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Recent Automation Trends in Portugal: Implications on Industrial Productivity and Employment in Automotive Sector

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Abstract: Recent developments in automation and artificial intelligence (AI) are leading to a wave of innovation in organizational design and changes in the workplace. Techno-optimists even named it the "second machine age," arguing that it now involves the substitution of the human brain. Other authors see this as just a continuation of previous ICT developments. Potentially, automation and AI can have significant technical, economic, and social implications in firms. This paper will answer the following question: What are the implications on industrial productivity and employment in the automotive sector with the recent automation trends, including AI, in Portugal? Our approach used mixed methods to conduct statistical analyses of relevant databases and interviews with experts on R&D projects related to automation and AI implementation. Results suggest that automation can have widespread adoption in the short term in the automotive sector, but AI technologies will take more time to be adopted. The findings show that adoption of automation and AI increases productivity in firms and is dephased in time with employment implications. Investments in automation are not substituting operators but rather changing work organization. Thus, negative effects of technology and unemployment were not substantiated by our results.

Keywords: artificial intelligence; automation; productivity; employment; automotive industry

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Citation: Boavida, N.; Candeias, M. Recent Automation Trends in Portugal: Implications on Industrial Productivity and Employment in Automotive Sector. *Societies* **2021**, *11*, 101. https://doi.org/10.3390/soc11030101

Academic Editor: Gregor Wolbring

Received: 8 July 2021
Accepted: 11 August 2021
Published: 18 August 2021

1. Introduction

The arrival of the first steam-driven machines in factories in the late 18th and early 19th century started waves of passionate discussions about the future of work. There are arguments in favor of the belief that technology will continuously be improved and will lead to an end-of-work scenario. One of the main arguments today is that we are now facing an unprecedented level of interaction between humans and machines, due to a combination of technological breakthroughs in artificial intelligence, miniaturization, the internet, and social media [1–3]. Techno-optimists named this present phase the "second machine age," arguing that it now involves the substitution of the human brain [4].

On the other hand, the present level of human–machine interaction can also be described as not more than the natural prolongation of the previous ICT macro-trajectories [5]. There are many non-automatable tasks that make jobs less vulnerable than suggested by, for example, the study by Frey and Osborne [6–9]. Within the same occupation the automation potential can vary greatly from job to job; threats in occupations vary significantly by qualifications and, importantly, by countries [10]; and complementarity instead of substitution might prevail in many workplaces [11]. Therefore, despite the resurgence of the debate and social angst about the future of work, there is not a clear consensus on whether we are on the verge of a quantum leap in human–machine interaction or seeing a continuation of previous trends.

Current approaches use mainly quantitative models with drawbacks associated with occupations [6] and tasks [7]. One way to refine the implications of automation in work and employment is to select a technological innovation (e.g., artificial intelligence) and to study its impact in companies in a given society. We use an approach based on mixed methods, bringing not only quantitative analysis but also qualitative evidence to support findings in one sector (automotive) for one country (Portugal). As described in more detail in Sections 2 and 3 of this paper, this approach is innovative and allows for a closer examination at the company level of ways in which work is being redefined and what the future expectations are, and an understanding of the extension of complementarity that might prevail between machines and humans. This paper will answer the following question: What are the implications of recent automation trends on industrial productivity and employment in the automotive sector in Portugal? The paper will focus on artificial intelligence (AI) as the most relevant emergent technology to understand the development of automation in areas related to robotics, software, and data communications in Europe [12]. The relevance of intelligent manufacturing in the automotive sector has also been vastly documented in terms of working conditions, qualifications, and skill requirements [12].

Furthermore, the article describes the automotive sector in the world and in Portugal. Evidence from interviews around cases related to AI implementation are presented, approaching the implications of R&D projects in productivity and employment in the Portuguese automotive sector. Last, the implication of these cases in the automation debate are discussed.

2. Automating Our Intelligence

Many debates assume that automation—-as the general processes of substitution of labor by software or machines [7]–is one single phenomenon that homogeneously impacts work and employment. However, automation is a process that encompasses different technologies, and each one will impact labor in different ways [1,13]. For example, an industrial robot may be complex and expensive to implement and might replace a few workplaces, whereas a software algorithm is relatively simple and inexpensive to implement and can swiftly generate unemployment. Furthermore, the effects of technological change can be differently distributed, depending on the institutional framework that each society sets for itself [2]. The impacts on work and employment of each technology will vary depending on the national innovation institutions [14], industrial relations system [15], and even type of capitalism [16].

A much-debated form of automation is artificial intelligence (AI). It can be defined as a computer system that performs tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, or translation [17]. AI involves the system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation [16]. A more operational concept of industrial AI is a "systematic discipline focusing on the development, validation, deployment and maintenance of AI solutions (in their varied forms) for industrial applications with sustainable performance" [18] (p. 220122).

Nevertheless, AI is not one monolithic term but instead needs to be seen in a more nuanced way [19]: It can be observed through the lens of evolutionary stages (artificial narrow intelligence, artificial general intelligence, and artificial super intelligence), or by focusing on different types of AI systems (analytical AI, human-inspired AI, and humanized AI). Furthermore, AI is an umbrella that includes several technologies, such as technology expert systems, recommender system apprentices by demonstration, machine translation speech recognition, facial recognition, text recognition, transport and scheduling systems, self-driving cars, home cleaning robots, negotiation agents, and virtual assistants [20]. Importantly, due to the rise of Big Data and improvements in computing power, the development of large spectrum algorithms of AI will have a significant technical, economic, and social impact. In fact, it is expected that the introduction of AI will meaningfully transform the organization of work in firms, the tasks being developed at workplaces, and the skills and qualifications necessary to cope with its challenges [11,16,21]. These developments are leading to a wave of innovation in organizational design and changes to institutionalized norms of the workplace [22]. Advanced algorithms that can have a broad range of applications and be applied to many situations can generate more concern, as they may produce significant technical, economic, and social effects in firms. However, to avoid speculation, these systems have to be at least in development phase seven of the European Technology Readiness Levels (i.e., have a system prototype demonstration in an operational environment).

Most reports estimating the impact of AI are based on quantitative modelling of employment by occupations or tasks. In Europe, the impacts of AI were estimated to lead to a reduction of millions of workplaces by 2030. In Finland, AI will destroy some 15% of jobs by 2030 and change the nature of work in a considerably larger proportion of tasks, and the country should be prepared to retrain one million Finnish workers [20]. In Portugal, a study reported that AI can reduce 1.1 million workplaces and suppress 50% of the work hours by 2030 [19]. In Hungary, 49% of work hours can be automated based on existing technologies, which is equivalent to the work of about 2.2 million people [21].

Research on AI and improved productivity or performance in organizations is scarce, most probably because it is an emergent technology. However, there are some reports based on qualitative data analysis of the impact of AI. In two recent European projects about virtual work and digital platforms, we identified significant difficulties of social partners to deal with the broad effects of automation phenomena [23,24].

Nevertheless, this difficulty can be bypassed by conducting interviews on cases from the automotive and components sector, selected by using keywords that signal intelligence automation developments and AI applications in Portuguese R&D projects. The technology effects of each AI project can be validated by innovation experts and technology managers. Experts on organizational change and labor processes can also provide details about the effects on work organization, skills, and qualifications required.

3. Methodological Approach

The methodology consisted of a literature review, international database analysis, Portuguese databases of R&D projects, and fieldwork with experts in R&D related to automation projects in the automotive sector to investigate the implications of AI in productivity and employment. Desk research included a systematic literature and grey literature review (reports, official documents, newspapers), as well as exploratory interviews with three experts in industrial productivity and employment. Fieldwork included in-depth interviews that lasted for more than one hour with the executive manager as well as with the innovation manager of an experienced and recognized technology company developing many R&D projects for the automotive sector. Last, three non-structured interviews were conducted with work organization and labor experts. In Section 4, many insights and citations are referred to in these interviews. The work was carried out from September 2020 to June 2021. In Portugal, we were confronted with a lack of data about the investment and adoption of AI by the Portuguese industry. To overcome this constraint, we performed a data analysis in the Portuguese databases of R&D projects, funded by the European Regional Development Fund (ERDF). Through the analysis of funded R&D projects from this database, we gained an indication of the investment done in AI in Portugal at the pilot level. It also enabled us to identify experts with specific AI cases in the automotive industry. To select cases at the factory floor rather than in other departments of a company (e.g., sales, management, customer support, etc.), the concept of industrial AI previously mentioned was used [18].

A search string was constructed based on core concepts associated with industrial AI (algorithm, artificial intelligence, augmented reality, automated decision-making, computational vision, machine learning, predictive analysis, robot), constrained by keywords related to manufacturing and the automotive sector, as presented in Table 1. To make sure we were detecting all projects related to the automotive industry, three extra criteria were used: searching by the names of the eight car manufacturers in Portugal, based on the data from the European Automobile Manufacturers' Association—ACEA [25]; selecting projects from the automotive sector (NACE 29.10 and NACE 29.32); and selecting projects finished by the end of 2021, to have substantial results applied in real production environments. Table 1 sums up the search strings adopted in the identification of R&D projects related to AI in the Portuguese automotive sector from the Portuguese R&D projects database between 2007 and 2020.

Table 1. Search strings adopted in the identification of funded AI projects in the automotive industry with an end date of 2021.

Group 1—By Technologies	Group 2—Automotive Sector
Keywords: algorithm, artificial intelligence, augmented reality, automated decision-making, computational vision, machine learning, predictive analysis, robot	Keywords: manufacturing, Industry 4.0, automotive, car Keywords: Auto Europa, Volkswagen, Caetano, PSA, Peugeot, Citroen, Renault, Toyota NACE 29.10 and 29.32

Following the identification of 25 projects resulting from the presence of at least one element of each of the groups listed in Table 1, a first screening process was carried out to assure the projects selected were only from the automotive sector. The results were narrowed down to 13 projects. Out of these, three projects were selected for analysis after applying the following eligibility criteria: projects with car manufacturers (NACE 29.10) as partners or end-users, and different projects with the same beneficiary (company). These criteria allowed us to collect data about implications of AI in car manufacturers in those cases and conduct accurate interviews only with very successful and experienced industrial researchers in the field.

According to information on the company's website, since 2004 it has become a reference in the field of robotic control systems, with contributions to the global robotic manufacturing industry. Its focus is on the development of software to operate robots and industrial arms, with a special focus on the automotive and aeronautical sectors. According to the company, their research and development areas are in artificial intelligence algorithms, mechatronics, 3D design and simulation, artificial vision, and Industry 4.0. Currently, this company also provides training for the automotive industry and related subsidiaries in Germany, Mexico, and China, and has projects in development in several industrial areas around the world. It is an SME, located near an automotive greenfield near Lisbon and with 32 employees, mostly engineers.

The cases about which the experts were interviewed were related to computer vision and predictive analysis, with prototypes developed at the industrial level (Technology Readiness Level 7). According to the project descriptions on the company's website, the cases are as follows:

- Project A developed an automated robotic system of universal application for different control philosophies to overcome the challenges posed by a new generation of production lines for the automotive industry: more durable in the face of constant changes, with lower costs and adaptation times, simple reconfiguration, and flexibility for product changes. Results: two demonstration cells at the industrial level. The cells are now back in the company's facilities and are used to give training.
- Project B used computational vision and predictive analysis in the quality inspection of structural glue bead application in doors. It developed a quality inspection system for the automotive industry to improve its strict level of quality so that the safety of the driver and passengers of vehicles is guaranteed. Results: industrial prototype, demonstrated at the industrial level, of a non-destructive testing and predictive maintenance system with customizable solutions, covering all parts manufactured in a production line, integrated into the production process, and aiming for a zero-defect strategy, without neglecting the productive capacity of the current production lines, as well as continuous and systematic evaluation of the quality of parts manufactured

on the production line and the condition of the machinery that contributes to their manufacture.
- Project C, currently being developed, intends to create a generic automation platform that integrates and harmonizes standardized and emerging methods, processes, and systems in the world of automation. The project includes open-source structures for the introduction and integration of technology in production lines, investing in the reuse of processes and machines, in the reconfiguration and optimization of parameters, in the digitalization and virtual representation of industrial automation equipment, and in zero-defect quality manufactured products, allowing the industry to keep up with the customer's needs and expectations, namely in terms of product customization and the constant creation of new offers.

Project A turned out to be not that relevant to the research question of this paper, and Project C, because of the pandemic, suffered a delay and did not yet have results to reflect upon.

The most interesting findings resulted from the discussion of project B and several other examples from the company's current business. It was possible to identify several implications for productivity and employment from the demonstration of AI in an automotive industry factory floor, which are presented and discussed in the next section.

4. Results and Discussion

4.1. Productivity

There are many ways to measure productivity, but two remain consensual to understand the factors contributing to increased productivity in industrialized societies: labor productivity and capital productivity. First, labor productivity, measured as gross domestic product (GDP) per hour worked, is one of the most widely used measures of productivity at the country level. Productivity based on hours worked better captures the use of the labor input than productivity based on numbers of persons employed (head counts) (OECD 2019).

Labor productivity in the Portuguese automotive industry increased from 2010 to 2016, according to the author's calculations based on data from OECD Statistics [26] In fact, the average annual growth rate of labor productivity was 4.3% in this period. In 2016, labor productivity was significantly higher in Portugal (261) than in Spain (42) and Austria (43), and close to the Slovak Republic (286), France (374), and Belgium (422), to name a few countries that are comparable, referenceable, and have available data.

To take account of the role of capital input in the production process, the preferred measure is the flow of productive services that can be drawn from the cumulative stock of past investments, such as machinery and equipment [27][1]. Capital productivity shows how efficiently capital is used to generate output. The series of gross fixed capital formation by asset type are used to estimate productive capital stocks and to compute an aggregate measure of total capital services. The gross fixed capital formation may take the form of improvements to existing fixed assets, such as buildings or computer software that increase their productive capacity, extend their service lives, or both. We assume that this indicator is a proxy of the investment in automation, related to ICT, machinery, electronics, and electricity, even though it also includes construction. Relevantly, the gross fixed capital formation in the Portuguese automotive industry increased significantly from 2010 to 2017, according to author's calculations based on data from OECD Statistics [26]. In fact, the average annual growth rate was 7.9% in this period. A more in-depth observation showed (Table 2) a decrease from 2010 (EUR 455 M) to 2013 (EUR 256 M). The year 2013 marked a turning point in this type of investment, as the gross fixed capital formation has been steadily increasing since then at an average annual growth rate of 32% between 2013 and 2017.

Table 2. Gross fixed capital formation in the Portuguese automotive industry from 2010 to 2017.

Years	2010	2011	2012	2013	2014	2015	2016	2017
Gross fixed capital formation (EUR M)	455	339	310	256	293	391	557	775

Source: OECD STAN Database [26].

In addition, from data collected through the interviews and in the case of project B, we observed benefits of introducing AI technologies at the factory floor. According to the innovation manager,

> "*using computational vision and predictive analysis in the quality inspection of the structural glue bead application in doors, one of the most important manufacturing processes in the automotive parts assembly line, it was possible to increase process efficiency, improve product quality and reduce waste resulting in savings and, thus, contributing to an increase in productivity of the car manufacturer.*"

However, according to her, despite the positive effects on productivity the solution was not adopted by the end-user. She stated that,

> "*there are areas within the factory that are more receptive to the introduction of new technologies than others; the decision makers themselves may be more open; contextual conditions can act as a constraint, such as the closure of the activity in which the solution would be implemented.*"

Furthermore,

> "*in the specific case of large OEMs, with several factories around the world, there is great resistance to the introduction of solutions that are not absolutely standard or are consistent with other solutions already introduced in other factories,*"

added the executive manager. According to him,

> "*the project took place during a period in which the solution was developed and demonstrated on one of the most advanced and relevant lines in the factory, at that time, but when negotiating the contract, this production line was being discontinued and did not make sense the additional investment.*"

The executive manager added,

> "*After the project finished and we went to pick up the demonstrator installed in the line they said it would be very good if it stayed in the line. This shows its added value was recognized, namely, in the greater efficiency of the process by reducing the number of non-compliant products, reducing waste, and increasing quality of the final product.*"

In conclusion, capital productivity grew higher annually on average (7.9%) than labor productivity (4.3%) in the Portuguese automotive sector. Thus, capital investments are the main reason for productivity increases in the sector, which translates into improvements in productive capacity by automation efforts. Nevertheless, regardless of the increase in productivity, there are a variety of factors, such as low return on investment, competences/knowledge to operate the system not available or accessible and OEM managers not traditionally open to new, non-standard solutions, that can influence the adoption of a new technology by industries.

Investment in AI in the Automotive Sector

Improvements to increase productivity in a production system can be made in many parts of a factory. Often, upgrades in the manufacturing sector are made through investment in automation, which can be both automation hardware (e.g., mechanical parts and/or the electrical and electronic parts) and software [28].

As described previously, gross fixed capital formation may take the form of improvements to existing fixed assets, such as buildings or computer software that increase their productive capacity, extend their service lives, or both [27]. Hence, the share of gross fixed capital formation invested in ICT equipment, software, and databases in the total gross fixed capital formation is a proxy of AI investment. In fact, this investment represents the efforts conducted to improve computational power applied in companies.

In Portugal, the investment in ICT in gross fixed capital formation was steady from 2010 until 2015 at an average of EUR 22 M. Afterwards, the investment grew significantly to EUR 36 M in 2017, which represents an annual average growth rate of 30.3% between 2015 and 2017. The overall increase between 2010 to 2017 (when the data are available) resulted in an annual average growth rate of 6.7%. Furthermore, the OECD data allow limited, but still interesting, comparisons with other countries. Figure 1 presents the evolution of the share of ICT investment in the total gross fixed capital formation in the automotive sector in four countries.

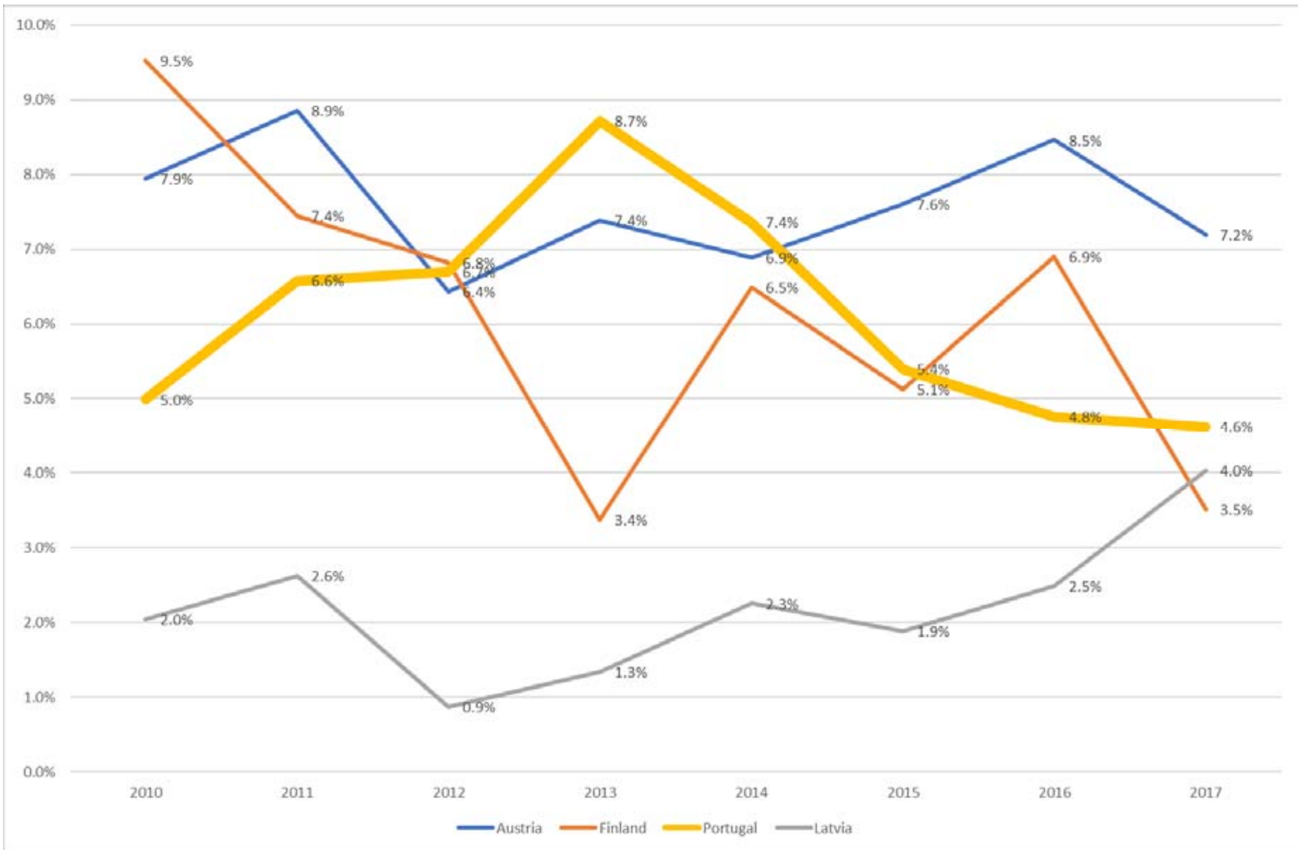

Figure 1. Evolution of the share of gross fixed capital formation invested in ICT equipment, software, and databases in the total gross fixed capital formation in the automotive sector in a selection of countries at current prices. (Source: OECD STAN Industrial Analysis (2020 ed.), accessed on 30 April 2021).

Figure 1 shows that in 2017, Portugal had a share of investment in ICT of 4.6% in relation to all the investments made in the automotive sector, which is lower than Austria (7.2%), but higher than Latvia (4.0%) and Finland (3.5%). The Portuguese share of investment in ICT in the total investment saw a slight decrease, with an average annual growth rate of −1.1, in the period between 2010 to 2017. The same trend was seen in Austria (−1.4) and Finland (−13.3), but not in Latvia (10.2). In summary, there was substantial growth of AI investment in the automotive sector of 30.3% between 2015 and 2017. However, the growth in all automation investments was 41% during the same period. Therefore, it could be argued that the recent general automation investments are more significant than those only in AI in the Portuguese automotive sector. The analysis of the national comparative data available also points to the same conclusion.

Furthermore, this conclusion is also supported by empirical data from the interviews. Both the executive manager and the innovation manager agreed and stated that, "*Industries in Portugal understand the inevitability of adopting Industry 4.0 technologies if they want to be competitive and increase productivity.*" According to them, "*Portuguese companies are more open to these new technologies.*" Moreover, the innovation manager stated that,

> "*this is true for robotics, automation, and predictive analysis, and we can expect this type of technology to be adopted in a couple of years. However, technologies (e.g., cloud, plug & produce, blockchain, artificial intelligence) that may involve connectivity, monitoring, data collection and automated decision making, will take longer to be implemented.*"

Through the analysis of the Portuguese R&D project database, in the period from 2007 to 2020, of the 3151 R&D projects, 543 R&D projects related to AI were identified with a budget of EUR 655 M. R&D projects related to AI accounted for 19% of the total investment in R&D projects. This database includes several types of projects, from collaborative to individual and research-oriented to industrial applications, with an average investment per project ranging from EUR 600 K to EUR 27 M, depending on the type of project. Therefore, AI technologies are expected to be spread across the different development stages. Based on the author's calculations from the Portuguese R&D project database, in the period from 2008 to 2020, the investment of EUR 655 M in R&D projects related to AI corresponds to an average growth rate of 20%, demonstrating the hype around this technology. According to the author's calculations (Table 3) from the Portuguese R&D project database, the automotive sector accounted for EUR 225 M (34% of the total investment in R&D projects related to AI), corresponding to 43% of the total investment in R&D projects in the automotive sector (EUR 518 M).

Table 3. Portuguese R&D project data from 2008 to 2020.

2008–2020	Total	AI	Automotive Sector	AI in Automotive Sector
No. of projects	3151	543	275	50
Project budget (EUR M)	3 422	655	518	225

Source: author's calculations from Portugal's R&D project database.

From 2008 to 2020, investment in R&D projects related to AI in the automotive sector grew (Figure 2) at an average rate of 17%.

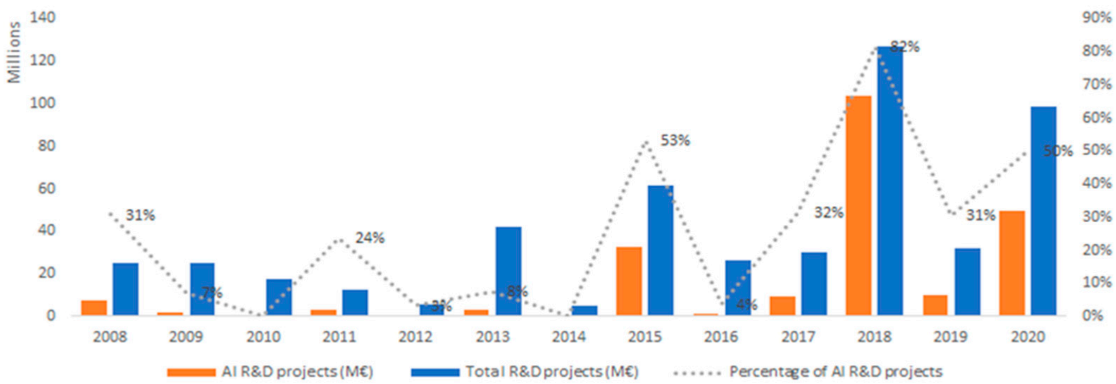

Figure 2. Variation of R&D project investments in the automotive sector from 2008 to 2020. (Source: author's calculations from Portugal's R&D project database).

There are no studies or evidence to explain this growth. However, the executive manager noted that companies are more open to the adoption of these technologies associated with Industry 4.0 and they realize that it is practically inevitable to move along this path if they want to be more productive and more competitive: "*I don't know if this is the result of* *the excellent work of publicizing the Industry 4.0 initiative, but I can see that companies are very motivated towards these new technologies. The problem is not knowing how to manage them.*"

In fact, in 2017 the Portuguese Industry 4.0 initiative was launched. According to the Portuguese Agency for Innovation and Small and Medium Enterprises (IAPMEI) website, the Industry 4.0 initiative is integrated in the National Strategy for the Digitization of the Economy, with the objective of generating favorable conditions for the development of national industry and services in the new paradigm of the digital economy. It was organized in two stages. Phase 1, from 2017 to 2019, was above all demonstrative and mobilizing and was based on six priority areas of action: human resources training, technological cooperation, creation of the startup I 4.0, financing, investment support, internationalization, and legal and regulatory adaptation [29]. Phase II, from 2019 to 2021, intends to be transformative and it is estimated that public and private investments will be mobilized in the amount of EUR 600 million over two years, involving 20,000 companies in the various initiatives, training more than 200,000 workers, and financing more than 350 transformational projects [30].

This information seems to be aligned with the executive manager's statement about the awareness of companies on the importance of industrial transformation through digital technologies and might explain the growth of investment in R&D projects related to AI. According to him, these technologies are a trend, and his company has created a new business area around computer vision to respond to the expected demand from the market:

> "*We see interest from companies in inspection systems with computer vision. We have created computer vision as a new business area, since we have verified the industry's great receptivity for these systems given that the issue of efficiency and productivity is a topic across all industries.*"

In addition to computer vision technology, he added that,

> "*We have made strong investments in other areas, some of which are complementary to computer vision. Currently, all projects that are contracted by the industry have a mechanical component and a computer vision part. In the commercial pipeline for a total of 12 to 13 M€ under negotiation, 3 M€ are for vision systems.*"

This evidence seems to corroborate the data from the statistical analysis, where the investment in general automation is higher than in ICT, proxy for AI. Even if there is a growth in R&D projects related to AI there is still less investment in adopting AI when compared with investments in automation in general.

According to the executive manager of the company, due to the pandemic situation they were faced with the need to diversify their markets. The executive manager indicated that,

> "*Based on the technology of Project B we are now developing several contracted projects with Portuguese companies, in the automotive components industry (exhaust pipes), in the automotive industry (final assembly department), in a textile supplier (zippers) for the automotive industry and in the food industry.*"

In this regard, the executive manager also indicated challenges that may influence the integration of AI daily: "*In terms of computer vision, the technological challenge is not in capturing the image (vision system) but in information processing, decision making (AI) and integration with other systems (legacy systems).*"

Furthermore, he also mentioned a recent assessment on a traditional fishing yarn factory:

> "*this company has existed since 1946 with production systems dating from 1970/80. The challenge of integrating new technologies into these systems is as big as it is to introduce a completely new system (stand-alone) on a customer's shop floor.*"

Although this is not the case in the automotive industry, it can reflect the situation of other Portuguese low-tech sectors.

In summary, according to the company, new technologies such as computer vision, predictive analysis, and artificial intelligence do have positive productivity effects in the automotive sector. However, these technologies will only have implications in the sector's productivity if they advance from the pilot project to a broader adoption of the technology, and this decision is based on several factors beyond technological performance. The wide dissemination of these technologies appears to be a challenge because of the different levels of modernization needed across sectors.

4.2. Employment

In 2017, the automotive sector represented 1% of total employment in Portugal. The average annual growth rate from 2010 to 2017 was 3.1%. However, if we analyze OECD Stan Database figures, from 2013 to 2017, the employment in the automotive sector grew from 32,400 to 41,300 persons. This growth was significant in this period because the automotive sector had an average annual growth rate of 6.19% compared to an increase of only 1.92% in total employment. In comparison with other countries, the data show that the volume of employment (adjusted to the population) in Portugal (0.9%) is not very significant. For example, it was comparatively lower in Spain, Italy, France, Belgium, the Netherlands, the UK, and the US. Thus, we can conclude that the automotive sector has a significant volume of total employment in Portugal and grew in the period observed (OECD Statistics—STAN [26]).

Figure 3 shows that the levels of employment had two different phases. From 2008 to 2013, employment levels in the automotive sector decreased from 31,659 to 26,215, an annual average growth rate of −3%. In a similar trend, the levels of employment in other manufacturing industries decreased from 665,653 to 541,161, an annual average growth rate of −4%. However, from 2014 until 2018, the employment levels started to rise in the automotive sector from 26,984 to 41,183. The automotive sector grew on average annually by 9%, whereas the manufacturing sector increased only by 3% (Quadros do Pessoal —Séries Cronológicas 2008–2018) [31].

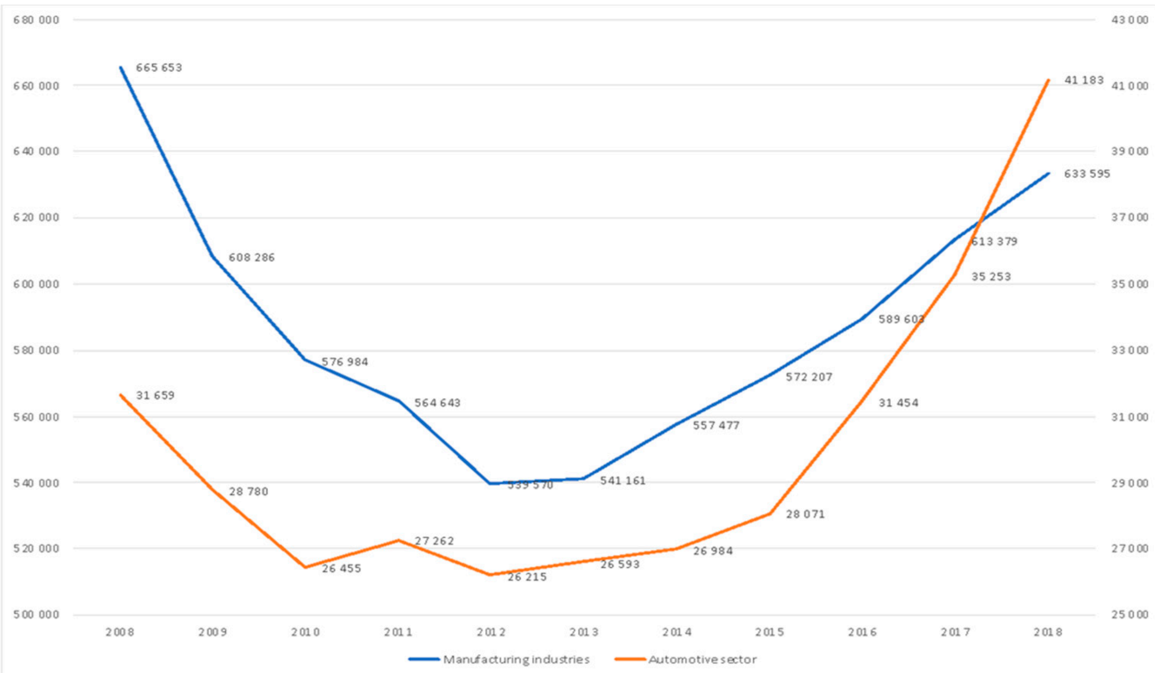

Figure 3. Evolution of employment in the automotive and manufacturing sectors from 2008 to 2018. (Source: Quadros de Pessoal—Séries Cronológicas (2008–2018) [31] based on the authors' calculations).

In Table 4 it is shown that formal qualification in the automotive structure was very low. It was concentrated at the basic schooling level, which represented 48% of employment, which was lower than the manufacturing sector with 61%. Employees with the secondary level in the automotive sector also represented 37% of employment in the sector, which was higher than the manufacturing sector with 27%. Circa 11% had a graduate degree (B.SC or similar) and 2% had a master's degree.

Table 4. Distribution of formal qualification in the automotive and manufacturing sectors in Portugal in 2019.

Qualifications	Manufacturing (%)	Automotive (%)
Primary school	61	48
Secondary school	27	37
Technical school	2	2
Graduate	9	10
Master's	2	2
Ph.D.	0	0

Source: Quadros de Pessoal (2019) [32].

In Table 5 it can be observed that the seniority levels in the automotive structure were more evenly spread than the formal qualifications. Circa 36% of employees had been working from one to four years in the automotive sector, which was higher than the manufacturing sector with 31%. Employees working for more than 10 years in the automotive sector also represented 38%, which was the same as the manufacturing sector. Circa 13% had worked for less than one year, which was lower than the 16% in the manufacturing industries. Circa 15% had worked from five to nine years in the automotive sector, which was equal to the rest of the manufacturing.

Table 5. Distribution of seniority in the automotive and manufacturing sectors in Portugal in 2019.

Seniority	Manufacturing (%)	Automotive (%)
<1 year	16	13
1–4 years	31	36
5–9 years	15	15
10–14 years	11	9
15–19 years	9	10
20 years or above	18	18

Source: Quadros de Pessoal (2019) [32].

In Section 4.1, we established that productivity in the automotive sector increased and was mainly due to the adoption of automation technologies. However, we can observe that for the same period, employment in this sector also grew, suggesting that although automation technologies were adopted, it did not affect employment.

Empirical evidence shows that these investments in automation are not substituting operators but rather changing work organization. According to the description of project B, the quality inspection system developed in the project is completely automated, from detecting the most typical defects in glue beads to automatic diagnosis of the equipment status through historic data processing and automated correction of the correctable bead defects. Although the system can complete its tasks by itself, it still needs human intervention to add any additional features or resolve any obstruction that may arise in the production line. For this case, the innovation manager stated that, "*implications on employment in this specific case are not foreseen to be expressive.*" Another example happened in a zipper company, a supplier for the automotive sector. In this case, according to the innovation manager, due to the complexity of the requirements to be inspected, automated artificial vision systems are an added value because they can perform a quality assessment more efficiently than humans. Still, human presence continues to be necessary in other tasks in the process.

> *"In the zipper production plant there are many nuances of what is ok or not ok. Especially in the situation where there are many characteristics to be analyzed and difficulty in defining requirements (what is considered a stain, from what size on, different tones, etc.). When there is a lot of data available, as is the case because the factory produces a lot of zippers, the AI/Machine Learning is a solution. It allows to analyze situations that are too fast for the operator to notice, identifying defects that are not visible to the naked eye and is consistent in the decision to reject a non-conforming product. On the other hand, operator intervention is still necessary. It may have to unlock the system."*

Another example shared by the innovation manager was the following:

> *"In another project, which is based in human-machine interaction (. . . .) to pick and place the parts, the human presence is essential. In case the parts are inaccessible because, for example, they came from logistics in a wrong position and the robot cannot perform its function, the operator must stop the line, put the part in the correct position, and start the line again."*

Data show that there was an increase in employment despite the increase in capital investments (proxy for automation). Evidence from the interviews also corroborate this fact and seem to indicate that these systems, in essence, assist operators as they manage to make a detailed analysis more adequate to the objectives of the task, increasing the efficiency of the process. On the other hand, these technologies seem to lead to a displacement of the operator to conduct control and supervision tasks. Thus, although data do not show implications for employment in the Portuguese automotive sector, empirical findings suggest there may be implications for the organization of work, in line with Autor 2015 [7].

The introduction of automation technologies is also linked to higher levels of complexity at the management level. The executive manager stated that, "*If they (managers) don't know how to deal with it, it can lead to resistance to adopting the solution despite gains in efficiency and productivity.*" According to him, this additional complexity is related to the knowledge/skills of the client's staff on how to use the new solutions:

> *"For example, in terms of production management, using people is more flexible, if there is less product outflow, instead of having two people checking product quality, the manager will only have one. These are situations known to the manager and which the manager knows how to deal with. Or, if he has three features to check on the product and he needs to add a fourth, he just goes to the people who are doing the inspection and tells them what to look for from that moment on. However, if he is using the vision system, although the system is prepared to be customized and it is possible to add new features, if necessary, there are no people with knowledge to do this at the outset. Even though the systems are designed with easy-to-interact interfaces, being integrated in cyber-physical systems, in a data network through which it is possible to receive support from anywhere in the world, it is nevertheless, a challenge for a person without basic knowledge/training, to program the system to incorporate a new requirement."*

Furthermore,

> *"Companies want to invest in new solutions, but they do not have people with knowledge/skills to work with the new systems (in their workforce or in the market). Or even if they have one or two people and they get training, there is always a set of unforeseen events (illness, change of job, retirement, etc.) that can affect availability and access to knowledge/skills."*

In summary, according to the company, computer vision, human–machine interaction, and predictive analysis are changing operators' tasks but are not resulting in the dismissal of workers from companies. Technologies are more efficient than humans in some tasks, but they still have limitations that make humans essential in the overall process performance. Companies perceive the need to automate but, despite being more open to adopting these technologies, they are faced with the lack of available human resources, skills, and/or access to knowledge.

In a small foresight exercise, both the executive manager and the innovation manager were asked a question on what their expectations would be, in a range of two to 10 years, about the implications for productivity and employment regarding AI adoption in the automotive industry.

According to the executive manager, the final assembly department of car manufacturers is where there is still a set of technological challenges associated with automation and significant implications can be seen in terms of productivity and employment. In this department tasks continue to be carried out by human resources.

A car factory has four large areas: part production, glue welding and joining, painting, and final assembly. The executive manager explained that,

> "*The final assembly is the area that creates jobs in a car factory because most of the systems for assembling and assembling components inside a vehicle continue to be executed by people today. For example, at a car manufacturer, about 80% of human resources are allocated to the area of final assembly. So, it is here that there is an interest in investing in technologies.*"

Furthermore,

> "*Contrary to what one might think, it is not a question of people going out of work, but because it is difficult to attract and retain people to do the functions that are associated with it in the final assembly.*"

The tasks performed by people in the final assembly lines of car manufacturing are boring, repetitive, and physically demanding, and, therefore, he stated that they "*often result in several costly health problems, which is a big issue nowadays.*" In this sense, the motivation for investments in the automation of car assembly lines is linked to the lack of people to perform this work due to physically intensive and repetitive tasks. In addition, according to the innovation manager, human–machine collaboration can help in this area:

> "*The quality inspection has to be done by a human-machine system in the final assembly, where all the characteristics are inspected before the car is released. Currently, technological limitations related with robot's limited time cycle prevent this task to be done by the robot alone. However, when performed through human-machine collaboration it augments workers capacity and increases the process efficiency.*"

Therefore, the expectation is for automation not to replace workers but to augment their capacity to perform their tasks and/or alleviate burden.

The transfer of automation technologies to other less technology-intensive sectors faces additional challenges related to labor costs. The adoption of the technology is based on two factors: savings in terms of workers (reduction of health problems, relocation, or dismissal) and gains in productivity/efficiency. The executive manager stated that,

> "*Do I earn more for doing it automatically or do I have savings from being done automatically? This is the logic that is inherent to the implementation of technology. And this logic may not be competitive in view of labor costs in Portugal. In the country, the minimum salary is very low, and the trend is to continue to be low.*"

Nevertheless, the innovation manager thinks that,

> "*robotics, automation, and computer vision will have widespread adoption in one to two years. However, cloud, plug & produce, blockchain and artificial intelligence will take longer to be implemented as they involve connectivity, monitoring, data collection and automated decision making.*"

Based on the evidence analyzed, four possible scenarios can be identified. First, there is a need to understand how to work with the new solution—for instance, whether to solve a problem within the new system or to add a new feature to the system. Since there is usually no knowledge or competences in the workforce about a new artifact, the introduction of a new technology may lead to a qualification of work. In adopting the new system, operators that previously did the inspection by sampling are now only backing the system in case something goes wrong, thus probably leading to a displacement effect and disqualification of work. Both situations are based on human–machine interaction that can lead to an augmented performance of the operator's tasks with an implication for work qualification and organization. Third, the adoption of new systems increases productivity and creates the demand for new labor, usually with more qualifications. Last, the investment in automation leads to unemployment of the workers performing the task. This scenario can happen and depends on many internal and external factors, such as time cycle, production line, human resource management, and work organization, as well as external variables like sector, demand for product, geo-economic context, etc.

5. Conclusions

This paper shed some light on the implications of automation and AI in the Portuguese automotive sector. The findings point to the idea that productivity increases are mainly due to capital investments (proxy for automation). These improvements to productive capacity are derived from automation efforts, including the development of artificial intelligence. However, though automation affects productivity in a positive way, it is only one of several factors that weigh in the investment decision to adopt automation and/or AI. Many factors can be considered in the decision to automate: improvement of productivity needs, return on investment, lack of competences, knowledge and/or human resources to operate the new automated systems, and end of product life cycle. Obstacles can also come from the resistance of managers to adopt new technological solutions in OEM, and they may imply job displacement or dismissal.

AI presents further obstacles related to industrial mass production. There are questions related to the lack of flexibility to respond to variation in production; the need for specific knowledge associated with the development, understanding, and recomputing of new algorithms; control of the AI system and production; and the immateriality of software, among others. The wide dissemination of automation and AI appears to be a challenge. The transfer of these technologies inside the value chain or outside the sector requires companies with high levels of modernization. Thus, there can be asymmetric social and economic implications because different dynamics (delay or an acceleration) can occur when trying to implement automation and AI solutions across companies. In other words, this may lead to polarization within sectors and/or value chains when the majority of companies are not able to cope with these solutions, and only a few are better connected in the global production system and have resources to adopt it.

The automotive sector is classified as a medium-high-technology industry. However, this sector still has a lot of tasks done by humans that could be automated in the final assembly line of the OEM. The motivation for investments in automation and AI seems to be linked to the lack of workers to perform physically intensive and/or repetitive tasks. Although some research and innovation projects may already have some results, there are still technological challenges that remain unsolved. These systems, in essence, assist operators as they manage to make a detailed analysis that is more adequate to the objectives of the task, increasing the efficiency of the process. On the other hand, these technologies seem to lead to a displacement of the operator to conduct control and supervision tasks. Thus, although during the period of analysis the data did not show implications in employment in the Portuguese automotive sector, empirical findings suggest there may be implications for the organization of work. Therefore, in the short term, these investments in automation will be pursued by firms without substituting operators but rather by changing work organization. Thus, the debates and social anxiety about automation and AI are not totally substantiated by our results.

It can be envisaged that four scenarios are plausible: qualification of work, disqualification of work, augmented work, or unemployment. In all scenarios, the expectation is an increase in productivity and an increase in complexity of the technological apparatus and management by the company. The intensification of the dependency on new automation and AI artifacts requires the company to be prepared to deal with technical problems, maintenance, health and safety, and security regarding its investment. Nevertheless, automation can have widespread adoption in the short term, but AI technologies are still in their initial phase of implementation and will take more time to be adopted. Implications regarding increases in productivity and consequent changes in employment will be slowly dephased from each other. It takes time to design an automation and AI system, and test and pilot a technical solution. Furthermore, the decision to invest in such a solution is complex, as described before. The preparation to implement it on the shop floor for mass production also requires expertise and reorganization of work. Moreover, if an automation or AI project is designed to improve productivity disregarding the developments in work organization, the projects may face difficulties in their implementation phase and even be postponed (or forgotten). In turn, this may create difficulties for efficient implementation of the technical solutions with low returns on investment.

In our research, we found some limitations that can be overcome in future research. Although this research found statistics related to AI, the interviewees systematically approached AI as part of the automation process. In fact, these process innovations are difficult to dissociate in the production process of the automotive sector because the interviewees saw the technical solution as a whole, including both hardware and software. The R&D cases selected also incorporated automation hardware. Future research should thus be extended to other cases and sectors that do not usually require automation hardware to explore further AI-specific implications, such as finance and/or logistics.

Author Contributions: Conceptualization, N.B.; methodology, N.B. and M.C.; validation, N.B. and M.C.; formal analysis, N.B. and M.C.; investigation, N.B. and M.C.; resources, N.B. and M.C.; data curation, N.B. and M.C.; writing—original draft preparation, N.B. and M.C.; writing—review and editing, N.B. and M.C.; supervision, N.B.; project administration, N.B.; funding acquisition, N.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the Santander-Nova 2020 collaborative research award and Portuguese national funds through the FCT (Foundation for Science and Technology, I.P.) within the scope of the project "UIDB/04647/2020" by CICS.NOVA (Interdisciplinary Centre of Social Sciences of Nova University of Lisbon).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: OECD STAN (https://stats.oecd.org, accessed on 30 April 2021), Quadros de Pessoal 2019 (http://www.gep.mtsss.gov.pt/documents/10182/10928/qp2019pub.xlsx/e2d128f4-123d-406d-8f51-ddf4f112b1a3, accessed on 4 June 2021), Portuguese databases of R&D projects, funded by the European Regional Development Fund (no link available).

Acknowledgments: We would like to acknowledge the valuable contributions to this text made by António Brandão Moniz from Nova University of Lisbon, by the reviewers for this Special Issue, by ANI (National Innovation Agency of Portugal) through the access to Portugal's database on R&D projects funded by ERDF, which allowed for empirical analysis on investment in R&D projects related to AI to be performed, and by António Bob Santos and Filipa Borrego who kindly read and commented on this paper.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

[1] These services, provided by capital goods to the production process, are known as capital services. Capital services provided by each type of capital goods are estimated by the rate of change of the productive capital stock, taking into account wear and tear, retirements, and other sources of reduction in the productive capacity of fixed capital goods. The overall volume measure of capital services (i.e., capital input) is computed by aggregating the volume change of capital services of all individual assets using asset-specific user cost shares as weights.

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