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ROBOTS AND SOCIETY

How to compete with robots by assessing job automation risks and resilient alternatives

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The effects of robotics and artificial intelligence (AI) on the job market are matters of great social concern. Economists and technology experts are debating at what rate, and to what extent, technology could be used to replace humans in occupations, and what actions could mitigate the unemployment that would result. To this end, it is important to predict which jobs could be automated in the future and what workers could do to move to occupations at lower risk of automation. Here, we calculate the automation risk of almost 1000 existing occupations by quantitatively assessing to what extent robotics and AI abilities can replace human abilities required for those jobs. Furthermore, we introduce a method to find, for any occupation, alternatives that maximize the reduction in automation risk while minimizing the retraining effort. We apply the method to the U.S. workforce composition and show that it could substantially reduce the workers' automation risk, while the associated retraining effort would be moderate. Governments could use the proposed method to evaluate the unemployment risk of their populations and to adjust educational policies. Robotics companies could use it as a tool to better understand market needs, and members of the public could use it to identify the easiest route to reposition themselves on the job market.

INTRODUCTION

Robotics and artificial intelligence (AI) are at the core of what is often referred to as the fourth industrial revolution (*1*). Sustained progress in these fields is leading to robots that are more autonomous, dexterous, and safer to interact with than their predecessors. Intelligent systems are also outperforming humans in tasks that once appeared out of reach for machines, such as the very complex board game of Go. Such advances—combined with equally important breakthroughs in high-performance computing, "Internet of Things," and new materials—are already producing a visible effect on manufacturing and service sectors (*2*). As a result, a wide-sweeping transformation of the whole economic and productive system is expected over the next few decades.

Although many analysts (*3*) predict that this revolution will positively affect overall productivity and growth, its potential effect on jobs and employment has raised substantial concerns (*4*). Robotics and AI look poised to automate many tasks that are currently done by humans and to reduce the demand for human work across many economic sectors. In principle, this is nothing new: Past waves of automation (such as the mechanization of the textile and agricultural sectors, the introduction of industrial robots in manufacturing, and the computerization of the service sector) have initially increased and then reduced the share of the working population employed in specific sectors (*5*, *6*). The most notable example is probably agriculture, which in 1870 employed 50% of the U.S. workforce. Little more than a century later, in 1980, the share was down to 4%, largely as a consequence of the greater efficiency brought about by mechanization (*7*).

It is often noted that, in past waves of automation, machines mostly replaced humans in low-skill, physical, repetitive work (*8*). In addition, the resulting increase in productivity and growth in gross domestic product (GDP) allowed the expansion of other more labor-intensive sectors, creating enough new jobs to replace the old ones (*9*). As U.S. workers voluntarily shifted from low-income agricultural jobs to high-income manufacturing jobs in the city, this called for more agricultural mechanization, ultimately markedly diminishing the number of agricultural workers and fundamentally reshuffling the labor market equilibrium (*10*).

It has been suggested (*11*) that the social effects of the fourth industrial revolution will be substantially different because the next wave of robotics and AI will affect also medium- and high-skill jobs, including jobs with relevant cognitive and creative components and jobs requiring qualified manual crafts that were hitherto untouched by automation. Although in the long run the effects on productivity and overall economic growth could still be positive, the transition may be painful (*12*, *13*). The disruptive effects of the first and second industrial revolutions on the labor market were slow enough to be absorbed by a generation, and the pace of change was sufficiently slow for the new generation of workers to be trained adequately. Today, with the exponential acceleration of technologies, the convergence of mega trends, and innovations (such as deep learning, nanotechnology and new materials, energy technologies), changes may happen within a lifetime and workers will have to reskill and upskill several times before retirement. These aspects will put pressure on welfare systems to help workers reposition in the job market and on educational systems to train future generations for jobs that will still be performed by humans.

Previous studies tried to assess what jobs are most at risk of being automated using expert opinions (*14*) or by identifying job tasks that could be performed by machines (*15*). However, those studies did not provide indications or advice on how workers displaced by automation could effectively be retrained to move to more future-proof

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jobs. In addition, those studies focused primarily on AI (i.e., algorithms used to automate cognitive tasks) rather than robotics (i.e., machines performing physical work or tasks that combine a physical and cognitive aspect). Recent progress in intelligent physical machines—such as autonomous vehicles, wearable robots, dexterous manipulators, and personal assistants, to mention a few—may make the effects of robotization just as relevant as that of AI-based automation.

In this study, we present an assessment of the likely outcome of the next wave of robotization on almost 1000 different occupations. We assessed to what extent technology is ready to endow robots with the abilities required for jobs and used these assessments to calculate the automation risk of each job. The approach described here provides an objective method for characterizing workers at risk of being displaced by automation and redirecting them toward jobs that are less at risk of being automated and close to their previous jobs in terms of required abilities and knowledge. To this end, for each existing job, we computed an automation risk index (ARI), which assesses the risk of that job being automated by a robot. The ARI is based on how many of an occupation's required abilities can be performed by robots and on the importance of those abilities for that specific occupation. ARI varies within and across occupation families, indicating that it is possible for workers to move to a job with a lower ARI without excessive retraining. Furthermore, for each possible pair of existing jobs, we computed a resilience index (RI), which measures how feasible (in terms of retraining effort) and how convenient (in terms of ARI reduction) it is to switch from one job to another. Thus, for each occupation, we could suggest alternative jobs with the best RI, i.e., the alternative job with the best mitigation of automation risk per unit of retraining effort.

The results of our method can contribute to assessing the unemployment risks of the working population and to designing effective welfare and retraining policies that mitigate the socioeconomic effects of the next industrial revolution. These results could also be relevant to companies and researchers in robotics and AI, who could anticipate sources of social backlash that their work may cause.

ARI and RI model

To build our model of ARI and RI, we started by breaking down a job description into a list of required abilities and knowledge. Furthermore, we measured to what extent abilities can be fulfilled by robots, taking into account how advanced they are in terms of technological development.

The Occupational Information Network (O*NET) is a publicly available dataset (*16*) of 967 job profiles. For each job, O*NET provides a profile consisting of a list of required abilities (i.e., enduring attributes of the individual), skills (i.e., developed/trained capacities), and knowledge (i.e., organized sets of notions that can be learned through education and applied in various domains). For the sake of simplicity, in this study, the 35 skills and the 52 abilities in the O*NET database were grouped and collectively defined as human abilities (for a total of 87 abilities). Furthermore, for measuring the cost of transitioning from one job to another in the RI computation, we also used the O*NET list of 33 human knowledge items, because retraining for a new job typically implies the acquisition of new notions. A given skill, ability, or knowledge can be required in different jobs: For example, both chief executives and taxi drivers require time management skills, although chief executives may need to have these skills at a higher level and use them more extensively. Therefore, O*NET also includes information about the importance of each human ability and knowledge for a given job and at what level the worker must have them to perform that job (see Materials and Methods).

A previous study (*14*) relied on the O*NET dataset to assess how likely a job can be automated, but it did so based on the subjective assessment of only nine requirements (picked from the list of skills, abilities, knowledge, and other categories found in O*NET) by a group of machine intelligence experts. In this study, instead, we propose a method for objectively comparing 87 human abilities with a list of robotic abilities and their level of technological development. Furthermore, we include a method for objectively finding alternative jobs with lower ARI and lower retraining effort that also takes into account 33 human knowledge items listed in the O*NET database.

Our list of robotic abilities is derived from the European H2020 Robotics Multi-Annual Roadmap (MAR) (*17*) released by SPARC, a public-private partnership between the European Commission and the European robotics industry. The MAR document lists a large number of abilities that robots can have, but it is different from the O*NET database in terms of granularity and organization: MAR describes nine ability areas (such as "manipulation"), further divided into specific families (such as "grasping" and "handling"). These families are, in turn, broken down into "levels" (such as "handling of unknown objects"), which are, in effect, the realization of that ability in specific application scenarios. This latter level is the one that—for its granularity and its grounding in operational scenarios—is best comparable with the human abilities as defined in O*NET. Differences in language and organization between the two resources, O*NET and MAR, do not allow a one-on-one matching of abilities. Therefore, for each human ability found in O*NET, we looked for a MAR robotic ability whose definition is conceptually similar. We were thus able to match 36 of the 87 human abilities to 26 robotic abilities. Each of these 36 human abilities was matched to one or more robotic abilities (because, in some cases, the key elements found in one O*NET definition are spread over two MAR definitions), and some robotic abilities were matched to multiple human abilities (see the Supplementary Materials). As for the remaining 51 human abilities, 7 (such as "stamina" or "mathematical reasoning") are intrinsic to the very nature of machines, and thus, they are not even defined in the MAR document. Therefore, we considered them to be intrinsic abilities that machines have at the highest level. The other 44 human abilities could not be matched to any robotic ability because the MAR document does not provide comparable definitions. This does not necessarily mean that machines could not display those abilities, either now or in the future: It only reflects different semantics of the O*NET and MAR documents. We accounted for these unmatched abilities by providing two possible scenarios. In the low-automation scenario, we assumed that unmatched abilities will not be met by intelligent robots in the foreseeable future. In the high-automation scenario, instead, we assumed that those unmatched abilities will be met by robots with the highest level.

In all cases, to measure to what extent a robotic ability could replace a human ability, we used the technological readiness level (TRL) scale as defined by the European Union (*18*) (see the Supplementary Materials for the explanation of the TRL assessment).

We performed a literature search (see the Supplementary Materials for details) to assign a TRL value to each of the 26 robotic abilities directly matched to human abilities. For the seven human abilities labeled as "intrinsic," we considered them as if they were matched to robotic abilities with the highest TRL. For the unmatched human abilities, we considered them as if they were matched to robotic abilities with either the highest TRL in the high-automation scenario or the lowest in the low-automation scenario.

RESULTS

Our method (detailed in Materials and Methods) is composed of two parts. The first part computes, for each job, the ARI as a function *f* of the required human abilities' importance (what share of the job each ability represents), level (how proficient the worker needs to be in that specific ability to perform the job), and the TRL of the corresponding robotic abilities

$$\mathrm{ARI} = \frac{1}{2}\left(f(\mathrm{HA}_{\mathrm{importance}}, \mathrm{HA}_{\mathrm{level}}, \mathrm{TRL}_{\mathrm{ha}}) + f(\mathrm{HA}_{\mathrm{importance}}, \mathrm{HA}_{\mathrm{level}}, \mathrm{TRL}_{\mathrm{la}})\right) \tag{1}$$

where "HA" stands for human ability. For matched abilities, the TRL ranges from 1 to 9 as described previously. For unmatched abilities, instead, TRL has two possible values: $\mathrm{TRL}_{\mathrm{la}} = 0$ in the low-automation scenario, which assumes that the corresponding technology is not developed at all, or $\mathrm{TRL}_{\mathrm{ha}} = 9$ in the high-automation scenario, which assumes that the technology is fully developed. Assuming a uniform prior probability of the two scenarios, ARI is the average of the function *f* separately computed for the low-automation scenario ($\mathrm{TRL}_{\mathrm{la}}$) and for the high-automation scenario ($\mathrm{TRL}_{\mathrm{ha}}$). ARI values are correlated with Frey's and Osborne's automation probabilities (*14*) and with the classification of routine jobs and nonroutine cognitive jobs by Autor *et al.* (*19*) (see the Supplementary Materials). Alternatively, ARI has also been computed using a missing-at-random approach for a sensitivity analysis (see the Supplementary Materials).

ARI can be interpreted as the proportion of human abilities required by a job that machines can perform too. ARI does not correspond to automation probabilities but provides a measure of the relative automation level of a job with respect to all other jobs. ARI = 1 means that machines outperform humans in all the human abilities required by the job, and ARI = 0 means that robotic technologies cannot replace even a single human ability required by the job (see the Supplementary Materials for details). Thus, ARI provides a method for objectively ranking the 967 jobs from the lowest to the highest level of automation risk (see Table 1). In our data, ARI varies from 0.44 of physicists, who score the lowest automation risk, to 0.78 of slaughterers and meat-packers, who score the highest automation risk. Within these bounds lie all other occupations, such as robotics engineers with an ARI of 0.55 (rank 122), economists with an ARI of 0.57 (rank 203), and electrical engineering technicians with an ARI of 0.61 (rank 458). ARIs for physicists, robotics engineers, and economists all lie within the first quartile of the ARI distribution, whereas ARI of electrical engineering technicians lies in the second quartile, and the ARI for meat-packers lies in the fourth quartile. The low-automation component of ARI is lower for all jobs, suggesting that slower technical progress could shield jobs from automation; conversely, the high-automation component of ARI is higher for all jobs, suggesting that accelerated technological development could substantially increase the automation risk of all jobs (Table 1).

O*NET categorizes occupations in families, which are defined as groups of "similar occupations based on work performed and on required skills, education, training, and credentials" (*16*). ARI levels vary both within and across job families, and job families distribute across a continuum from low to high median ARI values (Fig. 1).

Table 1. ARI of five selected jobs. ARI values are obtained by averaging the low-automation and high-automation scenarios (respectively shown in brackets).

Rank	Job	ARI (low-automation, high-automation)
1	Physicists	0.44 (0.20, 0.67)
122	Robotics engineers	0.55 (0.31, 0.80)
203	Economists	0.57 (0.31, 0.83)
458	Electrical engineering technicians	0.61 (0.38, 0.85)
967	Slaughterers and meat-packers	0.78 (0.57, 0.99)

Automation is a key driver of structural change. For example, when U.S. manufacturing started to adopt information technology and automated routine tasks in the late 1970s, workers subsequently switched into lower-paid jobs in the service sector (*15*), which reduced employment in manufacturing. Using ARI as a proxy for assessing exposure to automation risks of occupations in the last two decades, we find that occupations with high ARI (high automation risk) experienced lower employment and wage growth than occupations with low ARI (see the Supplementary Materials for more details).

Retraining and upskilling is a promising strategy for mitigating employment loss (*20*), but it is not always clear how to identify a new job with the lowest retraining effort and highest resilience to future automation. At a first glance, one may think that occupations with smaller ARI are more promising. However, it may be difficult to transition to occupations with the lowest ARI because the required human abilities or human knowledge could differ too much from those of the currently held occupation. Resilient career moves should decrease the risk of automation and, at the same time, require minimum retraining effort to match the required abilities and knowledge.

Let us define $\mathrm{HA}_{\mathrm{retraining\_effort}}$ the retraining effort to improve the abilities required by the new job and $\mathrm{HK}_{\mathrm{retraining\_effort}}$ the retraining effort to improve the knowledge required by the new job. Both efforts range between zero and one and measure to what extent ability or knowledge requirements in the new job B exceed the requirements in the current job A (see Materials and Methods for details). For example, if $\mathrm{HA}_{\mathrm{retraining\_effort}}$ is zero, the current job A is equally or more demanding than the new job B in terms of all abilities. Conversely, if $\mathrm{HA}_{\mathrm{retraining\_effort}}$ is 1, the new job B is more demanding than the current job A in terms of all abilities. The same logic applies to the measurement of $\mathrm{HK}_{\mathrm{retraining\_effort}}$ from job A to job B. We performed a pairwise analysis of all possible combinations for job pairs in the O*NET database and found that low retraining efforts are more common than high retraining efforts (Fig. 2).

A job transition can imply both a change in ARI values and an average retraining effort (ARE) between $\mathrm{HA}_{\mathrm{retraining\_effort}}$ and $\mathrm{HK}_{\mathrm{retraining\_effort}}$. A job change should attempt to maximize the trade-off between automation risk reduction and retraining effort. Therefore, the second part of our method estimates for any given pair of jobs A and B an RI defined as the ratio between the ARI difference when moving from job A to job B and the corresponding retraining effort ARE

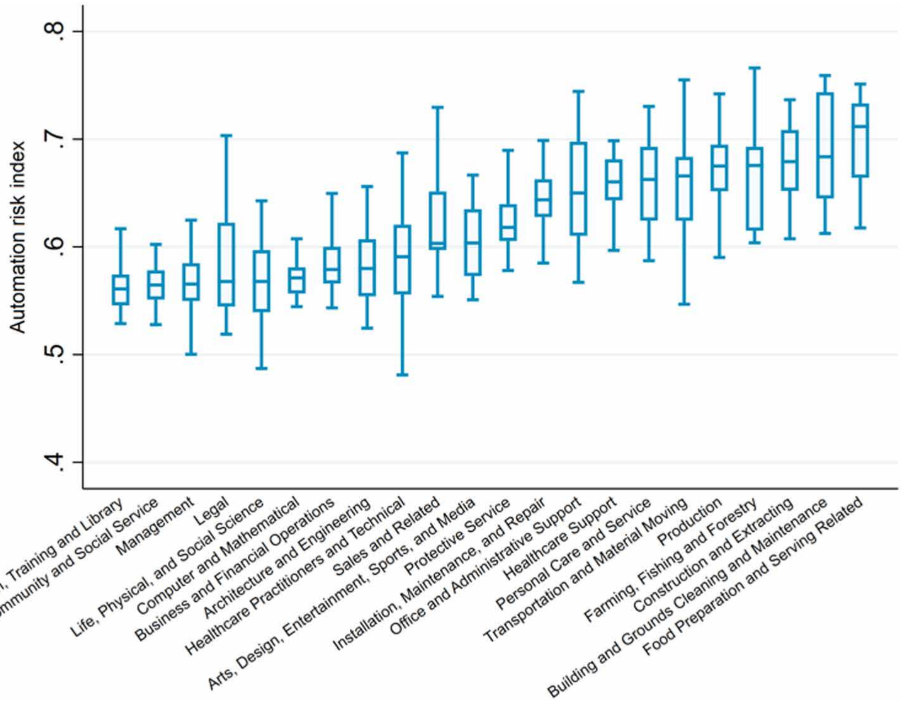

Fig. 1. Automation risk for occupation families. ARI by job families sorted by median ARI values (line inside the box). For each job family, the boxplot shows first quartile (Q1), median (Q2), and third quartile (Q3) of the ARI distribution, and the whiskers indicate the upper and lower adjacent values [within one and one-half of the interquartile range 1.5 (Q3-Q1) of the upper (Q3) and lower (Q1) end of the box].

$$RI_{BA} = \frac{ARI_B - ARI_A}{ARE} \tag{2}$$

Lower RI values indicate job transitions with better trade-offs between automation risk and retraining effort. To illustrate the use of the RI in the identification of a job change, let us consider the example of an electrical engineering technician, which falls approximately in the middle of the automation risk distribution (see Table 1). Different career moves offer different combinations of ARI difference and ARE, whereas the current job has, by definition, retraining effort and ARI change corresponding to zero (black square in Fig. 3). Career moves that increase ARI are not convenient (gray dots in Fig. 3). However, career moves with lower ARI (green dots) display a high diversity of ARE values. The RI yields the lowest value for a job transition to software quality assurance engineers and testers by the connecting line with the steepest slope among all the lines connecting the current job (the black square at the origin in Fig. 3) with the jobs offering an ARI reduction (green dots).

We then applied our method to the U.S. economy to assess how much resilient job transitions would reduce ARI scores of workers and how large the accompanying retraining efforts would be. Specifically, for each occupation, we calculated its percentile in the ARI distribution so that the 1% occupations with the lowest ARI are in percentile 1, and the 1% of occupations with the highest ARI are in percentile 100. To simplify the explanation of the results, we then grouped all occupations in three brackets: the "high-risk" group includes occupations in the 67th to 100th percentiles, the "low-risk" group includes all occupations in the 1st to 33rd percentiles, and the "medium-risk" group includes all occupations that fall between the 34th and 66th percentiles. For each occupation, we simulated a move to the occupation with the best RI and reported the weighted average change in ARI score, in ARI percentile, the human abilities retraining effort, and the knowledge retraining effort. We weighed each occupation by its percentage of the total U.S. workforce based on the 2018 Occupational Employment Survey of the U.S. Bureau of Labor Statistics (*21*), which provides employment and wage estimates for more than 800 occupations in the United States.

Next, we simulated occupation moves according to the largest RI value, i.e., a transition to the occupation that offers the largest reduction in automation risk per unit of ARE (Table 2). Workers in the high-risk group face an average ARI of 0.694, corresponding to an average ARI percentile of 85.78. If all workers in the high-risk occupations were to move to the occupation with the best RI, their average ARI would decrease from 0.694 to 0.626, corresponding to an average ARI percentile of 54.52. This corresponds to a substantial risk reduction that would shift them from a high-risk occupation to a medium-risk occupation. These RI-based career moves demand a retraining effort. For the high-risk group, the human ability retraining effort is equal to 0.116. Similarly, the human knowledge retraining effort between the current job and the new job is 0.071.

Workers in the medium-risk group display an average ARI of 0.614, corresponding to an average percentile of 49.73. If all workers in the medium-risk occupations were to move to the occupation with the best RI, their average ARI would decrease to 0.549, corresponding to an average ARI percentile of 20.60. This corresponds to a substantial risk reduction that would shift them to the low-risk group. The average human ability effort and the average human knowledge effort between current and new jobs would amount to 0.128 and 0.120, respectively. These efforts are higher than those that apply to career moves of high-risk workers (0.116 and 0.071, respectively), suggesting that AREs required by RI-based career moves would be slightly larger for workers currently holding medium-risk occupations than for workers currently holding high-risk occupations.

Workers in the low-risk group display an average ARI of 0.563, corresponding to an average percentile of 19.59. If all workers in the low-risk occupations were to move to the occupation with the best RI, their average ARI would decrease to 0.479, corresponding to an average ARI percentile of 4.07. The average human ability retraining effort between current and new jobs would amount to 0.196, and the average human knowledge retraining effort would be 0.171, which are both higher than the career moves of medium-risk workers. This means that workers in low-risk jobs who move to jobs with considerably higher resilience require the highest retraining efforts among all worker risk groups. Additional simulations, based on RI calculations that give the retraining effort more weight [$RI^2 = (ARI_B - ARI_A)/(ARE)^2$] or less weight [$RI^{1/2} = (ARI_B - ARI_A)/(ARE)^{1/2}$],

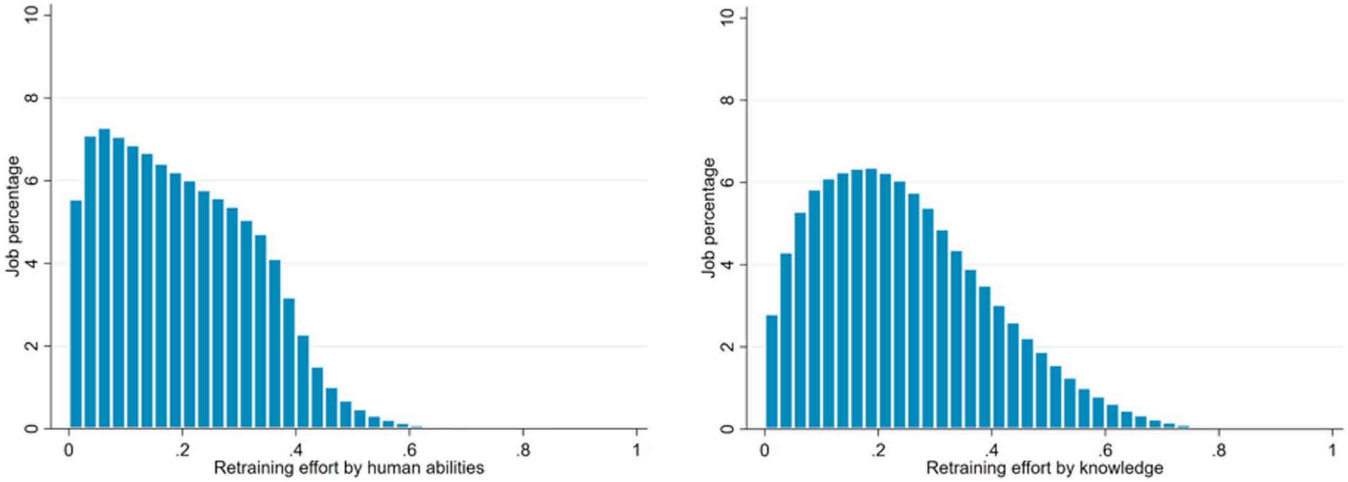

Fig. 2. Retraining effort distribution. Distribution of retraining efforts between any pair of jobs in the O*NET database in terms of human abilities (left) and of knowledge (right). Retraining efforts range between 0 (smallest) and 1 (highest). Percentage sums to 100%. The skewness of the distribution to the left indicates that low retraining efforts are more common than high retraining efforts.

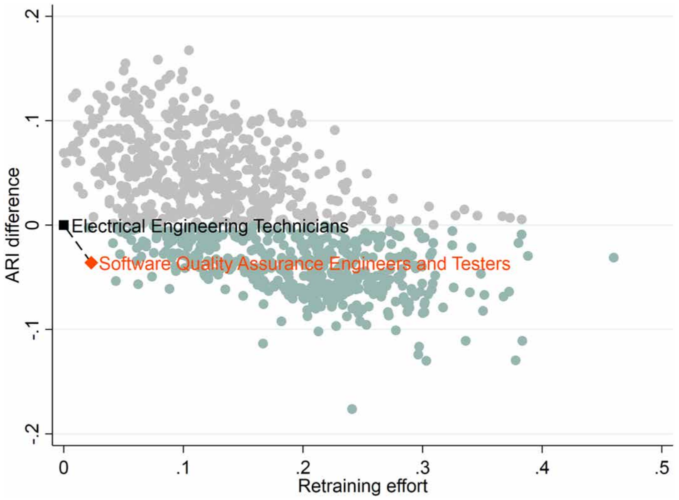

Fig. 3. Mapping career moves. Automation risk difference versus retraining effort for electrical engineering technicians, represented as a black square at the origin. The green dots represent all the occupations having lower automation risk with respect to the origin job, whereas the gray dots are the ones with higher automation risk. The career move suggesting the job with the best RI is the green dot (software quality assurance engineering and testers) connected to the origin through the steepest line and is here identified by the red diamond.

yield qualitatively similar results, although the retraining effort's weight does affect the range of proposed career moves (see the Supplementary Materials).

DISCUSSION

Unlike previous studies of the risks of job automation, the method described here is based on an extensive correspondence between human abilities defined in the O*NET database and robot abilities defined the European H2020 Robotics MAR, further weighted by the assessment of technology readiness levels (TRLs) (*22*).

Although the ARI values obtained with the method described here are correlated (correlation coefficient = 0.67) with probabilities of automation provided by Frey and Osborne (*14*), that study focused primarily on AI (i.e., algorithms used to automate cognitive tasks) rather than on robotics (i.e., machines performing physical work or tasks that combine a physical and cognitive aspect). Recent progress in intelligent physical machines—such as autonomous vehicles, wearable robots, dexterous manipulators, and personal assistants, to mention a few—will make the results of robotization just as relevant as those of AI-based automation. Furthermore, our method systematically considers all abilities and skills that are relevant for an occupation according to the occupational O*NET database, whereas Frey and Osborne (*14*) used expert assessments about the automation of a few "bottleneck tasks," as they defined them. As a result, our approach delivers a more granular and comprehensive assessment of automation risks. Frey and Osborne (*14*) did not provide indications or advice on how workers displaced by automation could effectively be retrained to transition to better future-proof jobs, whereas here we proposed an RI to generate recommendations of career transitions that reduce risk exposure and require smaller retraining effort.

Because our method takes into account AI abilities in physical robotic machines, whereas previous studies focused on AI in computer software, it captures a larger share of the abilities and knowledge deployed by the working human population. We expect that the difference between the low-automation scenario and high-automation scenario computations of the ARI will reduce over time as robotic abilities improve and robotics companies bring to the market new intelligent machines.

A limitation of this study is the subjectivity in the source data. Although O*NET data are extensively used in the economic literature, they are based on subjective evaluations provided by respondents to periodical surveys. Similarly, the definitions of robotic abilities listed in MAR are provided by several expert groups that work in specific areas of robotics. Even the TRL scale, although widely used in industry and research, is not immune from criticism (*23*). In addition, in this study, we add further subjectivity when matching robotic abilities with human abilities and when we assign

Table 2. Simulation of job change based on RI. Results refer to employment weighted averages based on 2018 U.S. employment percentages (*21*). Statistics: own calculations with *t* test.

Occupation group	Average ARI (average percentile)	Average ARI of the best RI suggestion (average percentile)	Average ARI change (average percentile change)	Average human abilities retraining effort	Average human knowledge retraining effort
High risk	0.694*,† (85.78)	0.626*,† (54.52)	−0.069 (−31.26)	0.116†	0.071*,†
Medium risk	0.614†,‡ (49.73)	0.549†,‡ (20.60)	−0.065 (−29.13)	0.128†	0.120†,‡
Low risk	0.563*,‡ (19.59)	0.479*,‡ (4.07)	−0.085 (−15.52)	0.196*,‡	0.171*,‡

*Different from the medium risk at 5% significance level. †Different from the low risk at 5% significance level. ‡Different from the high risk at 5% significance level.

TRL values based on the analysis of the technical literature. To address this issue, future work could consider a larger pool of experts repeating and complementing those analyses and a blind-coding protocol. Furthermore, in the future, it would be interesting to include an estimate of robotics installations and operation costs to further refine the assessment of the effect on the labor market.

In addition, here, we proposed a quantitative method to identify resilient career transitions that offer the best reduction of automation risk per unit of retraining effort. When applied to the 2018 U.S. workforce, the method substantially reduced the average automation risk of the workforce. In particular, the method would allow workers in the occupations with the highest risk to shift toward medium-risk occupations while undergoing a relatively low retraining effort.

The method described here could thus be used by governments to measure how their employment base could face automation risks and possibly adjust retraining policies, by companies to assess the costs of increasing automation, by robotics companies to better understand and tailor their products and services to the market needs, and by members of the public as a tool to identify the easiest route to reposition themselves on the job market. As an example of the latter use, we provide a website that generates the automation risks of jobs and suggests three resilient alternatives (*22*).

MATERIALS AND METHODS

Data

O*NET is an online service developed for the U.S. Department of Labor for information on the capability requirement profiles of jobs. The 2019 version of O*NET contains information on 967 data-level occupations, closely adopting the Standard Occupational Classification (SOC): a standard used by all U.S. federal agencies to classify workers into occupational categories. The O*NET data were initially collected from labor market analysts and have since been regularly updated by surveys of each occupation's worker population and related experts to provide up-to-date information on occupations as they evolve over time. O*NET defines the key features of an occupation as a standardized and measurable set of abilities, skills, and knowledge. For each ith occupation, we extract from O*NET the following pieces of information: w_{ij} and l_{ij}, i.e., the normalized importance and required level of the jth human ability, and v_{ih} and p_{ih}, i.e., the normalized importance and required level of the hth human knowledge.

Original O*NET importance values range from 1 to 5, whereas the required level ranges from 0 to 7. The importance measures follow the same dimension for all abilities. Therefore, we construct the normalized importance measures by simply subtracting 1 from the original value and dividing the difference by 4. Conversely, the required level measures build on different minimum and maximum anchor levels. We take these levels into account in our normalizations (the word "normalization" is used in this context to refer to a transformation to a 0 to 1 scale): The normalized required level measures are produced by dividing the value by the maximum anchor level. The normalized human ability values are then used to measure the human characteristics with respect to the robotic technology, as shown below.

We introduce the matched technology level, τ_j, which is the normalized TRL value of the robotic ability matched with the jth human ability (for an overview on the human-robotic abilities matching and the corresponding matched TRL, see Table 2). If one human ability is matched to more than one robotic ability, we consider the lowest TRL value, because all of those robot abilities are required to replace the human ability. The variable τ_j is thus used to express the level of the technology linked to each human ability and ranges from 0 to 1. The special case of intrinsic abilities is handled by setting the corresponding τ to 1. For the unmatched abilities, we provide the double scenario analysis: the low-automation scenario prediction by assessing $\tau = 0$ and the high-automation scenario by assessing $\tau = 1$.

Computation of the ARI and the RI

The ARI is computed from the following quantity

$$r_i = \frac{\sum_{j=1}^{N} w_{ij}\, d(\tau_j - l_{ij})}{\sum_{j=1}^{N} w_{ij}}, \forall i = 1, \ldots, P \tag{3}$$

where N and P are the number of human abilities and jobs considered in our study, respectively, and d is a logistic distribution function, chosen to describe the possible takeover of the human jobs by robots, with location and scale parameters set to 0 and 0.05, respectively. Equation 3 is computed for both the low-automation (r_i^{la}) and high-automation scenario (r_i^{ha}); the ARI is thus obtained by averaging the two versions

$$\mathrm{ARI}_i = \frac{1}{2}(r_i^{\mathrm{la}} + r_i^{\mathrm{ha}}) \tag{4}$$

The RI is based on the ARI and on the retraining effort required to move from one job to another. Our measure of retraining effort builds on those human abilities and knowledge that are more important or that are required at a higher level in the new job than the old one. The human abilities and knowledge that are less demanding on the new job do not create retraining effort. To measure retraining effort, we first assess similarity of the human abilities and knowledge required by the two jobs. Specifically, consider a worker that moves from job A to job B; the similarity with respect to the jth human ability importance is called W^j_{BA} and defined as

$$W^j_{\mathrm{BA}} = \frac{g(k(w_{\mathrm{B}j} - w_{\mathrm{A}j}))}{g(0)} \text{ if } w_{\mathrm{B}j} > w_{\mathrm{A}j},\ W^j_{\mathrm{BA}} = 1 \text{ otherwise} \quad (5)$$

recalling that $w_{\mathrm{A}j}$ and $w_{\mathrm{B}j}$ are the jth normalized importance required by job A and B, respectively. Note that only the abilities that are more demanding in job B than in job A are considered. Specifically, in Eq. 5, if job B has a lower or equal importance requirement on the jth ability than job A, we set the similarity of importance to 1 because the new job B is less demanding than job A. Conversely, if job B has a higher importance requirement on the jth ability than job A, we assume that similarity is computed from the function g, a normal density function designed with the mean parameter equal to 0, and variance equal to 1. As in nonparametric statistics, we use this bell-shaped normal density as a kernel function to assess to what extent the values on normalized importance, i.e., the values $w_{\mathrm{B}j}$ and $w_{\mathrm{A}j}$ in Eq. 5 are similar for the two different jobs. The bell-shaped curve assumes that the similarity is greatest when the normalized importance $w_{\mathrm{B}j}$ and $w_{\mathrm{A}j}$ are exactly the same for the two jobs; the similarity declines as $w_{\mathrm{B}j}$ and $w_{\mathrm{A}j}$ become more and more different. In Eq. 5, the scalar parameter k is used to tune the sensitivity of W^j_{AB} with respect to small differences between $w_{\mathrm{B}j}$ and $w_{\mathrm{A}j}$. We set k equal to 5 using heuristic (we have also explored uniform kernels, and our results vary only little).

Using the same rationale, we also compute the similarity of jobs A and B with respect to the human ability level $\left(L^j_{\mathrm{BA}}\right)$, human knowledge importance (V^j_{BA}), and human knowledge level (P^j_{BA}). These quantities are defined as follows

$$L^j_{\mathrm{BA}} = \frac{g(k(l_{\mathrm{B}j} - l_{\mathrm{A}j}))}{g(0)} \text{ if } l_{\mathrm{B}j} > l_{\mathrm{A}j},\ L^j_{\mathrm{BA}} = 1 \text{ otherwise} \quad (6)$$

$$V^j_{\mathrm{BA}} = \frac{g(k(v_{\mathrm{B}j} - v_{\mathrm{A}j}))}{g(0)} \text{ if } v_{\mathrm{B}j} > v_{\mathrm{A}j},\ V^j_{\mathrm{BA}} = 1 \text{ otherwise} \quad (7)$$

$$P^j_{\mathrm{BA}} = \frac{g(k(p_{\mathrm{B}j} - p_{\mathrm{A}j}))}{g(0)}, \text{ if } p_{\mathrm{B}j} > p_{\mathrm{A}j},\ P^j_{\mathrm{BA}} = 1 \text{ otherwise} \quad (8)$$

to which the same analysis done for W^j_{BA} applies.

The jobs similarities are then used to compute the retraining effort required to move between two jobs. The effort to retrain the human abilities to move from job A to job B is called H_{BA}. We assess what proportion of the new requirements in B can be already covered by requirements in job A, and retraining effort is the part that remains. The part that job A already covers for B is measured by joint similarity, $W^j_{\mathrm{BA}} L^j_{\mathrm{BA}}$, i.e., the product of importance similarity, W^j_{BA}, and level similarity, L^j_{BA}. The remaining part, retraining effort on the single jth ability, is $1 - W^j_{\mathrm{BA}} L^j_{\mathrm{BA}}$.

The human ability retraining effort is then the sum of the retraining effort on each ability, divided by the number of abilities

$$H_{\mathrm{BA}} = \frac{\sum_{j\in 1}^{N} (1 - W^j_{\mathrm{BA}} L^j_{\mathrm{BA}})}{N} \quad (9)$$

Similarly, the effort to retrain the knowledge to move from job A to job B is called K_{BA} and defined as

$$K_{\mathrm{BA}} = \frac{\sum_{j\in 1}^{Q} (1 - V^j_{\mathrm{BA}} P^j_{\mathrm{BA}})}{Q} \quad (10)$$

where Q is the number of knowledge items extracted from O*NET.

The difference between job A and job B in terms of ARI is simply computed as

$$\mathrm{ARI}_{\mathrm{BA}} = \mathrm{ARI}_{\mathrm{B}} - \mathrm{ARI}_{\mathrm{A}} \quad (11)$$

The quantities H_{BA}, K_{BA}, and $\mathrm{ARI}_{\mathrm{BA}}$ are finally combined together to compute the RI to move from job A to job B

$$\mathrm{RI}_{\mathrm{BA}} = \frac{\mathrm{ARI}_{\mathrm{BA}}}{\sqrt{H_{\mathrm{BA}} K_{\mathrm{BA}}}} \quad (12)$$

This index relates the difference in ARI, $\mathrm{ARI}_{\mathrm{BA}}$, to the geometric ARE, defined as $\mathrm{ARE}_{\mathrm{BA}} = \sqrt{H_{\mathrm{BA}} K_{\mathrm{BA}}}$, which captures the average human ability and knowledge retraining effort to move between two jobs. Recent data on job transitions extracted from 16 million resumés (*24*) show that transitions occur more frequently between jobs with small ARE values and decrease for jobs with larger ARE values, probably because of large educational or ability barriers. Furthermore, all transitions recommended by our RI correspond to frequent job transitions observed in the data and are thus feasible (see the Supplementary Materials). Note that H_{BA} and K_{BA} are strictly positive; therefore, the denominator is never zero, and $\mathrm{RI}_{\mathrm{BA}}$ is well defined. For any job, all the other existing jobs can be sorted according to the corresponding RI using Eq. 12, actually providing a ranking of resilient alternatives.

SUPPLEMENTARY MATERIALS

www.science.org/doi/10.1126/scirobotics.abg5561
Supplementary Text
Tables S1 to S6
Figs. S1 to S4
References (*25*–*123*)

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