

## Article

# Technological Development and the Labour Market: How Susceptible Are Jobs to Automation in Hungary in the International Comparison?

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**Abstract:** In our study, we analyse data from the Hungarian Microcensus (2016) in order to map the proportion of Hungarian jobs threatened by the spread of automation. In doing so, we use the internationally well-known methodology of Carl Benedict Frey and Michael A. Osborne who estimated the probability of computerization for 702 occupations. The analysis was then repeated by Panarinen and Rouvinen for the Finnish labour market by converting the probabilities defined for the US occupational statistics to the European International Standard Classification of Occupations. Similar calculations were conducted for the Swedish and Norwegian labour markets. According to our results, almost every second Hungarian employee (44%) works in a job that is threatened by the development of digital technologies. The same ratio is 47% in the US and 53% in Sweden, while it is much lower in Finland (35%) and Norway (33%). It is especially alarming that 13% of the Hungarian workforce (i.e., almost 600,000 employees) works in an occupation where the probability of computerization is above 95%, while the number of those working in occupations where the same ratio is above 90% exceeds one million (i.e., 25% of the total Hungarian labour force). Diving deeper into the analysis, we can state that those with higher educational qualifications are more likely to work in an occupation that is more protected against computerization. Overall, there are no significant differences in the probability of computerization by gender; however, women are over-represented in the most endangered occupations.

**Keywords:** automation; labour market; occupation; Hungary



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## 1. Introduction: Industrial Revolutions in the Context of the Technical–Technological Paradigm Shift

Although there is widespread agreement in both professional and public discourse that technological developments will result in massive economic and social changes, there is some degree of uncertainty regarding how many industrial revolutions will occur over the next few decades. Jeremy Rifkin [1–3] argued that we are at the dawn of the third industrial revolution that will be marked by the integration of emerging communication technologies and renewable energy regimes. Klaus Schwab, executive chairman of the World Economic Forum, spoke of the Fourth Industrial Revolution in a voluminous report [4] (five years later claiming that it differs from previous revolutions in speed, width, depth, and regarding the systemic nature of change). Carlota Perez [5] provided a more comprehensive historical analysis of the characteristics of industrial revolutions, suggesting that the fifth industrial revolution has been unfolding since the 1970s. Her work is worth closer attention considering that over the course of her decades of study, she has discovered remarkable parallels in the structure of the previous technological revolutions.

The first common point is that innovation has been the primary catalyst of fundamental economic and social change. In general, it is not a question of a single technology

emerging but of the simultaneous growth of technical innovations that seem to be distinctly different from one another, in addition to their interconnection and integration beyond a certain point of development. Perez also discovered remarkable parallels in the progression of industrial revolutions over time that she divided into three main internal stages. According to this, emerging technologies are developing at a rapid pace but in absence of a clear path in the early stages of recovery and actors are sensing the potential of innovations intuitively rather than understanding intellectually. The role of the state in this phase is characterized by deregulation in this process to break down barriers to technological growth and encourage capital inflow into innovation. This method may be compared to blowing bubbles of expectation that sooner or later burst or in some cases be superseded and merged into a new bubble. This is often how the second stage of an industrial revolution begins, marked by a series of crises. The state will regain its dominant role in the third post-crisis phase of the the so-called deployment period, establishing a new regulatory environment, providing some guidance to the rapidly converging technical innovations<sup>1</sup>, and shaping the determinants of the new growth model.

We do not intend to scrutinize Perez's historical accuracy; rather, we embrace it as a general context of understanding within which the subject of digitization and automation can be framed. In this context, we are now in a digital age experiencing a crisis that differs from past industrial revolution crises in that it lasts longer and currently has had at least two culminating points: the first was the collapse of the dot-com bubble at the turn of the millennium and the second was the financial crisis and economic recession triggered by the U.S. real estate sector. In addition, the first was fuelled by unrealistic expectations for advances in information and communication technology according to Perez and the second was centred on the convergence of these technologies into the real estate and banking sectors that have increased the likelihood for bubbles to form as the regulatory requirements for financial institutions were eased. However, with the convergence of other factors including the public health and socio-economic impacts of COVID-19 and ever-increasing pressure to address climate and environmental challenges [6–8], we are most interested in what kind of world could emerge following these overlapping crises, particularly at the scale of the roughly ten million people living in Hungary.

For our analysis, we begin with the acknowledgement that digital technologies such as artificial intelligence, robots, sensors, the Internet of Things, algorithmic management, and so on are gaining ground in an increasing range of industrial and service activities from production through logistics to after-sales services. In our research, we examine the percentage of Hungary's jobs that are threatened by automation in the near future. To do so, we (1) examine the potential labour market consequences of automation, (2) review attempts to quantify susceptibility to automation, (3) present our calculations for Hungary, and (4) contextualize our findings in the context of international research and current theoretical approaches.

The scientific community has expressed considerable concern about the social consequences of each of the technical–economic paradigm changes. Concerns about automation have existed as of the 18th century [6,9,10]. These problems are divided into four categories:

1. Analyses that attempt to predict the job-destroying impact of digitalization in the short and medium term receive the most coverage [11–14]. The number of calculations, methodologies, and countries studied follow a broad and varied trend, ranging from 9% to 47% of jobs that could be lost due to automation in the next several decades. We will examine this issue in more detail below.
2. We also find a substantial body of literature that attempts to capture the impact on the labour market of emerging technologies by tracking shifts in the skill level demand in the labour market rather than focusing on aggregate losses. In this regard, the literature contains two narratives that are partly overlapping and contradictory. The first focuses on educational attainment and the second explores the degree of routine content of work tasks in jobs that will have the highest susceptibility level to automation (i.e., which are most susceptible and at risk). According to the

skill-biased technological change (SBTC) theory, the spread of ICT tools will mostly eliminate low-skilled jobs, while higher-skilled jobs will not be affected or will increase directly in numbers [15]. In contrast, the theory of routine-biased technological change (RBTC) states that digital technologies primarily threaten jobs that have a high routine content regardless of whether it is cognitive or manual work as these tasks can be easily codified, programmed, and replaced by algorithms [16]. The first theory is a technology-optimistic scenario in which a general increase in ability levels is implicitly predicted, while the second theory is technology-pessimistic as it envisions a worsening of skill polarization as digital technology advances. Growing employment is expected at the bottom of the occupational hierarchy (jobs requiring manual and empathic-emotional skills but with low prestige) and at the top (jobs requiring high abstraction skills but with high prestige), while in the middle (routine cognitive or manual occupations) hollowing out is considered.

3. Faced with the social consequences of technological transition, the most pessimistic theory predicts the immediate end of jobs at least in the sense they have been defined in over recent centuries [3]. This theory is based on the implicit assumption that the number of available jobs is finite, implying that the more jobs that utilize digital technology, the less work there is for people, but the record of the past two decades runs counter to this assumption. Rifkin, who expected a drop in jobs, was mistaken with employment increasing steadily between 1995 and 2015 despite the fact that two serious crises occurred during this period [6] (p. 3). Nonetheless, similar predictions emerge from time to time; for example, some proponents of a universal basic income rely on this assumption.
4. Finally, while it receives less coverage, a fourth area of concern is the impact of the digital revolution on working practices and conditions. Longer working hours, increased work intensity, work–life balance disruption, and further softening of conventional employment relationships are all negative consequences of increased job flexibility in this context. In contrast, some researchers argue that digital technology and robots will liberate workers from monotonous and dehumanizing physical work, thus raising the overall intellectual content of the work experience. Both effects are likely to occur; the question is to what extent. Even the earliest studies on platform work emphasize that digital technologies simultaneously allow for digital precariousness to experience substandard working conditions while also allowing highly skilled software engineers to choose when, how much, and what kind of work they want to do based on their own preferences [17].

While all four of these overlapping challenges are important to consider, we confine our investigation here to the first.

## 2. Data and Materials

As previously mentioned, several studies have been conducted to estimate the possible effects of automation<sup>2</sup> on jobs. Different in terms of methods and findings obtained, these analyses can be divided into two main groups with some simplification. Some of them calculate an automation susceptibility multiplier<sup>3</sup> by analysing the characteristics of occupations, then estimating the population within the labour force based on the proportion of the employees in jobs that are at risk by the deployment of new technologies. Others attempt to calculate susceptibility to automation based on the content of specific job tasks. The value of learning and creative skills in the work process, the role of manual dexterity at work, the degree of employee autonomy, and the network of social interactions are all variables that are considered.

In our present analysis, we deploy the first approach of analysing the characteristics of occupations and estimating the population at risk. We draw upon the previous research of Oxford authors Carl Benedict Frey and Michael A. Osborne whose influential 2017 research study received almost 7000 citations up to 22 October 2020, although their first results were already published in 2013 [1,11]. As it is one of the most prominent papers of the last

decade and has inspired a number of new studies and analyses, we use their approach to examine the Hungarian context. The theoretical starting point is Autor and Acemoglu's [18] work which stated that the routineness of work tasks is a determining factor in terms of its susceptibility to automation. A two-by-two matrix was created with four types of work tasks: routine cognitive tasks, non-routine cognitive tasks, routine manual tasks, and non-routine manual tasks. It is important to keep in mind that when authors state, "routine tasks", they do not necessarily mean "boring" or "down-to-earth" but rather "well-defined, predictable" tasks that are easier to programme and automate. In fact, we revert to Mihály Polányi who distinguished between easily (1) codifiable, explicit knowledge and (2) private and tacit or hidden, secret knowledge that cannot be revealed or expressed in writing [16]. Job activities based primarily on the former type of knowledge are programmed and then performed by machines rather than humans in the digitization process. While these are mostly repetitive manual and cognitive activities, Frey and Osborne claim that recent technological advancements have resulted in substantial change in other areas as well. This is due to the ability to automate non-routine cognitive and manual activities using technologies such as big data, machine learning, sensors, and mobile robots.

The authors support their point with already existing working examples from the fields of health, law, transportation, and agriculture. What is essential for the reconstruction of the argument is that, according to Frey and Osborne, technological advancement creates new fracture lines in the determination of the susceptibility to automation. The previous dividing line between routine and non-routine has become obsolete. Frey and Osborne, in contrast, have found three engineering bottlenecks in job automation that in place of routine are substantial obstacles to replacing human labour by machines that are as follows:

- Tasks that require perception and manipulation. Programming a task requires a well-structured work environment with a small number of variables. Many of these operations will benefit from these conditions including logistics warehouses, hospitals, stores, factories, and so on. Most of them are, for example, designed to allow wheeled vehicles and thus robots to move freely but this is difficult or impossible in many other cases (e.g., a construction site). Currently, robots are not better than humans at perceiving and dealing with unforeseen, unexpected events.
- Tasks that require creative intelligence. While artificial intelligence and related digital programming can handle many tasks, we have not yet progressed far enough in researching the psychology of creativity to be able to transplant it into automated processes.
- Tasks that require social intelligence. As part of our employment, we are inevitably involved in a variety of situations involving social interactions with our colleagues, clients, and other partners in which we must use a variety of social skills such as negotiation, persuasion, empathy, and care-giving. Although robotics is progressing in this field as well, we are still a long way from mass-producing robots that recognize human emotions and can respond to them appropriately.

Frey and Osborne used the so-called O\*NET database that included job descriptions for 903 occupations to estimate the susceptibility of each occupation to automation in the United States. These descriptions were created with the help of labour practitioners, experts, and employees. This database has been applied to the US Department of Labour's database of 702 occupations to gain access to salary data and other characteristics of a profession (on the methodology for aggregation and aggregation of certain occupations see Reference: Frey–Osborne [1] (pp. 262–265). This was followed by a workshop with machine learning experts from Oxford University's Faculty of Mechanical Engineering, discussing how they observe each job being automated at the current technological stage. Each of the 702 jobs was given a value between 0 and 1 at the end of an analytic procedure that combined qualitative and quantitative methodological elements to estimate their susceptibility to automation, with 0 denoting the lowest exposure and 1 denoting the maximum. The occupations were then categorized into three groups: low, medium, and high risk. Low risk occupations had a value below 0.3, medium risk occupations received a value between 0.3 and 0.7, and a value above 0.7 was assigned to high-risk occupations.

The result is well-known and has elicited a strong response in the United States: nearly half of the population (47%) works in occupations with a susceptibility to automation of more than 0.7, indicating they are more likely to be automated and thus human labour will be replaced by machines in the next two decades. Employees in positions with medium and low risk to automation account for 19% and 33% of the workforce, respectively. We do not want to include a systematic analytical critique of the technique outlined in a somewhat simplified manner above in this article. Instead, we focus on only two points. The first is that while the researchers attempted to begin with a summary of job task descriptions relevant to occupations, they did so in an abstract manner: they worked from labour statistics manuals rather than from individual employee's specific work tasks<sup>4</sup>. However, the unit of analysis has moved from specific work tasks to individual occupations; thus, findings are difficult to interpret. The second point stems in part from this as it is difficult to imagine that the same profession covers the same job tasks particularly in a country as geographically large and culturally diverse as the United States. In comparison, it is reasonable to conclude that the same occupation in a small rural business entails a radically different form of work activity than in a plant of a cosmopolitan city where the division of labour is much more differentiated than the ad hoc work organization for smaller businesses.

As previously mentioned, the study was first published in 2013 and inspired the work of other researchers including Pajarinen and Rouvinen who conducted the same research in 2014 on Finnish occupational data from 2011 [2]. A year later, with the involvement of a staff member from the Statistical Office of Norway, results were compared with the Norwegian data for 2013 [19]. This involved a methodological challenge as the Standard Occupational Classification (SOC) of the United States had to be matched to its European equivalent, the International Standard Classification of Occupations (ISCO). This necessitated further compromises, resulting in 410 cases in Finland and 374 in the case of Norway. Nonetheless, the narrowed sample was essentially the same as the total employment for both countries [ibid] (p. 4). The authors also calculated the results using 2012 US data to overcome comparability issues caused by the time variations in databases. As compared to the United States, the two Scandinavian countries exhibited significant differences in susceptibility to automation. Although the proportion of employees in high-risk occupations in the United States increased to 49% in 2012 from the 47% of two years prior, the same proportion was 35% in Finland and 33% in Norway. The researchers attributed the difference to two key factors. The first is in occupational structure: Although the two northern European countries displayed substantial similarities in this regard, the same could not be said for the United States. The second explanatory factor is that of methodology: As previously stated, there were trade-offs in the matching of job categories used in the United States and Europe, and aggregations usually took the arithmetic mean of susceptibility to automation into account that inevitably contributed to a rise in the proportion of occupations with medium risk. The researchers also measured U.S. data by categorizing ISCO to mitigate this "centring." While the result was slightly lower (45%), the difference was still important. Stefan Fölster, similar to his Finnish and Norwegian colleagues, used this methodology to calculate the percentage of employees in Sweden who worked in occupations with a high susceptibility to automation ( $p > 0.7$ ), indicating that according to the above methodology, 53% of employees in Sweden work in occupations with a risk of becoming obsolete in the next two decades [20] (p. 11). The main reason for the surprisingly high value according to the author may be that a higher proportion of the Swedish labour force works in sector, which are highly susceptible to automation.

### 3. Results: Susceptibility to Automation in Hungary

Fruzsina Nábelek and Eszter Vági [21] examined the evolution of susceptibility to automation in Hungary. Their research is largely focused on Frey and Osborne's methodology that aims to assess susceptibility based on the automation probabilities of various occupations. Unlike the classifications used in international studies, they assigned probabil-

ity values to each FEOR code<sup>5</sup> on their own based on a keyword analysis of the definition of each occupation. Then, based on the degree of susceptibility to automation, five classes were created with 18% and 9% of employees performing work that includes entirely non-automated or mainly non-automated subtasks, respectively, while 28, 15, and 4% are composed of partially, mostly, or fully automated subtasks.

To ensure that our findings are internationally comparable, we use the methodology established by Frey and Osborne and refined by Pajarinen and Rouvinen, retaining the probabilities used in Frey and Osborne's original work. For our purposes, the first step was to convert the automation probabilities associated with occupations to the FEOR08 nomenclature. We used Pajarinen and Rouvinen's ISCO-based probabilities<sup>6</sup> for this. As a result, a translation work for SOC and ISCO was conducted. As the FEOR is based on ISCO, there was less ambiguity in the translation in this case: the vast majority of four-digit ISCO and FEOR codes are clearly compatible<sup>7</sup>. However, there have been cases (40) where a FEOR code was linked to multiple ISCO codes with varying automation probabilities. In these cases, we used the average of the probabilities associated with the various ISCO codes in an approach similar to Pajarinen and Rouvinen's method<sup>8</sup>. Three FEOR occupations, in contrast, did not have an automation probability and in these situations we averaged the automation probabilities of jobs in the same occupational subgroup (three-digit FEOR code). We have data on the occupation of over 99% of employees due to these procedures. In the following section we make an estimate of the level of susceptibility to automation in Hungary based on the baseline data of the 2016 microcensus<sup>9</sup>.

According to our research, 44% of Hungarian employees had a job in 2016 that was highly susceptible to automation based on the 70% threshold set by Frey and Osborne. This figure is marginally lower than the results for the United States but substantially higher than Finland's 35% and Norway's 33% (see Table 1).

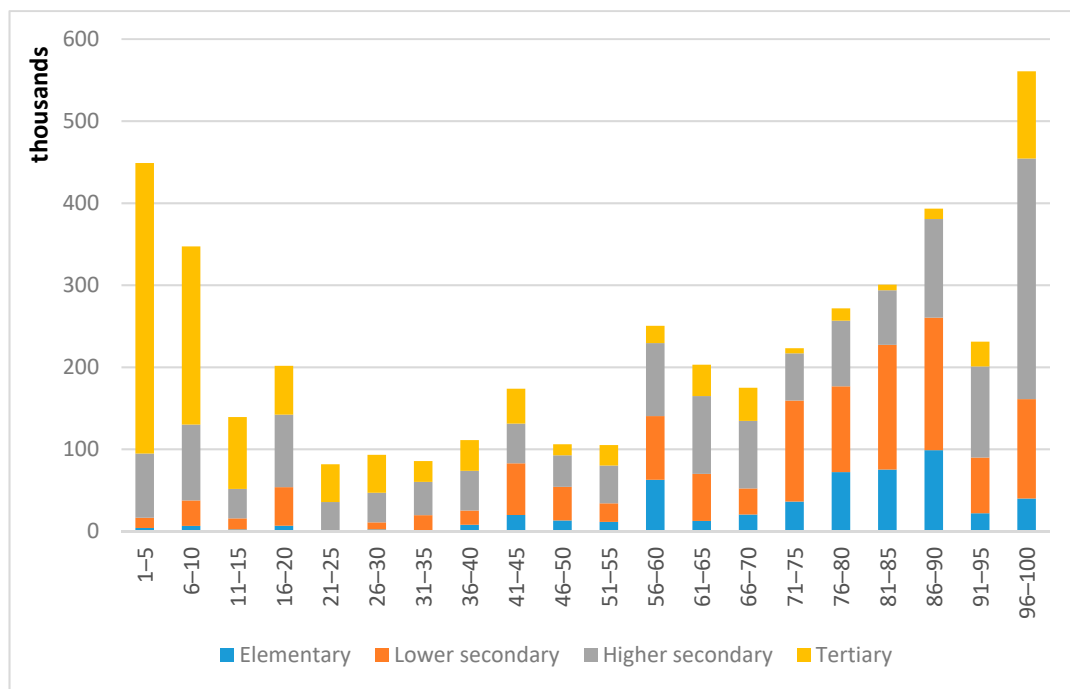
**Table 1.** The aggregated indicators of susceptibility to automation in the examined countries.

Country	Automation Susceptibility *	Year of Analysed Data
Sweden	53%	N/A
USA	45% **	2012
Hungary	44%	2016
Finland	35%	2011
Norway	33%	2013

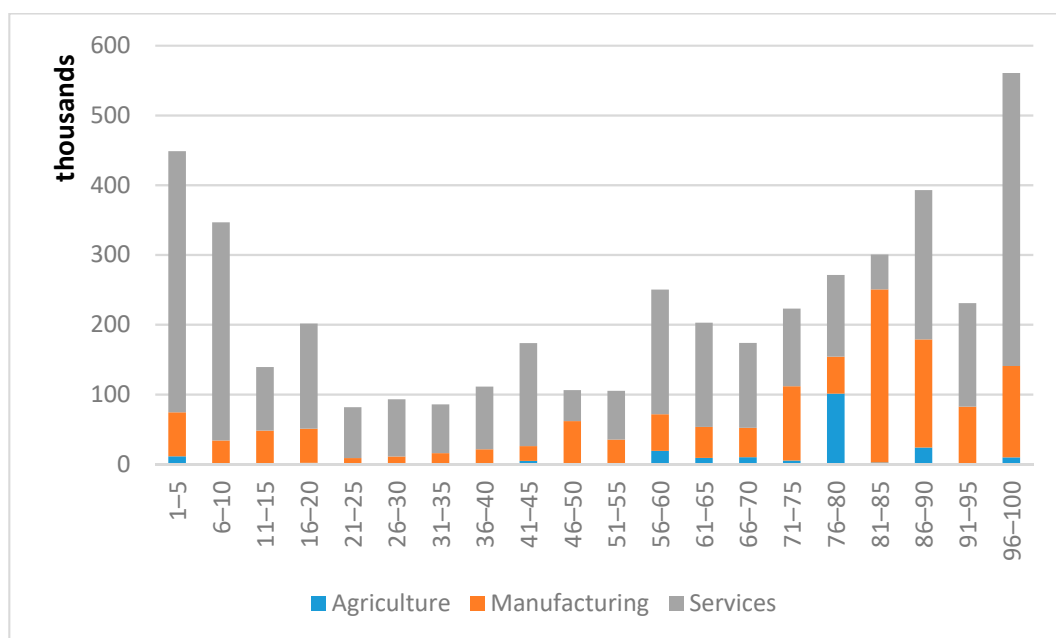
Source: authors' own editing. \* indicates the proportion of the labour force as of total employed population who work in jobs where  $p > 0.7$  in Frey and Osborne's methodology. \*\* indicates that to improve the quality of comparability, we used the U.S. indicator counted from ISCO codes by Pajarinen et al. [19].

Overall, the Hungarian metrics of susceptibility to automation are in the higher ranges in the international comparison; they are roughly on par with those of the United States but lag behind those of Sweden and are significantly higher than those in Finland and Norway.

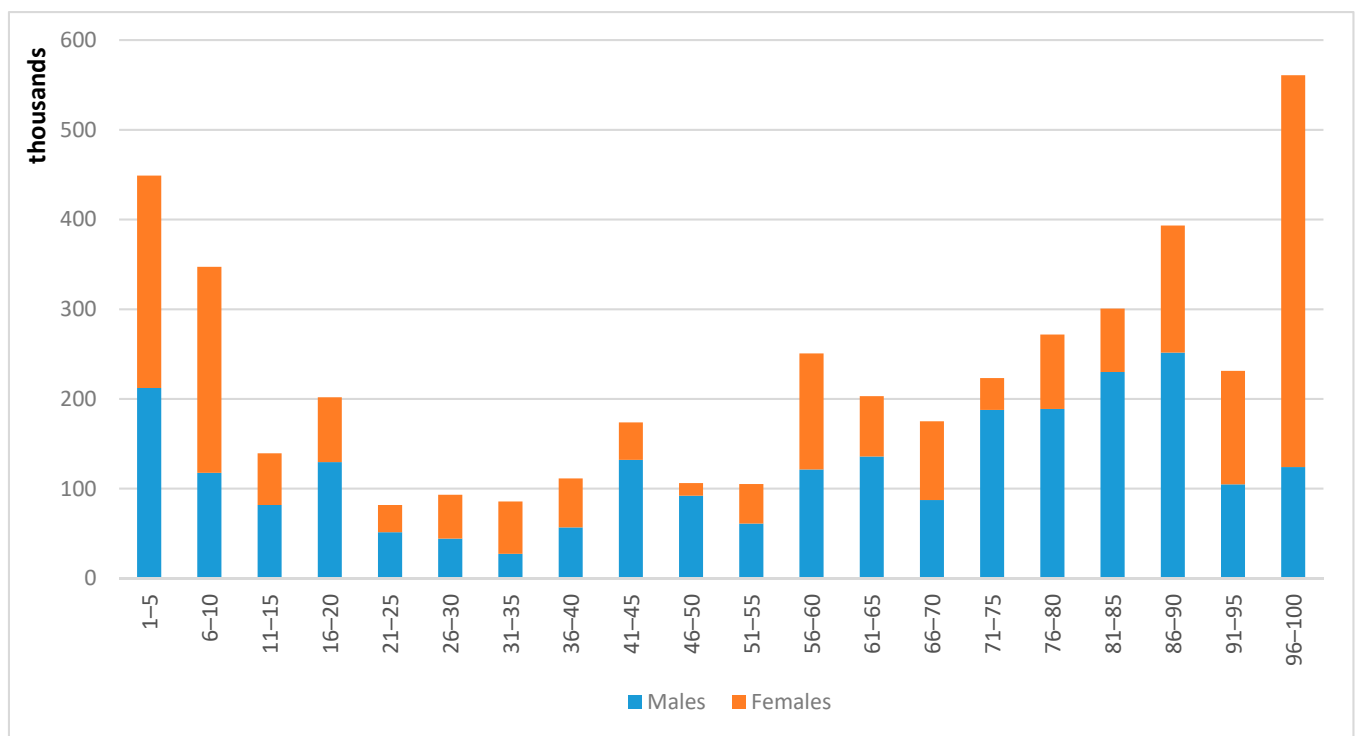
From several aspects, the data in Hungary are close to the findings of previous studies when considering the distribution of workers according to the probability of automation (See Figures 1–3 that illustrates the employee distribution by the 5th percentile.) Accordingly, the majority of employees in each country are concentrated at the two extremes of the distribution. As a result, while many jobs are not threatened by automation, there is still a large proportion of jobs whose risk of being automated are close to 100% and may thus be directly and in the short term at risk of being affected by technological change. As a domestic feature, Hungary, like Sweden and the United States, has a high proportion of the most vulnerable groups: 13% of workers or nearly 600,000 have a job with a likelihood of automation of 95% or higher, and the number of those with a 90% higher chance of being automated has surpassed one million, accounting for nearly a quarter of all employees.



**Figure 1.** Breakdown of employees by susceptibility to automation and educational attainment per person in 2016. Source: Microcensus 2016. Note: International Standard Classification of Education (ISCED) categories are as follows: ISCED 0: early childhood education (‘less than primary’ for educational attainment); ISCED 1: primary education; ISCED 2: lower secondary education; ISCED 3: upper secondary education; ISCED 4: post-secondary non-tertiary education; and ISCED 5: short-cycle tertiary education.



**Figure 2.** Breakdown of employees by susceptibility to automation and industry per person in 2016. Source: Microcensus 2016.



**Figure 3.** Breakdown of employees by susceptibility to automation and gender per person in 2016. Source: Microcensus 2016.

In the following section, we examine how susceptibility to automation changes in Hungary according to different socioeconomic factors. In each of the countries surveyed, differences in educational attainment are identical and Nábelek and Vági's analyses reveal the same correlations. The higher a person's education level, the more likely they are to work in a field that is less susceptible to automation. Although only 14% of people with a tertiary education are considered at risk, this proportion rises to more than two thirds for those with a primary education (see Figure 1 below). However, the differences in results between Finland and Norway compared to Hungary in terms of the level of susceptibility to automation can almost certainly be explained by this factor. While the proportion of occupations that require a high level of education is especially high in Finland and Norway, the proportion of occupations that do not require a high level of education is particularly low. In Hungary, the situation is reversed [22–24]. It is also worth noting that a high level of education alone does not protect jobs against automation; it only does so if it is combined with creative work and the correlation is not obvious for a low level of education. Routine intellectual work requiring a high level of education is at risk of being more susceptible to automation than care-giving work is with a lower level of education that requires a high degree of empathy and emotional ability.

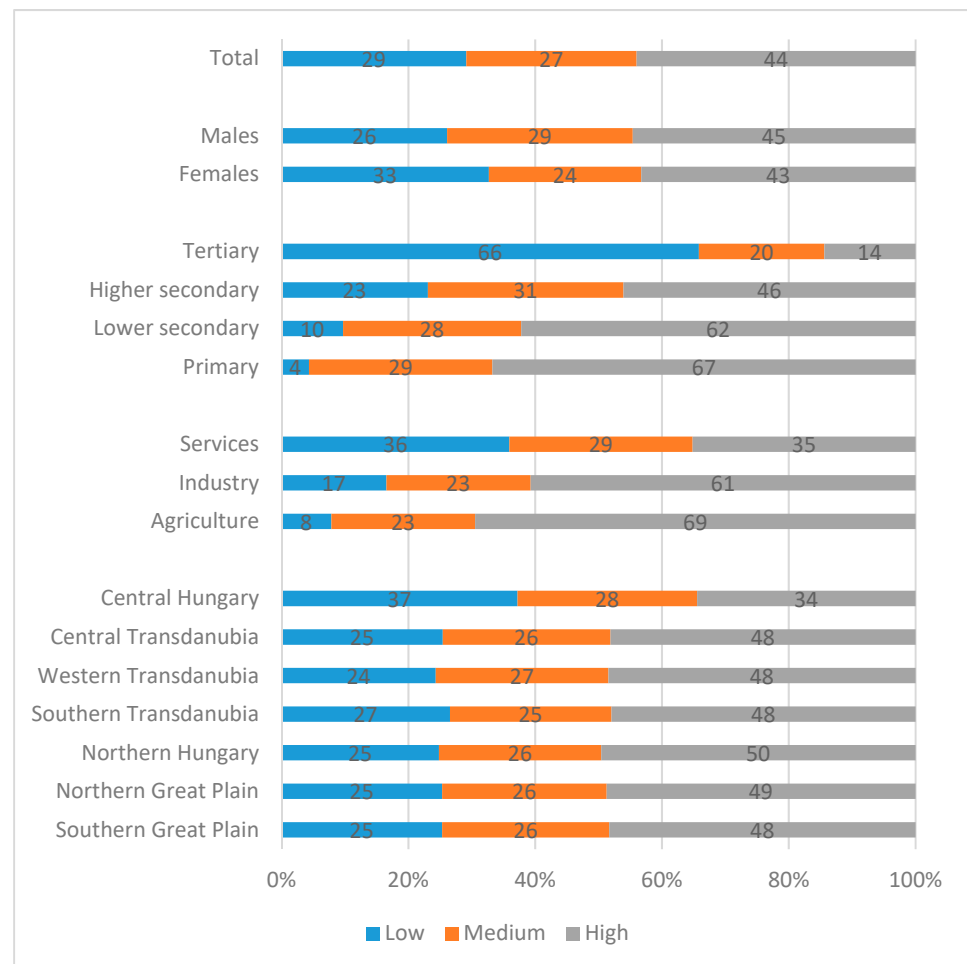
As it is shown in Figure 2, there are also significant variations by industry. Employees in agriculture (69%) and industry (61%) are the most susceptible to automation, whereas service workers (31%) are less vulnerable. Different segments of the occupational structure can have different explanations for these variations. Consider, the service sector has a high proportion of administrative and intellectual occupations that require a high level of qualification and responsibility, as well as occupations that require the employee's personal presence or customized service. This similarity can also be seen in Finland but the variations between sectors are smaller in Norway.

When considering the gender differences, we discover that the proportion of men and women in the groups at risk is nearly identical (slightly higher for men at 45% and slightly lower for women at 43%) but the size of the low-susceptible group is significantly larger among women and the mean is significantly higher among men (see Figure 3 below). These findings are similar to those in Finland where the gender distribution in the at-risk



community is both similar and different from the Norwegian study where the proportion of men is significantly higher. The high proportion of women in the low-risk group is because many occupations traditionally filled by women in Hungary and elsewhere are difficult to automate, particularly in the fields of education, training, nursing, and care-giving. The gender ratio in the highly susceptible community is similar but there are significant inequalities within the group. Women make up nearly 80% of the workforce in the most susceptible (96–100%) occupations and in the 91st–95th percentile their ratio is 55%, while in the 71st–90th percentile, men account for the majority. Women are perceived to be at high risk within the susceptible category as the threat of automation disproportionately affects repetitive routine cognitive occupations such as secretary, clerk, and cashier jobs that are primarily filled in by women.

Regional variations in susceptibility to automation represent differences in occupational structure. In Budapest and the central region, the proportion of higher-status and higher-skilled professions is much higher but a lower proportion of workers are at risk. The other regions have no major differences in susceptibility to automation. See in detail in Figure 4!



**Figure 4.** Breakdown of low, medium, and highly susceptible groups to automation by gender, educational attainment, industry, and region in percentage in 2016. Source: Microcensus 2016. Note: According to international examples, those with high susceptibility were considered to be  $p > 70$  and those with low susceptibility were considered to be  $p < 30$ .

The breakdown of Hungarian data by socio-demographic characteristics reveals that women are in the majority in both the most susceptible (especially in the 96th–100th percentile) and relatively more secure ( $p < 0,3$ ) occupations. Simultaneously, the susceptibility

to automation decreases with the level of education. Regarding regional differences, we have discovered that a higher proportion of the population of Budapest were employed in more secure occupations, while no significant differences between the other regions of the country were found.

Finally, we provide some theoretical, methodological, and practical guidance on how to interpret these data in the following section.

#### 4. Discussion: Is There a Cause for Concern?

The anxiety that technological advancements, mechanization, and in particular automation would put employment at risk has been a constant if not evolving theme as of the first industrial revolution [10]. Data from the United States calculated using Frey and Osborne's methodology have sparked widespread interest among social scientists as well as the general public. The automation literature contains certain implicit presuppositions that are more or less common to all that restricts the accuracy of projections based on these assumptions, which can be traced back in some way to technological determinism and can be summarized as follows:

- The impacts of automation on employment are being assessed under unchanged social and market conditions. Predictions on automation estimate what effects technological advancements will have on the labour market within a decade or two by ensuring that all other variables remain constant in the extrapolation. If in the future robots perform a large portion of human work, communities will naturally react as technology, its work organization, and the overall social environment are evolving together. The same is true of market conditions: As production costs decline, prices will fall, allowing demand to rise, as observed with many commodities in the past. For example, as the textile industry became industrialized in the 19th century, it greatly decreased prices, resulting in increased demand that in turn increased labour demand until the number of textile workers in the United States reached 400,000 by 1940. However, after that, the market became saturated, prices and profitability began to decline, and globalization emerged, as only 20,000 employees remain in this industry today. The automobile and steel industries have experienced similar inverse U-shaped employment effects. In these industries, automation has resulted in a temporary increase in employment, whereas job-destroying effects have only been felt in the long run [25] (pp. 5–7). In this regard, it is important to note not only the elasticity of the demand side of product markets but also the versatility of the supply side of the labour market (i.e., how quickly large numbers of people can respond to changing skill requirements and other labour market demand side automation conditions are important factors [2016]). Factors in determining how fully processes are automated are complex and over-automation is a possibility according to the experience of a German automotive case study [26]; for example, in the case of the family business in question, production processes were automated to the point that the level of flexibility they had previously been able to adapt to the rapidly changing needs of demand was lost. By integrating mechanization with a “clever use of manual human labour”, there was a consensus to reduce the level of automation and return mechanization to the flexibility of the production process [27]). In general, most analyses on the effects of automation on jobs focus exclusively on labour cost reduction, while other positive effects (higher quality, better planning, and more sophisticated logistic systems) are not included. However, they affect changes in demand, for example.
- Previous automation experiences do not apply to the employment effects of digital technologies; instead, something completely new emerges. Past forecasts of the end of the world of work have thus far proven to be premature and the number of workers participating in the globalizing labour market continues to grow. In contrast to previous leaps in technological growth, one of the most important novelties of the industrial revolution is machine learning that opens new dimensions to automation.

In any case, history indicates that technological revolutions have not only decreased but also increased the demand for labour.

- The number of jobs that people can perform is finite, indicating that the more we automate, the less job opportunities there are. This argument is closely coupled to the first point concerning when the results of automation are estimated to be constant under all other circumstances. In such conditions, it is still possible to forecast how many jobs technological advancements will save but projecting credible assumptions regarding what new industries will emerge as a result of the growth of digital technology is difficult. It was impossible to foresee how the advent of telegraphy would impact the stock market or even sports betting in the 19th century. We are similarly puzzled as to what new industries will emerge from the current development. According to Perez, the structure of industrial revolutions has caused drastic changes in daily life: it was inconceivable during the Great Depression of the 1930s that most people living in deep urban poverty would drive from their suburban homes to work in just two decades. Instead of the industry-based metropolitan lifestyles of the Victorian era, a suburban lifestyle was developed [28].<sup>10</sup> As a result, most automation research largely excludes employment enhancing impacts and focuses exclusively on negative job consequences, which is understandable considering that it is difficult to foresee whether new goods, services, or jobs will arise from social transformations of digital technology in the future.
- Non-automation may also have a destroying effect on employment even more so than automation. There are few better examples of the one-way mechanism of technological determinism than failing to take advantage of the opportunities of automation. Another flaw with automation analyses is that they are unable to predict the job-destroying consequences of businesses that do not take advantage of the efficiency gains provided by technological development.

In addition to the theoretical shortcomings mentioned above, there are a few methodological obstacles that can help determine how significant the job destroying impacts of automation are. As previously stated, studies of the impact of automation on jobs usually employ two methodologies or a combination of them. The findings suggest that the methodology used has a substantial influence on how drastic changes are predicted: Occupational-based approaches have a greater impact than approaches based on the content of specific job tasks (see Table 2).

**Table 2.** Findings of the most important studies on automation.

Authors	Level of Analysis	Source of Data	Main Findings
Frey and Osborne (2013)	jobs	US Bureau of Labour Statistics	USA: 47% of jobs are directly susceptible
Arntz, Gregory, and Zierahn (OECD, 2016)	work task	PIACC, 21 countries	USA: 9% of jobs are susceptible. In OECD-member countries, the extent of susceptibility is between 6% (Korea) and 12% (Germany).
Nedelkoska and Quintini (OECD, 2018)	work task	PIAAC, 32 countries	USA: 10% of jobs are susceptible. In OECD-member countries, the extent of susceptibility is between 6% (Norway) and 33% (Slovakia).
McKinsey Global Institute (2017)	employment	US Bureau of Labour Statistics	At 70% probability, 26% of jobs are susceptible, and at 30% probability, 60% of jobs are very susceptible.
Employment Advisory Council (FR, 2017)	employees	French survey	10% of jobs are very susceptible
Dengler and Matthes (DE, 2015)	employment	Federal occupational database (Germany)	14% of employees are very susceptible

Source: [6] (p. 7).

In this regard, it is worth noting that automation can have two effects on the workplace. The rarer case regards when the machines completely substitute the human labour (substitution effect), while the more usual case regards when the machines perform only

certain subtasks. The above systemic disparity in the depth of the effects of automation on employment may be due in part to the fact that task-based approaches are better suited to capture this graduality. Nonetheless, we can understand that conducting these calculations was worthwhile as they are based on the methods of a study with a remarkable international reputation and it is vital that the subject receives more coverage in both professional and public discourse.

## 5. Conclusions: Public Policy Challenges

No one can predict how technology will affect the labour market as the social effects of technological change are heavily affected by country-specific institutional characteristics. Even if Sweden is more vulnerable to the job-destroying impact of automation than Hungary, the Swedish institutional environment is in many respects better suited to mitigate these negative effects. In a recent research study, Warhurst et al. attempted to evaluate the factors that can influence the effect of technological advances not only on employment but also on the quality of working conditions [29]. A distinction was made between mediating and contextualizing factors. The latter is widely defined as an institutional environment in which workplace industrial relation structures, national education and training systems, labour law and workers' security, and the welfare system all play important roles. Why and how these factors can divert the social impacts of developments in individual countries may not require any further explanation. Practices such as competitiveness strategies, individual managerial decisions and choices, and the features of human resource management and innovation management in addition to contextual considerations are equally relevant in the day-to-day operations of companies. As for competitiveness strategy, for example, it can be assumed that the same innovation will have different effects on quality than for companies applying a cost-effectiveness-based competitiveness strategy. Among the human resource management techniques, the methods practiced by companies for coordination within the organization, individual and collective knowledge development, knowledge sharing, and organizational learning deserve special attention.

In examining the management practices of French, Swedish and English companies in aircraft manufacturing, Gautié et al. [30] found that French managers raised in the culture of *Grandes Ecoles* tend to develop more formalized, technocratic, and bureaucratic organizational structures (*lean a la française*) in which employees are given a theoretical opportunity to be involved in the introduction of innovation. Although, Gautié found that such an approach does not work well in reality. In contrast, Swedish companies tend to actively include employees in the implementation of innovations by allowing them to express their opinions and be involved in decision making. As a result of the discrepancies and complex interactions between the above-mentioned intermediary and contextual variables, the French companies surveyed have often implemented early retirement of the elderly with the introduction of the three-dimensional CAD systems, while Swedish companies have heavily invested in training staff using this technology, allowing older workers to keep up with changes as dictated by technological developments.

It is also worth noting that during the "big number battle" [31] over the possible job-destroying consequences of technological development, far less attention was given to the effects of automation on the quality aspects of working conditions. However, in the least, we can foresee substantial changes in this field as we can in the structure of occupations. In workplaces where automation has no substitutional impact on human labour, the additional effect [2016] that may affect a greater number of jobs can be expected more than for creative destruction. Working conditions, physical workplaces, and the content of work activities will all be drastically altered by digital technology. It would be worthwhile to put more emphasis on this in the future to avoid massive technological unemployment.

If one of the public policy goals is to reduce the socially disruptive effects of automation, only complex methods that simultaneously target the above-listed mediating and contextual variables will be able to achieve this. In this regard, Hungary is not performing

well; in the last ten years, the institutional structure of labour market security, the welfare state, and labour relations has been gradually dismantled, while the training system has been substantially reshaped [32]. Simultaneously, market practices have changed in an adverse direction. According to the European Working Conditions Survey, while 44% of workers surveyed in 2005 were employed at creative workplaces, the proportion of workers working in creative jobs has decreased significantly (providing them with a high degree of autonomy in addition to learning and skills development). Meanwhile, by 2015, their market share dropped to 37%. In parallel, the proportion of Taylorian jobs with low levels of autonomy and limited learning opportunities rose from 27% to 33% over the same period [33] (p. 40).

In conclusion, Hungary's institutions supporting the management of temporary labour market conditions by further training, temporary income supplementation, and housing mobility have declined dramatically, and businesses are increasingly relying less on one of the most essential skills while facing job-destroying automation (i.e., creative intelligence). As a result, the threats associated with an already elevated level of automation susceptibility are more likely to materialize. Recently, Finnish researchers examined the potential impacts of labour substituting technological development on government revenues, social expenditures, budget balances, population-level poverty rates, and Gini coefficients for disposable income in the EU-28 countries [34]. The authors investigated the resilience of the EU-28 countries (including the UK) for a pessimistic and an optimistic employment scenario. The data demonstrated that if the pessimistic scenario would become a reality (which is closer to the methodology applied in this paper), Hungary would be among the five most negatively impacted countries in terms of government revenue (4th) and poverty (3rd), while in terms of the Gini-coefficient it is ranked 9th. Currently, to what extent government initiatives such as the Digital Workforce Initiative<sup>11</sup> and the Hungarian Artificial Intelligence Strategy<sup>12</sup> be able to counter these risks in the future is the concern. As the present analysis is based on pre-pandemic conditions, another separate research issue regards how the pandemic and its aftermath will impact automation.

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## Notes

- 1 Valenduc and Vendramin cite mobile phones as an example of this convergence that has become astonishingly “indispensable” with the simultaneous development of technologies that are not necessarily closely related: GPS, mobile internet, Java programming language, and mobile applications based on it [6] (p. 4), in addition to other hardware (e.g., processors, memories, and lenses).
- 2 It is worth emphasizing partially overlapping concepts. In our interpretation, automation occurs when work tasks previously performed by humans are replaced by machines including robotization when these machines are robots. Finally, digitization refers to the conversion of analogue data to digital data. In this sense, automation is a centuries-old process in production and services with robots as the products of the second half of the 20th century, while digitization is a novelty in recent decades. The extent of technological and social change is caused by the interconnection of these processes.
- 3 Susceptibility to automation is hereinafter referred to as the probability that a certain job or occupation will be performed by machines instead of people within a certain time interval.
- 4 They did so out of coercion as only the OECD-funded Adult Skills and Competence Survey and the European Working Conditions Survey (EWCS) conducted by Eurofound in Europe allow it to occur every five years.
- 5 FEOR is the Hungarian Standard Classification System for Occupations (Foglalkozások Egységes Osztályozási Rendszere in Hungarian).
- 6 We would like to express our gratitude for their generous support in allowing the list of occupations to be available to us, which has greatly facilitated our work.
- 7 See the translation key published by the CSO (KSH): [http://www.ksh.hu/docs/osztalyozasok/feor/fordkulcs\\_feor\\_isco\\_hu.pdf](http://www.ksh.hu/docs/osztalyozasok/feor/fordkulcs_feor_isco_hu.pdf) (accessed on 4 August 2021)
- 8 In one case we deviated from this procedure: Two ISCO occupations were associated with the FEOR code 9310 (Simple industrial occupations: 9311: Mining and quarrying labourers,  $p = 0.370$ ; and 9329: Manufacturing labourers not elsewhere classified,  $p = 0.840$ ). In this case, in applying the dominance principle, we used the probability associated with code 9329.
- 9 The 2016 microcensus collected information of about 10% of the population. The large number of items thus allowed for a detailed examination of the occupational structure. For more information on data collection, visit <https://www.ksh.hu/mikrocenzus2016>, (accessed on 4 August 2021).
- 10 This is true even if the heavy industrialization during World War II certainly helped this process. In addition, those living in urban poverty who moved to the suburbs often did so because new minority groups were replacing them in the urban areas. This is sometimes called “the white flight” (We are thankful for this comment to Mark McCaffrey).
- 11 <https://digitalisjoletprogram.hu/files/2e/86/2e865bc650f57539da2dbccf7b169eda.pdf> (accessed on 4 August 2021).
- 12 <https://ai-hungary.com/api/v1/companies/15/files/137203/view> (accessed on 4 August 2021).

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