starting from the evolutionary theory – thus with an emphasis on learning and knowledge – they intersect work organisation and labour process theories. By looking at power, skills, cognitive and manual dexterity, and teamwork, they found that autonomy and control tend to diverge from learning dynamics in Italy. This study pinpoints to the importance of examining specific countries' productive structures, where important heterogeneity – due to institutional factors, among others - lies.

Among the five types of technologies described in the Appendix, most of the studies assessing the impact of new technologies on labour take industrial robots at the object of the analysis. This is due to multiple reasons; on the one hand, advanced industrial robots are the only "new" technology that is fairly diffused, something that allows empirical analyses on their deployment. On the other hand, and relatedly, industrial robots are the only technology for which data exist since the International Federation of Robotics (IFR) dataset has been collecting detailed data on robots at four digits (ISIC rev. 4) for over two decades. Results from studies that use these data are mixed; analyses that focus on IFR data find a negative relationship between technological change and employment, while those that use microdata find a positive relation. Generally, even studies that find a positive correlation between robotics and employment present a small effect of robotisation, pointing to the fact that job variations depend on other factors.

| | Authors | Type of effects on employment |
|---|---|---|
| | (Graetz and Michaels, 2018) | Negative. 1993–2007 in 14 sectors and 17 countries |
| | (Carbonero et al., 2018) | Negative. 2000 to 2014 in 15 sectors and 41 countries |
| | (De Backer et al., 2018) | Positive 2000- 2014 in developed countries (depending on the years analysed) and no correlation for developing countries |
| | (Borjas and Freeman, 2019) | Negative in particular low-skill employment, in the US. |
| | (Klenert et al., 2020) | Positive 1995-2015, EU countries |
| Robots are matched to regions based on the distribution of employment, so to identify the effects based on spatial variation | (Antón et al., 2020) | First period (1995-2005), association between robots and employment negative; second period (2005-2015) the association is negative with a high increase in productivity. |
| | (Acemoglu and Restrepo, 2019) | Negative effect of robots on employment and wages |
| | (Dauth et al., 2017) | Negative in Germany (each robot destroys two manufacturing jobs), but it is counterbalanced by the effect of robots on the rest of the economy. The overall effect is thus neutral. |
| | (Chiacchio et al., 2018) | Negative impact of robotisation on employment and wages in six European countries. |
| Studies based on micro-level data | (Jäger et al., 2016) | Neutral effect on employment and positive effect on productivity. Data from the European Manufacturing Survey across 3000 firms in six EU countries and Switzerland for the year 2012. |
| | (Koch et al., 2019) | Positive 1990-2016 on 1900 manufacturing firms in Spain. |
| | (Domini et al., 2019) | Positive for the case of France. |

Table 2. Source: Author’s elaboration

Almost the entire array of studies is on advanced economies; the few contributions on developing countries do not find evidence for polarization in least developed countries while highlighting strong heterogeneity (Maloney and Molina, 2016). For what concerns other specific studies on other types of production technologies, these are scarce and often anecdotal. There are various pivot projects regarding IoT, AI and 3D printing but due to the lack of data and to the lack of diffusion, there are few systemic studies. For example, for what concerns AI, Tolan et al. (2020), developed a framework that combines occupations and tasks from the labour market with AI research intensity through an intermediate new layer of cognitive abilities. Their study finds that AI applications are built to perform certain abilities, rather than to executed full work-related tasks and that most tasks will require multiple abilities to be executed (Tolan et al., 2020).

On a different level, heterogenous evidence has been found on how these technologies impact the level of control and autonomy of workers. Before getting into this, it is interesting to note that there are some criticisms over the fact that technologies may benefit workers through more autonomy (Adler, 2007; Butollo et al., 2019). These authors point out that given the interdependency of actors working along value chains, individual autonomy is hardly feasible, especially when coordination and synchronisation increase with the use of digital technologies. Along these lines, they question whether it is even desirable that workers have more autonomy in a working environment with high pressure to comply with time schedule and to minimize errors. Rather, the question about workers' conditions would become whether they enjoy more intra firm participation, integration between different groups and flexibility of working hours (Butollo et al., 2019).

In theory, higher levels of automation and digital technologies – which are often interrelated in a such a way that automation is a pre-condition for digitalisation - could imply that workers are freer and do not have to stay along with machines all the time; however, as already discussed, the impact that new technologies have on workers depends on how these technologies enter the production process. A study by Butollo et al. (2019) depicts a situation where the use of digital technology intensifies the tendencies towards standardization and control of work. Cirillo et al. 2021 distinguish discretion and autonomy, the former is more about decision making authority and forms of control – and they find digital technologies increase discretion - and the second is more related to the breadth of action space and the possibility of making own rules – which is found to remain the same or decrease.

In another case study on automotive performed by Cirillo et al. (2020), a general intensification of working time is registered, with takt time and dead time that have been generally reduced. A survey conducted by the German Trade Union Confederation (Gewerkschaftsbund, 2016) found that 46% of responding employees thought that digitalisation increases monitoring levels for both employees and work processes, with the sectors most affected being finance (60%), recycling (59%) and logistics/transport (58%) (Peruffo et al., 2017). Again, the real challenge at stake is whether the rules of interdependence and cooperation – which are typical of more integrated digital systems – will evolve in a participatory and cooperative process rather than falling in a top-down direction.

In relation to the degree of control and autonomy, there are different empirical findings that emerge from firm-level studies. Albano et al. (2019) discuss digital Taylorism and the so-called electronic panopticon. According to the former, management would enhance the opportunity to deepen standardization and routinization of work stemming from the adoption of new technologies. Such tendency would potentially affect employees from the shopfloor to the managerial side, realizing the Taylorian utopia through the elimination of any opportunity for workers at all hierarchical levels to exercise autonomy. In this case, constant control by supervisor would be complemented by a narrow space for human and social experience in the workplace. According to the latter hypothesis, i.e., the electronic panopticon, preliminary qualitative studies in Germany find that new technologies would enhance the importance of teamwork and cooperation between different units of the firm integrated through IoT and cyber-physical systems. The tendency towards decentralization of decision making would go in parallel with enhanced centralized control. This is also confirmed by a study that uses a socio-technical framework exploring the effects of work organisation, looking at the number of technologies introduced and the level of integration between different technologies along the manufacturing process (Cagliano et al., 2019). They found that with few technologies introduced, there is a tendency towards job specialisation, centralisation and standardisation, while the higher the number of technologies and their interrelation, the stronger job breadth and bottom-up decentralised flow of information. Pfeiffer discusses a third way, the living labouring capacity (Pfeiffer, 2014): such hypothesis, in a more optimistic way, put forwards how the intensive use of digital technologies may open opportunities for workers to influence the decision-making process and the work organization.

These technologies may have different implications for workers and production processes. While the disruptive substitution effect seems not to be the case yet, these technologies are likely to change considerably the control over workers activities – e.g., sensors are increasingly used on workers - and the skill-demand to the market, where more and more technicians and engineers are likely to be needed. The interesting aspect is that such skills are rarely encountered in one worker only, and this could be a major obstacle for SMEs attempting to digitalise their production processes due to the size of their workforce (Compagnucci and Da Empoli, 2016). As managers will need to interpret data and formulating ideas on how to improve, it is more likely to move production control from managers to skilled technicians (Barbato, 2015).

To conclude, the managerial and operational aspects of such trend of new technologies' adoption are crucial for the redesign of productive processes and organisational renewal. Business model transformation can originate organisational innovation at any level (Zott et al., 2011; Chesbrough, 2010) and determine what types of technology effects there will be on productive structures. A number of scholars have been investigating the importance that different managerial decisions have in the technological and organisational restructuring, reaching the conclusion that effects of technology on work depend on the work organisation and the production structure in which it is deployed (Bailey, 1993). The same technology can be used either in the deskilling mass production framework, or in a flexible specialisation with employee participation and involvement leaving the choice between cooperative capitalism and managerial capitalism (Best, 1990; Lazonick, 1990).

### 3.2 Automation and gender

Very rarely technological changes impact society in the same way, levelling positive and negative effects. More often, they exacerbate existing inequalities. Automation, in fact, may lead to a widening of inequality gap in terms of wage and power inequality, skill inequality and gender inequality, among others. For example, it is very unluckily that technological change and automation will affect male and female workers equally, and for various reasons; apart from a social and cultural bias against female workers in high tech production processes, female and male workers still present very different skills and occupational trends, with the former that are less inclined to study STEM (Science

Technology Engineering and Maths) disciplines, and to enjoy more stable working contracts. Being less involved in such disciplines, women are less likely to be part of high skilled jobs that tend to be complementary to the introduction of new technologies. The gender dimension is scarcely studied, especially in empirical terms, in both developed and developing countries, with the latter that are underrepresented in academic analyses, but whose situation will be crucial to assess whether more women entering the job market has been an occasional trend due to globalisation (Balliester and Elsheikhi, 2018). The two broad areas in which automation has effects on employment, i.e., the structure of employment, and the organisation of work, can be observed through a gender perspective.

There are some tentative analyses to present future challenges and opportunities. A scenario analysis with six European countries expects the female labour force to increase and reach 75.1% on average, with Sweden having the highest rate (89.7%) and Italy the lowest (68.8%) (Bisello and Mascherini, 2017). Also, women are expected to gain participation in more highly qualified jobs, with France presenting the best scenario. A positive projection comes from a gender-focused contribution stemming from the Technequality Horizon project (Suta, 2021). Although she acknowledges that the progress towards gender equality may have a setback due to the pandemic – as women are more employed in occupations that were most affected (Alon et al., 2020) – she reaches three predictions using more than 20 scenarios: first, in all these scenarios job losses due to automation see more men affected than women as automated occupations are more likely to be man dominated; second, if there is a higher risk of an occupation replaced by technology, and if adoption happens quickly – by 2035 – the gender gap narrows. Thirdly, if there is low risk for an occupation being replaced by new technology and adoption happens slowly – by 2075 – the gender gap narrows very slightly (Suta, 2021). A McKinsey study reported by Madvagkar et al. (2019) finds that automation would displace men and women equally over the next decades. Nonetheless, women are expected to need a more significant transition to capture new opportunities due to the barriers they face, both culturally and historically. For example, globally, men are 33% more likely than women to have access to the internet, and women account for only 35% of STEM students in higher education (Madgavkar et al., 2019). Using a task-based approach, a study performed by the International Monetary Fund6 finds that women perform more routine/codifiable tasks than men across sectors and occupations, and fewer tasks that imply analytical input or abstract thinking, where it is more likely that technologies complement human skills. They find that a larger proportion of the female workforce is at high risk for automation than the male workforce, 11% versus 9% (Rubery, 2015; Brussevich et al., 2018). Gender differences are likely to be reproduced because of women's more vulnerable position vis a vis employers and because of old inequalities in the workplace linked to gender discrimination also in the division of caring and housework responsibilities (Rubery, 2007; Cranford et al., 2003; Vosko et al., 2009). Although such hypotheses and speculations are important to maintain a careful focus on these challenges, different authors agree on the fact that labour market institutions, social norms and public policies will be responsible for the gender impact of occupational restructuring under the adoption of new technologies (Rubery, 2018).

Beyond scenario-based analysis, studies that empirically assess the current situation regarding automation and employment through gender lenses are very few. A large scale evidence on the impact of industrial robots on the gender pay gap was performed in 20 European countries, showing that robot adoption increases both male and female earnings and the gender gap, with results driven by countries with high initial levels of inequality (Aksoy et al., 2021). Piasna and Drahokoupil (2017) studied the transformation of the occupational structure in the EU between 2011 and 2015 and did

[6] Brussevich et al., 2018

not find benefit categories dominated by one gender, with only a weak relationship between the share of women and job growth across 37 occupational categories. They found that women are more likely to perform repetitive and routine tasks across most occupational categories, and less likely to perform complex activities (Piasna and Drahokoupil, 2017). A large study covering 30 countries finds that a larger proportion of female workforce is at high risk for automation than the male workforce (11% versus 9%), with 26 million female jobs potentially at risk (Brussevich et al., 2018). The likelihood of automation is decreasing in education, numeracy and literacy skills, and in firm size. For instance, the risk of automation is less than 1% among workers who have a bachelor's degree or higher. The study also stresses that women are underrepresented in ICT jobs and vastly overrepresented in education, health and social services, which are at low risk of being automated.

A detailed and granular study such as the one performed by Fana et al. (2021) with reference to the French economy found that gender discrimination within the same job exists and it is a persistent characteristic of the labour market; they also found that gender matters both in terms of work organisation and of distribution of power, with women having less authority and autonomy. This latter point was also found on a precedent study by Smith et al. (2008) where they assess that women have a lower degree of autonomy and authority within the same occupation. Another study by Babcock et al. (2017) find that women tend to perform less attractive activities compared to men, which can eventually lead to lower promotion possibilities, thus enlarging the gender gap. Finally, a study that adopts Frey and Osborne methodology confirms that female workers are more exposed to higher risks of computerization and that the already existing trend of technology and gender bias effects is getting worse with AI type of technology (Hamaguchi and Kondo, 2018) with a focus on Japan).

# 4. Automotive and garment sectors: the impact of automation on employment

The previous section provides a general overview on the impact of automation on employment, and on gender. As the focus of this review is on the manufacturing sector, and specifically on automotive and garment, the rest of the paper reviews existing studies on these two sectors. The choice of the sectors is based on a contraposition between a highly automated and men dominated sector, i.e., the automotive, and a less automated and female-dominated one, i.e., garment. These sectors are also highly different in their global production structure, with the automotive sector characterised by a producer-driven GVC, with high standards and where the final producer has the strongest power (Sturgeon et al., 2008); the garment sector is a buyer-driven GVC, driven by low production process and an important role played by middlemen (Appelbaum and Gereffi, 1994). Not in garment nor in the automotive sector, the adoption of new technologies has been radical and disruptive; it rather appears to be part of an incremental process where some steps within production are automated faster due to different reasons, such as production process fatigue, material-driven automation, volume, quantity of the task performed, etc. The next two sections discuss such effects in the automotive and garment sectors.

## 4.1 Automotive

*Production process and automation*

The automotive sector has been a fertile field for many improvements in production technologies, as it is characterised by intensive economies of scale and by the use of automated machines since the

1970s (Sjoestedt, 1987). The first use of industrial robots was in 1960, a Unimate robot implemented at Ford in the United States. In this sense, the sector has always been an influential ‘trend-setting industry’ (Womack et al., 1990), due to its continuous innovation trend both on the technological and organisational aspects. On the technology side, the automotive sector has always been the bedrock of manufacturing automation advances due to its high-volume production, high sophistication processes, high levels of standardisation and modularisation that allowed the deployment of advanced technologies. On the organisational side, it is where Fordism mass production and lean production firstly emerged, and where outsourcing mechanisms and the emergence of global value chain were more visible.

If it is true that automation in the automotive sector is not something recent, it is also true that it has been slowly evolving, showing high heterogeneity across countries and firms. Generally speaking, the automotive sector is highly automated to better comply with international standards, as well as with the required stability of automotive specific production processes (Sjoestedt, 1987; Krzywdzinski, 2017).

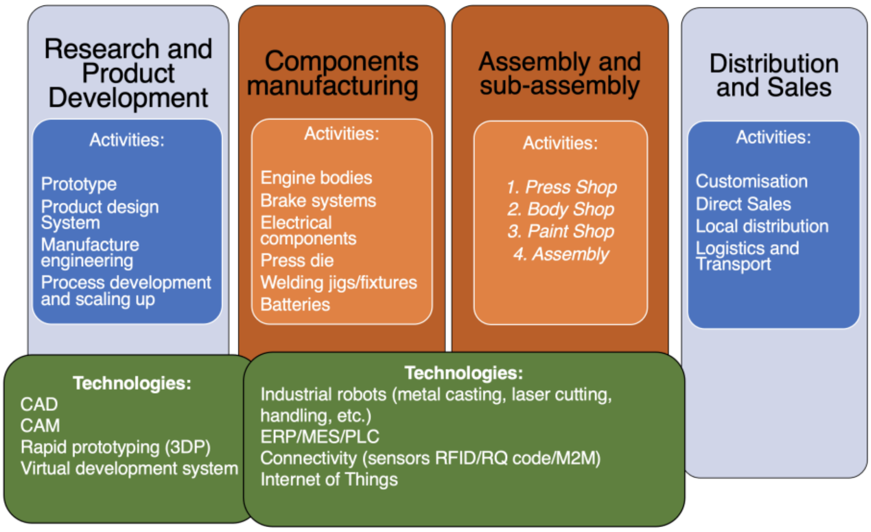
Different automated technologies are deployed along the automotive value chain. The bottom part of Figure 3 presents these technologies matching them to different functions of the value chain. We focus our attention on final assemblers, which are organised into factories that are generally[7] divided into four parts presenting similar levels of automation but deployed differently depending on different business models:

- pressing shop – where metal sheets are pressed and moulded.
- body shop – where parts are welded together to form the body of the vehicle.
- paint shop – where the body vehicles are painted
- final assembly - where the rest of the parts are assembled.

The level of automation between such stages is different, and it has been historically different. Since the mass production era, stamping, welding and painting have been mechanised and automated in the 1970s-1980s. Differently, previous attempts to automate final assembly – which is the segment where almost 60% of total employment in factories lies (MacDuffie and Pil, 1997) - did not work because workers’ teams have allowed more flexibility and efficiency in dealing with high complex processes such as the ones involved in final assembly. This was still the case at the beginning of the new century and for two main reasons: on the one hand, millions of workers were added to the world supply workforce with the entrance of countries such as China, India, Vietnam, which are characterised by extremely low salaries that have been making more profitable to build local regional value chains in these regions, rather than automating in advanced economies. On the other hand, there has been higher variation that increases complexity and challenges the automation process (Pardi, 2018; Pardi, 2019; Jürgens and Krzywdzinski, 2016).

[7] Sometimes the pressing shop is not part of the final assembly operations, but it is outsourced.

*Figure 3. Matching graph between automotive stages of production and automation technologies*




Source: Author.

Attempts to automate final assembling – a first wave at the end of the 1970s by Western carmakers and a second wave in the 1980s by Japanese firms – led to very problematic aspects due to extremely expensive factories and frequent downturn of machines that - in a more automated process – risks to stop the entire line. As mentioned, these aspects, together with the lack of flexibility that automation implies, and confronted with the necessity to be flexible in the final assembly, caused the abandonment of such automation attempts by carmakers (Jürgens and Krzywdzinski, 2016; Pardi, 2019). Leaving by side unrealistic technological expectations and considering the complexity of the processes involved and the long-time horizon associated with them (Pollock and Williams, 2010), it is unlikely to expect a sudden increase in automation technologies in the automotive sector.

Existing technologies that are progressively catching up are divided into software and hardware. On the one hand, there are software technologies that are already quite spread in the automotive sector such as ERP systems, MES, PLC and various types of supply chain management that connect different areas of the firm, and the supply chain. Moreover, these technologies are responsible for the profound technological change, which started in the 1990s, of indirect areas such as product development, planning, production control, and quality among many others (Krzywdzinski, 2020). On the other hand, hardware automation technologies such as:

- Industrial robots
- 3D printing, mainly for jigs and fixtures making.
- IoT, sensors and actuators
- Virtual Reality Technology, mainly for training purposes.
- Cobots, exoskeleton, mainly in the last final assembling stage.

The implementation of new technologies and their high degree of interconnectedness make such integration complex and often not economically viable. In fact, within the current debate about automation, some of the assumptions behind the digital revolution are already being challenged and empirically contested (Paus, 2018). Analysing different types of OEMs, Pardi (2019) states that there is little scope for a digital manufacturing revolution taking place in the automotive sector. So far, the impact of new technologies (so called Industry 4.0) in the automotive industry is small and future implementation and diffusion do not seem to be a reality for the near future, at least in mass production firms (Pardi, 2019). In niche luxury car manufacturers, such as Lamborghini, the situation is different; they present widespread adoption of new technologies such as IoT, collaborative robots, big data analytics, and they have workstations everywhere from engineering departments to assembly lines (Cirillo et al., 2021)

A game changer in terms of effects of technologies on labour and production organisation seems to be - as already mentioned in the previous section - the different managerial and business model strategies that firms adopt within firms. At the firm level, Lazonick's analysis illustrates that investment in effort saving technologies activate cooperative relations between workers and managers. It is within these relations that lies the ability of businesses to generate value by utilising the productivity potential of past investments in organisation and technology, as alternative to undertake costly investment required to develop the productive potential of new effort saving technologies (Lazonick, 1990). The continuity with the past comes also from a closer observation of Industry 4.0 organisational changes, which are based on the promised of higher flexibility and streamlined organisation of work (Osterman, 1994). Such changes appear to be a natural step from the lean production paradigm of customisation, inventory reduction, tracking errors, etc. (Jaikumar, 1986). In this sense Industry 4.0 seems to be only the topping on the cake, which makes lean production more flexible (Rüttimann and Stöckli, 2016; Mokudai et al., 2021), in line with many scholars arguing that different work practises are a precondition of new technologies' deployment.

The decision to adopt specific technologies and the way in which this is deployed within the shopfloor depends on how the organisational process is structured. Pardi (2017) distinguishes two models, the imperialist strategy and the multi domestic strategy8, with the former being still more common among big multinational companies and the latter being more adaptive and based on resource-based organisational management. Imperialistic strategies are challenged under a series of aspects as they are more expensive and often non-efficient; if we consider employment and technologies, modern factories require very high production standards and maintenance of sophisticated machinery and robots. Such training is often offered by the local government, but it fails to enhance individual and collective capabilities since it is geared towards implementing standards developed by the central corporate engineering department (Pardi, 2017).

### *Automation and labour effects*

Although the scope for a manufacturing revolution based on automated and digitalised technologies appears limited in the automotive sector, there are a number of studies that attempted to analyse the relationship between a higher level of automation technologies and its effects on employment – both quantitatively, i.e., displacement effects, and qualitatively, i.e., on skills. Some interesting contributions reveal a blurred relationship between automation and deskilling, also revealing that the reasons why firms automate are heterogenous. A study by Smith and Thompson found that the impact of automation on skills and employment depends on workplace politics (Smith and Thompson, 1998); while the decision to automate is not directly related to deskilling – certainly less than during the mass production mechanisation processes – this nonetheless leads to a polarisation of skills

[8] In the multidomestic strategy model, motor vehicles are designed and developed tailored to local markets, with a sort of reversed innovation process: it starts from the needs and features of emerging markets whose translation into design and development phases lead to new technological solutions. In this way, local skills are significantly developed, both in terms of R&D centres development and local industrial optimization that takes over global optimisation.

requirements (Jürgens et al., 1993). The restructuring process embedded in new technologies adoption involves high capital intensity in the final stages of manufacturing. The cost of such capital intensive process is amortized by flexible use of the labour force and a considerable amount of subcontracting that require organisational capabilities and established work practices. In the auto industry, the introduction of new technologies is not only a matter of cost consideration but a complex decision where employees representatives and collective bargaining play an important role (Jürgens et al., 1993).

Although the cost of labour is often called to be the reason why firms automate, there is little evidence of it. For example, in a comparative study between Germany and CEE (Central Eastern Europe) automotive firms, Krzywdzinski (2017) finds that the lower cost of labour in CEE countries does not mean lower level of automation. Rather, he finds that institutional factors and the type of firm account for the lion's share9. Also, he finds that when automation takes place, there is a rigid division of labour in the shopfloor between direct workers that only operate tasks feeding the machine and indirect workers who have regulation tasks. In fact, among the consequences of automation processes, polarization and the increasing segmentation of the labour force is something that could occur (Lüthje and Tian, 2015). This is in line with the study reported above from Cagliano et al. (2019), where they argue that an initial use of technologies and a lower level of technological integration increase segmentation and task standardization.

There are numerous studies on the automation effects of the automotive sector in Germany (Dauth et al., 2017; Krzywdzinski, 2017; Krzywdzinski, 2020; Jürgens et al., 1993). These studies find no evidence of displacement but rather of changes in the composition of employment. Comparing Germany, Japan and the United States, Krzywdzinski (2020) find the most dramatic decline among blue collars in Germany. However, such decline has not resulted in job losses due to the high increase in engineers, technicians, and data scientist's employment: thus, the absolute value remained stable while relatively more engineers and technicians have been employed. In addition, robot-exposed workers have a higher probability of keeping a job at their original workplace, thus having higher stability, although they may end up to perform different tasks (Dauth et al., 2017). Similarly, Drahokoupil (2020), in a book discussing automation and employment effects in a number of European countries, finds that there is no evidence of appreciable cuts in employment. However, there are initial indications of workers being reassigned to new tasks for new skills (Drahokoupil, 2020). A more pessimistic analysis is the situation depicted in a developing country such as South Africa. The study based on the automation of the final stages of automotive assembly finds that the high level of redeployment typical of when automation technologies were adopted in stamping, welding and painting, is less likely to happen in final assembly automation (Chigbu and Nekhwevha, 2020).

Although it is still too soon to have a definitive picture of the situation, there are reasons to believe that the negative effect of robots on aggregate manufacturing employment are not linked to direct displacement, but to task modification. A lack of displacement effects has also been found in recent studies on Italian automotive firms. With a focus on the level and type of control over workers, Moro et al (2019) studied the introduction of MES (manufacturing execution systems) and digital torque wrenches in the automotive sector. They find that such technologies facilitate workers' interaction with tools and machines while contributing to the establishment of impersonal rules and constraints.

[9] Particularly, two dimensions are relevant: the public commitment to vocational training and the involvement of firms initial vocational training. In addition, whether firms are leaders in the introduction of new technologies or they are laggards matters, as plants that are responsible for testing and implementation of new technologies have higher implementation and vocational training.

On a similar line, Gaddi (2020) and Virgillito and Moro (2021)10 reported that the faster reconfiguration of lines and machinery and a reduced time of resetting the organisation of production enabled by new technologies contributed to intensifying working rhythms. Carbonell (2020) studied the French case of PSA, finding that workers tend to lose autonomy in discretionary power. Using a more granular framework, Cirillo et al. (2021) reported above found that the efforts in terms of digitalisation increase workers' discretionary while there is not a similar pattern for autonomy.

In conclusion, sectoral studies with a firm-based approach agree that organisational practises matter significantly for the adoption of new technologies and the ways in which these are deployed. Dynamics such as outsourcing, Taylorism management type of decisions and business models anchored to a hierarchical and rigid structure have a much stronger effect on employment structures in comparison to machines displacing labour effects.

## 4.2 Garments

### *Production process and automation*

The garment sector is conceived as a low value-adding manufacturing industry, where manual labour is still prevalent, especially for low labour costs associated with countries such as Bangladesh, India, Cambodia that have been increasingly taking part in textile and garment GVCs in the attempt to capitalise on the opportunity to promote industrialization based export (Gereffi and Memedovic, 2003).

The sector characterises early stages of development, and national industrial policies often target it to favour capabilities accumulation (see for example Hauge, 2019 for South Korea). In Europe, there are similar cases, as the sector has been the manufacturing bedrock of industrial development for England in the XIX century, and more recently for Eastern European countries like Romania. In the latter, the garment sector has been operating for over 100 years, and it still is the sector that employs the largest number of people – especially women - in manufacturing. Yet, the main competitive advantage is still the low cost of the labour force accompanied by a low level of technological innovativeness (Şerbănel, 2014). Similarly, another example is Mexico, the maquiladora country par excellence, which is still characterised by a low level of automation. In the late 2000s, only 31.39% of Mexican firms in the sector were using automated/numerical controlled machines, and only 0.04% was using robots (Minian et al., 2017).

Looking at the production side of the story, the way in which goods are produced in the garment sector is just as labour intensive today as it was 100 years ago, with a lot of cheap labour deployed in developing countries. However, the sector is not a typical mass-production industry with almost exclusively unskilled labour; rather, it is dominated by low-skilled low-wage operators pushing materials through sewing machines (Bailey, 1993).

Although there is a wide scope for automation in the garment production process11, this has not become a reality yet, and due to three main reasons: first, technical bottlenecks such as the difficulty in linking automation to the flexibility required to handle fabrics and a wide variety of products that change rapidly (Bárcia de Mattos et al., 2020b; Yue, 2005). Second, economic impediments such as high investment costs in an industry that runs on tight margins and squeezed suppliers unwilling to

[10] http://gerpisa.org/node/6415

[11] The opportunity to automate stems also from the fact that variations in the garment production process are unacceptable as they generate defects, higher production costs, etc. (Dinulescu and Dima, 2019)

invest in technologies whose return is less than six months (Bárcia de Mattos et al., 2020b). For example, installing a robotic assembly line for sewing, which replaces around 15–16 workers, needs an investment of more than US$1 million. So, a medium-size firm with 100 tailors needs an investment of US$8–9 million to adopt the robotic process; this is not economically feasible for many developing - but also developed - countries (Vashist and Rani, 2020). Third, the shift in the workforce and skills is a challenge due to low resources for training and worker's formation in a sector running on tight margins (Bárcia de Mattos et al., 2020a)12.

Nonetheless, advancements have encouraged the applications of technological innovations in garment manufacturing, including high sewing machine speed, CAD, CAM, and new techniques in cutting, fusing, pressing, and robotics (Yan and Fiorito, 2007). As this field is at an exploratory stage, most of the research follows case study approaches to identify major challenges and opportunities linked to technology adoption (Bertola and Teunissen, 2018; Fernández-Caramés and Fraga-Lamas, 2018).

Similarly to the automotive sector, technologies have been of two types. Software technologies: CAD, CAM, ERP software for production planning and inventory management. Particularly, CAD and CAM are used for automated body scanning, a non-contact technique that captures body dimensions over 360 degrees by using white light, laser light (Nayak and Padhye, 2016), and the development of virtual fit model. The technology also helped in decreasing product development time and increasing efficiency allowing trial and error before initiating cutting operations on the fabric (Sayem et al., 2010; Hoque et al., 2021; Zhang et al., 2016). Among hardware technologies, the following are the most discussed (Nayak and Padhye, 2018; Hoque et al., 2021; Kumar et al., 1999):

- Automated sewing: it is a very new technology, which can explore new dimensions in sewing, and it allows to produce high-quality high-tech garments. The CNC technology is the most important 2D-sewing operation for small and large area flat sewing applications - vs the new 3D sewing technology, which makes it possible for the first time to sew 3D seams automatically, through an adjustable mould which can be adapted to different sizes and shapes of the garments (Gries et al., 2018; Moll et al., 2009).
- Automated identification using RFID to trace products during the whole manufacturing process. RFID technology deserves attention as it has been spreading in the sector lately. RFID minimises human interaction by tracking and transferring items using radio signals, and it allows an error-free system from suppliers to manufacturing, distributors and retailers (Tajima, 2013), while increasing efficiency and accuracy (Azevedo and Carvalho, 2012). Some studies explore this technology: Chan (2016) examined Zara, Marks and Spencer and American apparel companies and found that they had significant improvement in the visualization of product flows and efficiency inventory management, finding that the most applied aspects of RFID are shop floor management, logistics, distribution management and customer relationship.

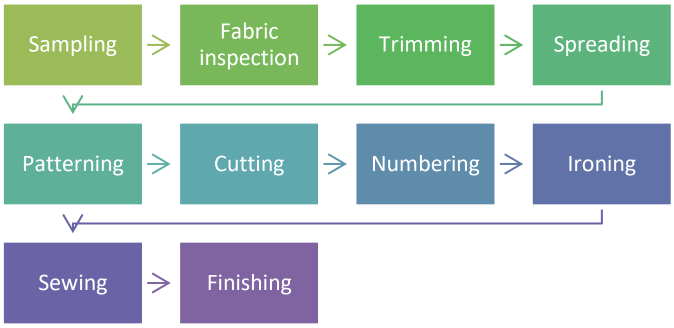
  Other types of less explored technologies are:
- Programmable Production Controller
- Automated material handling, which is a promising area not fully explored yet
- Automated inspection systems

[12] In addition, the level of automation depends on industry size, export market, garment styles, profitability, capex, management policy and technical skills.

- Fabric spreading and cutting

Preliminary studies investigate the application of digital production technologies on garment manufacturing. For example, Sun and Zhao (2017) explores 3D printing technology within the new realm of direct digital manufacturing (DDM), and they critically assess four impacting components that 3DP may have on the fashion industry: design and product development, sourcing and manufacturing, retail distribution and consumer and sustainability and optimization. Mattos et al. (2020) confirm that 3D printing has a high potential in prototyping and custom-made products (potentially this technology would not require assembly anymore!), yet it is not imminent, and it had more success in the footwear industry. Other technologies are discussed in the literature, such as augmented reality in prototype design and e-shopping (Hlaing et al., 2013; Liu et al., 2017), and new machines such as the promising Sewbo. Although at a very preliminary stage, Sewbo technology would allow to sew complete articles automatically. Making use of collaborative robots, the main innovation of Sewbo is the treatment of pieces of fabric, making them temporarily rigid with water-soluble chemicals. At the moment, one of the main production-related limitations of this technology is that it cannot work with material that would be damaged by soaking water and waterproof fabric (Bárcia de Mattos et al., 2020a).

*Figure 4. Garment manufacturing process*




Source: Author based on ILO, 2017 and Nayak and Padhye, 2018

If we look at different stages of the production process (Figure 4), the most automated part is cutting. In contrast, the least automated is sewing, which contributes to approximately 35% to 40% of total costs, and it is where considerable value addition of garment products lies (Textile and Made Jahrbuch, 2011). Pressing and ironing lack automation processes. They are generally activities performed in inhospitable environments by workers with less skills; these activities are believed to be more suitable for male workers because of the strenuous work in poor working conditions are counterbalanced by a higher pay.

The types of technologies as well as the deployment of new techniques is highly heterogeneous in the industry, and it depends on the types of company13, as each model implies a different set of

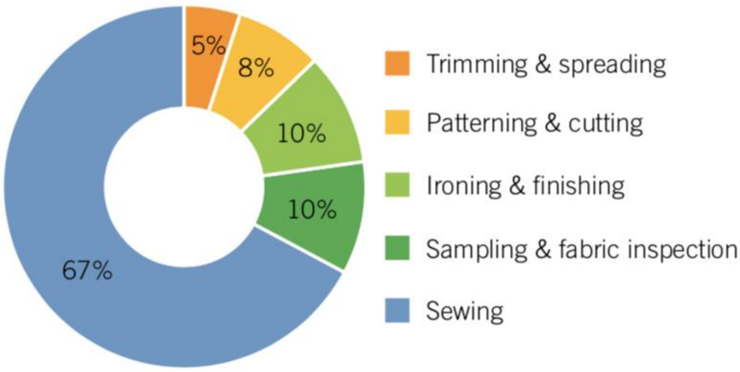
[13] There are four main types of companies in the garment production: i) Assembly/cut, make and trim: manufacturers cut and sew woven or knitted fabric or knit fabrics directly from yarn. Generally, very limited decision making, and low profits, strong competition between these subcontractors; ii) Original equipment manufacturing/ free on board: manufacturers are responsible for all production activities, including the cut make and trim activities, as well as finishing. They have upstream logistics and procurement capabilities; iii) Original design manufacturing (ODM)/Full package with design. manufacturers focus on adding design capabilities in addition to production (Chang et al., 2017).

technologies that can be adopted. For example, original design manufacturers may use 3DP for rapid prototyping, which may not be the case for cut-make-and-trim companies. Moreover, within these companies, technologies are heterogeneously distributed along different stages of the process; for instance, product development and design are characterised by increasing use of 3D printing and CAD, while in production there is an increased use of automated cutting machines, ironing machines and – to a lesser extent - sewing robotics.

Automation and employment effects

Being at a very preliminary stage of analysis, it is hard to determine which impact there will be on automation in garment manufacturing employment. If certain conditions do not materialise, such as lower capital goods' costs, higher salaries, better skills, automation could never take off in this sector. As expected, the less automated stage, i.e., sewing, is also where the highest share of employment is distributed (Figure 5).

*Figure 5: Employment shares per stages of garment production*




.Source: ILO, 2017

Whether sewing will be automated or not – thus producing an impact on labour – depends on many factors. The process is done predominantly by traditional methods – with workers manipulating pieces of fabric through sewing machines – that better suit the high dexterity and flexibility required to work with fabrics of different weights and grades. Surveys suggest that while businesses are interested in AI, few are rolling them out for commercial use (McKinsey, 2018).

A respondent from an ILO case study mentioned that sewing machines are far from allowing full automation of any technical production (Bárcia de Mattos et al., 2020b). The latter study discusses a series of interviews with fashion conglomerates reporting how firms do not perceive a need for automation and digitalisation, despite an industry characterised by routine and repetitive work. In addition, the case study reports that when firms foresee automation to specific processes, this is, almost exclusively, a worker-machine type of collaboration rather than a machine substituting worker. For example, Kucera and Bárcia de Mattos (2020) discussed a case of the Italian-based company MAICA. The company adopted a strategy with workers hand-feeding the fabrics into machines that break down the shirt and making the process into discrete steps. This semi-automated approach may present a transitional stage towards full automation, or it may be the most effective incremental way to adopt technologies in the sector. If the latter will become the dominant trend, the impact on employment would be much different than what it is assessed in forecasting studies. If and when firms decide to automate, business model and management strategy are key considerations, also because it is not rare that companies partner with technology developers to better engage in technology transfer, as also expressed by firms at different stages of the value chain (Bárcia de Mattos et al., 2020b).

In line with findings discussed in previous sections, most of the time, the introduction of new technologies does not substitute workers. Still, it modifies the ways, the pace, the quality of the activities that the worker performs. For example, when the unit production system was introduced in the apparel sector, it meant the introduction of mechanical control of the work "rhythm"; the tasks remained the same, but the throughput time and the inventory levels were reduced, also implying more isolated workers (Bailey, 1993)

Estimates report that in both developed and developing countries, workers in the industry are also disproportionately female (Kucera and Tejani, 2014). Findings based on the controversial Frey and Osborne (2013) methodology found that textile, clothing, and footwear in the ASEAN countries (Malaysia, Thailand, Philippines, Cambodia, Vietnam, Indonesia) are at high risk of automation ranging from 64% in Indonesia to 88% in Cambodia (Chang et al., 2016). These are estimates based on technological feasibility, which is necessary but not sufficient to have automation. The other necessary component is economic feasibility. To the best of our knowledge, none of the empirical cases analysed in the literature found job displacement due to automation. A study on India found that, although theoretically robots could displace 80% of workers in the garment sector, actual displacement is much less due to economic feasibility.

Vashist and Rani (2020) found that investment in technology had a huge positive impact on labour productivity and that firms did not shed any employment. Rather they reported that: "Indian garment sector created more than four million additional jobs during this period of technology up-gradation. Notably, job creation occurred both in the organized and in the unorganized segments". Interestingly, the authors also found that although there was no negative quantitative impact, there has been a significant qualitative shift in labour demand, favouring highly skilled managers and professions at the expense of craftsmen like tailors and cutters. Another study comes from the South Africa garment sector found that an increase in automation technologies leads to more productivity and more workers employed, as reported by the entire sample of the 24 firms interviewed, emphasizing that improving productivity was the dominant motivation for such technological upgrade (Parschau and Hauge, 2020).

# 5. Conclusions

This report reviews the relationship between recent technological change, mainly in automation and digitalisation, and labour, both in terms of tasks modification and impact on gender. In undertaking a review of the main studies and methodologies that looked at such aspects, the attention is on specific digital production technologies and two manufacturing sectors, namely automotive and garments. These are sectors that are both highly fragmented and that have been put at the centre of numerous industrial policies for countries at different stages of development (e.g., the maquiladoras in Mexico and Central America for garments or the automotive centred policies in the United States, Japan, United Kingdom, South Korea, among other countries). The automotive sector is characterised by automated production, international standards that firms must comply with, a series of regional networks of final assemblers and suppliers, and a generally skilled labour force. On the other hand, the garment sector is not very automated, and it is still characterised by cheap labour, low skilled workers and very tight margins.

The report looks at these two sectors in terms of their automation and digitalisation trends, and how these shape their process of recent technological change. However, while automation has been evolving for decades and does not seem to be the most prevalent trend, digitalisation – and the related connectivity - is already changing both work and production organisation. Empirical evidence on such phenomena is growing, although with heterogeneous findings that can hardly determine precise and unidirectional effects on employment and gender.

There are at least three directions that emerge from this report. First, a static perspective on automation and how this may displace workers is misleading. Jobs are seldom substituted – Atkinson estimated that only one job had been entirely substituted in recent history, which is elevator operator! (Atkinson and Wu, 2017) – rather, they are modified with effects on tasks complementarity and skills polarization. Second, it is within the reorganisation of the production process that future studies should focus, as technologies' effects essentially depend on how technologies are introduced and deployed within firms. Third, within these changes, women are more likely to be affected than men, both due to cultural and social biases and to the weaker participation of women in STEM disciplines, where a high majority of good, well-paid future jobs will be.

As this report explores, there are different challenges for different sectors and for different stages of each value chain. Future analyses may consider this heterogeneity as something to unpack and understand at a more micro level of analysis, where labour and skills inequality lie. A focus on the organisation of labour and work practises may shed further light on the relationship between work organisation and opportunities to adopt new technologies.

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# Appendix

**Industry 4.0 and diffusion dynamics: assessment on the main production technologies**

We consider the last evolution of traditional industrial production tools, which are the digital production technologies resulting from incremental changes in hardware (i.e., machines), software (i.e., the functionalities and data use) and connectivity (e.g., the integration with other production technologies and product), enhancing the opportunity for production system integration, through – for example - virtual design, digital control and reconfiguration (Andreoni and Anzolin, 2019; Sung, 2018). We examine below five types of these technologies that are likely to (or already have) automate specific tasks and/or to modify them (Martinelli et al., 2021). These technologies are: 3-D printers, industrial robots, virtual reality, Artificial Intelligence (AI) and Internet of Things (IoT). This paper considers automation technologies that due to their automation and/or digitalisation trends may have or are already having an impact on new technologies.

**List of technologies:**

**3-D printer**: has been around since 1980s, but its diffusion grew only recently due to decrease in costs of production and on the availability of new materials (Fernández-Macías, 2018; Andreoni and Anzolin, 2019; Laplume et al., 2016). The European Commission defines 3D printers as a group of technologies that build physical objects directly from 3D CAD data (Peruffo et al., 2017). They are increasingly utilised in a range of industries, from basic to complex manufacturing, presenting potential disruptions to the existing production processes and to the value chains where they are adopted (Rehnberg and Ponte, 2018). In the automotive sector they are deployed as the best way to produce automotive jigs and fixtures (Cornelis, 2019). 3D printer technologies have known a certain diffusion across developing countries mainly in rapid prototyping processes. For example, a study on lead firms in machinery and equipment industry in South Africa found that 3D printing reduced the time spent on manufacture and testing a prototype from six to eight weeks to two to three days (Bell et al. 2018).

**Industrial robots**: Industrial robots are today defined according to ISO 8373:2012 as "an automatically controlled, reprogrammable, multipurpose, manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". These more recent types of robots are an evolution of the robotic arm system, with more flexibility in terms of computer reconfiguration, but similar constraints in terms of task variety. In fact, if we look at applications performed by industrial robots there is a high concentration, with handling & tending, and welding & soldering that cover respectively 43% and 27%; both types of applications are related to the automation of physically demanding tasks. Industrial robots have grown more in those sectors where work is more routine and manual and where there are fewer highly educated workers and where wages and union rates are higher (Fernandez-Macias et al., 2020).

**Artificial Intelligence**: Neural networks, which are the basis for AI, have been developed in 1943, but major interest on them will wait until the latest 1970s due to important breakthrough in algorithms. In the past few years, AI has been mentioned as a key driving force behind automation (Pérez and Falótico 2019). Among the realm of Industry 4.0 technologies, AI and big data seem to be the only two general purpose technologies (Martinelli et al., 2021). Nonetheless, the benefits from this technology are yet quantitatively low on productivity growth, and there are a number of challenges that need to be overcome (Lee et al., 2018). At the moment, the so-called weak AI is more diffused than the strong, more fiction inspired, and this is also due to the fact that it is extremely expensive to produce high quality AI (Dignam, 2020). Moreover, despite the infrastructure in terms of internet connectivity and machines sensors to gather data, there are challenges that concern machine interactions. For example, AI can easily map inputs to output, but there may be small variations from machine to machine, so it is of crucial importance to ensure that individual AI solutions do not interfere with the working of other systems down the line. Among the major benefits that AI solutions provide, they enable firms to reduce equipment downtime, to spot defects, to improve supply chain and shorten design time. One of the most common ways in which AI systems are already used is predictive maintenance systems, which combine IoT technologies with machine learning forecasting the exact time in which equipment need maintenance, thus allowing adaptive decisions to be made quickly (Traini et al., 2019).

**Virtual reality** was invented in the 1960s at it started to be applied in 1980s both with industrial applications and with wider public applications such as cinema spectators believing that they were immersed in the movie (Schroeder, 1993). Visualization and simulations are great part of Industry 4.0 applications, although their potential has yet to unfold. Diffused applications of this technology can be found as new ways to facilitate phases for training and education, but these still have considerable costs and can mainly be found in large, high tech, firms (Liagkou et al., 2019).

**Internet of Things** (IoT) the term was used for the first time in 1999 at a conference about sensors and supply chains (Ashton, 2009), to give a sense of the idea of using internet and supply chain through RFID (Radio Frequency Identification). It was firstly explained as a way to enable computers to gather data, which needs a platform for data collection and exchange through a cloud service closer to the ground and to the devices (Bonomi et al., 2021). It is a recent type of technologies, Gubbi (2013) estimates 2014 as the year when firms started to use sensors in retail and industrial ecosystems, but as 2021 the process seems to be slower. IoT is closely related to the discussion on industrial robotics and AI, as the interconnectedness, or the fusion, between an increasing number of IoT devices offer opportunities for firms seeking to innovate (Del Giudice, 2016). It is a highly promising technology that would help agile decision-making process at three levels: the operational level, continuous improvement level and the organisational development level (Ghiringhelli and Virili, 2019). One of the interesting facets of IoT is that it does not require the replacement of current systems with totally new systems, but a redesign of organisational structure and operating systems in line with innovative and more participative business models.

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