The Risk of Automation of Occupations at European Level

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Abstract

The research paper aims to estimate the risk of automation of occupations defined by the ISCO-08 standard, at European level. The idea came from the work of the pioneers of this subject, Carl Benedikt Frey and Michael A. Osborne. Basically, we will highlight the importance of skills and knowledge in determining the risk of job automation at European level. For this we used logistic regression, which helped us to classify occupations according to the risk of automation. The results indicate that occupations that require knowledge in the fields of agriculture, forestry, fisheries, veterinary, natural sciences, mathematics, statistics, social sciences, journalism and information, but also those that require skills such as communication, collaboration, creativity and management skills, have a lower risk of automation. The risk of automation is increased instead for occupations that require skills in the categories of information skills and handling and moving skills. More specifically, occupations that involve a monotonous, repetitive activity and that require mediocre skills and knowledge, will be replaced by technology. The solutions offered by technology will be much more efficient than a human resource. Obviously, this automation will not happen for all countries at the same time and will not have the same consequences.

Keywords

automation risk; skills; labor market, digitization, logistic regression.

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Introduction

Industrialization 4.0 has a variety of consequences, more or less positive for the workforce. The nature of the consequences is debatable and can be viewed from several perspectives. However, this industrial revolution, like the others so far, has pursued socio-human progress. The economy tends to streamline activities and work faster. Basically, this industrial revolution proposes new ways of doing things, innovative ways of testing the adaptive spirit of the workforce in the economy.

Automation seems to affect the workforce differently, in the sense that professionals benefit from improved work, while for blue-collar employees it is a threat (De Witte and Steijn, 2000). Also, due to the cheapening of technology, it is more cost-effective for companies to replace the repetitive human labor force (Sebastian, 2018). Technology is an opportunity for the employee to facilitate his work, becoming a consultant in the activity he carried out, and artificial intelligence would perform the activities (Bissessur, Arabikhan and Bednar, 2019).

Thus, we considered it appropriate to identify areas in the labor market with a high risk of automation and what knowledge, skills and abilities they require. Automation is not a negative element for the economy, but it can be a risk for that segment of the workforce that cannot adapt to the new market conditions. The study started from the work of pioneers Frey and Osborne (2017), who proposed a certain classification of occupations according to the attributes of each occupation. The plus with which we come to complete their reasoning is that we will translate the algorithm on the European labor market and try to extend the forecast to the entire catalog of occupations described in ISCO-08. We intend to do this by using the supervised learning algorithm. This estimate will help us to identify the main risk areas of the labor market, but also what makes some occupations so risky. Today's society is no longer based on how much information we have, but on what we do with this information and how it will help us survive the new economic current determined by digitalization. Human resources can develop their attractiveness on the labor market only by cultivating new skills needed in a digital economy, but also by developing its affinities.

1. Literature review

The labor market is a complex adaptive system, because the complex elements within it, which interact, have the ability to adapt. Some researchers who have studied complex systems have concluded that social systems can adapt, as opposed to physical ones (Miller and Page, 2007). In fact, the workforce needs to build a lifelong learning routine that trains them with intellectual flexibility and professional adaptability (World Economic Forum, 2018).

The uncertainty of predicting the future of the labor market, caused by the unprecedented evolution of technology, is another characteristic principle of the complex adaptive system (Horváth et al., 2019). We can say that the fear generated by the risk of job automation can be rational and justified by the pace of technology evolution (Kozak, et al., 2020). Over time, this research topic has been discussed by several authors. The extent to which new technologies can replace human activity in certain occupations, industries and which states have a greater predisposition to digitalization, but also which jobs will suffer notable structural changes (Arntz, Gregory and Zierahn, 2016; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018). It has also been shown that highly productive states have a high employment rate in sectors with a low risk of automation (Foster-McGregor, Nomaler and Verspa, 2021). However, it has been observed that people with a higher level of education have jobs that have a lower risk of automation and will also cause a wage imbalance in the labor market (Gardberg et al., 2019). The effects of technology on the labor market are not 100% certain, in the sense that we cannot say with certainty that human resources will be complementary to technology and that technology will act for the well-being of workers (Nazareno and Schiff, 2021). The transition to the green economy is a factor that determines the adaptation of skills on the labor market, creating both opportunities and risks for employees (Pașnicu and Ciucă, 2020). Regarding the situation at European average, around 33% (EUROSTAT, 2021) of the workforce is at risk of losing their jobs due to the automation of their employment.

2. Materials and methods

To develop an application based on which to predict the risk of automation of occupations we used the entire portfolio of occupations defined by Eurostat on the ESCO platform (European Skills, Competences, Qualifications and Occupations). The databases on this platform contain 2,942 occupations, 13,485 general skills, but also 500 transversal skills (European Comission, ESCO, 2021). In addition, we needed a risk indicator similar to that calculated by Frey and Osborne. Thus, we identified a site (https://willrobotstakemyjob.com/) that is updated and calculates in real time the risk of automation of occupations according to the model of the two authors mentioned above. As the probability of automation is calculated at the level of the United States, an adjustment of this probability was needed using a European digitization index calculated starting from the Digital competitivness ranking (IMD World Competitiveness Center, 2020).

The top analyzed contained 63 states, of which 31 are from Europe. The United States ranked first in digitization in 2020. To obtain an index describing digitization in Europe, we calculated the weighted arithmetic mean of the scores of each state included in the ranking. We considered that each state has a specific weight in the calculation of the index, which is why we chose this weight to be inverse rank. Thus, we established that the digitization index of Europe is 78.81, compared to the USA which has a score of 100. Next we used the difference between the United States and Europe, from the perspective of digitization, to adjust the risk of automation of occupations. The reasoning started from the idea that automation does not happen uniformly worldwide, but according to the possibilities related to infrastructure and knowledge in the direction of digitization.

$$Digitalisation\ Index_{EU} = 100 - \frac{\sum_{i=1}^{n=31}(Digital\ competitiveness\ ranking_i * Inverse\ rank_i)}{\sum_{i=1}^{n=31} Inverse\ rank_i} \quad (1)$$

After adjusting the risk of automation for each of the 707 occupations analyzed, it was necessary to map them according to the International Standard Classification of Occupations valid in Europe. Some of the occupations defined in the Standard Occupational Classification System, the United States standard, find an exact correspondent in ISCO-08. For some of the occupations the mapping was done approximately, based on the description that each of them has.

$$Adjusted\ automation\ risk_j = Automation\ risk_{USA,j} * (1 - \frac{Digitalisation\ Index_{EU}}{100}),\ \text{where j- jobs} \quad (2)$$

In order to estimate the risk of automation we used a supervised data learning algorithm, logistic regression. The specified algorithm is useful because some of the occupations have been labeled as automable or not, and we will use this information and the specifics of each occupation to find out the risk of automating occupations that have similar specifications. Estimated regression model:

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_i x_i\ , \qquad i = \overline{1,7} \quad (3)$$

where:

ODD ratio = $\frac{p}{1-p}$

$\beta_i x_i\ ,\ i = \overline{1,7}$, are the coefficients of the explanatory variables in the model

$p = \frac{e^{\alpha+\beta_i x_i}}{e^{\alpha+\beta_i x_i+1}} = \frac{1}{1+e^{-(b^{\alpha+\beta_i x_i})}}$, , $i = \overline{1,7}$, is the probability of occurrence of an event

3. Results

We selected a sample of the 707 occupations, which should respect approximately the general structure of the population. For this step we used a training base of 230 observations and a test base of 94 observations. The dependent variable used is precisely the risk of automation of the occupation, and as explanatory variables we used the categories of skills necessary to perform the activities within an occupation, presented in Tab. A1. Although the risk of automation has values between 0 and 1, we decided that occupations with values below 0.5 should be classified as without risk of automation, and those with values above 0.5 should be considered with a high risk of automation. This adjustment is justified, if we consider, for example, the possibility of whether or not that job still exists. In principle, if an occupation has a high risk of automation (over 0.5), it will certainly disappear, but it is possible to find another occupation somewhat similar, but we are already talking about another occupation / job.

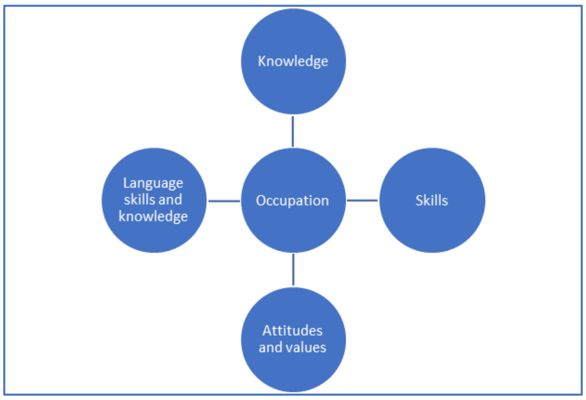

Figure no. 1. Occupation structure

ESCO presents the skills pillar in the form of a hierarchy of concepts containing four categories: knowledge (K); skills (S); attitudes and values (A); language skills and knowledge (L). The explanatory variables used in the application card indicate the number of skills or competences in the specified category, required in each type of occupation. Each occupation may require either all the categories described in the skill hierarchy or different combinations of them. In turn, these categories can be segmented to a very particular level. The working hypothesis according to which the automation risk can be calculated as a result of segmenting an occupation according to its basic activities and correlating them with the skills and knowledge necessary to perform them.

The concept of knowledge mainly refers to the qualifications acquired in one of the fields of activity defined in the Statistical Classification of Economic Activities in the European Community. Thus, starting from the 21 categories of economic activities (EUROSTAT, RAMON) ESCO groups the knowledge into 12 main categories, covering the entire universe of occupations. The first category of knowledge is the category of knowledge in the field of agriculture, forestry, fish farming and animal husbandry. The second category of knowledge includes the humanities and the arts. The third category of knowledge consists of the notions of business, administration and law. The necessary knowledge in the field of education forms an independent category. The 5th category is represented by technical knowledge in the field of engineering, manufacturing and construction. Another very important category of knowledge is in the field of health and social welfare. The following category indicates internet communication and technology knowledge. Category number 8 includes knowledge in the field of natural sciences, mathematics and statistics. The field of services also requires specific knowledge classified separately. We can also identify a category of knowledge in the field of social sciences, journalism and information. A separate category has been created for programs and general qualifications that a person can obtain. A previously unclassified group of knowledge has also been built.

Skills are capable of being developed that an individual must have in order to learn more easily (O*Net OnLine, 2021) or to be more efficient in the workplace in the performance of their duties (Gouvernment of Canada, 2021). According to ESCO, the skills were divided into 8 categories. The first category consists of 3 of the 4Cs that define the basic skills of the 21st century: communication, collaboration and creativity (Stauffer, 2020). The second category brings together the informational skills of manipulating data and information, which are essential for autonomous learning (Pinto, Doucet and Fernandez-Ramos, 2010). A very important category of skills are those of assistance and care. This category of skills is a little different from the others, because they are also an emotional component (Pietrykowski, 2017), which is why it is a little harder to imitate by Artificial Intelligence, but not impossible. Robots can develop care and health care skills by learning (Möller et al., 2021). Managerial skills are an important category needed in the labor market and encourage the creation of an organizational culture (Shamsi, 2017). Computer skills category is the most important skill group in the digital economy (Falck, Heimisch-Roecker and Wiederhold, 2021). A distinct skill category consists of skills in handling tools and equipment. The field of construction involves a series of skills that have defined a different group. The last category of skills refers to the use of specialized machines, machinery and equipment.

Basic concepts that describe skills are also attitudes and values. Attitudes are ways in which an employee can react in a given situation at work. Values are concepts and perspectives that an employee must have depending on the activity they carry out. Jobs sometimes explicitly require attitudes and values that employees have. Last but not least, language skills are quite important in the workplace. Linguistic knowledge is divided into two categories: knowledge of foreign languages and knowledge of classical languages.

Given the skills classifications presented above, we counted how many skills in each category are required for each job analyzed. Thus, the explanatory variables in the job classification model according to the risk of automation are represented by the number of skills in each category, necessary for carrying out the activity. Initially, we introduced in the model all the variables from Appendix 1, but due to the lack of representativeness for some of them, we kept only those with explanatory power (Table no. 1).

Table no. 1. Logistic regression coefficients

	B	S.E.	Wald	Sig.	Exp(B)
K1	-0,37568	0,164451	5,218671	0,022346	0,686823
K8	-0,38634	0,127628	9,163217	0,002469	0,67954
K10	-0,734	0,41038	3,19904	0,073682	0,479985
S1	-0,14592	0,043941	11,02856	0,000897	0,864223
S2	0,138425	0,041447	11,15445	0,000838	1,148464
S4	-0,11327	0,057563	3,872325	0,049088	0,892906
S6	0,144192	0,054145	7,09185	0,007744	1,155106
Constant	0,062878	0,416581	0,022782	0,880025	1,064897

Source: own processing in IBM SPSS Statistics

According to the result of the logistic regression model, the risk of automation of occupations is positively influenced by information skills, but also handling and moving skills. The risk of automation is negatively influenced by three categories of knowledge, but also by an ability that is not related to theoretical knowledge. Estimated regression model:

$$\widehat{risk} = -0.3757 * K1 - 0.3863 * K8 - 0.7340 * K10 - 0.1459 * S1 + 0.1384 * S2 - \\ -0.1133 * S4 + 0.1442 * S6 \qquad (4)$$

Thus, we note that the risk of automation is reduced by 31% in occupations that require as much knowledge as possible in the field of agriculture, forestry, fisheries and veterinary. Occupations that require as much knowledge as possible in the field of natural sciences, mathematics and statistics have a 32% lower risk of automation, and occupations that require knowledge in the area of social sciences, journalism and information have a 52% lower risk of automation. There are also skills that reduce the risk of automating an occupation. These skills we are talking about are those in the category of communication, collaboration and creativity (reduces the risk of automation of occupations by 14%) and in the category of management skills (reduces the risk of automation by 11%). We also identified two groups of significant skills that increase the risk of automation of the analyzed occupations. These skill groups are information skills and handling and moving skills. If an occupation requires more skills in the information skills category, it has a 15% higher risk of automation, and if an occupation requires more skills in the handling and moving skills category, it has a 16% higher risk of automation.

Table no. 2. Confusion matrix for training sample

MODEL			
	PREDICTED		
OBSERVED	0	1	TOTAL
0	143	15	158
1	35	37	72
TOTAL	178	52	230
MODEL			
Accuracy	78%		
Sensitivity	51%		
Specificity	91%		

Table no. 3. Confusion matrix for test sample

TEST			
	PREDICTION		
OBSERVED	0	1	TOTAL
0	48	7	55
1	21	18	39
TOTAL	69	25	94
TEST			
Accuracy	70%		
Sensitivity	46%		
Specificity	87%		

Source: own processing in Microsoft Office Excel

The estimated logistic regression model has an accuracy of 78% (Table no. 2), and on the test sample we obtained an accuracy of 70% (Table no. 3). The difference in accuracy between the estimation on training and the test is reasonable to avoid overfitting estimation. Because in reality the “positive” event is a negative one, when the false positive rate is higher it is not necessarily a deficiency, but if the false negative rate has an impact that is not beneficial. Sensitivity has a percentage of 52%, which means that approximately 52% of the analyzed occupations that risk automation were correctly predicted through the model. In terms of specificity, we have a percentage of 91%, so that the model correctly predicts in this proportion the occupations that do not risk being replaced by automatic technologies. Taking into account the results obtained based on the estimated regression model, we will further calculate the share of jobs that risk automation, depending on the category of occupations to which the job belongs (Table no. 4).

Table no 4. International Standard Classification of Occupations 2008 groups (ISCO-08)

ISCO-08 code	ISCO-08 name	Percentage of jobs with automation risk
0	Armed Forces Occupations	10%
1	Managers	10%
2	Professionals	7%
3	Technicians and Associate Professionals	21%
4	Clerical Support Workers	17%
5	Services and Sales Workers	12%
6	Skilled Agricultural, Forestry and Fishery Workers	34%
7	Craft and Related Trades Workers	81%
8	Plant and Machine Operators and Assemblers	84%
9	Elementary Occupations	84%

Source: own processing in Microsoft Office Excel

Thus, we notice that jobs in the category of elementary occupations, plant and machine operators, but also in the category of skilled workers have a very high risk of automation. Approximately 84% of the jobs in the first two categories of occupations indicated above are at risk of automation. Approximately 81% of jobs in the category of occupations Skilled and assimilated workers are at risk of automation. Of the jobs analyzed in the category of skilled workers in agriculture, forestry and fisheries, 34% risk automation. Also with an average share of automation are jobs with the code ISCO-08 3,4 and 5. Only 10% of jobs in the category of managers and armed forces laugh to automate. Occupations in the specialist category do not have a risk of automation in Europe, noting that only 7% of the jobs analyzed have a risk of automation.

Conclusions

The automation risk was estimated as a European average. At the level of each state the situation can be slightly different. For example, Denmark has a very high degree of digitization, very similar to that of the United States. This thing may indicate that the risk of automation for some occupations may be higher. At the opposite pole is Ukraine, which would have a lower digitization rate than the European average.

Basically, this risk of automation indicates that currently the solutions offered by technology can perform certain tasks that make up the normal activity of an occupation. Every occupation requires certain skills and knowledge that may or may not be replicated by technology. Of course, these technology solutions can have high costs, costs that investors or the state cannot afford every time.

The main purpose of the research was to exploit the specifics of each occupation and how much it correlates with the risk of automation. In principle, all skills are important, but some are more abundant than others, and some better describe the risk of being taken over by robots. The results showed that occupations that are mostly operational, manual or information storage can be easily replaced by technology. It is much more efficient to use a solution offered by technology, which has an unlimited capacity to store information and knowledge, but also which can have an exponentially higher production capacity than a human.

Thus, we noticed that jobs that require a greater number of skills in the category of information skills and handling and moving skills have a higher risk of automation, while jobs that require more managerial skills, but also skills of communication, collaboration and creativity do not risk being automated. In fact, we noticed that certain groups of knowledge reduce the risk of automation, namely: knowledge in the field of agriculture, forestry and fish farming; knowledge in the field of natural sciences, mathematics and statistics; knowledge of social sciences, journalism and information.

It is not the jobs that are automated, but the tasks that make up a particular job. The more skills a job requires that can be automated (repetitive, simple), the more likely it is to be automated in the future. The solution to reducing technological unemployment, which is a direct result of task automation, could be to redefine jobs so that the employee can better exploit their skills that can be successful in the digital age and that can add value.

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Appendix A

Abbreviations used

A1	Number of attitudes	K11	Number of generic programmes and qualifications knowledge
A2	Number of values	K12	Number of field unknown knowledge
K1	Number of agriculture, forestry, fisheries and veterinary knowledge	L1	Number of languages
K2	Number of arts and humanities knowledge	L2	Number of classical languages
K3	Number of business, administration and law knowledge	S1	Number of communication, collaboration and creativity skills
K4	Number of education knowledge	S2	Number of information skills
K5	Number of engineering, manufacturing and construction knowledge	S3	Number of assisting and caring skills
K6	Number of health and welfare knowledge	S4	Number of management skills
K7	Number of information and communication technologies (icts) knowledge	S5	Number of working with computers skills
K8	Number of natural sciences, mathematics and statistics knowledge	S6	Number of handling and moving skills
K9	Number of services knowledge	S7	Number of constructing skills
K10	Number of social sciences, journalism and information knowledge	S8	Number of working with machinery and specialised equipment skills

Source: own production based on ESCO Platform (https://ec.europa.eu/esco/portal/skill)