Technequality

Understanding the relation between technological innovations and social inequality

Labour market forecasting scenarios for automation risks: Approach and outcomes

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Description of deliverable

Deliverable 1.4 reports on how the baseline Cedefop Skills Forecast 2018 were adapted to make it possible to compute likely scenarios for impact of automation on jobs in Europe till 2030. The deliverable describes methods and results. We use OECD data on the automation risk by occupation to develop a number of hypothetical, but realistic scenarios. The extent of the penetration of automation in industries and occupations and the speed at which automation will penetrate the economy are the key determinants of the scenarios we consider. The estimated number of jobs lost ranges from 12.5 million to 106.6 million depending on the scenario considered. These are the estimated direct job destruction effects of automatization but not account for the indirect (compensatory) effects.

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1. Introduction

Technological innovations such as robotics and Artificial Intelligence (AI) are predicted to have a profound impact on the economy and the labour market (Acemoglu & Restrepo, 2018). It is however unclear how large the impact of automation of jobs will be as estimates for the automation risk of occupations range from 47% (Frey & Osborne, 2017) to 9% (Arntz et al., 2016). The impact of automation on occupation crucially depends on the task content of occupations: routine tasks can easily be automated, but non-routine tasks are, at this stage, harder to automate (Autor, 2015). However, that tasks –and hereby crucial aspects of jobs– are automatable does not mean that they *will* be automated. This is because actual automation depends on the cost of automation, the national legal context, the exposure to international competition as well as the social acceptance. Although technological innovations are penetrating all industry sectors (Oxford Economics, 2019), technology also generates employment and increases productivity (Graetz & Michaels, 2018) such that the net effect on employment is unclear. There is evidence that automation so far has not resulted in a net loss of jobs (Autor & Salomons, 2018). At any rate, it is clear that automation will affect the way we work.

One purpose of the Technequality project is to develop the evidence base and further our understanding of potential consequences for labour markets of automation in Europe. The work we report in this paper combines the standard EU forecasting model for the labour market developed for Cedefop (Cedefop, Eurofound, 2018), and updated data of automation risks in Member States (Nedelkoska & Quintini, 2018). The basis for this exercise is the Cedefop Skills Forecast model 2018 that offers quantitative projections of the future trends in employment by industry sector and occupational group using harmonized data and methodologies for all countries of Europe. This is explained in Section 2. The novelty of our approach is fourfold:

- We make use of recently published OECD data on automation risks of occupation to further develop the Cedefop Skills Forecast model to make it a unique tool for forecasting the impact of technologies on labour in a way that is comparable across countries of Europe (Section 3).
- We discuss factors that affect the adoption and deployment of automation (Section 4) that are key in better understanding the uncertainty with its potential effect on labour markets.
- We develop a range of plausible scenarios of automation to account for these uncertainties with respect to the development, deployment, and adoption of new technologies (Section 5). We estimate direct job destruction effects of automatization but do not account for the indirect (compensatory) effects. An uncertainty we will not be able to address with the model, is how new technologies affect the nature or task content of jobs (Levels et al., 2019). This is because it is rather hazardous and speculative to try to quantify the job creation potential of technologies.
- This allows us to be the first to develop a quantitative assessment of the potential consequences of technologies for the labour market across realistic scenarios (Sections 6 and 7). These scenarios pertain to the technical and deployment potential, and the socio-political restrictors (Section 6), as well as to the pace of adoption of technology (depending on labour costs and international competition) and the role that employment regulations play in slowing down the adoption rate (Section 7). A qualitative judgement of the relative likelihood of different scenarios can then be applied.

2. Baseline Projections

The baseline labour market forecast used is the Cedefop Skills Forecast 2018, hereafter Cedefop forecast (Cedefop (2018b), Cedefop (2018c), & Cedefop, Eurofound (2018)). The Cedefop forecast provides data of the current structure, and future trends, of the EU labour market. The time horizon

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of the forecast is 2030. Forecasting for further time horizons entails a higher risk of economic and policy uncertainties.

Figure 1

Figure 1 illustrates the structure of the Cedefop modelling procedure (Cedefop, Eurofound, 2018). The Cedefop forecast employs seven modules to forecast demand and supply of labour, disaggregated by sector, occupation, and qualification level.[1] Briefly, the main elements of the approach are:

1. Demand side of the economy, giving labour demand.
2. Supply side of the labour market: number and characteristics of the economically active, including skills and qualifications.
3. Imbalances, comparing demand and supply side modules, and reconciliation.

The prime information source for these forecasts is Eurostat's Labour Force Survey. The population projections are from Eurostat's Europop (2015).[2] Long-run GDP forecasts are consistent with these population forecasts, from the European Commission 2018 Ageing Report (EC, 2017). Short-run GDP forecasts are sourced from the European Commission's annual macro-economic database (AMECO), specifically, the May 2017 GDP projections.[3] The modelled Cedefop forecast is peer-reviewed, and adjusted as required, using judgements of individual country experts.

Automation in the Baseline Projections

The Cedefop baseline assumes productivity improvements continue in line with the historical trend. The historical trend is captured via the econometric specification in the E3ME estimation procedure.[4] The baseline, therefore, captures general labour productivity improvements but does not take account of new and disruptive technologies such as AI, robotics, and blockchain. Cedefop, Eurofound (2018) states that in the Cedefop forecast, 'current robotisation trends in the EU are not expected to lead to job destruction on a large scale, although they are expected to result in new jobs not being created'. Cedefop, Eurofound (2018) notes that the current assumption in the Cedefop forecast 'is that existing workers in automation-prone sectors are likely to keep their jobs when robots are brought in, though they may see a role change or accept lower wages'.

[1] See Cedefop, Eurofound (2018) for the latest details of the Cedefop methodology. For full details, see Cedefop (2012).

[2] Eurostat population projection data: https://ec.europa.eu/eurostat/web/population-demography-migration-projections/population-projections-data

[3] AMECO: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/macro-economic-database-ameco_en

[4] See 'Section 4.9 Industrial employment' in Cambridge Econometrics (2019).

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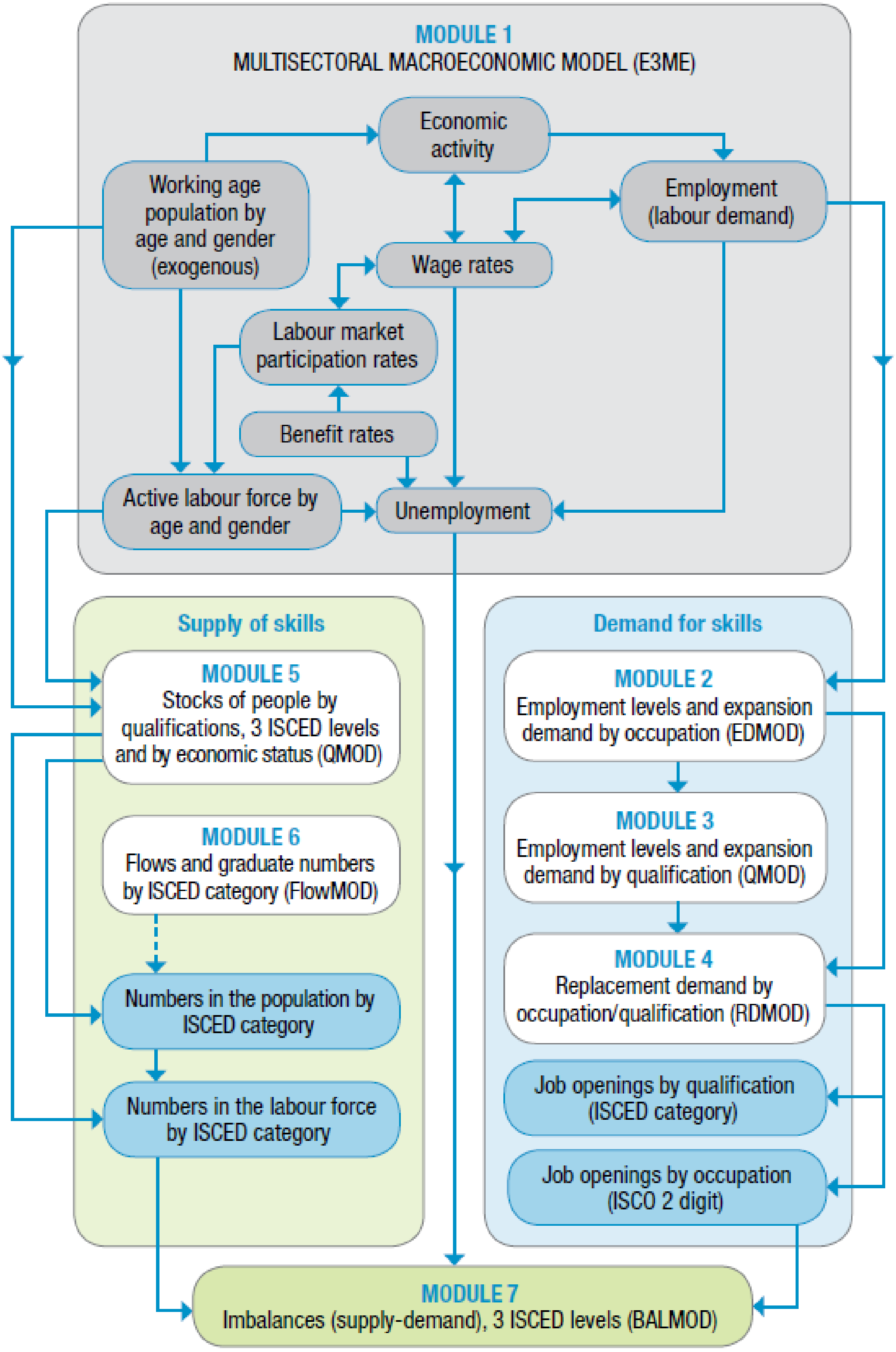
Figure 1 Cedefop forecast modelling structure



Source: Cedefop, Eurofound (2018, p. 15).

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3. Automation Risk Data

A body of literature has built upon Frey and Osbourne's (2017) seminal estimation of automation risk.[5] This study uses automation risk data estimated by the OECD, from Nedelkoska and Quintini (2018).[6] The OECD study builds on the expert assessment reported in Frey and Osborne (2017) and estimates the risk of automation by occupation based on job tasks information reported by individuals in the Survey of Adult Skills (PIAAC). By doing so, the OECD better reflect the extent to which some tasks within occupations are more prone to automation than other tasks. While the data by Frey and Osbourne's (2017) suggest that 47% of jobs in the USA are at high risk of being automated, Nedelkoska and Quintini (2018) find that 14% of job in the OECD are highly automatable, meaning they have a probability of automation of 70% or more.

The source data provides occupation-specific automation risk for 20 EU Member States, Norway, and Turkey. The level of detail of occupation classification is the International Standard Classification of Occupations (ISCO) sub-major groups (2 digits occupations).[7] The data give the share of jobs in each of three categories of automation risk: high (>70%), significant (50-70%), and low (<50%). These data cover over 88% of employment in the EU28 in 2018. Details of data coverage are found in in Appendix 2. The figure in Appendix 2 details the data availability in the OECD automation risk data. Red cells indicate missing data. Green cells indicate available data.

For application to the Cedefop forecast, the source data required the following processing steps:

- The EU28 weighted average automation risk was calculated for each occupation. The weights for the calculation used were employment levels in 2018 by occupation by Member State of the EU, missing data being assigned a weight of zero.
- The OECD does not contain information for all EU countries. The missing Member States were assigned the EU28 weighted average automation risk, per occupation.
- The non-EU countries in the Cedefop data, not represented in the OECD automation risk data, were also assigned the EU28 weighted average. These countries are Iceland, Switzerland, and Macedonia.
- Where data was missing for individual occupations within a Member State or non-EU country included in the OECD dataset, the EU28 weighted average was used.
- Where data was classified only as a major ISCO group, rather than sub-major group, the data was not used. 0.5% of data points are not used because of this decision.
- The OECD dataset includes data for England, and for Northern Ireland, but not for the UK. The UK was assigned the values for England, and data for Northern Ireland was not used.[8]
- Several occupations have no automation risk data: 0 Armed Forces (including all constituent sub-major groups); 6.63 Subsistence Farmers, Fishers, Hunters and Gatherers; and 9.95 Street and Related Sales and Services Workers. These were treated as having no risk of automation. Armed forces automation is a complex socio-political decision. Occupations 6.63 and 9.95 account for 0.3% of EU28 employment in 2018. No risk adds a fourth category to the automation risk data: high, significant, low, and no.

The dimensions in the automation risk source data are occupation by country. The data, therefore, do not make any distinction between sectors or qualification level. Therefore, it is assumed that the automation risk of a given occupation is equal across all sectors of the economy, and across all levels

[5] Arntz et al. (2016), Suta et al. (2018), Nedelkoska and Quintini (2018), and Cedefop (2018a).

[6] We have not presented the full automation risk data because we do not have permission to publish this.

[7] See Appendix 1 for details of classification.

[8] This decision was made for the sake of pragmatism. A weighted average of the values for England and Northern Ireland could be calculated, but this would require data for employment by each occupation within each country. The sample sizes in the OECD data are not appropriate for a weighted average.

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of qualification. Qualification level is not used in this analysis, however, and therefore this assumption makes no material difference.

4. Factors Affecting Automation

The development of plausible automation scenarios requires an assessment of the factors which will affect the *pace* and *extent* that the risk of automation is realised. From the conception of a given technology, there is a significant journey to its full economic exploitation. Once a general-purpose technology is 'discovered', commercial applications are developed. Commercial applications will only be exploited once it is profitable to do so. After initial application, technology takes substantial time to reach its full potential; there is an extensive literature on technology diffusion (World Economic Forum, 2018).[9]

Levels et al. (2019) discuss a number of conditions that affect the extent to which technological innovations impact the labour market. In this paper, we consider three broad categories of factors that affect the deployment of technology: technical, economic, and socio-political factors.[10] In our scenarios, the technical potential and deployment potential pertain to what Levels et al. (2019) refer to as 'speed of adoption' and 'speed of innovation' (see Section 6).

4.1 Technical

Technical feasibility is the first barrier to deployment and adoption of new technologies. The technology required to realise the estimated automation risk has already been developed; automation risk is estimated as the application of currently demonstrated technologies. However, commercially applicable solutions and systems must be developed to realise technical potential. For example, technology for autonomous vehicles has already been demonstrated. However, a satisfactory commercial application for heavy-goods vehicles has yet to be developed (MGI, 2017a).

4.2 Economic

The market will adopt new technologies only when there is a business case to do so. There are three key dimensions in this (MGI, 2017a): cost of developing and deploying solutions; labour market dynamics; and economic benefits. The cost of deploying solutions is the most obvious economic barrier. Deploying new technology is likely to require substantial capital investment, especially where hardware is required. Firms are only likely to make this investment if there is a strong economic case to do so, and if they have capital available (i.e. either due to accumulated profits or borrowing). A key dynamic in transitions, however, is the learning-by-doing effect, where costs of a given technology decrease with cumulative production.[11]

Firms must consider labour market dynamics, including supply by skill in both the short and long term. In the case of automation and the substitution of capital for labour, the main cost calculation is the relative cost of capital and labour.

Finally, there are likely to be non-cost related implications of introducing new technology. These may include, but are not limited to quality, reliability, and safety. These could be negative or positive depending on the particular technology application, and how well developed/refined it is.

[9] See Rogers (1962) for seminal thoughts. More recently: Arthur (1989), Rip et al. (1998), and Geels (2002).
[10] See MGI (2017a), Suta et al. (2018), and Henderson (2019).
[11] See Arrow (1962) and Arthur (1989).

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4.3 Socio-political

Even when a technology is fully developed, and deployment is economically advantageous, the technology may not be adopted. Deployment of technology is restricted by socio-political dynamics. Historically, and presently, there is strong evidence to suggest that people resist technology. The classic example are the Luddites, who resisted the introduction of machinery in the textile industry. Today, there is scepticism regarding widespread use of AI, and fear of automation causing widespread unemployment.

Where there is societal resistance, there is likely to be political resistance also. Pressure on policy makers may be exerted through channels including the media, stakeholder interest groups (trade unions, industry associations, etc.), and ultimately, the polls and ballet box. Coverage of trade unions and collective bargaining is extensive in many European countries. The response of unions to industry's decisions could be a very strong barrier to automation. In the UK, the National Union of Rail, Maritime and Transport Workers (RMT) has been in dispute with train operators since 2016; the dispute concerns the driver-only operated (DOO) services.[12][13] DOO potentially removes the need for train guards; the train driver can operate the doors themselves. Two key issues in the dispute are the role of the train guard in ensuring safety and accessibility;[14][15] this highlights the potential for complex obstacles to automation despite a job being largely technically automatable, if measured by task content. The persistent industrial action of RMT, including strikes and protests, indicates the scale of potential resistance.

Given societal and political pressures, governments may introduce regulation which restricts the adoption of technology. Existing labour law restricts the ability of firms to make employees redundant, with the strictness varying across countries. The potential extent of change in the capital-labour dynamic from automation is likely to require the renegotiation of the 'social contract' in many countries.

Further to socio-political acceptance, the flexibility of current organisational structures will affect rate of adoption. Adoption of automation and AI may require changes in management structures, supply-chain management, physical work spaces, and working-schedules. Organisations take time to realise the full potential of technologies and adapt accordingly (Eurofound, 2018).

5. Design of the Model of Automation

The economic model of automation in this study was designed to take account of these three key factors as an extension to the baseline Cedefop forecasts. Figure 2 illustrates the calculations of the model. The following section details the definitions and calculations of each variable.[16] This initial work considers only the direct employment effects of automation. That is, the indirect and induced impacts of automation are not modelled. The focus of this modelling exercise is to develop plausible assessments of the direct effects of automation. See section '8.4 Job Creation' for further discussion.

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[12] See https://www.bbc.co.uk/news/uk-england-49370104

[13] See https://www.railmagazine.com/news/rail-features/is-there-a-way-to-break-the-doo-stalemate

[14] https://www.rmt.org.uk/news/govt-advisors-warned-doo-trains-are-toxic-for-disabled/

[15] https://www.rmt.org.uk/news/members-updates/further-strike-action-called-role-of-th16819/

[16] See Cedefop (2012) for full details of the Cedefop Skills Forecast Employment Demand and Cedefop Skills Forecast Replacement and Expansion Demand.

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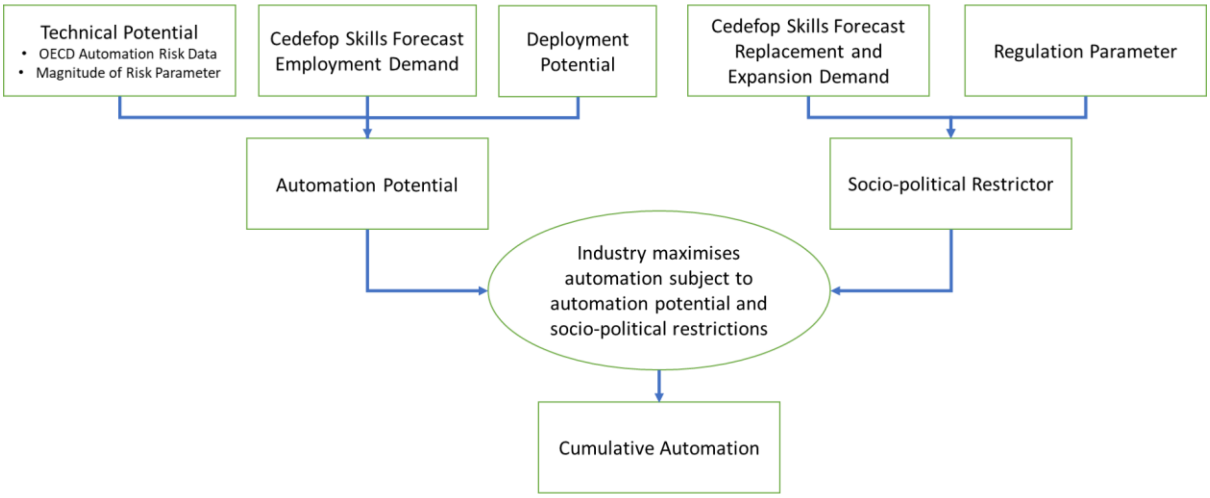
Figure 2 Model of automation: calculated by region, sector, occupation, and year



A key feature and implication of this model design is that employees experience a change in time-allocation across tasks as firms introduce automation. Time allocations shift toward the non-automatable tasks within each job. By way of example, consider a travel agency, where employees spend 50% of their time on booking and administrative tasks, and 50% of time on customer-facing tasks. Assume that the administrative tasks are fully automatable, and the customer-facing tasks are non-automatable. If the agency pursued automation, then we can expect two changes. First, the number of employees could be up to halved. Second, the time allocation for remaining employees would be wholly on customer-facing tasks.[17]

5.1 Technical Potential

Technical potential is defined as the share of jobs which could be automated each year, if estimated automation risk was fully realised. Equation 1 details the calculation of the share of jobs at risk of automation, for region *r,* sector *s*, occupation *o*, at time *t*. Categories, *c*, are no, low, significant, and high.

Equation 1 Technical potential

$$Technical\ Potential_{r,s,o,t} = \sum_{c=1}^{4}(Share\ in\ Category_{r,s,o,c} \times Magnitude\ of\ Risk_c)$$

where:

- *technical potential*: share of jobs which could be automated in given year, if estimated automation risk was fully realised
- *share in category:* share of total jobs in each risk category (no, low, significant, and high risk)
- *magnitude of risk:* risk of automation for each category, e.g., high: 70-100%

5.2 Deployment Potential

The deployment potential variable controls the pace at which technical potential can be realised. This variable reflects the economic and socio-political factors detailed in Section 4 'Factors Affecting

[17] Theoretically, if a job is entirely automatable, then the dynamic may be simpler: entire jobs could be automated, and any remaining employees could face no change in task composition.

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Automation'. The variable is relaxed linearly from 2020 to the year in which full deployment could be realised, see Equation 2.

Equation 2 Deployment potential

$$Deployment\ Potential_{r,s,o,t} = (Year_t - 2019)\ /\ (Full\ Deployment\ Year_{r,s,o} - 2019)$$

where:
- *deployment potential*: the percentage of technical potential which could be realised in the given year
- *full deployment year*: the year at which 100% of technical potential could be realised, full deployment of technology

The linear nature of deployment was chosen as a simplification. In real-world dynamics, diffusion is non-linear and generally can be characterised by an S-shaped curve. However, the level of uncertainty with respect to the actual shape of the diffusion shape is high. This is the reason we choose the linear simplification.

5.3 Automation Potential

The automation potential variable measures the absolute number of jobs which could be automated each year, given technical and deployment potential, see Equation 3.

Equation 3 Automation potential

$$Automation\ Potential_{r,s,o,t} = Technical\ Potential_{r,s,o,t} \times Deployment\ Potential_{r,s,o,t} \times Employment\ Demand_{r,s,o,t}$$

where:
- *automation potential*: the total number of jobs which could be automated each year, given technical and deployment potential
- *employment demand:* employment demand in Cedefop baseline forecast

5.4 Socio-political Restrictor

The explicit socio-political restriction variable models the fact that industry's choice of automation may be limited by additional regulation. In this model, the socio-political restrictor variable acts as a restriction on the number of jobs which can be automated each year. In this model, automation is calculated annually. The social-political restrictor is a flow restriction. In the absence of regulation, industry would automate to the value of 'Automation Potential' each year. This value considers all technical and economic constraints. The number of jobs which industries wish to automate is therefore the difference between cumulative automation as of the previous year, and automation potential in the given year. This value is compared to any flow restriction from the socio-political restrictor. Industry maximises desired automation subject to the flow restriction. The logic of this is demonstrated in Equation 4. The socio-political restrictor operates through new job opportunities only; i.e., the maximum number of jobs which can be automated is equal to the number of new job opportunities in that year.

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Equation 4 Calculation of automation, given job opportunities as socio-political restrictor

$$
\begin{aligned}
&If\ Job\ Opportunities_{r,s,o,t} \leq 0\\
&\quad Cumulative\ Automation_{r,s,o,t} = Cumulative\ Automation_{r,s,o,t-1}\\
&If\ Job\ Opportunities_{r,s,o,t} > 0\\
&\quad If\ Cum.Automation_{r,s,o,t-1} + Job\ Opportunities_{r,s,o,t} < Automation\ Potential_{r,s,o,t}\\
&\qquad Cum.Automation_{r,s,o,t} = Cum.Automation_{r,s,o,t-1} + Job\ Opportunities_{r,s,o,t}\\
&\quad If\ Cum.Automation_{r,s,o,t-1} + Job\ Opportunities_{r,s,o,t} \geq Automation\ Potential_{r,s,o,t}\\
&\qquad\qquad Cum.Automation_{r,s,o,t} = Automation\ Potential_{r,s,o,t}
\end{aligned}
$$

where:

- *job opportunities*: the sum of replacement and expansion demand
- *cumulative automation*: total number of jobs already automated until the given period
- *automation potential*: the total number of jobs which could be automated each year, given technical and deployment potential

Note that in this scenario methodology, the deployment potential and socio-political restrictor are not additive. Rather, the methodology shows that, for a given regulation, the degree to which it affects automation is a function of the other conditions. For example, the replacement demand condition is much more restrictive under the highest technical potential sensitivity, than the lowest.

6. Scenario Design

The development of scenarios in this paper aims to select plausible ranges for modelling parameters, given the factors which affect the pace and extent of automation. The scenarios are developed as sensitivities, which reflect uncertainties within each of the parameters. In terms of the mechanics of applying automation risk data to the Cedefop forecast, there are three key parameter categories:

1. Technical potential. This captures uncertainty in the estimation of automation risk. This parameter concerns only technical potential and is time invariant.
2. Deployment potential. This parameter controls the maximum realisation, each year, of the technical automation potential. This parameter captures developments of commercial solutions, economic feasibility, and aspects of the socio-political dimension. This parameter is relaxed over time, reflecting:
    - Development of new commercial solutions.
    - Increased coverage of economically feasible opportunities; reducing costs through learning-by-doing effects.
    - Organisational restructuring over time.
    - Increases in social and regulatory acceptability.
3. Socio-political restrictions. These parameters model explicit restrictions, such as labour law restricting the pace of automation to expansion demand. The logic behind this is that in regulated labour markets, it is hard to automate the jobs of incumbent workers.

Table 1 details the range of values selected for each of the parameters. Table 2 details the eighteen scenarios produced, given the cartesian product of scenario parameters.

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Table 1: Scenario parameters

Parameter	Description	Values
Technical potential.	Value within OECD risk category ranges.	Low: lower bound in range, for 'significant' category equal to 50%.
		Middle: mid-point of range, for 'significant' category equal to 60%.
		High: upper bound in range, for 'significant' category equal to 70%.
Deployment potential.	Year in which full technical potential could be realised.	2035.
		2055.
		2075.
Socio-political restrictor.	Restriction on automation.	No restriction.
		New job opportunities.

Table 2 Scenarios across parameter combinations

Restrictor: none

Technical/Deployment	2035	2055	2075
Low	Low_35_Free	Low_55_Free	Low_75_Free
Middle	Mid_35_Free	Mid_55_Free	Mid_75_Free
High	High_35_Free	High_55_Free	High_75_Free

Restrictor: job opportunities

Technical/Deployment	2035	2055	2075
Low	Low_35_ND	Low_55_ND	Low_75_ND
Middle	Mid_35_ND	Mid_55_ND	Mid_75_ND
High	High_35_ND	High_55_ND	High_75_ND

6.1 Technical Potential

Scenarios are modelled across three sensitivities of the technical potential parameter. Using the lower bound, midpoint, and upper bound of the automation risk range. By way of example, for the significant risk category, the risk category value is set at 50%, 60%, and 70%. This sensitivity, therefore, addresses uncertainty in the magnitude of risk, whilst maintaining the categorisation/rankings across occupations. In terms of the scenarios discussed in Levels et al. (2019), the technical potential pertain to what the authors call the 'speed of innovation'.

The magnitudes of automation risk in the literature vary substantially. Nedelkoska and Quintini (2018) find substantially different absolute levels of risk when applying the same methodology to different data sets; they suggest caution in interpreting results from the literature. Our reading of this literature is that the relative risk *rankings* of occupations are more robust than the estimated *magnitude* of risk.

6.2 Deployment Potential

Scenarios are modelled across three sensitivities of the deployment potential parameter. The deployment potential parameter is varied such that full technical potential would be realised by 2035, 2055 and 2075 across the sensitivities. The parameter is equal across all regions, sectors, and occupations, in these scenarios. In terms of the scenarios discussed in Levels et al. (2019), the deployment potential pertain to what the authors call the 'speed of adoption'.

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The time horizons for full deployment potential are informed by MGI (2017a), which estimates that '49 percent of the activities that people are paid to do in the global economy have the potential to be automated by adapting currently demonstrated technology'. MGI (2017a) develops scenarios of adoption and find that 50 percent of activities could be automated by 2055, and 'posit possible scenarios where that level of adoption occurs up to almost 20 years earlier or later'.

6.3 Socio-political Restrictor

Scenarios are modelled across two sensitivities of socio-political restrictor: no restriction and new job opportunities. In the development of the work, two other restrictors were considered: replacement demand and expansion demand. These are detailed in Appendix 3. The job opportunities method is a refinement of the replacement and expansion demand methods.

No Restrictions

There are no additional restrictions.

Job Opportunities

Job opportunities, in this study, are defined as the sum of replacement and expansion demand. Given scenario design, any negative value is set to zero. The value of job opportunities is derived from the Cedefop forecast; there is no consideration of additional job creation from automation (manufacture of robots, programming, cyber security, etc.). For the job opportunities methodology, the maximum pace of deployment is determined by job opportunities each year. This is a refinement of the 'Replacement Demand' and 'Expansion Demand' scenarios. Expansion demand may be negative[18], and therefore job opportunities may be less than replacement demand. However, it is unlikely that legislation would allow a firm to automate all jobs from replacement demand and dismiss workers to address negative expansion demand; more likely is that the net could be automated.

7. Further Scenario Development

The initial scenarios provide indicative ranges for automation adoption and deployment. These scenarios, however, are characterised by parameter value assumptions covering all regions, sectors, and occupations. The key differentiator in the scenarios discussed in Section 6 is technical potential. The second stage of scenario development considers how adoption may differ across regions, sectors, and occupations, in light of their differing institutional, economic and socio-political characteristics. Such refinements are not discussed in Levels et al. (2019). Note that socio-political restrictors could operate on local markets for goods and services, which is something we now disregard.

7.1 Pace of Automation

The pace of automation, captured by the deployment potential parameter, is refined by considering the economic landscape for each sector and occupation. Two key variables in determining the economic imperative to automate are considered: international competitiveness and cost of labour.

International Competitiveness and Trade

Productivity improvements over time, including through automation, are an economic imperative in Europe, given exposure to international competition. This applies both to competitiveness of EU

[18] For example, in an industry that is in decline, or where labour productivity growth is faster than growth in output.

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exports in international markets, and of domestic supply in domestic EU markets. It is assumed that greater exposure to external competition (i.e., a higher level of import penetration, or higher exports share in production), increases the incentive to automate, and therefore increases the pace of adoption of automation technologies.

A trade indicator is calculated, as Equation 5 Calculation of trade indicator. The calculation uses the latest historical trade data in E3ME to estimate the importance of international trade in each sector. The trade ratio is calculated at the level of the European trade bloc in E3ME;[19] intra-European trade does not count in the calculation. The calculation of the trade indicator from the trade ratio yields a value between 0 and 1; this functional form is chosen to introduce a non-linearity in the relationship between trade ratio and automation incentive.

Equation 5 Calculation of trade indicator

$$Trade\ Ratio_s = \frac{(External\ Imports_s + External\ Exports_s)}{(Domestic\ Gross\ Output_s + External\ Imports_s)}$$

$$If\ Trade\ Ratio_s \geq 1 \text{ then } Trade\ Ratio_s = 1$$

$$Trade\ Indicator_s = \frac{2 \times (Trade\ Ratio_s)}{(1 + Trade\ Ratio_s)}$$

The trade indicator is used to estimate the time horizon for full deployment potential, see Equation 6 Estimating full deployment time horizon. In this formulation, the Deployment Potential parameter is differentiated across sectors, unlike in the initial scenarios.

Equation 6 Estimating full deployment time horizon using trade indicator

$$Full\ Deployment\ Year_s = 2055 - (Trade\ Indicator_s \times (2055 - 2035))$$

$$Deployment\ Potential_{s,t} = (Year_t - 2019) \ / \ (Full\ Deployment\ Year_s - 2019)$$

The weakness of this approach is that, by definition, it focuses on automation risk in sectors which are heavily traded. The effect is that the adoption rate is slow in most service sectors, because they are thinly traded. However, this is an assumption that makes sense as jobs in the service sector are heavy in interactive skills, in which humans have a comparative advantage over technology.

Labour Cost

The second option for adoption differentiation across jobs is relative labour cost. The economic incentive to automate any given job is driven by the cost of automation, and the cost of labour. We do not have data for the cost of automating these jobs, absolute or relative, and therefore rely entirely on relative cost of labour. Labour costs, chiefly wages, differ substantially across occupations and sectors, creating different incentives.

The source data chosen to estimate relative labour cost across industry and occupations is from Eurostat, namely the 'Structure of earnings survey; annual earnings' data.[20] Note, however, that also here we make necessary simplifying assumption because of data constraints. In reality, it is not labour costs that matter, but labour costs in relation to productivity. Since international comparative data on productivity and labour costs by occupation is lacking, we rely on wages only. See Appendix 4 for the classifications of the Eurostat data. The Eurostat data required processing, which we explain in Textbox 1.

[19] EU28, Norway, Switzerland, Iceland, Turkey, and Macedonia.
[20] https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=earn_ses_annual&lang=en

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Textbox 1: Data processing for the forecasts

- Data used: Eurostat 'earn_ses_annual'. Specifically: mean annual gross earnings in Euro, across all age groups and sexes, working full-time, data for 2014.
- Mapping of Eurostat and Cedefop occupation classifications follows the ISCO08 classification. Eurostat is only available at the major group level; this is applied to each corresponding sub-major group.
- Data is missing for ISCO08 Major Group 0 Armed Forces. The data is filled with the country value for the economy wide average (B-S_X_O). In this study, this is immaterial, because automation risk of 0 Armed Forces is zero.
- Mapping of Eurostat and Cedefop occupation classifications follows the NACE Rev 2 classifications, see Appendix 4. Source data does not include data for agriculture, forestry and fishing (section A of NACE), public administration and defence (section O), or activities of households as employers (section T). Each occupation within these is assigned the occupation average wage for the economy wide (B-S_X_O).
- Where data is missing for a single occupation-industry combination, the data is filled using the economy wide average (B-S_X_O), for that occupation.
- Data was missing for several countries for ISCO08 '6 Skilled Agricultural, Forestry and Fishery Workers' across all industry classifications: Austria, Belgium, Lithuania, and Iceland. To fill this data, the EU28 ratio for ISCO08 6 'Skilled agricultural' to ISCO08 6-8 'Skilled manual workers' was calculated, for each industry classification. This ratio is applied to the value of ISCO08 6-8 'Skilled manual workers' for each of the industry classifications for each of the countries.

Equation 7 Calculation of relative wage indicator

$$Relative\ Wage\ Indicator_{r,s,o} = \frac{(IndOcc\ Wage_{r,s,o} - Min.Wage\ in\ Region_r)}{(Max.\ Wage\ in\ Region_r - Min.\ Wage\ in\ Region_r)}$$

where:

- *min.wage in region:* minimum earnings value of all industry-occupation combinations, in given region
- *max.wage in region:* maximum earnings value of all industry-occupation combinations, in given region

The relative wage indicator is used to estimate the time horizon for full deployment potential, see Equation 8. In this formulation, the deployment potential parameter is differentiated across regions, sectors, and occupations.

Equation 8 Estimating full deployment time horizon using relative wage indicator

$$Full\ Deployment\ Year_{r,s,o} = 2055 - (Relative\ Wage\ Indicator_{r,s,o} \times (2055 - 2035))$$
$$Deployment\ Potential_{r,s,o,t} = (Year_t - 2019)\ /\ (Full\ Deployment\ Year_{r,s,o} - 2019)$$

The relative wage could have created an indicator across the EU. However, this would have resulted in very high automation in Western and Northern Europe (where wages are relatively high), and much slower automation in the Eastern and Southern regions of the EU (where wages are comparatively low).

7.2 Employment protection

The idea of regulation limiting adoption, captured in the socio-political restrictor, is refined in considering the employment protection legislation across countries. Data from the OECD indicators

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of employment protection legislation (EPL) are used.[21] The socio-political restrictor in this study models restrictions in redundancy and dismissal; the selected measure in the OECD data is therefore REG5 'Definition of justified or unfair dismissal'. For countries not covered by the OECD data,[22] several sources were used to examine redundancy laws.[23]

For REG5, each country is assigned a value of 0 to 6, the scale increasing with strictness. A value of 4 equates to 'when a transfer and/or a retraining to adapt the worker to different work must be attempted prior to dismissal'. In this scenario design, any country with a REG5 value of 4 or higher is assigned the job opportunities explicit restrictor.[24] If REG5 is less than 4, there is no restrictor. The justification is that if firms must seek alternative placement of an employee, they may be unable to realise a reduction in labour costs, and therefore, automation may no longer be cost effective. In countries where employees can be made redundant freely, there is no such barrier. The countries assigned the job opportunities restrictor are Estonia, Finland, France, Germany, Italy, Lithuania, Macedonia, Norway, and Sweden.

Please note that the weakness of this approach is that does not consider the relative cost of dismissal across countries. The cost of dismissal may be as prohibitive as the legal requirement to offer alternative employment. For example, in Belgium the employer has absolute dismissal power (of white-collar workers), but the cost of dismissal is substantial (Deloitte, 2012).

7.3 Scenarios with Specific Institutional, Economic and Socio-political Context

Table 3 details the final scenario specifications, employing the methodology described above.

Table 3 Scenarios with specific institutional, economic and socio-political

Scenario	Technical Potential	Deployment Potential	Socio-political restrictor
Low (A_Low)	Lower bound in each category.	Region-sector-occupation combination specific. Function of relative wages.	Region specific. Function of employment protection legislation.
Medium (B_Mid)	Mid-point in each category.	Same specification as 'Low' scenario.	Same specification as 'Low' scenario.
High (C_High)	Upper bound in each category.	Same specification as 'Low' scenario.	Same specification as 'Low' scenario.

8. Limitations of the Approach

8.1 Qualification Dimension of Labour Markets

The Cedefop data provides forecasts disaggregated by occupation, sector and qualification level. The automation risk data, however, does not provide the qualification dimension and therefore the qualification dimension is not used in this analysis. The inclusion of qualification level in the analysis

[21] See https://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm.
[22] Bulgaria, Cyprus, Romania, and Malta.
[23] EC (2007), Thomson Reuters, UK Practical Law, and Eurofound https://www.eurofound.europa.eu/observatories/emcc/erm/legislation.
[24] The REG5 indicator considers when an individual can be dismissed based on competence, amongst others. Detailed notes for Spain note the REG5 indicator is high because of issues regarding worker suitability, not redundancy arrangements. Spain is therefore not assigned a restriction in this study.

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would require an additional, strong, assumption: the relative risk of automation for a given occupation, across qualifications. Further, qualification level may well be endogenous across automation scenarios. Under scenarios of substantial automation, it is likely that there will be a surplus of skilled labour, and therefore less incentive to attain certain qualifications.

8.2 Processing and Application of Automation Risk Data

The OECD source data includes sample size for each country-occupation combination. The weighting procedure for estimating missing data could use the sample size as weights. For this study, size of labour force was instead used for the weighting procedure because this ensures the most representative weighted average, in terms of the European labour force. An alternative approach than assigning the EU28 calculated average to missing countries, would be to assign data from a 'comparable country' (e.g., in terms of its industrial structure and legal setting). However, automation risk differs significantly by country, even within an occupation. The choice of 'comparable country' could make a substantial difference. The more conservative approach is to assign the EU28 weighted average, whilst acknowledging substantial inter-country risk, which is missing.

8.3 Productivity and Linear Deployment Potential

Projections of labour productivity growth as a benchmark based on past performance raises two main issues. First, it is not known if levels of productivity are only a result of labour or whether they are affected by other factors such as market conditions, competition, regulations, etc. Second, past performance indicators say little about the replacement costs of current labour. We try to deal with this in scenarios described in Section 7, but this might not be sufficient.

For simplicity, we assumed that the rate of automation followed a linear trajectory over time. If the rate of automation instead was assumed to follow an S shaped diffusion (as is often the case in technology deployment data), then the labour demand projections would differ (i.e., with lower impacts on employment in the early years, as it takes time for firms to adopt new practices and technologies, followed by a faster transition in the middle years, and slower change in later years, when the new technologies reach saturation).

8.4 Job Creation

Our analyses only consider the substitution of jobs by new technologies (what Levels et al. (2019) call the substitution effect) and we do not consider how the remaining jobs is distributed among employed individuals. Two uncertainties which we do not address in this paper and with our model, are how new technologies affect the nature or task content of jobs, and the creation of new jobs, e.g., when investments in new technologies require human complementarities. Levels et al. (2019), e.g., discuss that increases in productivity induced by new technologies might feed the demand for labour. The empirical evidence to date on how automation affects the quality of labour is mixed (MGI, 2017b). Autor and Salomons (2018) discuss past waves of automation and suggest that automation so far has not resulted in a net loss of jobs. The MGI (2017a) study assumes that all workers displaced by technology find employment at baseline productivity, and argues that this does not result in structural unemployment. The recent Eurofound (2018) study argues that if all physical and intellectual work could be automated, whether it is routine or non-routine work, then humans would be displaced to social tasks such as teaching, caring, and entertainment. Using data on the deployment of industrial robots in the US, Acemoglu and Restrepo (2019a) provides evidence that automation may reduce employment. Acemoglu and Restrepo (2019b) also argue that, left to the market, the economy could invest too heavily in the 'wrong type of AI' that is more likely labour replacing than labour enhancing.

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9. Results

9.1 Overall Employment Effects of Automation

The scenarios discussed in Sections 6 (18 scenarios) and 7 (3 scenarios) were implemented in the Cedefop model, which, needless to say, generates a large number of country, industry sector, and occupation specific forecast data. In this section, we report the main findings in a concise fashion. The full details of the employment effects of the various scenarios are available on the following website: www.technequality-project.eu.

Table 4 reports the employment effects of automation in million jobs and percentages compared to the baseline Cedefop forecasts. In the baseline, employment in 2030 is expected to be around 242.2 million employed persons. The job loss due to automation in Europe is expected to ranges from 12.5 million to 106.6 million employed persons less, depending on the scenario considered. Mind, as indicated in Section 8, that these estimates have to be taken with caution. When the technical potential of automation, its speed of deployment is slow and automation only affects net job opportunities (scenario 14; Low_75_ND), then only 5.1% of total employment in the baseline will not be realized due to automation. Automation is expected to have the largest employment effect in the scenario with high penetration of technology (high technical potential), fast adoption and no socio-political restrictions upon adoption (scenario 5; High_35_Free). In that case, the impact of automation is 43.8% less employment compared to the base scenario. It is hard to tell which scenario is most realistic, but is seems to us that a scenario with high penetration of technology, fast adoption and no socio-political barriers to implementation of technology is overly pessimistic.

Our scenarios with specific institutional, economic and socio-political are interesting to consider because they not only rely on country specific automation risks associated to the technical potential (low, medium, high), as do the other scenarios, but also consider country specificities with respect to the deployment potential and the socio-political context as explained in Section 7. Accounting for such specificities in deployment potential and socio-political context, the scenario with low technical potential results in 9.8% lower employment in 2030 compared to the base. The impact on employment in the high technical potential is larger, with 24.7% employment being lost compared to the base. The employment loss in the medium technical potential scenario amounts to 17.3%.

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Table 4 Employment effects by 2030 of automation under various scenarios

Scenario	Employment (millions)	Loss to automation (millions)	Loss to automation (%)
0 Baseline	243.2	0	0
1 Low_35_Free	198.6	44.6	18.3
2 Low_35_ND	201.7	41.6	17.1
3 Mid_35_Free	167.6	75.6	31.1
4 Mid_35_ND	175.3	67.9	27.9
5 High_35_Free	136.6	106.6	43.8
6 High_35_ND	154.2	89.1	36.6
7 Low_55_Free	223.4	19.8	8.2
8 Low_55_ND	224.0	19.2	7.9
9 Mid_55_Free	209.6	33.6	13.8
10 Mid_55_ND	210.9	32.4	13.3
11 High_55_Free	195.8	47.4	19.5
12 High_55_ND	198.0	45.2	18.6
13 Low_75_Free	230.5	12.7	5.2
14 Low_75_ND	230.8	12.5	5.1
15 Mid_75_Free	221.6	21.6	8.9
16 Mid_75_ND	222.2	21.1	8.7
17 High_75_Free	212.8	30.5	12.5
18 High_75_ND	213.7	29.5	12.1
A Low_Scenario	219.4	23.8	9.8
B Mid_Scenario	201.2	42.0	17.3
C High_Scenario	183.3	60.0	24.7

Source: Own calculations based on Cedefop, Eurofound (2018)

9.2 Employment Effects of by Occupation

Based on the scenarios with specific institutional, economic and socio-political discussed in Section 7, Figure 3 shows the estimated impact of automation by occupation. In the low technical potential scenario, we estimate large employment losses compared to the base (more than 11 million altogether) among technicians and associate professionals, services and sales workers and elementary occupations. These are relatively large occupational groups. In relative terms, the impact of automation in this scenario is largest for plant and machine operators (17%) and elementary occupations (15%).

In the high technical potential scenario, we estimate the largest employment losses compared to the base for professionals (almost 11.7 million or 26% less employment) and technicians and associate professionals (almost 10.7 million or 25% less employment). The job loss in services and sales jobs is also high (almost 8 million or 21% less employment). Under the medium technical potential scenario these three occupations are also the ones to suffer the largest job loss by 2030.

The relative difference in automation across scenarios differs by occupation. The range of scenario estimates for professionals are substantially greater than for elementary occupations. The reason is that there is greater uncertainty in the low automatability classification (0-50%) than the significant (50-70%) or high (70-100%) classifications. The magnitude of risk in the low classification is 0, 25, and 50% in the three scenarios, compared to 70, 85, and 100% for the high risk classification. Estimates

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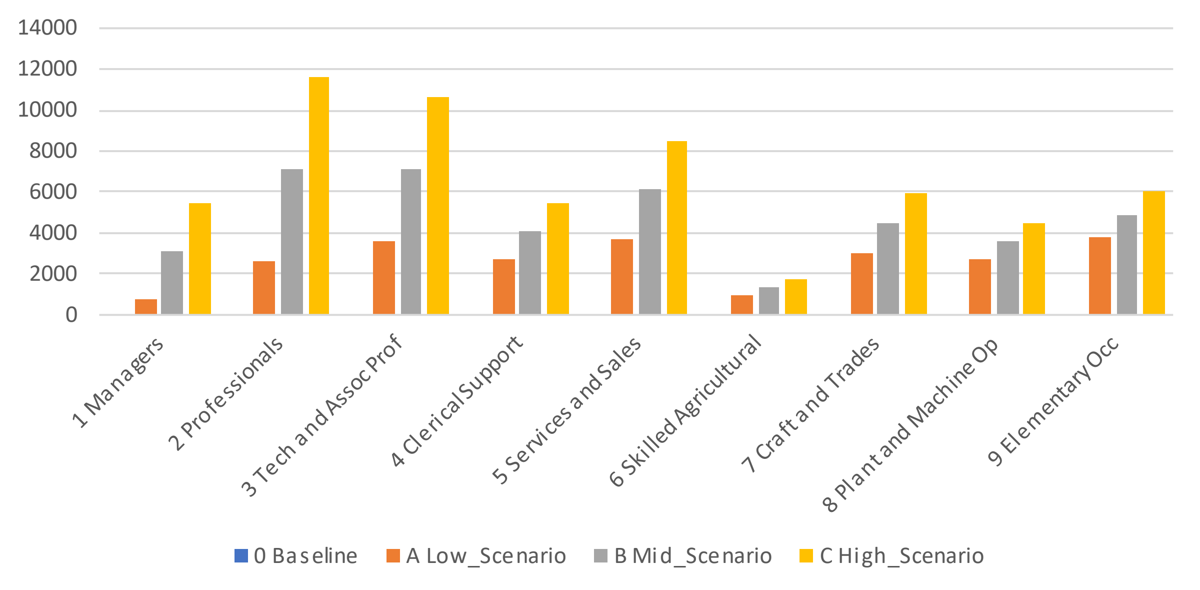
for those occupations which have a higher share in the low automatability classification, therefore, vary more across sensitivities of magnitude of risks.

Figure 3 Employment lost to automation compared to base scenario, by occupation, 2030 (thousands)



Source: Own calculations based on Cedefop, Eurofound (2018)

9.3 Employment Effects of by Country

The employment effects of automation by 2030 can also be computed by country. To limit the amount of data, we report here the country effects in Figure 4 for the technical potential of automation set at the mid-point of each category, deployment potential that is region-sector-occupation combination specific, and socio-political restrictor that is region specific and a function of employment protection legislation (B Mid_Scenario in Table 3). The data underlying the figure is reported in Appendix 5.

The country with highest aggregate automation risk is the Slovak Republic: under the scenario reported in the figure, 22.2% of 2030 employment will not be realized because of automation. Norway is the country with the lowest impact of automation (14.2%). Note, however, that the impact of automation in countries depends on many parameters, and that it is therefore hard to make good sense of the numbers. Factors that affect the automation risks in countries include the automation risk itself, the sectoral composition of the economy, the occupational composition of the labour force in the country as well as country specific institutions and wage costs.

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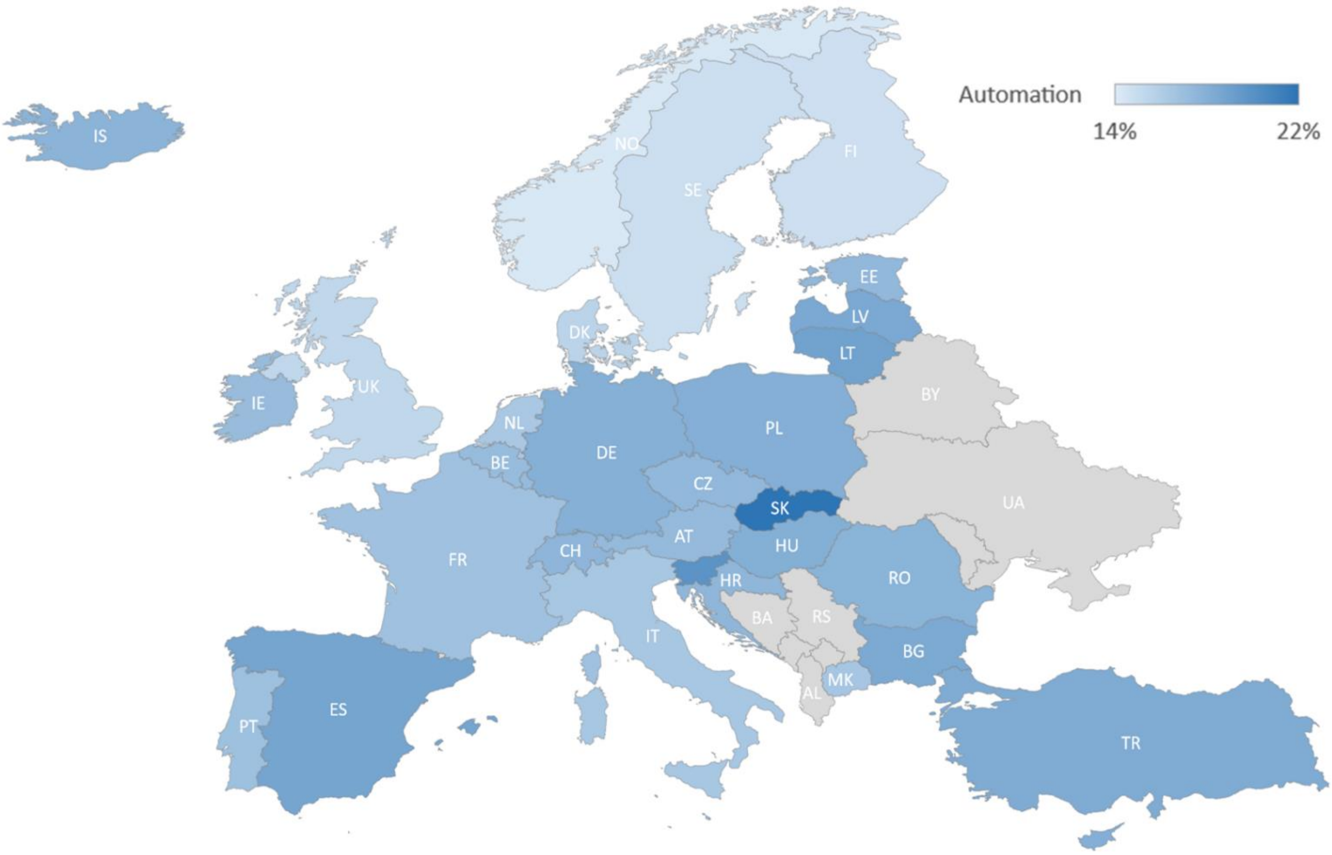
Figure 4 'B Mid Scenario' aggregate automation risk, by country, in 2030 (percentage)



Source: Own calculations based on Cedefop, Eurofound (2018). Darker shades represent higher risk. Countries coloured grey were not included in the analysis.

10. Conclusion

The general conclusion when overseeing the literature is that technological innovations such as robotics and AI are expected to deeply impact the economy and the labour market. First, technological innovations will affect the way we work as the penetration of it in daily work will have an impact on which tasks human labour perform and how the tasks are performed. Second, technological innovations will generate new demands for jobs in the market. Third, technological innovations will take over some jobs because the tasks performed become increasingly codifiable and because AI learns. In this paper, we focus on the latter since it is hazardous to come with well-founded job creation estimates due to technology (Autor and Salomons, 2018, Levels et al. 2019).

This research is the first we are aware of that uses a methodology that is comparable across countries of Europe to assess the future impact of technology on employment. It builds on the existing Cedefop Skills Forecast model 2018 to develop a range of realistic scenarios to account for the fact that the development, deployment, and adoption of new technologies is characterised by substantial uncertainties. The key characteristics of the scenarios are 1) the technical potential of automation, i.e., the share of job it is expected to automate, 2) the speed of the deployment potential, i.e., the year in which automation is achieved, 3) socio-political restrictors in the deployment of automation, i.e., the extent to which automation affects new jobs only or also existing jobs, and 4) region-sector-occupation differences in relative wages and employment protection legislation, i.e., the extent to which relatively high wage and low levels of protection could speed up the adoption of technologies.

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These scenarios lead to a range of estimates for lost employment by 2030 compared to the baseline estimates. These estimates range from 12.5 million to 106.6 million depending on the scenario considered. Occupations to suffer the largest job loss by 2030 are professionals, technicians and associate professionals, and services and sales occupations.

This paper highlights the methodology used to derive forecasts and the assumptions made under various scenarios. The details from the computations presented in this paper will be made available through a dashboard on the Technequality website (https://technequality-project.eu/) in the first half of 2020. It will allow to access the outcomes of all scenarios by country, industry sector and occupation.

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Appendix 1: International Standard Classification of Occupations, ISCO-08[25]

Code	Major Group	Sub-major Group
1	**Managers**	
11		Chief Executives, Senior Officials and Legislators
12		Administrative and Commercial Managers
13		Production and Specialized Services Managers
14		Hospitality, Retail and Other Services Managers
2	**Professionals**	
21		Science and Engineering Professionals
22		Health Professionals
23		Teaching Professionals
24		Business and Administration Professionals
25		Information and Communications Technology Professionals
26		Legal, Social and Cultural Professionals
3	**Technicians and Associate Professionals**	
31		Science and Engineering Associate Professionals
32		Health Associate Professionals
33		Business and Administration Associate Professionals
34		Legal, Social, Cultural and Related Associate Professionals
35		Information and Communications Technicians
4	**Clerical Support Workers**	
41		General and Keyboard Clerks
42		Customer Services Clerks
43		Numerical and Material Recording Clerks
44		Other Clerical Support Workers
5	**Services and Sales Workers**	
51		Personal Services Workers
52		Sales Workers
53		Personal Care Workers
54		Protective Services Workers

[25] See https://www.ilo.org/public/english/bureau/stat/isco/isco08/

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6	**Skilled Agricultural, Forestry and Fishery Workers**	
61		Market-oriented Skilled Agricultural Workers
62		Market-oriented Skilled Forestry, Fishery and Hunting Workers
63		Subsistence Farmers, Fishers, Hunters and Gatherers
7	**Craft and Related Trades Workers**	
71		Building and Related Trades Workers (excluding Electricians)
72		Metal, Machinery and Related Trades Workers
73		Handicraft and Printing Workers
74		Electrical and Electronic Trades Workers
75		Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
8	**Plant and Machine Operators and Assemblers**	
81		Stationary Plant and Machine Operators
82		Assemblers
83		Drivers and Mobile Plant Operators
9	**Elementary Occupations**	
91		Cleaners and Helpers
92		Agricultural, Forestry and Fishery Labourers
93		Labourers in Mining, Construction, Manufacturing and Transport
94		Food Preparation Assistants
95		Street and Related Sales and Services Workers
96		Refuse Workers and Other Elementary Workers
0	**Armed Forces Occupations**	
1		Commissioned Armed Forces Officers
2		Non-commissioned Armed Forces Officers
3		Armed Forces Occupations, Other Ranks

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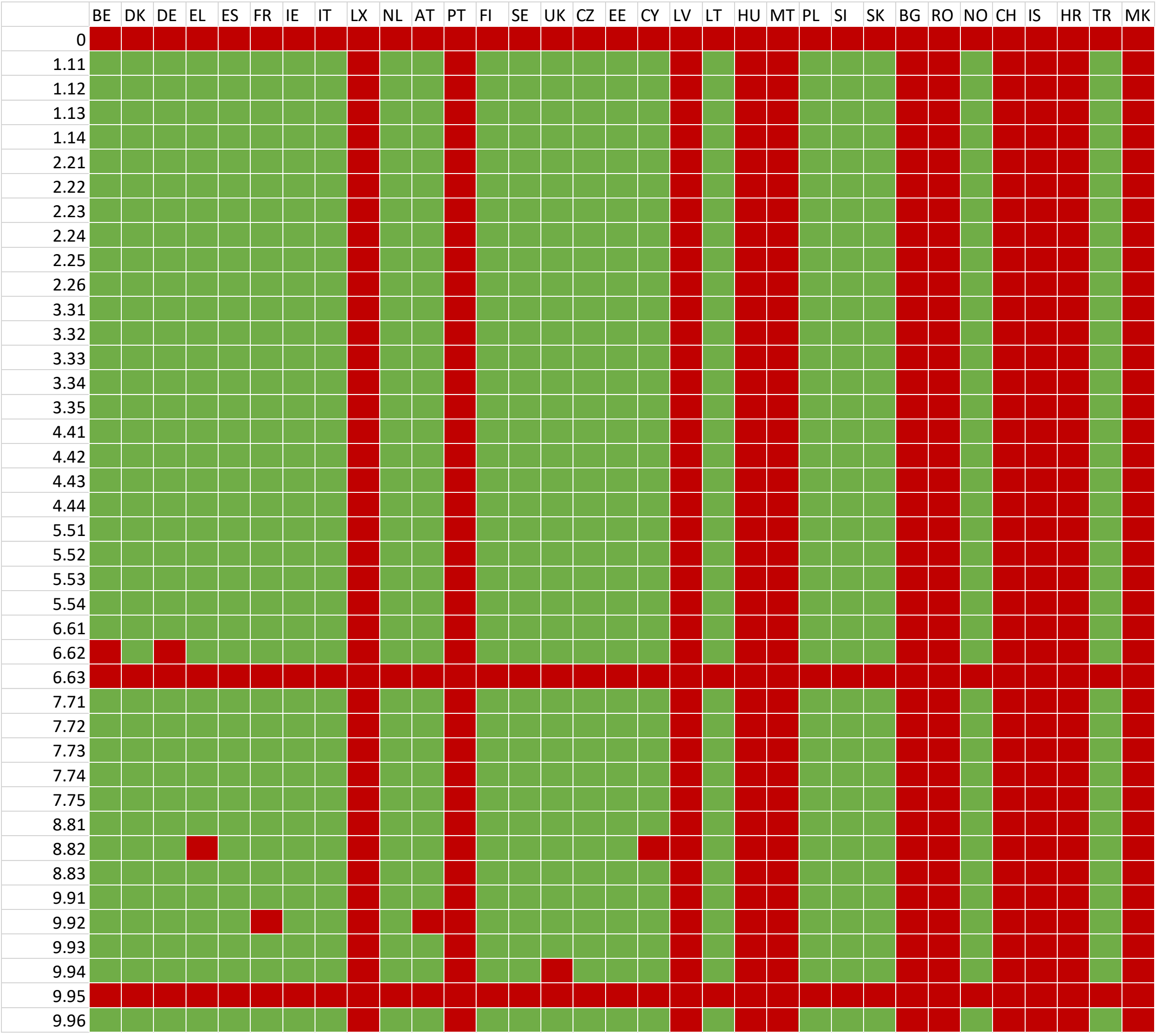
Appendix 2: Automation Risk Data Availability by Occupation and Country

The figure below details the data availability in the OECD automation risk data. Red cells indicate missing data. Green cells indicate available data.



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Appendix 3: Alternative Socio-Political Restrictors

Replacement Demand

Replacement demand measures outflow from an occupation. Using the replacement demand restrictor, it is supposed that legislation is passed which prevents firms from freely replacing labour with capital. Specifically, firms are unable to make workers redundant in order to automate the job. Maximum pace of deployment is determined by replacement demand each year; firms must wait for workers to voluntarily leave or retire.

Replacement demand includes retirements and deaths, transition to non-employment, net migration, and inter-occupational mobility. Replacement demand is calculated in the Cedefop forecast.[26] Replacement demand is only provided by occupation by country. To calculate the sectoral disaggregation, it is assumed that replacement demand is proportional to the share of employment by sector in each year, for each occupation.

This method builds on the approach set out in Suta et al. (2018), where replacement demand is used as a restrictor. Suta et al. (2018) notes that the 'Cedefop Skills Forecast is based, among others, on the assumption that all vacant jobs will be replaced and this chapter puts into question this assumption.'

The level of replacement demand is likely to be endogenous across scenarios of automation potential. People may be less likely to leave their job in an environment of automation and employment uncertainty. Replacement demand does not measure within-occupation turnover, however, which is the job transition category most likely to be affected. For example, in retail, the turnover rate is likely to be much higher than replacement demand. And it is the turnover rate most likely to be substantially reduced.

Expansion Demand

Expansion demand refers to the net change in employment over time. Given the scenario design in this case, any negative value is set to zero.

Using expansion demand as a restrictor, it is supposed that strict legislation is passed, which prevents firms from replacing labour with capital. Specifically, firms are not permitted to automate any job previously performed by a human. This effectively restricts automation to cases where firms' demand for effective labour is increasing over time. The maximum pace of deployment is determined by positive expansion demand each year. Other than restricting all automation, the most restrictive regulation would be to protect all existing jobs.

Expansion demand by industry by Member State is calculated using E3ME, in module 1 of the Cedefop methodology. A further module (EDMOD) calculates the occupation level expansion demand.[27]

[26] Chapter 7, Cedefop (2012) details the methodology.
[27] Chapter 5, Cedefop (2012) details the methodology.

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Appendix 4 Eurostat 'Structure of earnings' classifications

Table 4 Eurostat industry classifications

Eurostat Code	Label	NACE Rev 2
B-S_X_O	Industry, construction and services (except public administration, defense, compulsory social security)	All, excluding A, O, and T
B-N	Business economy	B to N
B-F	Industry and construction	B to F
G-N	Services of the business economy	G to N
P-S	Education; human health and social work activities; arts, entertainment and recreation; other service activities	P to S

Table 5 Eurostat occupation classifications

Eurostat Code	Label	ISCO08
TOTAL	Total	1 to 9, not 0
OC1-5	Non manual workers	1 to 5
OC1	Managers	1
OC2	Professionals	2
OC3	Technicians and associate professionals	3
OC4	Clerical support workers	4
OC5	Service and sales workers	5
OC6-8	Skilled manual workers	6 to 8
OC6	Skilled agricultural, forestry and fishery workers	6
OC7	Craft and related trades workers	7
OC8	Plant and machine operators and assemblers	8
OC9	Elementary occupations	9

Table 6 Mapping of Cedefop industry classification to Eurostat data

Cedefop Industry	Eurostat Data (Aggregate)
Agriculture [01]	B-S_X_O
Forestry [02]	B-S_X_O
Fishing [03]	B-S_X_O
Coal [05]	B-F
Oil and Gas [06]	B-F
Other mining [07-09]	B-F
Food, Drink & Tobacco [10-12]	B-F
Textiles, Clothing & Leather [13-15]	B-F
Wood and wood products [16]	B-F
Paper and paper products [17]	B-F
Printing [18]	B-F

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Manufactured fuels [19]	B-F
Other chemicals [20]	B-F
Pharmaceuticals [21]	B-F
Rubber and plastic products [22]	B-F
Non-metallic mineral products [23]	B-F
Basic metals [24]	B-F
Metal products [25]	B-F
Optical & electronic equip [26]	B-F
Electrical equipment [27]	B-F
Other machinery & equipment [28]	B-F
Motor Vehicles [29]	B-F
Other Transport Equipment [30]	B-F
Manufacturing nes [31-32]	B-F
Repair & installation of machinery [33]	B-F
Electricity [35.1]	B-F
Gas, steam & air conditioning [35.2,35.3]	B-F
Water supply [36]	B-F
Sewerage and waste [37-39]	B-F
Construction [41-43]	B-F
Trade and repair of motor vehicles [45]	G-N
Other wholesale trade [46]	G-N
Other retail trade [47]	G-N
Land transport [49]	G-N
Water Transport [50]	G-N
Air Transport [51]	G-N
Warehousing [52]	G-N
Postal and courier activities [53]	G-N
Accommodation & Catering [55,56]	G-N
Publishing activities [58]	G-N
Motion picture and broadcasting activities [59-60]	G-N
Telecommunications [61]	G-N
Computer programming, info serv [62,63]	G-N
Financial services [64]	G-N
Insurance [65]	G-N
Auxiliary to financial & insurance activities [66]	G-N
Real estate activities [68]	G-N
Legal and accounting [69-70]	G-N
Architectural & engineering [71]	G-N
Research & Development [72]	G-N
Advertising [73]	G-N
Other professional activities [74-75]	G-N
Rental and leasing activities [77]	G-N
Employment activities [78]	G-N
Travel agency, tour operators [79]	G-N

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Security and office administrative [80-82]	G-N
Public administration and defence [84]	B-S_X_O
Education [85]	P-S
Human health activities [86]	P-S
Residential care and social work [87-88]	P-S
Arts and entertainment activities [90-92]	P-S
Sports activities [93]	P-S
Membership organisations [94]	P-S
Repair of household goods [95]	P-S
Other personal service activities [96]	P-S
Households as employers of domestic personnel [97]	B-S_X_O

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Appendix 5: Automation Risk by Country

The employment effects of automation by 2030 in Table 7 are for the technical potential of automation set at the mid-point of each category, deployment potential that is region-sector-occupation combination specific, and socio-political restrictor that is region specific and a function of employment protection legislation (B Mid_Scenario in Table 3).

Table 7 Employment effects by 2030 of automation by country (B Mid_Scenario)

Country	Employment (millions)	Loss to automation (millions)	Loss to automation (%)
AT	4,538.1	788.4	17.4
BE	5,071.7	875.5	17.3
BG	3,550.7	658.4	18.5
CH	5,108.5	904.5	17.7
CY	462.2	83.9	18.2
CZ	5,366.4	940.2	17.5
DE	42,056.7	7,619.6	18.1
DK	3,175.3	495.4	15.6
EE	625.6	109.8	17.6
EL	4,401.1	864.5	19.6
ES	21,613.3	4077	18.9
FI	2603.6	385.5	14.8
FR	30,117.1	5,086.7	16.9
HR	1,583.4	279.4	17.6
HU	4475	811.5	18.1
IE	2,439.9	420.5	17.2
IS	243.6	43.4	17.8
IT	26,897.0	4,442.9	16.5
LT	1,374.8	261.6	19.0
LU	482.7	83.6	17.3
LV	898.0	166.8	18.6
MK	692.8	114.6	16.5
MT	220.1	37.7	17.1
NL	9,325.2	1,533.3	16.4
NO	3,152.0	448.1	14.2
PL	15,919.8	2,893.0	18.2
PT	5,123.7	867.5	16.9
RO	8,949.7	1,597.2	17.8
SE	5,258.9	780.2	14.8
SI	1,006.9	202.2	20.1
SK	2,492.1	553.4	22.2
TR	28,422.2	5,229.6	18.4
UK	33,200.8	5,108.8	15.4
EU28	243,229.8	42,024.5	17.3

Source: Own calculations based on Cedefop, Eurofound (2018).

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