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The Technological Impact on Employment in Spain between 2023 and 2035

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Abstract: The objective of this work is to predict the impact of technology on employment demand by profession in Spain between 2023 and 2035. The evaluation of this effect involved the comparison of two scenarios: a trend scenario obtained by predicting the evolution of occupations in demand and a technological scenario anticipated in the case of technological progress. To accomplish this goal, a new approach was developed in the present study based on previous research. Thus, we estimated the proportion of jobs likely to be automated using a task-based approach. Each occupation was examined based on its components to determine the degree to which these tasks could be automated. The results suggest that technology may influence job demand but with low percentages (between 3% and 5% for both low- and high-qualified workers) in the long term. However, job losses are greater in absolute difference in low-skilled professions, where a great share of the labor force is engaged.

Keywords: technological impact; technology; artificial intelligence; prediction; employment; tasks; professions; Spain

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1. Introduction

In recent years, technology has become more widely used in some industries and service sectors. Artificial intelligence, robotics, and automation are among the technology forms that can contribute to increasing productivity in sectors whose tasks are more mechanical. In labor economics, tasks are defined as units of work activity that generate a product [1]. A robot with or without AI remains operational without breaks for eating or sleeping; it does not require vacation time and it will not voice objections if it is not compensated appropriately [2]. Therefore, this reduces costs and repetitive tasks. In addition, these technologies can improve working conditions since robots equipped with advanced algorithms can operate in environments that may be too dangerous for humans. However, several studies have been conducted on the benefits and risks of technological increases on employment. The results vary greatly, ranging from significant job creation [3–5] to instances of job loss [6–10] and even scenarios where no change occurs at all [11–13].

Eurofound [14] analyzed the evolution of the professional structure in EU countries, taking into account several factors such as variations in salaries, tasks, working conditions, and the evolution of a professional structure's weight. The objective of the Eurofound project was to study the evolution of European labor market conditions. While it did not estimate the technological impact on occupations, it did conduct an analysis of occupations based on the tasks they performed by comparing data from the Occupational Information Network (ONET) and the Program for the International Assessment of Adult Competencies (PIAAC).

Hawksworth et al. [15] revealed that 37% of workers are at risk of losing their jobs due to automation. However, technology adoption might be important for overcoming the slowdown in productivity growth seen since the global financial crisis, especially in advanced economies such as the United States, the European Union, and Japan. Thus, Hawksworth et al. [15] conducted an in-depth study based on several works, particularly the research of Frey and Osborne [6], Arntz et al. [16], and OECD data analyzing in detail the tasks involved in jobs within 29 countries (27 OECD plus Singapore and Russia). They then estimated the percentage of occupations that would likely be automated by 2030 based on the technical feasibility of automation. Their forecasts were made between 2018 and 2037. Furthermore, they tested their model by simulating different scenarios and adjusting estimates of automation rates for both tasks and professions. Hawksworth et al. [15] defined three overlapping waves to identify the flow of this process: an algorithm wave, augmentation wave, and autonomy wave.

The objective of this paper is to analyze the potential impact of technological progress on employment demand by occupation in Spain from 2023 to 2035. It seems interesting to treat the case of this country because the Spanish economy is undergoing several transformations, especially after the financial crisis in 2008. In addition, it is one of the most industrialized countries in Europe with the highest robot density [5,11,17]. Finally, the data are available in the Labor Force Survey (LFS) provided by the Spanish National Institute of Statistics (Instituto Nacional de Estadística; INE). We chose to analyze trends up to 2035 for several reasons. First, it allows for a long-term perspective on the potential impacts of tech nological change on employment. This extended timeframe enables us to capture the gradual shifts and emerging patterns in the labor market, providing a more comprehensive understanding of the dynamics at play. Second, by extending the analysis to 2035, we can project the probable technological advancements and their implications for the world of work. This allows for a forward-looking assessment of how technology might shape job creation and skill demands and subsequently anticipate potential changes in occupational structure in Spain over the coming years. Finally, long-term projections can inform policy planning and decision-making by policymakers and employers. This can help them anticipate the future challenges and opportunities related to technological change and design effective strategies to enhance workforce skills. All of these described reasons show the importance of the current investigation.

The following key questions are addressed in this research:

- How would technology affect employment demand in the future in the Spanish labor market?
- Which tasks could be replaced by automation in Spain by 2035?
- Which professions would be more or less impacted by potential technological progress?
- Who would be more influenced by technological progress: highly qualified workers or unskilled laborers?

To conduct this investigation and answer the questions above, the methodological approach developed is based on the previous reference studies of Eurofound [14] and Hawksworth et al. [15]. In the first study, a task intensity matrix is given for the different occupations. Since the Eurofound [14] project did not specifically assess the technological impact on different professions, we used the relative impacts of various waves of automation on several tasks performed by workers from the second reference.

The contribution of this paper is to estimate an econometric model that allows the decomposition of the total demand for employment into occupations, which will in turn be broken down into tasks. Thus, we will outline the job demand in terms of tasks to see to what extent these skills can be replaced by technology. After measuring the impact of technological progress on tasks, the proposed model permits deducing and regenerating the percentages of occupations that are at risk of being automated. The current study facilitates an examination of the technological impact on occupations at a granular level of tasks. This approach provides a more precise assessment of which tasks are most susceptible to automation and which may necessitate human expertise or intervention.

By analyzing job demands by tasks, this study can provide insights into future job trends and emerging skill requirements. This information can be valuable for individuals planning their careers, as well as for businesses seeking to adapt to changing labor market dynamics, which contributes to the importance of this investigation.

The results suggest that technology may influence job demand but with low percentages (between 3% and 5% for both low- and high-qualified workers) in the long term.

However, job losses are greater in absolute difference in low-skilled professions, where a great share of the labor force is engaged.

This study is organized as follows. Section 2 briefly develops the theoretical framework. Section 3 presents the data and methods. Section 4 exposes the empirical results. Finally, Section 5 provides a brief discussion of the results obtained and the conclusions of this work.

2. Literature Review

With the development of technological progress in recent decades, much attention has been given to the study of the effects of technology on employment. Evaluating this impact is not new in the literature. In the past, several economists have predicted that the rapid development of technologies could lead to unemployment [18]. Furthermore, some of them have expected that machines used for several tasks will replace human labor [19,20]. However, even if these predictions have not been met, the risk of massive job losses due to the evolution of artificial intelligence is still present [7,21].

Researchers are divided into pessimists who see the destruction of jobs and the risk of disruption of labor markets due to technology [6–10] and optimists, who believe that such destruction positively affects work by creating more opportunities in the long term [3–5,15]. However, others see that the impact of technology on employment could be neglected [11–13].

This section briefly reviews the literature discussing the effects of technology on labor demand. This literature includes some of the fundamental investigations that formed the basis for the studies that followed them, as well as other more recent research. These chosen works seem relevant to understanding recent developments in occupational change in employment. In addition, it would help us to analyze the technological impact on occupations at a granular level of tasks.

Frey and Osborne [6] made pessimistic forecasts. They noted that some workers would lose their jobs in the coming years due to technological change and automation. Their studies are probably the most fundamental in contributing to and animating the debate on this subject in recent years, and their estimation model formed the basis for the studies that followed it. These authors were inspired by the classic work of Keynes [18] to assert that computerization could negatively influence the labor market in the United States in the future. Frey and Osborne [6] developed a model to estimate the technological impact on labor and specify which types of jobs are likely to be automated using different technological projections. They analyzed the tasks performed by more than 702 professionals in the US, taking into account academic training and salary variables. Thus, they concluded that the risk of automation will seriously threaten 47% of the US workforce. In addition, the results suggested that this risk is higher among certain technicians and for intermediate jobs in banking and insurance. On the other hand, professions related to psychology and art are among the categories least likely to be automated. However, their methodology is criticized because it does not take into account that automation will only replace certain tasks that compose professions, while each occupation is made up of several tasks that cannot be automated. Furthermore, for some reason, it is not necessary to replace all human tasks just because we have technology capable of replacing them.

In 2018, Acemoglu and Restrepo [22] set out to create a conceptual framework to study how human labor could be replaced by machines and why employment might decline or stagnate due to this replacement. They showed that robots and artificial intelligence have penetrated the economy by creating job losses. Thus, workers will not be able to compete with machines, which explains recent declines in the employment/population ratio in the US [23,24]. However, they see that there is a lack of a global framework integrating the effects of these technologies, which is necessary to understand when and how the labor market may be transformed by automation and to ascertain similar claims previously made about new technologies that have not always come true [22].

In 2020, Acemoglu and Restrepo [25] conducted an empirical study to examine the effects of the integration of industrial robots on the labor market in the US. Their findings indicate that the adoption of these machines negatively affects employment in commuting areas. Indeed, adding one robot per thousand workers reduces the employment rate relative to the population by 0.2 percentage points. According to the definition by the International Federation of Robotics (IFR) [26], an industrial robot is "an automatically controlled, reprogrammable and versatile machine". In other words, they are characterized by their total autonomy, and they can be programmed to perform various manual tasks such as welding, painting, assembly, material handling, and packaging without requiring human intervention [25]. However, Mishel and Bivens [27] criticized the work of Acemoglu and Restrepo [25]. Indeed, they found that their data and hypotheses are fragile. In addition, despite the reliability of the results of Acemoglu and Restrepo [25], the destruction of 40,000 professions per year in the US because of these machines is not enormous. This number is much lower than that lost due to the impact of trade with China since 2000.

Furthermore, Boundi [28] conducted a study to assess the impacts of technological change and mechanization on employment in the manufacturing sectors of the Organisation for Economic Co-operation and Development (OECD) countries over the period of 1995–2018. The results suggest that work could be reduced in the short and long terms due to technological advances and mechanization. On the other hand, skilled workers seem to benefit from these changes. However, the reduction in medium- and low-skilled occupations cannot be offset by this increase in demand for highly skilled professions.

On the other hand, the predictions of Frey and Osborne [6] have been contradicted by other studies, such as the work of Arntz et al. [16], which studied labor automation for 21 OECD countries using a task-based approach while distinguishing between the occupations and the tasks they involved. They showed that the probability of job destruction by automation is minimal (only 9% of North American jobs would be mechanized). However, the risk will be greater among low-skilled professions than among high-skilled professions. For instance, vending machines and digitally controlled machines can pose a greater or lesser threat to certain workers depending on their level of qualification. They then concluded that digitalization can change the content of jobs without necessarily destroying them, and only approximately 10% of occupations, which are mainly less qualified, could be automated.

This difference between the studies of Arntz et al. [16] and Frey and Osborne [6] can be explained by the fact that Frey and Osborne considered several professions to be highly automatable even though there is at least one nonautomatable task in these occupations. They concluded that when the skill level increases, the percentage of workers at high risk of mechanization decreases, which explains the importance of education in minimizing such problems. Furthermore, this threat is lower in countries that emphasize organizational communication tasks in the workplace.

In addition, Howcroft and Taylor [29] also rejected the pessimistic view expressed by Frey and Osborne, considering their study to be an exercise in statistical predictions that neglect several main variables. These factors include differences between skilled and unskilled work, the structure of the labor market, and other socioeconomic elements.

In this sense, the analysis of the PwC in 2017 [30] affirmed that although automation might initially cause some job losses, over time, new jobs are expected to be created because of the larger and richer economy enabled by these new technologies. This study assures that by the 2030s, automation will not cause widespread unemployment, as it has not since the digital revolution started. However, it acknowledges that automation will shake up job markets.

Adams's study in 2018 [31] showed that technological advancements will deeply influence job markets. These new technologies will significantly change the nature and types of occupations available, even if they will not necessarily eliminate them. The manner in which people seek employment and the methods of supervision during work will also be affected. In addition, he found that these changes will impact not only the labor market but also society and democracy. Therefore, a comprehensive policy approach is needed to prepare future generations and assist displaced workers in finding new and meaningful employment opportunities [31,32].

Nedelkoska and Quintini [33] analyzed the risk of automation and its relationship with the training and use of workers' skills at work. To perform this, they identified tasks that were difficult to automate, such as social intelligence (negotiation skills, complex social relationships, caring for others, etc.), cognitive intelligence, complex creativity and reasoning, and perception and manipulation. They then evaluated the risk of mechanization based on training and the use of information and communications technology (ICT) at work. Their results suggested that one in two jobs could be automated, but to different degrees, where 14% of occupations were highly automatable. Furthermore, they noted that the automation level could also vary depending on other factors, such as regulation, unit labor costs of mechanization, and worker training. Finally, they concluded that even if the technology threatens several professions, it could create other new jobs and could even increase in the opposite direction because AI advances very quickly.

In 2018, Cedefop [34] studied the impact of technology on employment in the EU based on the European Skills and Employment Survey (EU28). The results of this work showed that an employee in the EU would be threatened by the automation of their job, with an average percentage of 51%, of which 14% of occupations have a very high probability. In addition, the risk of automation is greatest for routine jobs, temporary contract workers, and low-skilled workers such as plant and machine operators. On the other hand, the threat of mechanization is lower for professions in the social and personal services, education, health, and cultural industries. Thus, they concluded that there are several factors to minimize the risk of mechanization, such as the improvement in education and vocational training, salary level, time to introduce technology, and important cost of creativity and innovation.

In 2020, the OECD [35] carried out a study of automation risk in the Basque Country in Spain. They found that 33% of jobs in this region would have a medium risk compared to an average of 32% in the OECD. More precisely, these professions have a lower or medium qualification. In industry, these include machine and stationary plant operators, metal workers, drivers, and mobile plant operators. In services, these occupations involve routine tasks such as cleaners, caregivers, and store clerks. Finally, they studied the substitution of jobs by technology according to different factors, such as the strategy aimed at reducing labor costs, the rate of adoption of technology within organizations and countries, the ability of workers to adapt to IT tools, and industrial and innovation strategies.

Webb [36] conducted a study to predict the impact of many technologies (artificial intelligence, software, and robots) on employment. He noticed a decrease in professions highly exposed to automation in the future. His predictions showed that, unlike software and robots, artificial intelligence will affect high-skilled tasks. On the other hand, he found it difficult to specify the impact of automation on job demand. Therefore, he developed a method for identifying tasks in an occupation that technology could perform instead of humans. Then, he empirically estimated the evolution of demand for this same occupation.

However, the Cedefop report in 2021 [37] presented an analysis of labor evolution based on the 2019 European Skills and Jobs Survey (ESJS). Their results proved that few occupations were replaced by automation despite the COVID-19 health crisis. They found that only approximately 16% of workers in the EU had been impacted by recent technological changes in their workplace. On the other hand, the percentage of EU workers who risked losing their jobs did not exceed 5%. They concluded that automation contributed positively to the complexity of tasks and skills. Thus, it appears that the results of Cedefop [37] contradict the work of Frey and Osborne since they showed that professions identified as fully automatable have not decreased. In contrast, 65% of companies indicated that there was no pressure for change generated by technological advances. Indeed, an employment increase of 2 to 3 percentage points was recorded in organizations that provided workers with information, development plans, and communications on their strategies related to the introduction of new technologies, which confirms the positive impact of technology on employment.

For his part, Bessen [38] addressed the relationship between the adoption of new technologies to increase productivity and employment in industries. While some expect automation and technological advances to reduce jobs, he proposed that an increase in demand can counterbalance this effect. Using a simple model based on two centuries of data, he analyzed the textile, steel, and automotive sectors in the US to explain the rise and subsequent fall of employment in these industries. He showed that employment in an industry will grow if product demand is sufficiently elastic despite the introduction of productivity technologies. Technology reduces the labor required to produce a unit of output, but it also reduces prices in competitive markets. Finally, he confirmed that understanding the responsiveness of demand is essential in determining whether major new technologies will reduce or increase employment in the industries concerned. In particular, information technologies appear to have positive effects on employment today, due to the high elasticity of demand in these markets.

To explain recent changes, such as increasing job polarization and wage inequality, some researchers have studied skill-biased technological change (SBTC) and routine-biased technological change (RBTC) [39–46]. SBTC refers to the adoption of new technologies that augment the productivity of skilled workers more than unskilled workers. It affects the demand for skilled labor, leading to greater income inequality [47,48]. However, RBTC refers to the adoption of new technologies that replace repetitive tasks. It impacts both skilled and unskilled workers, particularly those engaged in routine tasks, and can lead to social changes such as job and wage polarization in the labor market [46].

According to this view, Vannutelli et al.'s research [46] in 2022 added perspectives to the literature on RBTC and examined wage inequality between routine and nonroutine workers across the entire wage distribution. Workers were classified based on both actual and perceived levels of routine intensity. They found that self-defined measures of routine at the worker level are strong predictors of wages, with subjective measures being particularly powerful. The wage gap between subjective and objective routine measures is not substantial, indicating that subjective perceptions influence salaries. This allows for the evaluation of RBTC in terms of wage distribution using both subjective and objective routinary. Their study revealed a persistent wage gap between nonroutine and routine workers across different definitions of routinary, indicating significant social changes associated with RBTC. Workers in routine jobs experience a notable pay gap throughout the wage distribution, with greater gaps observed at the tails.

Nevertheless, the investigation of Goos et al. [44] critiques the SBTC theory because it cannot fully explain why some jobs are disappearing and others are growing in advanced countries. SBTC explains why more educated workers are in demand, but it does not explain job polarization, where both high-skilled and low-skilled jobs increase while middle-skilled jobs decrease. They showed that job polarization is occurring in 16 Western European countries, which means that it is widespread in advanced economies. They then suggested two main reasons: RBTC, which replaces routine tasks with technology, and task offshoring, where jobs move to other countries because of technology. They confirmed that RBTC is more important than offshoring for causing job polarization. Their study also explains how RBTC affects jobs within industries, pushing away routine tasks and bringing more high-skilled and low-skilled jobs. It also affects jobs between industries, with industries hit by RBTC seeing greater decreases in the cost and demand for their products.

On the other hand, Marcolin et al. [49] developed a new measure of the routine content of occupations across 20 OECD countries, including Spain, based on data from the OECD PIAAC survey. The measure was constructed based on workers' ability to modify task sequences and select task types on the job. Using various indices, occupations were categorized into four routine intensity classes: high, medium, low, and nonroutine-intensive. Their study explored the relationship between routine content and workforce skills, both in terms of workers' inherent skills and those utilized on the job. They concluded that more sophisticated occupations exhibit lower routine intensity, with approximately 46% of employed persons working in nonroutine-intensive or low-routine-intensive occupations on average across PIAAC countries. The analysis also considered correlations with other factors, such as ICT use, and revealed a negative but nonlinear association with routine intensity. Additionally, there is evidence of a negative but weak correlation between skill intensity and routine content, indicating that routine-intensive occupations tend to require fewer skills. Examining employment trends over 10 years, they observed that employment growth was primarily concentrated in nonroutine occupations, particularly in private market services, while manufacturing experienced downsizing, particularly in routine-intensive jobs. Changes in employment shares across routine intensity quartiles are driven by dynamics within industries, with manufacturing industries being the most intensive in routine workers. Finally, they confirmed that both technological advancements and organizational structures play a role in determining routine intensity.

Within the context of occupational polarization resulting from technological advancements, Autor [50] examined the evolution of the labor market in US cities over the past few decades. He found that although urban workers are now more educated and skilled, nonacademic jobs are less skilled than before, and the wage benefits of these occupations have stabilized. The disappearance of middle-level jobs, blue-collar production, and unskilled administrative support professions in urban labor markets partly explains these trends. Thus, he wondered whether countervailing economic forces could reverse this decline and restore demand for medium-skilled labor. In this sense, Acemoglu and Restrepo [22] suggested that automation could create new labor-intensive tasks, but the new occupations created would be polarized across skill categories, with well-paid technology jobs occupied mainly by male graduates and labor-intensive, low-paid, service-related jobs often occupied by women. Finally, Autor [50] confirmed that although many new occupations are concentrated in cities, there is currently no clear trend toward the reintegration of medium-skilled jobs for workers without diplomas.

At the firm level, Koch et al. [5] examined how automation, particularly the use of robots, affects businesses in Spain. Using data from a survey of Spanish manufacturing firms over 27 years, they explored three main questions: Which firms use robots? What happens to jobs and costs when firms adopt robots? How does the varying use of robots among firms affect industries as a whole? They found that larger and more productive firms and those that export are more likely to use robots. Firms that rely more on skilled labor are less likely to adopt them. When firms use robots, they see significant increases in output, lower labor costs, and more jobs in the long run. However, firms that do not use robots may lose jobs as workers move to firms that have adopted automation. In addition, they showed that the effects of robots vary across different industries. Interestingly, even for specific skills or types of workers, firms that use robots do not experience job losses. Instead, they tend to create more occupations over time compared to firms that do not use robots. This highlighted how automation changes the job landscape within industries, creating opportunities for some firms while others may face challenges. Overall, Koch et al. [5] showed that automation's impact on businesses and industries in Spain is complex and involves both gains and losses.

In addition, the investigation of Goel and Nelson [51] contributes to the existing empirical literature on the economic impacts of innovation, focusing on process innovation introductions and research and development (R&D) activity in small- and medium-sized firms across 125 mostly emerging nations. They highlighted the diversity of innovation within small enterprises and emphasized the significance of understanding their innovative behaviors and impacts. Their findings revealed that both innovation and R&D activities positively influence firms' employment, particularly in capital-scarce, labor-abundant, emerging nations. Furthermore, their analysis revealed differences in the impact of R&D and innovation on growing versus contracting firms' employment. While R&D fails to affect employment growth in shrinking firms, greater economic freedom slows employment losses in these firms, although this growth is undermined by informal sector competition [51].

Many papers offer literature reviews to explore the correlation between technology and employment across various sectors. According to this view, Mondolo [52] provided a review of the literature surrounding the employment implications of technological change. Since the literature does not agree on the potential economic and social impacts of technology on all productive activities performed by humans, Mondolo's study [52] aimed to clarify these impacts by critically examining various theories, models, and empirical analyses. This review contributes to a better understanding of how technological change affects employment trends, offering valuable insights into the complexities of this relationship. She considered the impact of technological progress on overall employment as well as on specific occupational, educational, and demographic groups. Recent studies have focused on complex automation technologies, particularly robots, and provided insights into the evolution, distribution, challenges, and potential of artificial intelligence.

Finally, to obtain an overall idea of the profile of the Spanish workforce, Bustelo et al. [53] addressed the economic landscape of Spain, highlighting the predominance of small companies in the service sector and large companies in the industrial sector. Various industries, including infrastructure, renewable energy, tourism, banking, and others, contribute significantly to the Spanish economy. However, they noted that the labor market faces challenges such as high unemployment rates among young people and those over 50 years of age. Although youth unemployment decreased since 2012 [54], it remained above 30% in the first quarter of 2020. The overall unemployment rate remains stable at 14%. Furthermore, issues such as overqualification, long-term unemployment, low-skilled workers, and reliance on temporary employment present structural challenges for the Spanish labor market [53,55]. In this context, Bustelo et al. [53] examined the relationship between worker characteristics and workers' attitudes toward automation. They noted that fear of automation appears to have little impact on preparing workers for the future, while perceived opportunities have a significant positive effect. Education level, job complexity, and job position were identified as key factors influencing both fear and preparatory actions. To meet future workforce demands, workplace and educational institutions must prioritize awareness and opportunities for personal development. The authors concluded that the COVID-19 pandemic could further accelerate the adoption of digital technologies, prompting all stakeholders to redouble their efforts to embrace digital progress [53].

The "task-based" approach is a granular model used to identify the relations between workers and technologies and to connect skills, tasks, and technologies [30,31]. In this kind of model, workers' skills and tasks performed in an occupation are distinct [37–39]. To perform tasks, laborers combine skills such as strength, reasoning, and creativity. This means that different skills come together to determine how well tasks can be performed. When we loosen the direct link between skills and tasks, we can better understand why workers with different skill levels perform different jobs, especially as the technology, demand and available workforce change. With this understanding, we can explore how technology both replaces and completes different skills needed for specific tasks in more depth [30].

Inspired by this scientific debate, this article aims to analyze the impact of technological progress on employment demand by occupation in Spain from 2023 to 2035.

3. Methodology

3.1. Data

According to the data from the Labor Force Survey (LFS) provided by the National Institute of Statistics (INE), professions were grouped into groups of occupations coded according to the National Classification of Occupations (CNO) of 2011. These aggregations of similar categories were adopted in this work because they helped in data management and provided insight into overarching trends rather than focusing on minor variations.

Initially, the employed population data provided between 2011 and 2022 were used to forecast employment demand between 2023 and 2035 for each occupation. The LFS database was chosen because it allows for homogeneous and annual data to be studied over a long period.

3.2. Method

An approach was established for a reference methodological model that would allow for the specification of technological scenarios adapted to Spain, with detailed predictions of a more disruptive technological impact on the professional structure in the long-term horizon (2035).

The proposed model permits decomposing the total labor demand into professions, which can then be decomposed into tasks. Thus, we will outline the demand for jobs in terms of tasks to see to what extent technology can replace these skills. Then, the percentages of occupations that are at risk of being automated will be deduced and regenerated from the percentages of the tasks that compose them.

The methodological approach developed is based on two of the reference studies identified in the review of the specialized literature: Eurofound [14] and Hawksworth et al. [15]. In the first study, a task intensity matrix is given for the different occupations. Since this project did not specifically assess the technological impact on different professions, we used the relative impacts of various waves of automation on several tasks performed by workers from the second reference. This information was used to quantify these impacts.

The three overlapping waves defined by Hawksworth et al. [15] to identify the flow of this process are described as the following:

- Algorithm wave (until the early 2020s)—Centered on the automation of simple computational tasks and the examination of organized data within domains such as finance, information, and communications.
- Augmentation wave (until the end of the 2020s)—Concentrated on the automation of repeatable tasks such as form completion, facilitation of communication and information exchange with the aid of dynamic technology, and conduct of statistical analysis of unstructured data in semi-controlled settings, such as aerial drones and warehouse robots.
- Autonomy wave (until the mid-2030s)—Centered on the automation of physical tasks and manual skills, as well as problem-solving in dynamic real-world scenarios demanding quick responses, such as within manufacturing and transportation (e.g., driverless vehicles). While these technologies are already in development, their complete maturity on an economy-wide scale might only be realized in the 2030s.

After examining the several studies carried out, an integrated scheme (see Figure 1) was adopted to describe the steps followed in this approach, in which the final demand for employment would be conditioned by the specific intensity of the tasks performed by workers and by the estimated impact of new technologies on each of these tasks.

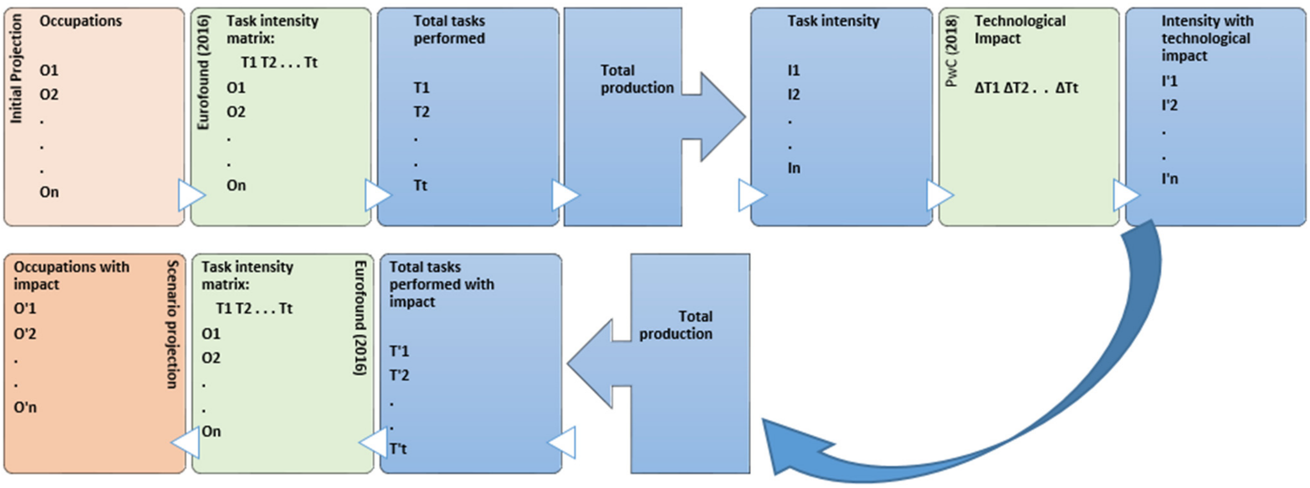


Figure 1. Steps of the methodological approach.

The process followed in this methodology is based on the sequence of calculations carried out as described below.

1. The projection of total employment demand until 2035 using a machine learning model is as follows:

The forecasting process adopted is based on time series projection, which was chosen since it exploits past data to predict future job demand in the long term and helps in understanding general trends. In addition, it is less expensive than other methods even if it requires high-quality and consistent data. The trend adjustments were perfectly useful in our case because they presented approximate long-term phenomena and responded to the slow automation process. Therefore, they allowed us to extrapolate historical trends into the future to determine not only the quantity of work that would be required but also the type of jobs in demand.

The general form of the prediction model is expressed as the following:

$$\mathrm{y} = f(t) + \varepsilon_t; \quad (\mathrm{t} = 2023, \ldots, 2035) \tag{1}$$

where $f(t)$ is the time function that represents the trend of the series, and ε_t is the random variable that represents the random fluctuations that can affect the forecast variable.

To establish the trend function y, we needed to define $f(t)$. For this purpose, we developed a system that automatically identifies and projects trends. Various mathematical methods have been suggested for characterizing long-term trends. Consequently, our estimation model enabled us to examine all possible trends and choose the most suitable one based on the mean square error criterion. Subsequently, an initial projection was generated for each of the trend alternatives.

The following analytical forms are proposed for long-term horizons:

- Linear Trend $$f(t) = \alpha_0 + \alpha_1 \cdot t \tag{2}$$
- Quadratic Trend $$f(t) = \alpha_0 + \alpha_1 \cdot t + \alpha_2 \cdot t^2 \tag{3}$$
- Polynomial Trend $$f(t) = \alpha_0 + \alpha_1 \cdot t + \alpha_2 \cdot t^2 + \ldots + \alpha_n \cdot t^n \tag{4}$$
- Exponential Trend $$f(t) = c_0 + c_1 \alpha^t \tag{5}$$
- Logarithmic Trend $$f(t) = c_0 + c_1\, log(t) \tag{6}$$

The results are presented in the form of a matrix $EMP_{o,i}$, where $o = 1, 2, \ldots, 61$ occupations and $i = 2011, 2012, \ldots, 2035$ years.

2. The total number of tasks performed for each period was calculated by applying the task intensity matrix by occupation type $M_{(61\times17)}$:

$$T_{(17\ tasks\times25\ years)} = M'_{(17\ tasks\times61\ occupations)} * EMP_{(61\ occupations\times25\ years)} \tag{7}$$

The matrix of intensities of tasks performed by type of occupation $M_{(61\times17)}$ is given in the Eurofound [14] report (see Table A1 in the Appendix A). A total of 17 tasks are described, grouped into two main categories, by type of profession classified according to the CNO 2011 (military professions were not taken into account). Figure 2 shows the tasks by type of work and their organization as follows.

3. Obtaining the relative intensities of tasks on the generated production (VA):

$$IT_{t,i} = \frac{T_{t,i}}{VA_i} \tag{8}$$

where $t = 1, 2, \ldots, 18$ tasks and $i = 2011, 2012, \ldots, 2035$ years

4. Projection of relative intensities from technological scenarios (ΔT_i):

$$IT^*_{t,i} = IT_{t,i}\left(\frac{\Delta \mathrm{T}_{t,i}}{\Delta \mathrm{T}_{i-1}}\right) \tag{9}$$

$$\forall \mathrm{i} = 2021, 2022, \ldots, 2035$$

5. The total number of tasks executed in the alternative technology scenario $\left(T^{*}_{t,i}\right)$ was calculated as the following:

$$T^{*}_{t,i} = IT^{*}_{t,i}\alpha VA_i \tag{10}$$
$$\forall \text{i} = 2021, 2022, \ldots, 2035$$

6. The task correction index was obtained by the technological impact $(rt_{t,i})$:

$$\text{rt}_{t,i} = \frac{T_{t,i}{*}}{T_{t,i}} \tag{11}$$
$$\forall \text{i} = 2021, 2022, \ldots, 2035$$

7. Transformation of task correction ratios into occupations $(ro_{o,i})$:

$$ro_{o,i} = \frac{\sum_t (\text{rt}_{t,i} * m_{t,o})}{\sum_o m_{t,o}} \tag{12}$$
$$\forall \text{i} = 2021, 2022, \ldots, 2035$$

where $m_{t,o}$ are the elements of the task intensity matrix.

8. Obtaining employment projections corrected by the type of profession:

$$EMP^{*}_{o,i} = EMP_{o,i} * ro_{o,i} \tag{13}$$

$$\forall \text{i} = 2021, 2022, \ldots, 2035$$

In terms of the object of work/task	1. Physical: Manipulation and transformation of things	a. Strength b. Dexterity
	2. Intellectual: Manipulation and transformation of ideas	a. Information-processing: Processing of codified information i. Literacy: Processing of verbal information (Business- Technical- Humanities) ii. Numeracy: Processing of numerical information (Accounting- Analytic) b. Problem-solving: Finding solutions to complex/new issues i. Information-gathering and evaluation ii. Creativity: finding a solution
	3. Social: Interacting with other people	a. Serving/attending b. Selling/persuading c. Teaching/coaching d. Managing/coordinating
In terms of the methods and tools used in the work/task	4. Work organization	a. Autonomy: Self-direction and latitude b. Teamwork: Working in small groups c. Routine: Repetitiveness and standardization of task i. Repetitiveness ii. Standardization
	5. Technology	a. Operation of mechanical machinery and tools (non ICT) b. Operation of ICT i. Basic IT ii. Programming

Figure 2. Types of tasks involved in professions.

3.3. Conditions of the Scenarios

The Hawksworth et al. [15] report was used in this work to quantify the technological impact. It presents the total influence of each wave (algorithm, augmentation, and autonomy) on the different tasks performed by workers as shown in Figure 3.

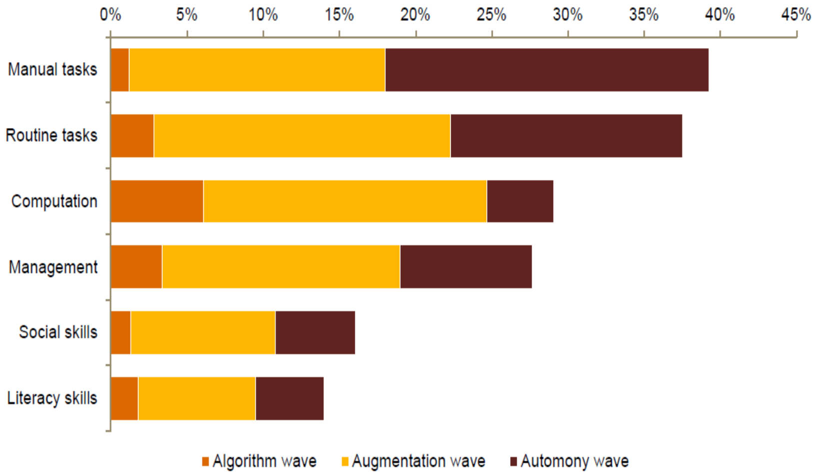
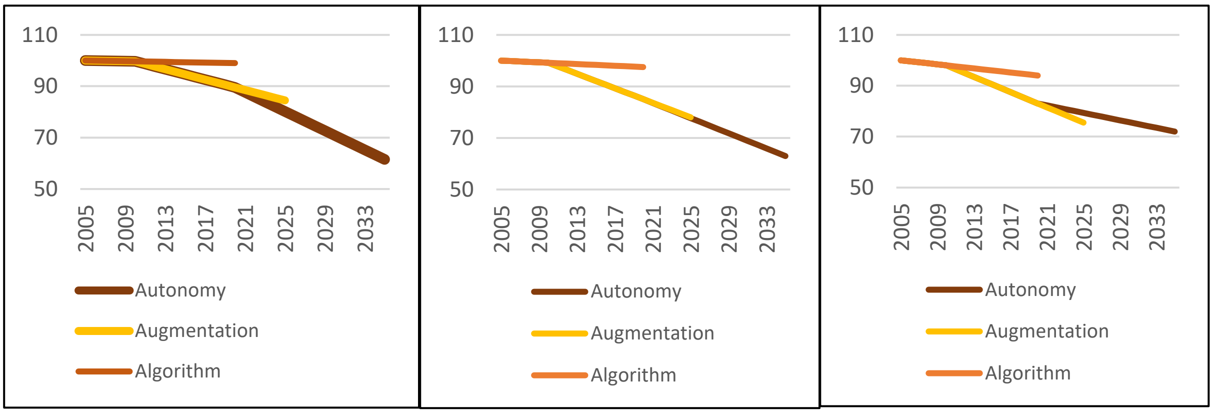
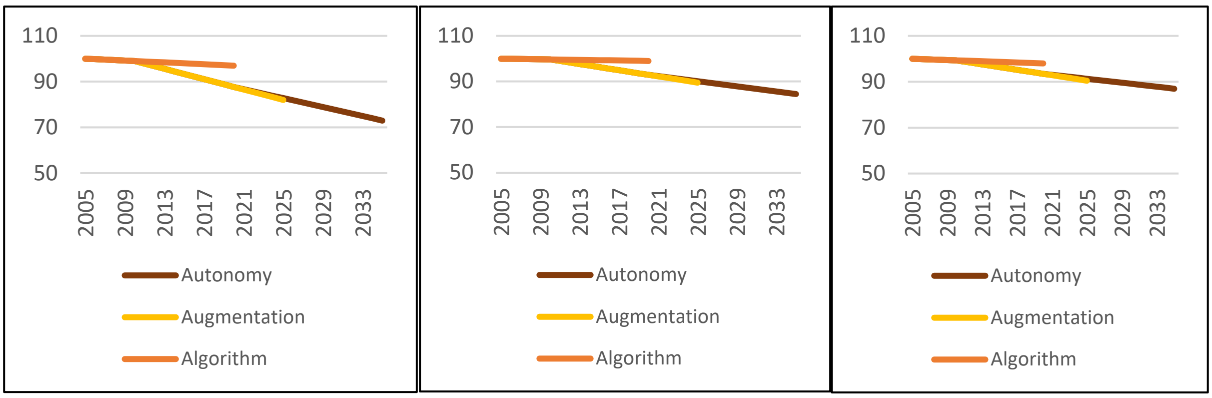


Figure 3. Proportions of high-risk job tasks.

For practical reasons, the total duration of each of the waves was considered equal to 15 years, defining an overlap of 5 years between them by carrying out a linear interpolation of the impact over their entire duration, as shown in Figure 4 below.



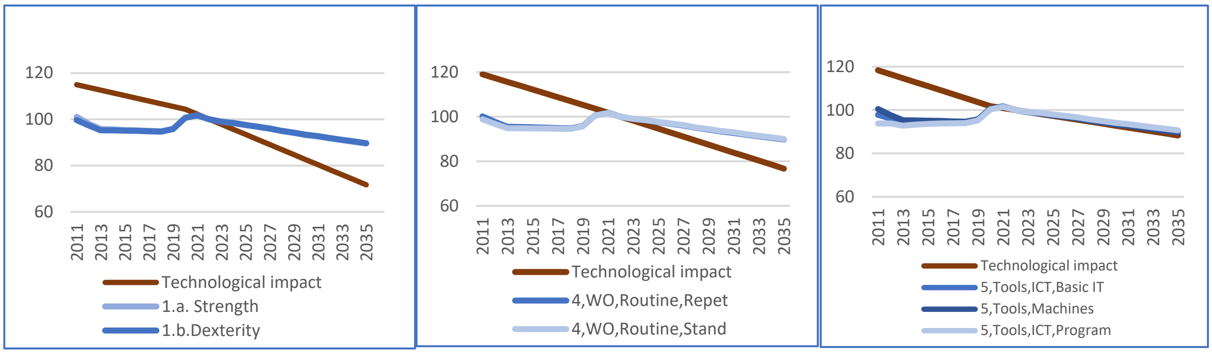
(a) Manual (b) Routine (c) Computation



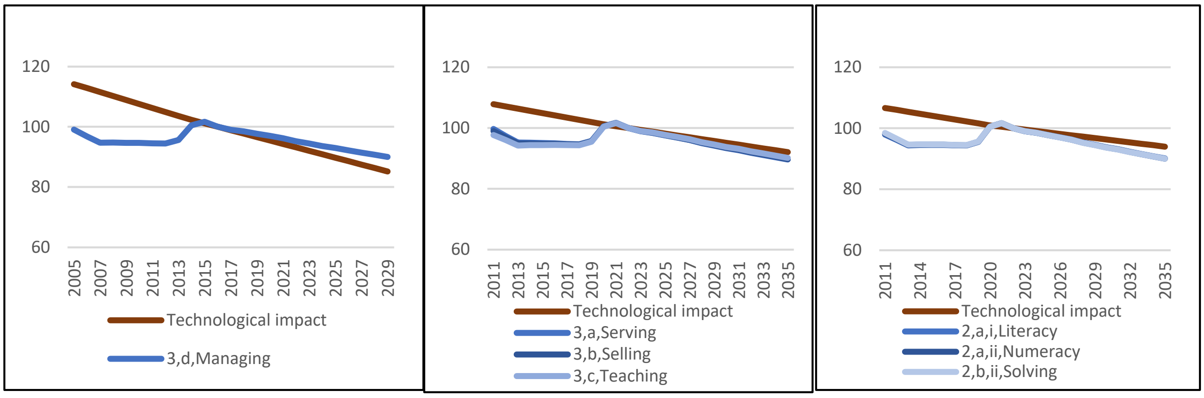
(d) Management (e) Social skills (f) Literacy analysis

Figure 4. Specific intensities of the different tasks during the three waves.

The combination of the impacts of these three waves generated the technological scenario. The following graphs in Figure 5 show the evolution of the specific intensities (in percentages) of several tasks calculated for total employment between 2011 and 2035.



(a) Manual tasks (b) Routine tasks (c) Computation



(d) Management (e) Social skills (f) Literacy analysis

Figure 5. Evolution of the specific intensities of the different tasks between 2011 and 2035.

According to Figure 5, the forecasts made on the impact of technology between 2023 and 2035 show that manual and routine tasks will decrease rapidly. Thus, they would be the most affected by automation.

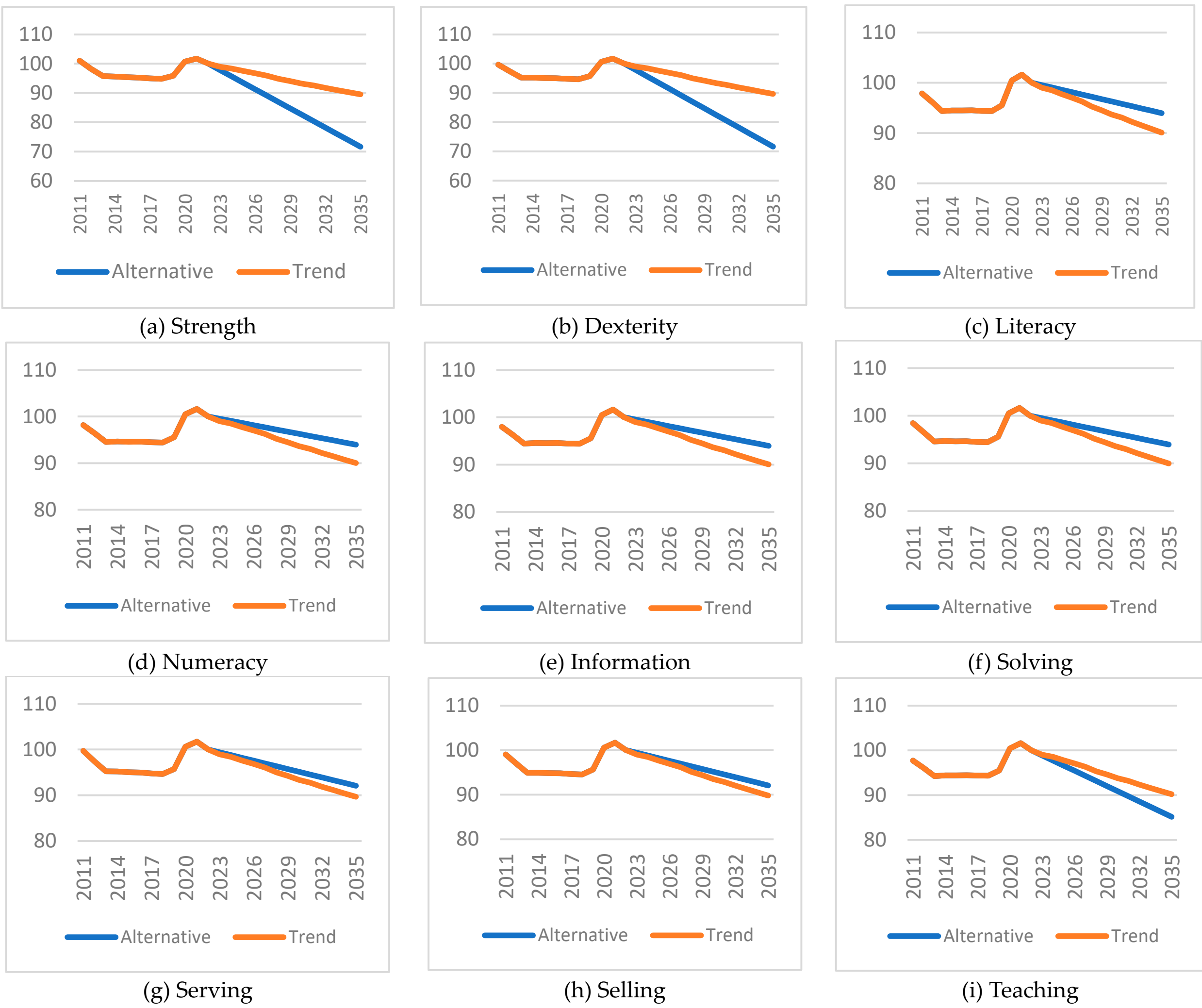
Based on the comparison between the trend scenario and the technological scenario, an alternative scenario will be built. For each of the 17 differentiated tasks, the specific intensities will evolve in the future according to the estimated technological impact for each of the typologies of tasks according to the following correspondences as described in Figure 6.

For tasks for which the corresponding technological impact reference was not available (autonomy, teamwork, and use of machines), an alternative scenario was constructed by extending the historical trend of the evolution of the specific intensity. Figure 7 presents the new specific intensities calculated for the alternative technological scenario.

The comparison of the estimated technological impacts (alternative scenario) with the evolution of the specific intensities of different tasks calculated for the trend scenario indicates that the evolution was very similar for the historical period from 2011 to 2022. The prospective scenario would have a slightly smaller impact on most tasks. However, the most influenced ones will be those of strength, dexterity, repetitiveness, and standardization routine of task (where the alternative scenario is under the trend lines).

Manual	1.a. Strength 1.b. Dexterity
Literacy analysis	2.a.i. Literacy 2.a.ii. Numeracy 2.b.i. Information 2.b.ii. Solving
Social skills	3.a. Serving 3.b. Selling
Management	3.c. Teaching 3.d. Managing
Historical trend	4.WO. Autonomy 4.WO. Teamwork
Routine	4.WO. Routine, repet. 4.WO. Routine, stand.
Historical trend	5. Tools, machines
Computation	5. Tools, ICT, basic IT 5. Tools, ICT, program

Figure 6. Task typologies used in the alternative scenario.



(a) Strength (b) Dexterity (c) Literacy

(d) Numeracy (e) Information (f) Solving

(g) Serving (h) Selling (i) Teaching

Figure 7. *Cont.*

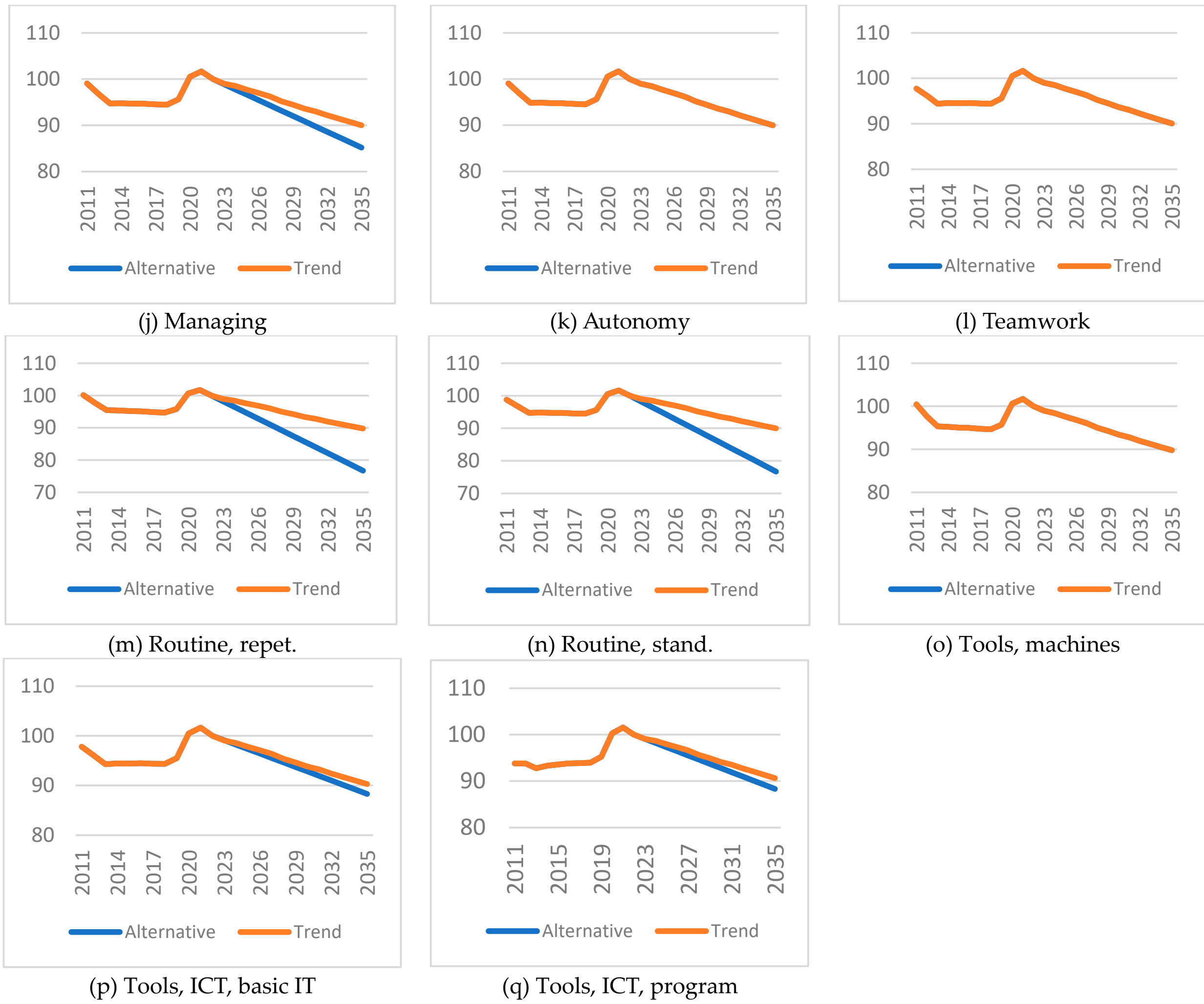


Figure 7. New specific intensities calculated for the alternative technological scenario.

4. Main Results

Applying the new specific intensities calculated for the alternative technological scenario, we obtained new projections of the total employment demand by type of profession. Figure 8 below presents the comparison of the trend scenario and the alternative technological scenario.

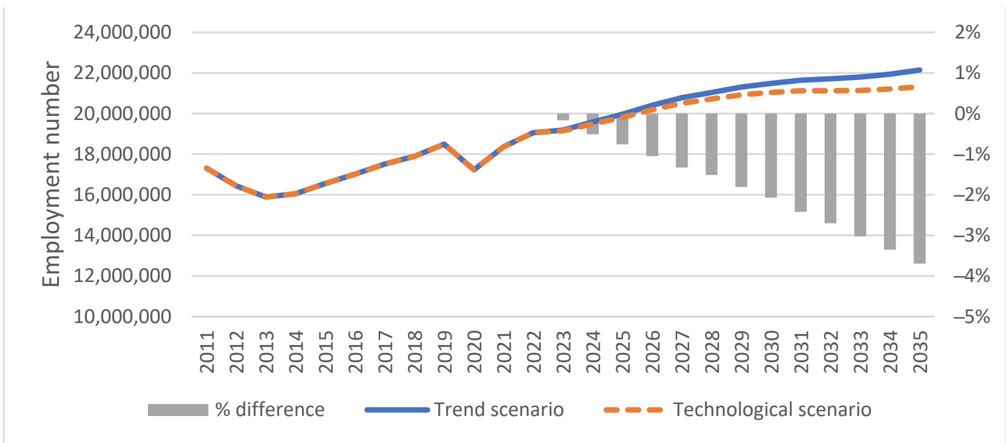
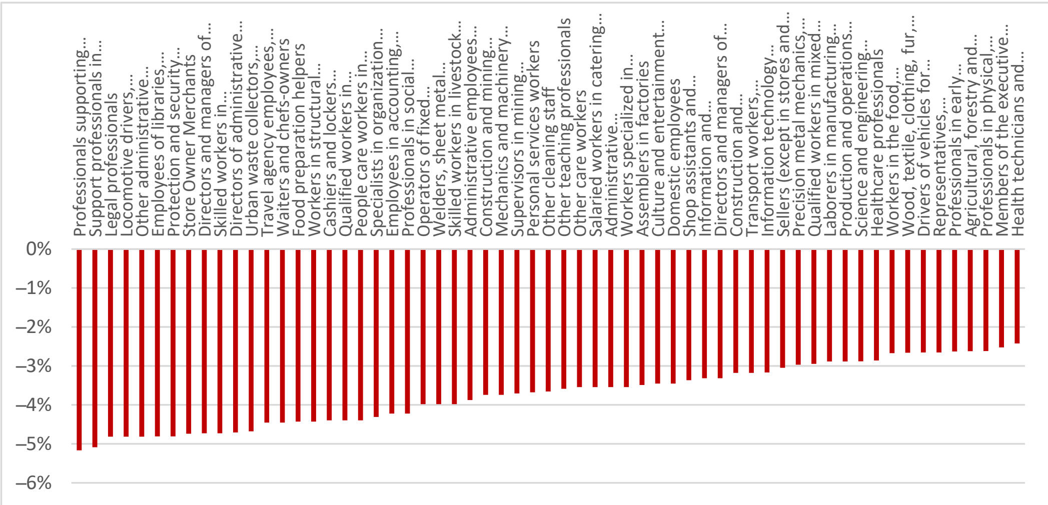


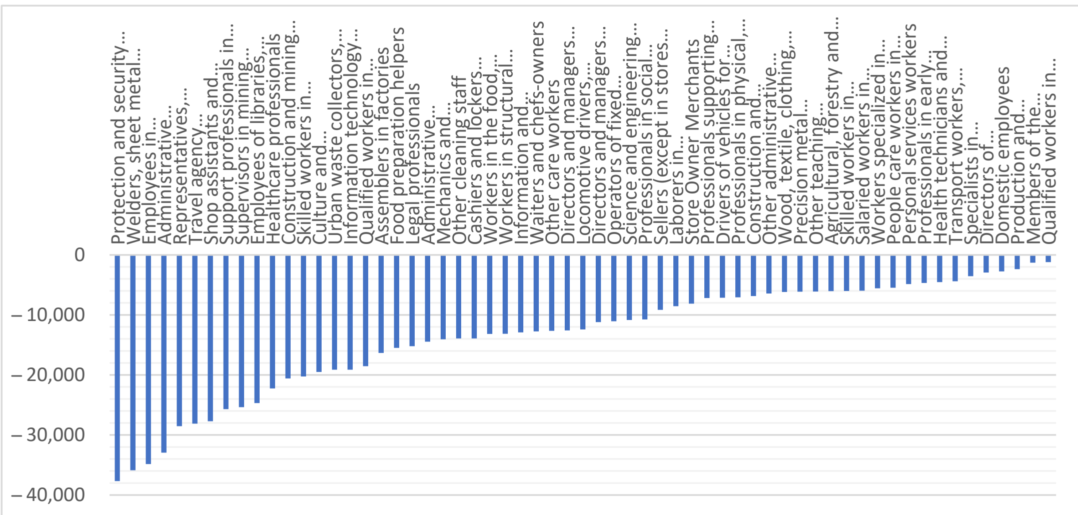
Figure 8. Evolution of the total number of employees between 2011 and 2035 in the trend and technological scenarios.

We observe that the total number of employees will always increase in both the trend and technological scenarios. However, the number of jobs in the technological scenario will be relatively lower than that in the trend scenario. This means that the impact of technology on labor demand will be recorded and present in the future. However, the difference between both scenarios will increase over the years. We deduced that technology will replace up to 4% of professions in 2035, which represents a total loss of approximately 820,000 jobs by 2035. We also observed that the evolutions of total employment application in both scenarios were very similar between 2011 and 2022, while they will be different between 2023 and 2035. This indicates that technology will replace humans in the future but at low percentages.

To study the evolution over time of each profession's demand in both the trend and the technological scenarios, we calculated the number of employees, as presented in Table A2 in the Appendix A. To avoid weakening this article with too many details, only the results for 2022 and 2035 are given for each scenario. The following graphs in Figure 9 show the differences between the trend and the technological scenarios (in percentage and number) for the employment demand by profession in 2035.



(a) Differences in percentages (%)



(b) Absolute differences

Figure 9. Differences in the numbers and percentages of employment demands by profession * in 2035. * The professions classified according to the CNO-2011 (military professions were not taken into account) are described in Table A1.

According to these forecasts on the potential impact of technology (Table A2 and Figure 9), we note that the demand for jobs in the technological scenario will always be lower than that in the trend scenario between 2023 and 2035. This means that some workers would lose their jobs because of future technological progress.

By the end of the forecast horizon (2035), the difference in percentage between both scenarios seems to be neglected since it would cover a range between 3% and 5% of employment by type of profession. Furthermore, we note that a high risk (5%) will be recorded for different workers, such as professionals supporting legal, social, cultural, sports, and related services; support professionals in finance and mathematics; and protection and security services workers. This means that both low-skilled and high-skilled professions could be affected by future technological progress.

However, in absolute difference, the highest number of lost jobs would be approximately 37,700 occupations for other cleaning staff (C.N.O. 92), more than 35,800 among salaried workers in catering services (C.N.O. 51), and approximately 34,800 among drivers of vehicles for urban or road transport (C.N.O. 84). At the opposite extreme, the lowest losses would be approximately 1200 occupations for skilled workers in mixed agricultural activities (C.N.O. 63), approximately 1300 for members of the executive branch (C.N.O. 11), and less than 2400 jobs for support professionals in finance and mathematics (C.N.O. 34). Finally, we note that the professions most at risk of potential automation progress, in absolute difference, are linked to low-skilled jobs that involve routine or manual tasks. This result is in agreement with those of other studies [28,34,56,57], affirming that low-qualified laborers are the most affected by technology.

Overall, our results suggest that technological progress will have approximately the same impact on low-skilled and high-skilled professions (between 3% and 5%) in the long term. However, the absolute differences between the two scenarios (trend scenario and technological scenario) are greater for low-skilled workers. This implies larger job losses in low-qualified professions, where a great share of the labor force is engaged.

5. Discussion and Conclusions

This study attempted to evaluate the potential impact of technological progress on employment demand by occupation in Spain from 2023 to 2035. The results of this article suggest that new technologies could affect the total job demand, but at low percentages (with a maximum of 5% of jobs being automated). Furthermore, we conclude that both categories of low- and high-skilled workers are influenced by technological progress in the long term at the same level (ranging from 3% to 5%). Nonetheless, in absolute difference, the impact of automation will be greater for low-skilled professions than for high-skilled professions (up to 2035), especially for occupations of other cleaning staff, salaried workers in catering services, and drivers of vehicles for urban or road transport who will record larger job losses. This is due to the large share of the labor force that is engaged in the low-qualified category. In addition, we note that the professions most at risk of potential automation progress, in absolute difference, are linked to low-skilled jobs that involve routine and manual tasks.

Our results agree with those of Cedefop [37], who analyzed the evolution of professions using recent data from the COVID-19 crisis and proved that few workers were replaced by automated workers. They concluded that technological changes have affected only 5% of EU employees. This shows that technology contributes positively to the task and skill complexity of jobs, while fully automatable occupations saw only a slight decline over the period under consideration, which contradicts the predictions of Frey and Osborne [6]. Cedefop [37] also studied the impact of technology on work within companies to determine whether it generates pressure for change. They showed that technological advances generated medium or high pressure for change within 35% of companies, while there was no such pressure in the remaining companies. Finally, they confirmed that new technologies have a beneficial impact on employment growth, especially in companies that have shared information, development plans, and communications about their strategies for adopting new technologies with their employees.

In addition, our conclusions are consistent with those of several studies [16,34,57]. Cedefop [34] showed that routine occupations with a low demand for qualifications are the most affected by automation. They affirmed that low-skilled personnel are at greater risk of mechanization, particularly among plant and machine operators and in elementary trade positions, as opposed to high-skilled occupations that are far from automation. Cords and Prettner [57] empirically demonstrated that technological change displaces low-skilled labor in developed countries while improving the employment of highly qualified workers. Furthermore, Arntz et al. [16] found that low-skilled laborers are more likely to be replaced by technology than high-skilled workers.

According to Boundi's study [28] on the technological impact on the manufacturing sectors of OECD countries, technological progress contributes to job loss in the long term, but it is not strong enough to cause the end of human work and complete automation of workers in the manufacturing sectors of OECD countries. Our results seem to agree with this conclusion. By contrast, our forecasts may disagree with the research fearing that new technologies could make labor redundant due to accelerated automation of tasks performed by humans [4,7,22,58,59]. In addition, other researchers [22–24] have suggested that the recent decrease in the employment/population ratio in the US is due to the penetration of technology in the economy, which prevents laborers from competing with machines.

The risk of automation varies primarily depending on the type of tasks performed in different occupations and the training required to perform them. In this sense, the analysis of Hawksworth et al. [15] affirms that the technological impact on employees in various occupations is expected to vary with time. For instance, algorithm and augmentation waves (until the end of the 2020s) had the greatest influence on technicians and clerical workers, where machines gradually surpassed humans in basic computational tasks and eventually in routine information processing tasks. However, during the autonomy wave (until the mid-2030s), machine operators and assemblers might face the highest risk of automation, with estimates exceeding 60% by the 2030s. These disparities may arise from the diverse nature of tasks within several professions and their respective educational requirements.

In general, the effects of technology on employment demand and the risk of automation vary depending on several factors, such as the match between skills and job requirements; the frequency of routine, independent, or learning tasks; and contextual data such as age, gender, education level, job size, economic sector, profession, etc. [34]. In addition, the work of Hawksworth et al. [15] revealed that the automation rate of the same profession can vary according to sectors and countries, depending on the level of education of staff, the processes put in place to divide work, and the specialization specific to each country.

On the other hand, some studies admit that technology influences the structure of jobs and not their general volume. Schumpeter's research [60] was among the fundamental investigations that demonstrated that technological progress presents a process of "creative destruction", which is based on the transformation of professions. This means that technology leads to the loss of some occupations and the creation of others to replace them. In other words, automation can change the content of jobs without necessarily destroying them. Thus, it is a redistribution of occupations toward other activities that require more skills.

Finally, the technological unemployment arising from task automation could have serious social consequences, since the unskilled labor force finds it more challenging to acquire new skills. However, the findings of this study can inform policymakers and employers about the potential impacts of technological innovations on the labor market. To address the negative impacts of technology, several strategies can be taken into consideration. For instance, low-skilled individuals can learn new skills that are in demand in the job market by enrolling in training programs that are specifically designed to meet their needs. The emphasis of these programs should be on cultivating skills relevant to growing industries and less vulnerable to automation. In addition, enhancing the quality and accessibility of training programs can make it easier for individuals, especially those with limited resources, to acquire new skills. This may involve subsidizing training costs, offering flexible learning options, and providing support services to help individuals transition to new careers. In this sense, Arntz et al. [16] proposed providing relevant training, especially for low-skilled workers. Additionally, to reduce the risk of job automation, Cedefop [34] suggested that several elements must be improved, such as the training conditions, level of remuneration, adoption time, and technical feasibility of technologies, investment requirements, and high costs of creativity and innovation.

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Data Availability Statement: The datasets generated and analyzed during the present study are available in the National Institute of Statistics (INE) database repository at: https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176918&menu=ultiDatos&idp=1254735976595 (accessed on 1 June 2023).

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

Appendix A

Table A1. Task intensity matrix $M_{(61\times17)}$ by type of occupations, classified according to the National Classification of Occupations (CNO) of 2011.

Professions classified according to the CNO-2011		1. a. Strength	1. b. Skill	2. a. i. Literacy	2. a. ii. Arithmetic	2. b. i. Information	2. b. ii. Solving	3. a. portion	3. b. Selling	3. c. Teaching	3. d. Management	4. WO. Autonomy	4. O. Teamwork	4. WO. Routine, repet.	4. WO. Routine, stand.	5. Tools, machines	5. Tools, ICT, basic IT	5. Tools, ICT, program
11	Members of the executive branch	11.5	21.6	63.4	51.8	72	74.5	53.8	73.6	52	61	79.5	60	24.1	55.4	13.5	85.1	9
12	Directors of administrative and commercial departments	7.1	15.3	62.4	56	69.6	70.6	47.4	64.7	52.5	56.5	77.5	55.7	29.5	67.1	8.9	91.3	12.7
13	Production and operations directors	13.8	19.4	62	52.1	68.2	71.7	58.9	63.3	56	65.3	73.5	56	29.5	76.6	16.9	85	12.2
14	Directors and managers of accommodation, restaurant, and commerce companies	25.7	32	56.2	48.7	59.7	69.8	70.4	68.7	50.6	61.2	73.1	40.6	38	60.8	17.8	73.3	8.3
15	Directors and managers of other service companies not classified under other headings	25.7	32	56.2	48.7	59.7	69.8	70.4	68.7	50.6	61.2	73.1	40.6	38	60.8	17.8	73.3	8.3
21	Healthcare professionals	29	42.6	60	38.1	73.3	64.3	66.2	53.1	52.5	45.9	58	58.5	35.4	61.4	15	63.2	5.8
22	Professionals in early childhood, primary, secondary, and post-secondary education	17.3	14.9	62	36.8	65.1	68.5	53.2	48.9	72.9	44.8	56.4	56	24.5	55.2	5.9	74.1	7.3
23	Other teaching professionals	17.2	15	62	36.8	65.1	68.5	53.2	48.9	72.9	44.8	56.4	56	24.5	55.2	5.9	74.1	7.3
24	Professionals in physics, chemistry, mathematics, and engineering	10	25	62.1	56.8	72	71.4	35.5	48.1	43.7	41.8	71.2	56.6	31.2	68.4	19.1	85.5	22.5
25	Legal professionals	12	16.7	59.5	31.1	67.4	68.3	58.3	52.8	45	36.8	70.5	47.9	25	52.8	6.5	77.2	7.9

Table A1. *Cont.*

26	Specialists in the organization of public administration, business, and marketing	6.1	13.8	60.5	51.2	68.6	66.1	37.1	56.2	45	37.7	73	51.4	30.3	61.6	6.6	88.3	12.8
27	Information technology professionals	4.3	29.5	58.6	48.6	74.4	72	23.4	43.8	42.5	33.1	74.8	54.8	29.9	58.2	12.9	89.9	60.5
28	Professionals in social sciences	12	16.7	59	31.5	67.4	69	58	52.8	45	36.8	70.5	47.9	25	52.8	6.5	77.2	7.9
29	Culture and entertainment professionals	12	16.7	59.5	30	67	67	59	52.8	45	36.8	70.5	47.9	25	52.8	6.5	77.2	7.9
31	Science and engineering technicians	22.4	40	52.2	43.7	67.8	60.4	33.6	41.5	41.9	39.6	59.9	56.7	38.3	75.6	30.1	68.5	14
32	Supervisors in mining engineering, manufacturing industries, and construction	23	41	52.2	43.7	67.8	60.4	33.6	41.5	41.9	39.6	59.9	56.7	38.3	75.6	30.1	68.5	14
33	Health technicians and alternative therapy professionals	32.3	42.5	51	31.6	62.8	55.3	58.1	44.8	38	33.1	52.2	64.2	34.1	56.1	17.5	55.8	7.2
34	Support professionals in finance and mathematics	8.9	19.3	56.3	44.9	62.3	57.4	45.1	53.4	35.6	34.8	66.5	43.5	33	55	7.9	81.8	9.5
35	Representatives, commercial agents, and refiners	8.9	19.3	56.3	44.9	62.3	57.4	45.1	60	35.6	34.8	66.5	43.5	33	55	7.9	81.8	9.5
36	Administrative management support professionals; technicians of security forces and bodies	8.9	19.3	56.3	44.9	63	57.4	45.1	53.4	35.6	35	66.5	43.5	33	55	7.9	81.8	9.5
37	Professional legal, social, cultural, sports, and healthcare services	23	28.2	49	25.7	60.4	64.6	53.2	48	43.2	35.3	63.2	62.1	30.8	46.3	9.6	62.5	5.1
38	Information and communication technology (ICT) technicians	13.6	38.4	54.5	37.5	72	64.5	28.1	41.1	37.6	27.7	66.5	54	35.3	56.3	21.2	78.3	36.9
41	Employees in accounting, financial services, and production and transportation support services	14.5	24.9	49.8	43.3	55.9	49.8	38.6	38.5	30.4	31.5	58.4	44.4	39.1	61.5	11.7	74.1	8.9
42	Employees of libraries, postal services, and refineries	14.5	24.9	49.8	43.3	55.9	49.8	38.6	38.5	30.4	31.5	58.4	44.4	39.1	61.5	11.7	74.1	8.9
43	Other administrative staff without attention to the public	6.8	22.5	51.1	34.3	56.6	48.9	44.7	35.5	26.1	24.9	60.8	44.1	40.6	49.6	8.4	77.9	6.5

Table A1. *Cont.*

44	Travel agency employees, receptionists, and telephone operators; counter and refinery employees	12	24.4	50.5	36	55.8	49.3	58.6	52	32.1	26.5	49.5	47.7	47.4	56	10.3	70.3	8.3
45	Administrative employees with public service tasks not classified under other headings	22.2	31	46.1	29.3	51.3	47.3	43.3	36.4	27.5	25.2	57.3	50.4	50.5	46.2	12.5	67.7	7.1
50	Waiters and chefs–owners	32.5	38.3	36.8	25.9	48.2	52	58.7	44.7	30.5	28.3	53	46.2	50.4	49.5	13.2	38.6	3.2
51	Salaried workers in catering services	32.5	38.3	36.8	25.9	48.2	52	58.7	44.7	30.5	28.3	53	46.2	50.4	49.5	13.2	38.6	3.2
52	Shop assistants and warehouses	29.2	32.9	42.8	36.6	50.3	52.7	61.2	60.2	33.3	31	53.6	38.6	44.5	46.4	12.9	42	4.9
53	Store owner merchants	29.2	32.9	42.8	36.6	50.3	52.7	61.2	60.2	33.3	31	53.6	38.6	44.5	46.4	12.9	42	4.9
54	Sellers (except in stores and warehouses)	29.2	32.9	42.8	36.6	50.3	52.7	61.2	60.2	33.3	31	53.6	38.6	44.5	46.4	12.9	42	4.9
55	Cashiers and lockers (except banks)	29.2	32.9	42.8	36.6	50.3	52.7	61.2	60.2	33.3	31	53.6	38.6	44.5	46.4	12.9	42	4.9
56	Employees in health services	37.4	37.2	42.1	21.4	54.1	56.4	50.4	38.3	36.6	32.4	51.3	57.6	35.7	45.3	11.3	38.2	4.2
57	Other care workers	37.4	37.2	42.1	21.4	54.1	56.4	50.4	38.3	36.6	32.4	51.3	57.6	35.7	45.3	11.3	38.2	4.2
58	Personal service workers	32.5	38.3	36.8	25.9	48.2	52	58.7	44.7	30.5	28.3	53	46.2	50.4	49.5	13.2	38.6	3.2
59	Protection and security service workers	31	33.9	50.2	18	59.6	52.5	59.9	43	40.9	31.1	44.3	59.5	33.2	49.3	16.9	60.9	5.7
61	Skilled workers in agricultural activities	40.3	44.6	38	21.9	51	54.1	27.5	31.1	24.5	29.4	70.8	28	42.8	58.7	36.6	47.9	3.9
62	Skilled workers in livestock activities (including poultry, beekeeping, and similar)	40.3	44.6	38	21.9	51	54.1	27.5	31.1	24.5	29.4	70.8	28	42.8	58.7	36.6	47.9	3.9
63	Skilled workers in mixed agricultural activities	40.3	44.6	38	21.9	51	54.1	27.5	31.1	24.5	29.4	70.8	28	42.8	58.7	36.6	47.9	3.9
64	Qualified workers in forestry, fishing, and hunting activities	44.7	41.9	30.6	22.2	48.8	46.1	31.8	35.1	24.2	27.8	48.3	46.6	57.5	60	35.1	53.3	2.5
71	Workers in structural construction and Finnish works	44	42.4	35.2	28.1	55.6	54.5	38.7	36.5	31.6	33.3	55.2	47.9	56.1	67.6	34.4	48.6	3.7
72	Workers finishing construction and installations (except electricians), painting, and refining	44	42.4	35.2	28.1	55.6	54.5	38.7	36.5	31.6	33.3	55.2	47.9	56.1	67.6	34.4	48.6	3.7
73	Welders, sheet metal workers, metal structure assemblers, blacksmiths, and tool and fine makers	38.6	46.9	40.1	29.9	59.6	50.7	29.1	34.1	31.4	27.6	50.2	49.8	49.8	74.6	46.8	38.5	9.5

Table A1. *Cont.*

74	Mechanics and machine adjusters	38.6	46.9	40.1	29.9	59.6	50.7	29.1	34.1	31.4	27.6	50.2	49.8	49.8	74.6	46.8	38.5	9.5
75	Workers specialized in electricity and electrotechnology	35.3	46.8	46.6	32.7	63.5	59.3	44.5	41.9	34.2	30.5	60.8	55.7	38.9	69.1	41.1	55.2	13.4
76	Precision metal mechanics, ceramists, glass workers, artisans, and graphic arts workers	31.5	48.3	41.1	30.9	53.6	56.7	40.8	34.8	27.7	27.1	57.2	39.5	48.1	73.7	40.3	47	11.6
77	Workers in the food, beverage, and tobacco industries	36.8	43.6	34.4	25.3	50.2	48.2	27.7	33.3	26.7	25.7	51	42.6	56.6	73.5	35	45	5.7
78	Wood, textile, clothing, fur, leather, footwear, and other trade workers	36.8	43.6	34.4	25.3	50.2	48.2	27.7	33.3	26.7	25.7	51	42.6	56.6	73.5	35	45	5.7
81	Installation and machine operators	40.2	44.4	32.9	22.9	48.8	41.1	15.5	24.5	28.4	24.2	38.8	55.4	61.7	82.9	51	28.3	5
82	Assemblers in factories	35.3	49.2	30.3	18.8	49.4	42.6	18.6	20.9	24.6	19.4	37.8	53.8	60.8	80	49	18.6	5.9
83	Locomotive drivers, agricultural machinery and heavy mobile equipment operators, and sailors	28.7	38.3	37.9	22.8	43.7	48.4	43.3	32.4	27.1	25	44.7	30.9	48	53.5	34	27.9	2.2
84	Drivers of vehicles for urban or road transport	28.7	38.3	37.9	22.8	43.7	48.4	43.3	32.4	27.1	25	44.7	30.9	48	53.5	34	27.9	2.2
91	Domestic employees	37.3	32.5	22.4	7.2	30.5	39.3	48.6	19	18.6	20.8	56.1	30.5	56.9	39.9	17.5	35.9	0.9
92	Other cleaning staff	37.3	32.5	22.4	7.2	30.5	39.3	48.6	19	18.6	20.8	56.1	30.5	56.9	39.9	17.5	35.9	0.9
93	Food preparation assistants	35.6	38.7	23.4	14.5	41.9	36.7	42	28.3	22.4	17.8	41.3	51.5	47.5	55.9	18.2	14.6	1.2
94	Registers of urban residents, street vendors, and other basic occupations in services	26.5	6.5	29.9	25.1	37	57.4	62.8	58	24	17.4	62	0	20	15	3	37.6	5
95	Agricultural, forestry, and fishing laborers	42.6	42.7	26.8	18.1	41	46.2	35.4	26	25.7	27.6	51.9	44.8	56.8	48	36.6	18.1	1.7
96	Construction and mining professionals	44.1	41.4	30.3	21	45.1	40.5	38.5	28.5	29.3	28.2	40	55.5	58.4	66.4	37.6	30.5	2.7
97	Members of the manufacturing industries	44.1	41.4	30.3	21	45.1	40.5	38.5	28.5	29.3	28.2	40	55.5	58.4	66.4	37.6	30.5	2.7
98	Transport workers, unloaders, and replenishers	44.1	41.4	30.3	21	45.1	40.5	38.5	28.5	29.3	28.2	40	55.5	58.4	66.4	37.6	30.5	2.7

Source: Eurofound [14].

Table A2. Employee numbers in the trend and the technological scenarios in 2022 and 2035 by profession.

	Trend Scenario				Technological Scenario			Comparison of the Trend–Techno.	
	2022	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**Variation of the Trend Response**	
Members of the executive branch	45,225	51,925	6700	15%	50,615	5389	12%	3%	−1311
Directors of administrative and commercial departments	202,497	232,498	30,001	15%	226,309	23,812	12%	3%	−6189
Production and operations directors	258,057	296,289	38,232	15%	287,742	29,685	12%	3%	−8547
Directors and managers of accommodation, restaurant, and commerce companies	188,381	216,291	27,909	15%	209,416	21,034	11%	3%	−6875
Directors and managers of other service companies not classified under other headings	113,514	138,122	24,608	22%	133,732	20,218	18%	3%	−4390
Healthcare professionals	717,690	824,023	106,333	15%	796,303	78,613	11%	3%	−27,721
Professionals in early childhood, primary, secondary, and post-secondary education	871,801	1,075,394	203,593	23%	1,046,865	175,064	20%	3%	−28,529
Other teaching professionals	219,326	269,095	49,769	23%	261,956	42,630	19%	3%	−7139
Professionals in physics, chemistry, mathematics, and engineering	548,273	629,505	81,232	15%	610,963	62,690	11%	3%	−18,542
Legal professionals	220,096	230,185	10,088	5%	224,153	4056	2%	3%	−6032
Specialists in the organization of public administration, business, and marketing	429,153	492,738	63,585	15%	479,571	50,418	12%	3%	−13,167
Information technology professionals	180,239	206,944	26,704	15%	200,799	20,559	11%	3%	−6145
Professionals in social sciences	210,546	269,977	59,431	28%	262,906	52,359	25%	3%	−7072
Culture and entertainment professionals	152,519	178,217	25,698	17%	173,534	21,014	14%	3%	−4684
Science and engineering technicians	318,698	381,169	62,471	20%	367,240	48,542	15%	4%	−13,930

Table A2. *Cont.*

	Trend Scenario				Technological Scenario			Comparison of the Trend–Techno.	
	2022	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**Variation of the Trend Response**	
Supervisors in mining engineering, manufacturing industries, and construction	109,015	132,526	23,510	22%	127,653	18,638	17%	4%	−4873
Health technicians and alternative therapy professionals	139,908	170,374	30,466	22%	164,262	24,354	17%	4%	−6112
Support professionals in finance and mathematics	76,613	82,657	6045	8%	80,273	3660	5%	3%	−2384
Representatives, commercial agents, and refiners	618,603	778,659	160,056	26%	756,403	137,800	22%	3%	−22,256
Administrative management support professionals; technicians of security forces and bodies	328,129	376,743	48,613	15%	365,884	37,754	12%	3%	−10,859
Professional legal, social, cultural, sports, and healthcare services	261,585	300,343	38,758	15%	291,190	29,604	11%	3%	−9153
Information and communication technology (ICT) technicians	299,718	389,025	89,307	30%	376,121	76,403	25%	3%	−12,904
Employees in accounting, financial services, and production and transportation support services	492,423	565,379	72,956	15%	545,867	53,444	11%	4%	−19,512
Employees of libraries, postal services, and refineries	74,372	79,667	5294	7%	76,917	2545	3%	4%	−2749
Other administrative staff without attention to the public	497,479	603,446	105,967	21%	584,325	86,846	17%	3%	−19,121
Travel agency employees, receptionists, and telephone operators; counter and refinery employees	330,823	379,837	49,015	15%	367,246	36,424	11%	3%	−12,591

Table A2. *Cont.*

	Trend Scenario				Technological Scenario			Comparison of the Trend–Techno.	
	2022	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**Variation of the Trend Response**	
Administrative employees with public service tasks not classified under other headings	581,518	684,554	103,036	18%	659,176	77,658	13%	4%	−25,378
Waiters and chefs–owners	245,528	278,232	32,704	13%	267,163	21,635	9%	4%	−11,070
Salaried workers in catering services	788,581	901,943	113,362	14%	866,059	77,477	10%	4%	−35,884
Shop assistants and warehouses	842,752	930,558	87,807	10%	897,605	54,853	7%	4%	−32,954
Store owner merchants	340,835	357,096	16,261	5%	344,450	3615	1%	4%	−12,646
Sellers (except in stores and warehouses)	137,191	157,517	20,326	15%	151,939	14,748	11%	4%	−5578
Cashiers and lockers (except banks)	158,123	168,470	10,348	7%	162,504	4382	3%	4%	−5966
Employees in health services	453,692	550,086	96,394	21%	529,498	75,806	17%	4%	−20,588
Other care workers	327,422	375,931	48,509	15%	361,861	34,439	11%	4%	−14,070
Personal service workers	443,608	509,333	65,725	15%	489,069	45,461	10%	4%	−20,264
Protection and security service workers	441,102	468,583	27,481	6%	452,240	11,138	3%	4%	−16,343
Skilled workers in agricultural activities	281,593	316,614	35,021	12%	302,700	21,106	7%	5%	−13,914
Skilled workers in livestock activities (including poultry, beekeeping, and similar)	108,641	124,737	16,096	15%	119,255	10,614	10%	5%	−5482
Skilled workers in mixed agricultural activities	23,906	27,448	3542	15%	26,241	2335	10%	5%	−1206
Qualified workers in forestry, fishing, and hunting activities	33,025	62,558	29,532	89%	59,613	26,588	81%	5%	−2945
Workers in structural construction and Finnish works	539,310	631,116	91,806	17%	603,003	63,693	12%	5%	−28,113

Table A2. *Cont.*

	Trend Scenario				Technological Scenario			Comparison of the Trend–Techno.	
	2022	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**Variation of the Trend Response**	
Workers finishing construction and installations (except electricians), painting, and refining	270,497	285,973	15,476	6%	273,235	2738	1%	5%	−12,739
Welders, sheet metal workers, metal structure assemblers, blacksmiths, and tool and fine makers	258,592	296,904	38,312	15%	283,758	25,166	10%	5%	−13,146
Mechanics and machine adjusters	304,778	349,933	45,155	15%	334,439	29,661	10%	5%	−15,494
Workers specialized in electricity and electrotechnology	325,071	373,232	48,161	15%	358,765	33,693	10%	4%	−14,468
Precision metal mechanics, ceramists, glass workers, artisans, and graphic arts workers	75,009	82,311	7302	10%	78,764	3755	5%	5%	−3548
Workers in the food, beverage, and tobacco industries	210,189	237,073	26,884	13%	225,864	15,675	7%	5%	−11,208
Wood, textile, clothing, fur, leather, footwear, and other trade workers	110,872	127,298	16,426	15%	121,280	10,408	9%	5%	−6018
Installation and machine operators	421,251	505,045	83,794	20%	479,355	58,104	14%	5%	−25,690
Assemblers in factories	121,385	139,369	17,984	15%	132,169	10,784	9%	5%	−7201
Locomotive drivers, agricultural machinery and heavy mobile equipment operators, and sailors	205,992	254,679	48,687	24%	243,931	37,938	18%	4%	−10,749
Drivers of vehicles for urban or road transport	719,956	825,459	105,503	15%	790,620	70,664	10%	4%	−34,839
Domestic employees	447,162	513,411	66,248	15%	488,720	41,558	9%	5%	−24,690
Other cleaning staff	663,465	783,631	120,166	18%	745,946	82,481	12%	5%	−37,686
Food preparation assistants	149,473	171,619	22,146	15%	163,487	14,014	9%	5%	−8132

Table A2. *Cont.*

	Trend Scenario				Technological Scenario			Comparison of the Trend–Techno.	
	2022	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**2035**	**Difference 2035–2022**	**(%) Difference 2035–2022**	**Variation of the Trend Response**	
Registers of urban residents, street vendors, and other basic occupations in services	163,342	187,543	24,200	15%	182,999	19,656	12%	2%	−4544
Agricultural, forestry, and fishing laborers	357,166	408,874	51,708	14%	389,744	32,579	9%	5%	−19,129
Construction and mining professionals	116,539	133,804	17,265	15%	127,363	10,824	9%	5%	−6442
Members of the manufacturing industries	208,316	257,797	49,482	24%	245,386	37,070	18%	5%	−12,411
Transport workers, unloaders, and replenishers	275,432	316,240	40,808	15%	301,016	25,583	9%	5%	−15,225

Source: Own elaboration based on LFS data.

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