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Analysing Labour-Based Estimates of Automation and Their Implications. A Comparative Approach from an Economic Competitiveness Perspective

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Abstract

Given the advent of Industry 4.0 and the importance of labour-based automation in ensuring competitiveness at the firm, regional cluster, or country level, the paper aims to explore, for the first time, the features of several estimates of occupational/labour automation and to assess the potential risks associated with it. A comparative analysis of the most well-established estimates of labour automation, the Occupational Information Network (O*NET) degree of automation estimates and Frey and Osborne's future probabilities of automation was carried out to see whether, and to what extent, these estimates are compatible. Results show significant distributional differences between them, which are quantified into automation-triggered disruption risks at the occupational level, as current levels of labour automation are, in some cases, well below their future estimates. Work context features were used to derive a typology of occupations, which can explain up to one-third of the current, and up to half of the future levels of labour automation. Finally, we identified which occupations and occupational groups are likely to be affected by the highest risk of automation-induced displacement and estimated the magnitude of different disruption classes. Conclusions are compatible with other economy-wide assessments of the impact of labour automation on the workforce, thus being valuable inputs for corporate strategy, decision-makers and human resource planners as they address a growing need for quantitative insights useful for adapting the labour force structure, workers' skills, and the task content of occupations to the competitiveness requirements related to the process of digitization in the Industry 4.0 context.

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1. INTRODUCTION

The results obtained by Frey & Osborne (2017) concerning the automation potential of labour, defined as the probability of future substitution of human labour following the adoption of new digital technologies (Arntz et al., 2017), have started a considerable debate about how jobs are likely to be displaced and led to predictions that automation, defined as labour substitution caused by the adoption of new technologies that can take over tasks performed by human workers (Acemoglu & Restrepo, 2019) will lead to massive job losses. In discussing some of their significant findings, several authors, such as Acemoglu & Restrepo (2019), PwC (2018), Cellan-Jones (2019), and WEF (2020), have portrayed a grim, if not apocalyptic, view of the impact of automation on jobs and workers. However, a sizable share of academic literature has offered a more balanced view of the impact of automation on labour/employment. Arntz et al. (2017) and Willcox (2021) concluded that the automation impact on employment numbers is likely to be relatively moderate. From a historical perspective, changes effected by digitalization and Industry 4.0 do not seem to be that unusual. They will not necessarily lead to a "job apocalypse", as the creation of new jobs may, in the long term, offset job losses due to automation (Barbieri et al., 2019).

In addressing the features of various jobs, and job prospects, the focus is on the degree of labour automation at the occupation level (expressed as the share of tasks of a job that are reported to be automated) for the entire economy, disseminated by O*NET (2021) the occupational resource system. This information is comparable with the probabilities of future substitution of jobs due to adopting new technologies, estimated by Frey & Osborne (2017) in terms of presentation of results, economy-wide scope, and the number of occupations. As these estimates are disseminated along with occupation-specific information, such as average pay, past employment trends, future outlook, etc., it can be stated that actual and future job seekers look primarily at the occupation-level information, which is the starting point for the educational requirements analysis, and for identifying the specific skills and tasks required by the jobs and careers of their choice.

In the context of Industry 4.0, labour automation stands as the key to ensuring competitiveness. It helps companies become more competitive, as its effects can improve productivity (Acemoglu & Restrepo, 2019), drive down costs, and enhance profits (Medeiros et al., 2019), especially for developing countries. As a large share of the global workforce may be at risk of being displaced through automation, having the necessary qualifications and skills is essential for companies and economies to maintain competitiveness (Vlasov & Chromjaková, 2018; WEF, 2020). Automation triggers structural changes, which must be tackled through adaptation of the skills structure, the labour market institutions, etc., to foster the competitiveness of firms, regions, and economies (Vermeulen et al., 2018; Acemoglu & Restrepo, 2019). In this context, a better-educated workforce adapted to the new economic structures is essential in improving competitiveness at regional and/or cluster levels (Tănase et al., 2019; Kleynhans, 2016).

As of now, no study has explored the differences between various estimates of labour automation at the occupation level. This has compelled us to analyse the main releases, identify occupations and occupational groups for which these estimates vary widely in terms of changes associated with a higher probability of future automation, and identify the main features that can help explain these differences.

Results can be used to show which occupation and occupational groups are likely to experience major changes in labour automation estimates. This will help researchers, potential job seekers, and policymakers to focus on occupations for which there are strong divergences in terms of automation potential. They will help fill a literature gap and, for the first time, will address potential weak spots that, if not adequately addressed, may result in mismatches between the existing occupational structure and the demand for jobs and skills induced by automation, with major impacts on competitiveness at the micro (company), regional, and macroeconomic levels.

2. THEORETICAL BACKGROUND

2.1 Key points on competitiveness, automation, and its effects on labour

The factors that shape competitiveness have been established by Porter (1998). For two main factors that appear in the Diamond of Competitiveness model, input supply (comprising an educated workforce) and strategy and rivalry, innovation and new technologies play a central role in shaping them (Kleynhans, 2016). Based on Porter's model, several improvements were carried out from different perspectives. Kleynhans (2016) identified the need for labour and innovation inputs as essential for increasing firm-level competitiveness. He argues that transfers of modern technology and higher levels of workforce education are instrumental in improving competitiveness. Medeiros et al. (2019) identify the degree of technological sophistication, labour, and training of human resources as systemic factors essential to achieving competitiveness at the country level. Other authors have reached similar conclusions. Thus, Tănase et al. (2019) point out that increased competitiveness at the cluster level depends on the existence of a specialized workforce. Developments specific to Industry 4.0 are essentially reframing the debate in the context of automation. Karacay (2018) points to the importance of having a workforce apt or re-trained, along with redesigned work processes to meet the new business requirements as key for enhancing sustainability and competitive advantage at the company level.

In the context of labour automation, accelerated by Industry 4.0, and its impact on the labour market, the literature has highlighted its importance for ensuring economic competitiveness. Autor (2015) points out the importance of building employees' skills to adapt to current and future technological changes. Also, the transition to the green economy may worsen skill mismatches, creating both new opportunities and risks generated by changes in the level and composition of labour demand at the industry and region levels (Pasnicu & Ciucă, 2020). Arntz et al. (2019) stress, in the context of automation, the importance of matching workforce structure to changing labour market requirements, both at the occupation and industry levels. Acemoglu & Restrepo (2019) point out that future productivity gains will be due to labour automation, whose evolution will need to match the emergence of new tasks as a prerequisite for sustainable growth and economic competitiveness. The expansion of labour automation depends upon the acquisition and training of skills through lifelong learning (Pouliakas, 2018). Business model innovation is key to fostering firm-level competitiveness through leveraging core competencies for the development of IoT solutions so that employees can develop new complementary technical skills (Foltean & Glovatchi, 2021).

Digitalisation and the possibilities of replacing tasks performed by employees with the help of "machines" have triggered a heated debate about "the future of jobs". Conclusions vary from gloomy views about "the end of work" (Rifkin, 1995; Ford, 2015) and a future when most of the current activities will be performed by robots or AI-based applications (Frey & Osborne, 2017; de Vries et al., 2020), to more moderate estimates which still point to significant changes effected by the advent of new technologies (Arntz et al., 2017; Dengler & Matthes, 2018; Scholl & Hanson, 2020). This would be in line with the evidence that technological progress has led to significant job creation (Roy et al., 2018; Barbieri et al., 2019), able to compensate for job losses caused by the technological transition. It should also be noted that labour market changes induced by automation represent lasting trends (Manning, 2019), and positive effects are not automatically guaranteed by market forces (Manning, 2019).

Recent changes triggered by the COVID-19 pandemic have also helped shape work prospects and work-related interaction in conjunction with the progress of labour automation. Thus, a report from World Economic Forum (WEF, 2020) points out that COVID-19 has accelerated the pace of labour automation and that, along with 85 million jobs to be displaced by 2025, another 97 million will emerge for a group of 26 countries. But conclusions of this kind are far from being unanimous. Klenert et al. (2022) conclude that labour automation through robotisation does not have a significant impact on employment in Europe. Parschau & Hauge (2020) obtain similar results for the manufacturing sector in South Africa while observing employment increases in some industries. In this context, substantial investment in work is a key driver of organisational performance (Radu et al., 2020), which can play a significant role in increasing competitiveness (Kleynhans, 2016).

Recent research has created a consensus that the future of the labour market is defined by human-machine collaboration. Thus, Spencer & Slater (2020) argue that jobs, especially those likely to be automated, can be reconfigured, allowing workers to integrate new tools and technologies in the future. Davenport & Kirby (2016) believe that automation will complement the duties and tasks specific to an occupation, and Kumar (2017) concludes that new technologies rely on the integration of employees into economic activities characterized by high technological content. Brynjolfsson et al. (2018) draw similar conclusions about the automation potential of labour, concluding that few occupations can be fully automated using artificial intelligence, while most will undergo a reorganization of tasks.

At the EU level, the progress of digitization/automation is heterogeneous due to different levels of development. While developed countries will make a faster transition to smart manufacturing, developing countries can leapfrog development stages and adopt new digital technologies. The "technology boom" strategy, comprising the implementation of smart manufacturing technologies in new companies, is the best example of skipping stages in the transition process towards Industry 4.0 (Marinas et al., 2021).

2.2 Features of automation probability estimates

Considering quantitative evaluations, there are several estimates of occupation-level labour automation. Frey & Osborne (2017) are the authors of the best-known labour automation probability estimates (Willcocks, 2020). They are built from a sample of 70 jobs, using an initial assessment of whether each of them is likely to be automated (1) or not (0), and trained a machine learning model to derive probabilities of automation for another 632 occupations using nine key O*NET input variables (Frey & Osborne, 2017). Using the model, probabilities of future labour automation were derived for 702 occupations, which refer to the entire civilian U.S. labour market from all regions and industries.

The second type of estimate is provided by the O*NET occupational information network, developed under the sponsorship of the U.S. Department of Labor (O*NET, 2021). Information comes from survey responses collected from holders of specific jobs or occupational experts and covers the entire civilian U.S. labour market, including all regions and industries. O*NET makes the degree of automation estimates available for over 850 occupations, derived from answers to the question "How automated is your current job?". The five possible answers, ranging from "not at all automated" to "fully automated", are weighted with automation probabilities from 0% to 100% in 25% increments (O*NET, 2020). The degree of automation for an occupation is computed as a weighted sum, using the product of the share of answers which indicate a particular degree of automation and the probabilities assigned to a particular answer. Thus, it can be described as a weighted probability of observed labour automation.

Methodological differences and the use of occupational classifications, e.g. the International Standard Classification of Occupations (ISCO), the US Standard Occupational Classification SOC2010, and the German Standard Classification of Occupations (KldB), make a comparison between different labour automation estimates very difficult. Therefore, existing approaches that model the impact of automation on labour are based on a single set of estimates, a limitation noted by various authors (Dengler & Matthes, 2018; Arntz et al., 2017). Another feature of these estimates is the magnitude of the impact of automation on labour (referred to as automation in the remainder of the paper), with different estimates of the percentage of jobs likely to be automated (Frey & Osborne, 2017; Arntz et al., 2017). Although the recognition and the quantification of automation risk at the occupation level are based on only one set of estimates, research indicates the broad applicability of their results and conclusions. Thus, Bisello & Fernández-Macías (2018) and CEDEFOP (2013) show that task distribution by occupations exhibits minor between-country differences. While O*NET estimates on the degree/probability of automation have not received the same level of attention as Frey & Osborne's (2017) estimates, significant research in the field of automation and its impacts on the labour force use O*NET information to analyse the factors that can explain the phenomenon (Frey & Osborne, 2017; Scholl & Hanson, 2020; Brynjolfsson et al., 2018).

3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

Given the importance of having a labour force structure that can adapt to the challenges and requirements of automation, we carry out a comparative analysis of the most well-known estimates of automation by assessing their compatibility, revealing the risk faced by occupation and occupational groups concerning their automation disruption/displacement potential, quantifying the automation disruption risk in terms of the size of the affected labour force, and seeing whether, and to what extent, work context features can explain differences in automation.

A search of labour automation-related literature revealed the estimated impact of automation differs widely. As an example, for the U.S., Frey & Osborne (2017) estimate that 47% of jobs are highly likely to be automated, whereas Arntz et al. (2017) result put their share at only 9%. The fact that these differences have also been noted by other authors (Dengler & Matthes, 2018) without being investigated, compelled us to explore the following research questions:

I1. What are the main characteristics of different automation estimates, and how do they differ?

I2. Can the estimates of the current degree/probability of automation developed by O*NET explain the future automation probabilities (Frey & Osborne, 2017)?

I3. Which occupations and occupational groups are most likely to be affected by automation in the future, and which are safer?

I4. Can work context characteristics explain the present and future estimates of automation?

I5. What is the potential impact of automation on the labour market, considering different sets of estimates, and what are the implications for competitiveness?

The first data source is Frey & Osborne's (2017) estimated probabilities of automation, referred to as FO, as estimates of future automation at the occupation level.

The second data source is the O*NET degree of automation estimates as of 2020, henceforth referred to as DA20, which are disseminated through their website, and correspond to the O*NET database release 25.1. As they are derived from interviews of job incumbents and occupational experts, we consider them the current estimates of occupational automation. To check for the stability and evolution of DA20 through time, we have computed the 2010 degree of automation estimates (DA10), using the same methodology used to generate DA20 estimates, with data from the Work Context tables from O*NET release 15.1. We refer to DA10 as past estimates of automation. To match the three sets of estimates, we have used the O*NET SOC 2010 occupational classification as a reference point and used the O*NET crosswalks between O*NET SOC2010 and O*NET SOC 2019. For FO estimates, probabilities of automation were expertly deduced for an additional 20 occupations by assigning values from other occupations based on their job content similarities and other similar occupations. Differences in the size of the three datasets (702 for FO, 836 for DA10, and 873 for DA20) are mainly explained by: 1) a lack of data for the nine key O*NET variables used to derive the FO probabilities of automation, 2) lack of responses to the question "How automated is your current job?". All data sets refer to jobs for all industries. Another important aspect is that in all datasets, automation is expressed as a probability and takes two-digit values between 0 and 1.

The methodology used comprises, in the first stage, a descriptive analysis, which highlights the main features (e.g. mean, standard deviation) of the three estimates of automation probabilities. The t-tests were used to see whether there are significant differences between the estimates, occurring when p-values are below 5% (or, equivalently, a 0.05 value).

Then, correlation and regression analysis were used to further compare the estimates and see whether a relationship can be inferred between them, when the correlation coefficients are above 0.5, or below -0.5, or when regression coefficients are significant at a 5% level.

Using the results obtained, we identified occupations for which there are relatively large differences for FO (future) and DA20 (current) automation estimates. First, we labelled probabilities of automation for each occupation, separately the FO and DA20 estimates, as low (L), from 0 to 30%, medium (M) between 30% and 70%, and high (H), from 70%, up, based on the conventions used by Frey & Osborne (2017) and Dengler & Matthes (2018). Then, we derived the following risk/

disruption classes based on the similarities or differences between the assigned L/M/H labels as follows:

- red, representing a two-notch increase in automation estimates (e.g. an occupation classified as having a probability L of automation for DA20 estimates and a probability H for FO estimates, respectively);
- orange, representing a one-notch increase of automation estimate (e.g. an occupation classified as M for DA20 estimates and an H probability for FO estimates respectively, or classified as L for DA20 estimates and M for FO estimates respectively);
- yellow a stable situation where both estimates are in the same automation category (L and L, M and M, or H and H), and
- green, representing a decrease in the estimates by at least one notch (e.g. an occupation classified as M for DA20 estimates and S probability for FO estimates, respectively).

In this approach, the red class is considered the riskiest, as it groups jobs with low current probabilities of automation according to DA20 estimates but high probabilities of automation according to FO estimates and, therefore, may be the most likely ones to be substituted/displaced in the future. Conversely, the green class groups jobs whose current probabilities of automation (DA20) are medium and future probabilities of automation (FO) are low, meaning that they are the least likely to be displaced in the future.

The 2019 occupational data for the U.S. was used to compute the share of employment that falls into the four risk classes, quantifying the share of employed individuals that are likely to be most affected in the future. We considered it the best choice as it was not affected by changes caused by COVID-19 lockdowns, whose effects are not fully analysed and understood (e.g. in terms of layoffs and job separations) and can affect the conclusions of our analysis due to factors not directly related to automation or competitiveness.

In addition, we have examined whether work context characteristics can explain differences in the estimated degree of automation at the occupation level. Using factor analysis, a method was used to extract common features from a large number of variables. We have isolated seven distinct factors to identify the main job context-related feature types. Then we used regression analysis to see how well they explain the variation of the automation estimates.

4. RESULTS

4.1 A descriptive analysis of the probability of automation estimates

The basic characteristics of automation estimates, presented in Table 1, give us a first image of the potential similarities and differences between them.

Tab.1 – Descriptive statistics of automation probability estimates. Source: own research

	DA10	DA20	FO
Average	0.30	0.28	0.54
Median	0.29	0.27	0.64

Standard Deviation	0.14	0.13	0.37
Kurtosis	-0.45	-0.19	-1.55
Skewness	0.30	0.44	-0.28
Minimum	0.00	0.01	0.00
Maximum	0.74	0.70	0.99
Count	836	873	702

The main difference observed between past, present, and future probabilities of automation are higher mean and median values for the latter. While FO estimates have the highest variance (68% coefficient of variation), the other estimates have a standard deviation of about 14% (46% coefficient of variation). Skewness indicates that, while the degree of automation estimates is mostly below average, probabilities of automation tend to be higher than average. All distributions are platykurtic, with relatively more values towards the extremities compared to a normal distribution, especially for the FO estimates. Whereas past and present estimates indicate that job automation does not exceed 75%, FO estimates range from 0 to 99%.

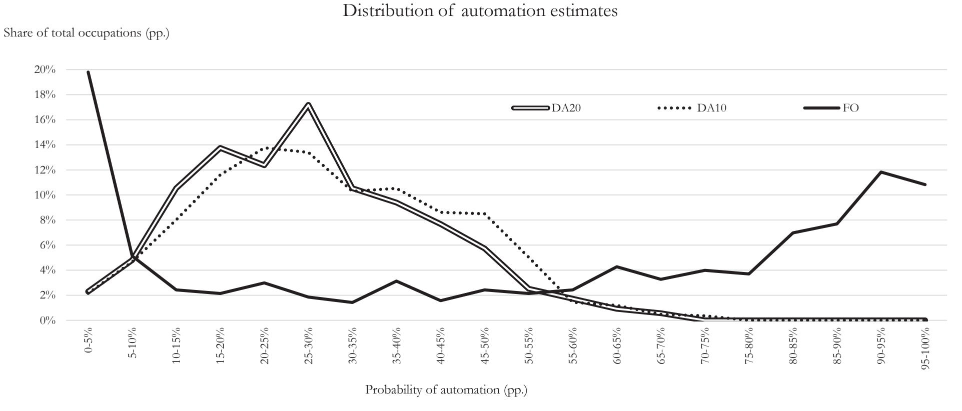

Fig.1 – Distribution of the estimates of automation. Source: own research

A further verification using paired t-tests on matched data, presented in Table 2, shows that there are statistically significant differences between estimates, as P-values are below a 5% level of significance. This means that we can treat these estimates, both statistically and functionally, as having distinct values.

Tab. 2 – Results of paired comparisons of estimates of automation. Source: own research

Pairs	Observations	Value of the test statistics	P-value
DA10 vs. DA20	793	4.727	0.000
DA20 vs. FO	722	-16.326	0.000

In conclusion, we can state that there are significant differences between the three datasets, and the FO estimates are distinguished by a U-shaped distribution, completely different from the DA10 and DA20 estimates, which tend to be expected.

4.2 Can the past explain the present? Is the present capable of explaining the future of automation?

Based on the fact that the three sets of automation estimations have shown significant differences and that the distribution of future probabilities of automation differs significantly from the others, we further analysed whether there is a link between past, present, and future probabilities of automation. Correlation analysis, as shown in Figure 2, on data matched by occupation, shows a significant positive correlation between past and present automation estimates of 72%. While the result is not surprising, given the methodological consistency, the univariate regression analysis and the scatter plot indicate a fair amount of variation between past and current degrees of automation.

Tab. 3 – Links between estimates of automation. Source: own research

	Correlation	Univariate regression coefficient	Adjusted R^2
DA20 vs. DA10	0.72	0.67	0.52
FO vs. DA20	0.28	0.10	0.08

Note: All correlation and regression coefficients are significant at 0.1% level. Variables on the right are explanatory variables for univariate regression.

The correlation between DA20 and FO automation estimates is relatively weak, a result confirmed by the univariate regression analysis, as shown in Table 3. However, differences in the shape of the distributions of FO and DA20 estimates play an important role in highlighting the limited explanatory power of current estimates for future automation probabilities.

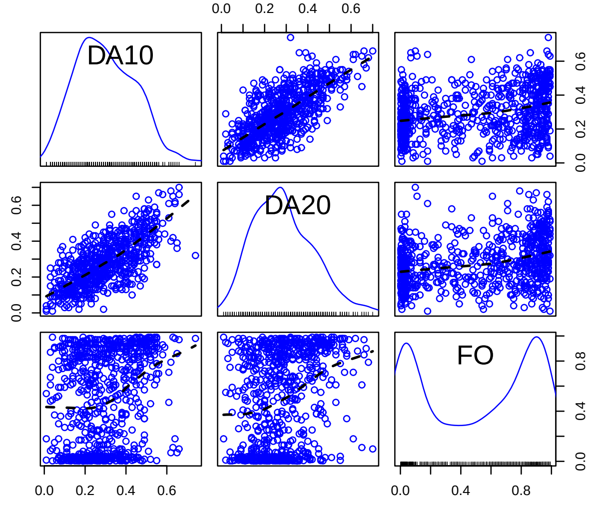

Fig. 2 – Correlation plots for estimated probabilities of automation. Source: own research
Note: Units of measurement are distribution shares (for correlation plots and y-axis for histograms) and probabilities of automation (x-axis for histograms)

Based on this, we conclude that the estimates of past and present automation are compatible. However, the current estimates have a weak explanatory power over the future ones, a finding that justifies constructing risk classes to assess potential future job disruptions with adverse impacts on achieving competitiveness (Kleynhans, 2016; Karacay, 2018).

4.3 Comparing estimates of automation

The results obtained so far point out the limits of the probabilities of automation. We know from the O*NET methodology that DA20 probabilities are derived from 5 distinct answers to the degree of automation question, weighted by their distribution. As to the FO probabilities of automation, we know that they may or may not materialize in a rather vaguely specified time horizon (Willcocks, 2020) of perhaps over 10 to 20 years (Frey & Osborne, 2017). Moreover, many research papers which analyse probabilities of automation do so by using ranges, not actual probabilities, to define high, medium, and low probabilities of automation, e.g. Frey & Osborne (2017), Dengler & Matthes (2018). Therefore, we opted for a similar approach given the properties of the estimated probabilities of automation at the occupation level, by labelling probabilities of automation as low (L), from 0 to 30%, medium (M) between 30% and 70% and high (H), from 70% up.

Tab. 4 – Classification of occupations into labour automation risk groups. Source: own research

Base level => current level	Green (M=>L; L=>M; H=>L)	Yellow (L=>L; M=>M; H=>H)	Orange (L=>M; M=>H)	Red (L=>H)
DA20 => FO	78 (10,8%)	255 (35,3%)	241 (33,4%)	148 (20,5%)

The results of the classification into risk groups are shown in Table 4. Most jobs are likely to be much more automated: 20.5% of occupations with a low degree of automation today are more likely to be highly automated in the future. Another 33.3% show a one-step transition, and for 35% of occupations, current and future estimates of the degree of automation match. For the remaining 10.8% of occupations, future probabilities of automation are lower than the current degree of automation.

In conclusion, we can say that there is a significant divergence between the DA20 and FO estimates, which reveals the extent to which present occupations may incur the risk of facing a higher degree/probability of automation in the future.

4.4 What are the professional characteristics that determine labour automation?

One of the research questions is to find out the professional (type of job) characteristics that may explain the estimates of automation. Our method differs from other approaches that look at "engineering bottlenecks" (FO) or at specific job description contents that are expertly selected (Scholl & Hanson, 2020). We have considered that looking at specific job types, defined in a more precise manner by the O*NET concept of work contexts, would complement other analyses, as they reflect the actual way skills and tasks are used to perform specific job-related duties (job contents). More specifically, in terms of the developers of O*NET, work context features were seen as being much more important than simple covariates and more like a structuring framework, which, from a systems approach to jobs and work, defines how inputs are transformed into work outcomes (Peterson et al., 1995), and how they define how skills, knowledge, and education characteristics are used/enabled during this process (Peterson et al., 1995).

O*NET data on work contexts were used to extract factors and calculate factor scores for 48 occupational characteristics. The grouping of these into significant factors and the calculation of factor scores allows outlining a relevant occupational typology for automation estimations. The optimal factor structure, presented in Appendix 1, identified 7 factors for the characteristics/ variables for which the factor loadings coefficients are at least 0.4 (close to the 0.5 level describing an average correlation between the factors and the original variables) for at least four characteristics. The typologies described in Table 5 reveal interesting features of the different categories of occupations, providing additional insight into existing research on automation.

Tab. 5 – Work context factors. Source: own research

Name	Factor	Description and examples
OPHYS	F1	Outdoor-based physically demanding/ risky environment *Oil & gas service unit operators; Freight Loaders; Wind turbine service technicians*
IPHYS	F2	Body coordination in indoor, tight spaces *Food servers; Maids, cleaners; Hairdressers, hair stylists and cosmetologists*
HINTDEC	F3	Human interactions in conflictual situations requiring decision-making *Compliance officers; Flight attendants; Social workers*
TEAMRESP	F4	Teamwork, coordination and responsibility *General & operation managers; First line supervisors, production/operation workers*
DECMKING	F5	Decision-making power that impacts others *Chief executives; Fine artists*
HAZARD	F6	Hazardous occupations with low error tolerance *Microbiologists; Nuclear technicians; Health professionals*
REPETTS	F7	Repetitive tasks under time pressure *Claims adjusters; Phone operators*

Note. Examples were based on occupations with high factor scores and are shown in italics.

Thus, occupations defined as involving mainly low-skilled, physical work appear to group into three categories: those involving working in the open, mostly outdoor spaces, facing extreme conditions, and involving equipment operation, others involving primarily indoor work in cramped spaces making intense use of physical skills, and others involving repetitive tasks performed under time pressure. The structure also allows distinguishing between occupations involving decision-making: those which involve teamwork and face-to-face contact from those characterized by decision-making freedom and impact on results and other people. The structure distinguishes two main types of jobs involving interactions with people: on the one hand, occupations involving dealing with challenging third parties, involving frequent decision-making, and others involving exposure to hazardous conditions, and high importance attached to error-making on the other hand.

The regression results, presented in Table 6, show that work context factors may explain between one-third and a half of the automation estimates, and coefficients for most factors are significant at a 5% level. As to the first two factors, regression coefficients indicate that higher non-routine physical work contexts are associated with significantly higher probabilities of future automation and lower present estimates. Working in hazardous occupations, where consequences of error are rather important, is associated with lower estimates of automation, which is also true for occupations involving decision-making. Occupations for which teamwork and responsibility are essential are currently more automated and are likely to experience lower probabilities of automation in the future. Jobs involving human interactions in challenging situations are to experience lower probabilities of automation, which, while significant, are lower than those estimated for other work contexts. For repetitive physical tasks, there are higher probabilities of automation for both the present and future, in line with current research results.

Tab. 6 – The influence of work context factors on estimated probabilities of automation. Source: own research

Dependent variable	DA20		FO	
	Coefficients	P-value	Coefficients	P-value
Intercept	0.280	0.000	0.472	0.000
OPHYS	-0.000	0.879	0.099	0.000
IPHYS	-0.022	0.000	0.096	0.000
HINTDEC	-0.003	0.410	-0.048	0.000
TEAMRESP	0.012	0.002	-0.117	0.000
DECMKING	-0.008	0.070	-0.063	0.000
HAZARD	-0.044	0.000	-0.140	0.000
REPETTS	0.060	0.000	0.120	0.000
R^2	0.33		0.48	

4.5 What is the estimated impact of automation from the perspective of future automation risk?

To have a better picture of the potential impact of future changes in automation estimates on the labour market, given the current occupational structure, we have used the 2019 BLS employment estimates and mapped them to the risk/disruption flags assigned to the DA20 - FO pairs of estimates of automation. The situation, presented in Table 7, shows that only 13% of the current jobs will experience a high disruption of automation, and around 30% of jobs will see moderate increases in automation. Another 30% of the jobs enjoy a stable situation, and for another 27%, the probabilities of future automation are lower than present estimates of automation.

A closer look at the occupational groups reveals which ones are likely to face disruptions in terms of automation and which ones are relatively safe. Most people holding Management, computer, and mathematical occupations are likely to experience lower probabilities of automation than the present estimates. At the other end of the spectrum, over half of the workers in Sales, construction, and extraction occupations are likely to experience major disruptions, transitioning from relatively low current estimates to high future probabilities of automation. To a lesser extent, most jobs in Food preparation and serving, transportation, and material moving groups are likely to become more automated. Almost all Building and maintenance jobs, and most occupations in farming, fishing, and forestry, are likely to experience moderate automation increases.

For some occupational groups, such as production, office and administrative support, food preparation and serving, and health care support, even though most existing jobs are likely to become more automated, increases in probabilities of automation can either be one-notch higher or two-notches higher than current levels.

Tab. 7 – Employment shares for major occupational groups by automation disruption classes. Source: own research

Main occupational groups (code and name)	Red	Orange	Yellow	Green
11 Management	3.8%	3.1%	19.2%	**73.9%**
13 Business and Financial Operations *	0.0%	**41.9%**	30.0%	28.1%
15 Computer and Mathematics *	0.0%	0.0%	10.9%	**89.1%**
17 Architecture and Engineering	5.1%	11.8%	**43.1%**	**39.9%**
19 Life, Physical, and Social Science	4.1%	19.0%	**62.9%**	14.0%
21 Community and Social Service	0.0%	0.0%	**51.9%**	**48.1%**
23 Legal	30.3%	8.8%	**60.9%**	0.0%
25 Educational Instruction and Library *	0.1%	6.2%	**92.2%**	1.4%
27 Arts, Design, Entertainment, Sports, and Media	3.6%	20.4%	**72.3%**	3.8%
29 Healthcare Practitioners *	0.0%	26.0%	**56.2%**	17.8%
31 Healthcare Support *	**35.9%**	**45.3%**	18.9%	0.0%
33 Security/Protective Services	34.1%	22.0%	**43.6%**	0.3%
35 Food Preparation and Serving	**47.0%**	**44.5%**	8.5%	0.0%
37 Cleaning and maintenance of buildings and land	5.2%	**92.4%**	2.4%	0.0%
39 Personal Care and Service	26.8%	5.6%	**66.8%**	0.8%
41 Sales and associated services	**65.2%**	17.4%	13.6%	3.8%
43 Office and Administrative Support	30.3%	**42.8%**	19.1%	7.8%
45 Farming, Fishing, and Forestry	22.5%	**65.5%**	12.0%	0.0%
47 Construction and Extraction	**53.2%**	22.7%	24.2%	0.0%
49 Installation, Maintenance, and Repair	20.8%	**58.0%**	12.4%	8.8%
51 Production	**37.7%**	**43.0%**	12.1%	7.3%
53 Transportation and Material Moving	**45.9%**	22.7%	30.3%	1.1%
TOTAL	13.0%	30.7%	29.8%	26.5%

Notes. Shares are computed based on BLS employment numbers by occupation codes as of May 2019. Starred items (*) show groups for which employment coverage (employment for the classified jobs divided by total BLS employment for that occupational group) falls below 70%. Figures in **bold** identify the highest employment share; those in bold and gray show the second highest share within 10 percentage points from the highest share.

Business and financial occupations face a more challenging situation, as 42% of the jobs show one-notch increases in automation, while the rest have a relatively low risk of disruption. For most occupational categories, the situation should remain stable, as most jobs experience the same degree of automation in the future as in the present. This mostly applies to jobs in educational services, personal care, health care (practitioners and technical), arts, design, entertainment and media, life, physical and social science, and legal categories. Architecture and engineering and community and social service groups have almost equal shares of jobs in the stable category, those for which present and future automation is similar, and those for which future automation is below current levels.

Tab. 8 – Occupations with the highest automation-induced disruption risk. Source: own research

Occupation	Occ. Grp.	Occupation	Occ. Grp.
Sewers, Hand	51	Log Graders and Scalers	45
Watch and Clock Repairers	49	Cashiers	41
Inspectors, Testers, Sorters, Samplers, Weighers	51	Dental Laboratory Technicians	51
Driver/Sales Workers	53	Pesticide Handlers, Sprayers, Applicators	37
Parts Salespersons	41	Shoe Machine Operators and Tenders	51
Legal Secretaries and Administrative Assistants	43	Camera & Photographic Equipment Repairers	49
Timing Device Assemblers and Adjusters	51	Office Clerks, General	43
Models	41	Cooks, Restaurant	35
Umpires, Referees, and Other Sports Officials	27	Rock Splitters, Quarry	47
Food Science Technicians	19	Secretaries and Administrative Assistants	43
Counter and Rental Clerks	41	Locomotive Engineers	53
Woodworking Machine Setters, Operators, Tenders	51	Model Makers, Wood	51
Team Assemblers	51	Gambling Dealers	39
File Clerks	43		

The analysis also allows for more nuanced estimates of the impact of automation on jobs. Thus, the share of jobs that are highly likely to be automated is 13%, those with a moderate risk of automation are 30%, and secure jobs are 26.5%, which gives an insight into the extent to which employees may be affected in the medium to long term.

The highest future risk of automation is incurred by 28 occupations listed in Table 8. They belong to the red risk group and have future probabilities of automation (FO) over 0.95 and current levels of automation of under 0.3. Out of them, 8 are classified as production occupations (code 51). Four sales and service occupations (code 41) and four office and administrative support occupations (code 43). Another two jobs belong to transportation and moving services (code 53). The remainder refers to other occupational groups whose codes appear in Table 7.

5. DISCUSSION AND CONCLUSION

The analysis of different estimates of automation that are widely available can offer helpful insights, revealing key features of the automation process. O*NET estimates of the degree of automation in the current period are in line with past estimates. However, a comparison of current and future period estimates reveals considerable differences. However, it should not be ignored that these estimates are subjective measures whose ability to track the degree of automation over time is limited at best and may be influenced by the actual adoption of technology, availability of a (highly) qualified workforce, sectoral and regional growth opportunities, etc. The weak yet significant link between the present and future estimates of automation may indicate that the automation process may not have a major impact from the perspective of the affected occupations. Hence, there may be significant differences for some occupational categories in terms of future estimates of automation compared to present ones, such as Business and Financial Operations, Legal and Health Professions, which call for more attention to be paid to directly concerned economic and political actors (e.g., job seekers, career planners, policymakers), as they comprise highly educated professionals, instrumental to ensuring the availability of a specialized workforce as a key premise for competitiveness (Tanase, 2008), and Karacay (2018) which emphasizes the importance of having a workforce adapted to new business requirements as a key to competitiveness.

The comparison of present and future estimates provides insight into the extent of changes triggered by automation. The extreme divergence between present and future probabilities of automation affects about 13% of the workforce; however, significant changes that may occur in the coming decades may affect more than 40% of the workforce. These results are compatible with the findings of Arntz et al. (2017) and Dengler & Matthes (2018) in terms of showing how many jobs are to be disrupted by labour automation and with Frey & Osborne (2017) in terms of how many jobs may be affected by it. Detailed results at the occupation level show that the risks of automation are not uniform, with occupational groups where a significant proportion of jobs fall into different risk categories.

This shows that more attention needs to be paid to occupational categories such as financial and commercial operations, as a significant share of jobs has a high risk of automation in the future, which may cause unemployment or underemployment in conditions of sustained job demand, which may affect the long-term competitiveness of an economy in the absence of an adequate supply of skills, able to match the needs and requirements of the Industry 4.0 digital economy, in accordance to the findings of Karacay (2018). When occupations assessed as having the highest disruption potential are considered against the occupational groups they belong to, they stand out as problematic in terms of their automation potential, which can affect critical labour inputs needed to achieve firm-level competitiveness (Kleyhans, 2016).

Linking estimates of automation to work context (job type) helps reinforce existing research results, which are limited to focusing on specific aspects (e.g. routine vs. nonroutine jobs) and give a wider perspective about the main features that define occupations, which go beyond the rather narrow, technical focus describing them as a collection of tasks and skills. Work context variables reveal a diverse typology of jobs, distinguishing among physically-intensive jobs (outdoor-based from indoor-based, and among indoor-based, those who require physical skill from those requiring repetitive tasks), activities which involve leadership (jobs involving intense human contact and teamwork from jobs involving decision making and impact other people and company results), and those which involve physical proximity with other people (interactions in unpleasant circumstances requiring decision-making as opposed to jobs involving exposure to hazardous conditions with high impact and a low tolerance for errors). The factor structure corresponding to the main characteristics of the work context explains between 33% and 48% of the differences in automation probabilities, allowing us to define occupational typologies relevant to their automation potential. Among notable results, we see that outdoor-based physical jobs are more likely to be automated in the future than indoor-based non-repetitive ones when results for different disruption categories are considered. They may help to further develop a methodology that takes these typologies into account when assessing the potential of occupations to help companies foster their competitiveness (Karacay, 2018).

Limitations of the estimates are also revealed by this analysis. For certain occupation categories, such as health care, management, education, computer and mathematics, coverage is low, and issues relating to the effectiveness of occupational classifications may need to be addressed so that interested stakeholders may be able to trace how automation evolves in the occupations of interest. Other limitations are given by the significant subjective and expert content of the labour automation estimates. A better reconciliation between subjective assessments of labour automation and underlying (objective) explanatory factors may help achieve a more reliable assessment of labour automation, which can allow better tracking of it.

While results refer to U.S. jobs, our analysis can inform research and policymaking for other countries. Bisello & Fernández-Macías (2018) show that the task distribution by occupations (a key element in deriving probabilities of automation) and industry are the main sources of variation and not their distribution by country. CEDEFOP analyses focusing on skills also show minor differences between countries at the occupational level and use O*NET data for building occupational skills profiles for European occupations (CEDEFOP, 2013).

In conclusion, it is safe to say that estimates of probabilities of labour automation offer a limited view of the process at the occupational level. However, our analysis reveals the risks associated with it and gauges the impact of the changes effected by automation. Results provide an insightful view of how the occupational structure can be affected by labour automation and inform companies, human resource professionals, and policymakers in taking appropriate measures to ensure that the workforce structure and its skill levels indeed foster competitiveness at the country level (Medeiros, 2018) through their ability to meet the requirements of Industry 4.0-induced technological changes (Kleynhans, 2016; Karacay, 2018).

References

1. Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives,* 33 (2), 3–30.

2. Arntz, M., Gregory, T., & Zierahn, U. (2019). Digitalization and the Future of Work: Macroeconomic Consequences. IZA Discussion Papers 12428.

3. Arntz, M., Gregory, T., & Zierahn, U. (2017). 'Revisiting the risk of automation'. *Economics Letters*, 159, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

4. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspective,* 29, 3–30.

5. Barbieri, L., Mussida, C., Piva, M., & Vivarelli, M. (2019). Testing the Employment Impact of Automation, Robots and AI: A Survey and Some Methodological Issues. IZA Discussion Paper No. 12612.

6. Bisello, M., & Fernández-Macías, E. (2018). Same job, different tasks? Skills Panorama, CEDEFOP. Available at: https://skillspanorama.cedefop.europa.eu/en/blog/same-job-different-tasks#_edn3

7. Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What Can Machines Learn, and What Does It Mean for Occupations and the Economy? *AEA Papers & Proceedings,* 108, 43–47.

8. Cellan-Jones, R. (2019). Robots to replace up to 20 million factory jobs by 2030, BBC News. Available at: https://www.bbc.com/news/business-48760799

9. Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. New York: Harper Business.

10. de Vries, G. J., Gentile, E., Miroudot, S., & Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics,* 66, 101885, https://doi.org/10.1016/j.labeco.2020.101885

11. Dengler, K., & Matthes, B. (2018). The impacts of digital transformation on the labour market: substitution potentials of occupations in Germany. *Technological Forecasting and Social Change,* 137, 304–316. http://doi.org/10.1016/j.techfore.2018.09.024

12. European Centre for the Development of Vocational Training (CEDEFOP). (2013). Quantifying skill needs in Europe. *Occupational skills profiles: methodology and application*. Cedefop Research Paper 30.

13. Foltean, F. S., & Glovatchi, B. (2021). Business Model Innovation for IoT Solutions: An Exploratory Study of Strategic Factors and Expected Outcomes. *Amfiteatru Economic,* 23 (57), 392–411, https://doi.org/10.24818/EA/2021/57/392

14. Ford, M. (2015). *The Rise of the Robots*. New York: Basic Books.

15. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

16. Karacay, G. (2018). Talent Development for Industry 4.0. In: Industry 4.0: Managing The Digital Transformation. Springer Series in Advanced Manufacturing. Cham: Springer. https://doi.org/10.1007/978-3-319-57870-5_7

17. Klenert, D., Fernández-Macías, E., & Antón, J. I. (2022). Do robots really destroy jobs? Evidence from Europe. Economic and Industrial Democracy, in press. https://doi.org/10.1177/0143831X211068891

18. Kleynhans, E. P. J. (2016). Factors determining industrial competitiveness and the role of spillovers. *Journal of Applied Business Research*, 32 (2), 527–540. https://doi.org/10.19030/jabr.v32i2.9594

19. Kumar, S. L. (2017). State of the art-intense review on artificial intelligence systems application in process planning and manufacturing. *Engineering Applications of Artificial Intelligence*, 65, 294–329. https://doi.org/10.1016/j.engappai.2017.08.005

20. Manning, A. (2019). Polarization(s) in Labour Markets: Synthesis and Perspectives. *Travail et Emploi*, 157, 13–24. https://doi.org/10.4000/travailemploi.8921

21. Marinas, M., Marin, D., Socol, A. G., & Socol ,C. (2021). The technological transition of European manufacturing companies to Industry 4.0. is the human resource ready for advanced digital technologies? The case of Romania. *Economic Computation and Economic Cybernetics Studies and Research*, 2 (2021), 55, https://doi.org/10.24818/18423264/55.2.21.02

22. Medeiros, V., Godoi, L. G., & Teixeira, E. C. (2019). Competitiveness and its determinants: A systemic analysis for developing countries. *CEPAL Review*, (129), 7–25. https://doi.org/10.18356/E03C81FC-EN

23. O*NET. (2020). Instructions for Work Context Questionnaire. Available at: https://www.onetcenter.org/dl_files/MS_Word/Work_Context.pdf

24. O*NET. (2021). About O*NET, https://www.onetcenter.org/overview.html

25. Parschau, C., & Hauge, J. (2020). Is automation stealing manufacturing jobs? Evidence from South Africa's apparel industry. *Geoforum*, 115, 120–131. https://doi.org/10.1016/j.geoforum.2020.07.002

26. Pasnicu, D., & Ciucă, V., (2020). Green Procurement Implications on the Labor Market in the Context of the Transition to The Green Economy. *Amfiteatru Economic,* 22 (53), 28–41. https://doi.org/10.24818/EA/2020/53/28

27. Peterson, N. G., Mumford, M. D., Borman, W. C., Jeanneret, R., & Fleishman, E. A. (1995). Development of Prototype Occupational Information Network (0*NET) Content Model. Vol I, Utah Department of Workforce Services Contract. Available at: https://files.eric.ed.gov/fulltext/ED455451.pdf

28. Porter, M. (1998). Clusters and the New Economics of Competition. *Harvard Business Review,* 76 (6), 77–90.

29. Pouliakas, K. (2018). Determinants of Automation Risk in the EU Labour Market: A Skills-Needs Approach. IZA Discussion Paper No. 11829.

30. PwC. (2018). *Will Robots Really Steal Our Jobs?* London: Price Waterhouse Coopers.

31. Radu, C., Deaconu, A., Misu, S. I., & Triculescu, M., (2020). The Impact of Work Investment on Performance. *Amfiteatru Economic*, 22 (14), 1103–1120. https://doi.org/10.24818/EA/2020/S14/1103

32. Rifkin, J. (1995). *The end of work: The decline of the global labor force and the dawn of the post-market era.* New York: G.P. Putnam's Sons.

33. Roy, V., Vértesy, D., & Vivarelli, M. (2018). Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. *Research Policy*, 47, 1762–1776. https://doi.org/10.1016/j.respol.2018.06.008

34. Scholl, K., & Hanson, R. (2020). Testing the Automation Revolution Hypothesis. *Economics Letters,* 193, 109287. https://doi.org/10.1016/j.econlet.2020.109287

35. Spencer, D., & Slater, G. (2020). No automation please, we're British: technology and the prospects for work. *Cambridge Journal of Regions, Economy and Society,* 13 (1), 117–134. https://doi.org/10.1093/cjres/rsaa003

36. Tănase, N. M., Caramihai, M., Marin, A., Boantă, L., & Purcărea, A. A. (2019). Appraisal of the regional competitiveness of the research-development sector in Romania by highlighting the correlations among clusters, workforce and expenses in CD. *UPB Scientific Bulletin, Series D: Mechanical Engineering*, 81 (4), 341–352.

37. Vermeulen, K., Pyka, A., & Saviotti, P. (2018). The Impact of Automation on Employment: Just the Usual Structural Change? *Sustainability*, 10 (5), 1661. https://doi.org/10.3390/su10051661

38. Vlasov, V., & Chromjaková, F. (2018). The Effect of the Fourth Industrial Revolution Economies and Management. In: Strielkowski, W., Chigisheva, O. (eds) Leadership for the Future Sustainable Development of Business and Education. Cham: Springer. https://doi.org/10.1007/978-3-319-74216-8_54

39. WEF. (2020). *The Future of Jobs Report 2020.* Geneva: World Economic Forum.

40. Willcocks, L. (2020). Robo-Apocalypse cancelled? Reframing the automation and future of work debate. *Journal of Information Technology*, 35 (4), 286–302. https://doi.org/10.1177/0268396220925830

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