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Labour automation and challenges in labour inclusion in Latin America

Regionally adjusted risk estimates based on machine learning

Ernesto Espíndola
José Ignacio Suárez

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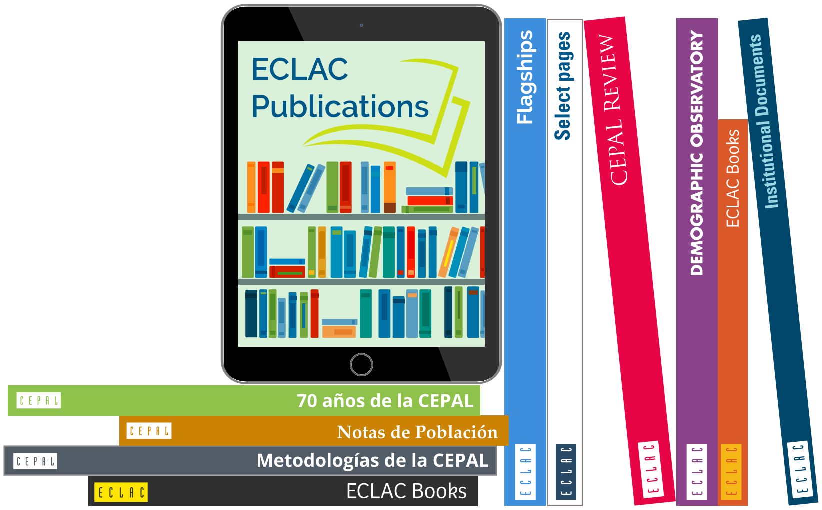

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This document was prepared by Ernesto Espíndola, Senior Research Assistant in the Social Development Division of the Economic Commission for Latin America and the Caribbean (ECLAC), and José Ignacio Suárez, consultant in the Division, under the supervision of Rodrigo Martínez, Senior Social Affairs Officer in the same Division. The document was prepared as part of the European Union Regional Facility for Development in Transition project "Stratification and social mobility in middle-income countries. Challenges facing an uncertain future", implemented by ECLAC under the coordination of Rodrigo Martínez.

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Introduction

In recent decades, rapid technological progress has generated a growing interest in the transformation of the world of work. This concern is based on the potential of emerging technologies to replace tasks and roles traditionally performed by human beings, either partially or entirely. It is, therefore, essential to examine and understand the social, economic, and ethical implications of this process and seek solutions to harness the benefits associated with the automation of production processes and mitigate possible negative impacts.

This paper seeks to estimate job automation's probabilities and risks and analyse its potential impacts on labour inclusion in Latin America. To this end, this document implemented a machine learning-based methodology adapted to the specific characteristics of the region using data from PIAAC surveys and household surveys. In this way, the aim is to build a probability vector of job automation adapted to the region. This vector can be reused in any source of information that contains internationally comparable occupational codes, such as household surveys or employment surveys.

The study provides novel estimates of labour automation based on Latin American data and analyses the phenomenon in different aspects of labour inclusion and social stratification. The results show that the risks of automation vary among different social groups, which points to the need to build adapted and efficient policies that address the diverse needs that this process imposes. To this end, the document addresses different policy areas to promote effective labour inclusion in an era of rapid advances in intelligent technologies, ensuring that all individuals can access decent employment and so that these inequalities can be addressed effectively.

This study is an expanded version of chapter III of the document "Automation and labour inclusion in Latin America. Potential impacts, vulnerabilities, and public policy proposals" of the "Stratification and social mobility in middle-income countries. Challenges facing an uncertain future" project, part of the Regional Mechanism for Development in Transition programme of the European Union and ECLAC. This document seeks to provide information and knowledge on the challenges and opportunities that labour automation represents for Latin America. By better understanding these challenges, it will be possible to design appropriate strategies and policies that promote sustainable development, equity, and prosperity in the region in an economy in constant technological transformation. It also presents the main challenges, limitations, and methodological and information source opportunities, which help map out future lines of research in this area.

I. Background

A. New technologies and their social and economic effects

The human capacity to develop technologies, tools and methods to improve productive efficiency has been a determining factor in the advancement of civilisations. In recent decades, however, there has been a growing concern about rapid technological progress and its implications for transforming human work. This concern is partly based on the possibility that emerging technologies may partially or entirely replace work tasks and roles traditionally performed by humans (Acemoglu and Johnson, 2023). This concern reflects the need to examine and understand the social and economic implications of this evolving phenomenon and the need to adapt and seek solutions to harness the benefits and mitigate the potential negative impacts associated with the automation of production processes.

Technological development in recent decades is characterised by integrating areas such as robotics, artificial intelligence and nanotechnology, sometimes summarised by the term "STARA" (Smart Technology, Artificial Intelligence, Robotics and Algorithms) (Brougham and Haar, 2020).By the end of 2022, the rapid development of new technologies was marked by the emergence of several applications based on generative artificial intelligence (using natural language processing models generically called "LLM" - *Large Language Models*) open to the public, such as the GPT, LLaMa, LaMDA or PaLM series. LLMs are capable of performing a large number of tasks through a text interface that can adapt to user requests. As a result, this set of innovative new technologies has opened up the possibility of automating cognitive and non-routine tasks previously considered difficult to address technologically (Author, Levy and Murnane, 2003). As such, this technological progress poses challenges and risks, as various tasks and occupations are in danger of being replaced or significantly transformed. Indeed, this impacts society in general and the world of work, requiring increasingly rapid adaptation to technological advances. Moreover, it is essential to assess the impact of these advanced technologies on creating new productive needs and demands, as well as on the generation and partial or total loss of jobs.

Technological progress also brings existential questions about the organisation of society and the role of human beings in the world. At the beginning of the 20th century, authors such as Heidegger (1996) warned of the dangers of how technology could separate human beings from the natural existence around them and relegate them to an alienated situation in which people lose their agency. The significant development of robotics and artificial intelligence has increased the complexity of the relationship between technology and humanity and how humans modify their environment by working for their benefit. As we enter the 21st century, and as Castells (2000) states, the dynamics of social relations are strongly rooted in technology and the increasing absence of presence in social micro-interactions, both in the sphere of work and in everyday life, introduces new forms of immediate communication that transform the vision and expectations we have of others and ourselves. For his part, Sennett (1999) also emphasises the danger of the dehumanising effects of technology and how there is a persistent risk of losing sight of technology as a means to benefit society rather than as an end. Such a dehumanising perspective is both socially and environmentally dangerous, as it fails to give special consideration to the effects of the means of production on the environment, placing more emphasis on personal productive benefits than the social and natural environment. More recently, and in line with the above, authors such as Crawford (2021) have developed major debates about the global costs of the advance of artificial intelligence, both in terms of its political and environmental dangers and its potential effects on increasing inequality as a result of changes in the world of work. Artificial intelligence may also have detrimental effects on certain traditionally discriminated social groups, as these technologies can help reproduce biases and prejudices in different areas of public decision-making (Eubanks, 2019; Suguri Motoki, Pinho Neto and Rodrigues, 2023).

Indeed, among the many challenges in implementing these new technologies, one of the most recently discussed in the literature is the impact on the world of work. Different authors have argued that the adoption of STARA technologies brings benefits such as increased productivity in specific industries and high costs for workers and society as a whole (Acemoglu et al., 2022; Damioli, Van Roy and Vertesy, 2021; Ing and Grossman, 2022; Noy and Zhang, 2023). Along these lines, there has been considerable scientific effort in recent years to estimate the impact of technology on labour automation, as technological capabilities allow workers to be replaced in certain roles, which could result in unemployment and economic hardship for those affected (Acemoglu and Restrepo, 2018; Arntz, Gregory and Zierahn, 2016; Frey and Osborne, 2017; Gruetzemacher, Paradice and Lee, 2020; Nedelkoska and Quintini, 2018). In this way, labour automation would also contribute to the polarisation of the labour market (Author, 2019), where highly skilled and highly educated workers would be less likely to lose their jobs due to technology implementation compared to those with lower skill levels.

The risks of automation are, in turn, framed by skills mismatch —a major global social and economic problem. This refers to the lack of workers with the skills required to meet the demands of the labour market, resulting in increased levels of unemployment, lower productivity and difficulties in filling vacancies (Gontero and Novella, 2021). This issue has been accentuated by rapid technological advances, which demand new skills and adaptation from workers at an ever-increasing pace. Thus, when gaps are too large or persistent, they come at a high cost for employers and workers and can exacerbate existing inequalities (OECD, 2019). This situation is even more relevant in an environment of profound technological change that may lead to many jobs' partial or complete automation.

Job losses and difficulties finding new job opportunities can lead to significant increases in inequality, job insecurity and job exclusion, especially if the workers most vulnerable to this process lack the capacity to adapt to such changes. These factors contribute to growing job insecurity among workers (Fischer, 2020; Nam, 2019), both because of the perception that technology threatens to replace their jobs and the pressure to adapt and acquire new skills to stay in the labour market. According to Brougham and Haar (2020), this technology-related job insecurity has been associated with more significant support for measures to mitigate its disruptive effects on the market in countries such as the United States, Australia and New Zealand. In this vein, several factors could influence the shape of jobs in the future, including government intervention, union pressure, reorganisation of work tasks and acceptance of new forms of work (Brougham and Haar, 2020; Kilkki et al.).

B. Labour inclusion and automation in the region

Promoting labour market inclusion is a crucial objective in social development and comprises two interconnected dimensions. The first dimension concerns labour market integration, which can be facilitated or hindered by the presence or absence of barriers limiting access. The second dimension focuses on the conditions for workers' participation, such as access to decent, quality jobs that guarantee labour income and pensions above the poverty line and offer employment free of abuse and danger to their workers (Espejo and Huepe, 2023).

Latin America is one of the world's most unequal regions in the world. Various structuring factors, such as social class, life cycle, gender and ethnic-racial status —among others— shape social inequality in the region. These factors are interconnected and mutually reinforcing, facilitating or hindering access to opportunities and the full exercise of social, cultural and economic rights, well-being and autonomy (ECLAC, 2017). Thus, the concept of labour inclusion provides the possibility to analyse structural and individual factors that influence the integration and characteristics of labour market participation of various vulnerable groups (Huepe, 2023).

Given its crucial role in inclusive and sustainable social and economic development, the goal of decent work was included, along with economic growth, in the eighth Sustainable Development Goal of the 2030 Agenda. Specifically, target 8.5 of this goal highlights the importance of labour inclusion of specific groups by seeking to "achieve full and productive employment and ensure decent work for all, including for young people and persons with disabilities, and equal pay for work of equal value".[1] Accordingly, considering what ECLAC has stated (2020) the labour sphere can reduce or mitigate existing inequalities. However, it can also reproduce or even aggravate them through the inequitable distribution of labour income and the processes of exclusion and inclusion inherent to the functioning of regional labour markets.

Accelerated technological advances may affect labour market inclusion in both constitutive dimensions. On the one hand, within the skills and competencies mismatch paradigm, workers may face increased barriers to employment due to a lack of skills needed to (re)enter a changing and increasingly digitised labour market. On the other hand, job stability and quality could also be affected, as several occupations could potentially be at risk of full or partial automation. In such a scenario, many workers may need more resources and time to adapt to changing job conditions, task reorganisations requiring new skills, or face job loss altogether.

In this context, informality is central to the challenges for labour inclusion in the region. According to the International Labour Organization's (ILO) Labour Outlook 2022 for Latin America and the Caribbean (2023), the informality rate of young people is close to 60%, while that of adults is around 47%. The lack of formal jobs, coupled with a non-existent or at least inadequate level of protection for informal workers, remains a significant source of vulnerability for workers and their families. In the context of potential labour automation, vulnerability becomes more evident; thus, informal workers are left out of training and retraining possibilities within the workspace and unprotected from unemployment due to technological change, among other possible vulnerability factors (OECD, 2023a).

[1] Available [online] https://sdgs.un.org/goals/goal8.

In this report, relying on the available data sources and the results' relevance, the analysis focuses on the job stability dimension (full or partial automation risk) rather than access difficulties or job quality. The study of possible gaps in access or job quality associated with the risks of automation goes beyond this research's scope, which can serve as a starting point for future studies addressing other aspects of labour market inclusion as they relate to technological change.

C. Estimates of labour automation: the contribution of Frey and Osborne

In recent years, there has been a growing interest in estimating the potential capacity of automation and describing its possible implications for the world of work and society in general. One of the most influential recent works is that of Carl Frey and Michael Osborne (2017), in which they set out to estimate the susceptibility of jobs to computerisation - understood as automation through technologies associated with computers and digitisation, such as robotics, big data and artificial intelligence, among others. In contrast to the pioneering work of Autor, Levy and Murnane (2003), Frey and Osborne (2017) argue that technological advancement at the time would be capable of automating not only routine and non-cognitive tasks but a broader set of activities. In 2010, the authors held a workshop at Oxford University in which they brought together experts in robotics and computer science to establish two essential consensuses: first, what were the "*bottle-necks*" of computerisation; that is, those aspects that were difficult or beyond the capacity of technological automation at the time. And second, which occupations they were sure would or would not be fully automatable in the foreseeable future.

During the workshop, areas were identified as key barriers to technological automation: (i) social intelligence, (ii) creative intelligence and (iii) perception and manipulation. First, social intelligence involves a complex set of communication, perception, empathy and prudence skills, which are difficult to process and recreate through technology. Secondly, creative intelligence involves complex problem-solving, imaginative and creative skills at an expert level, which are difficult to emulate. Finally, manual skills, especially those requiring precise physical coordination, speed, adaptability or dexterity in difficult positions, remained challenging to automate during the workshop in 2010, especially in robotics. In addition, during the workshop, a list of occupations was generated in which the experts had a high degree of certainty as to whether or not they would be fully automatable in the near future, taking into account the level of technological development at that time. This list was constructed using the 2010 O*NET survey, which provided information on the task composition and labour skill use of diverse occupations and allowed 70 occupations —out of a total of 702— to be ranked with a value of zero (0) if they were considered fully non-automatable, and with a value of one (1) if they were fully automatable. The remaining occupations were initially left unclassified.

Using these two elements as a basis, Frey and Osborne developed a methodological strategy to estimate the automation susceptibility of occupations in the United States using the 2010 O*NET survey. To perform a task or set of tasks, workers need to possess different types of skills to perform them. Thus, following the perspective of Autor, skills are associated with a series of tasks, which in turn are part of the respective occupations. The proposal of Frey and Osborne (2017) established that the level of automation depends on the skills that workers use in their tasks. As mentioned earlier, the bottlenecks were operationalised into a battery of nine indicators of non-automatable job skills associated with each bottleneck dimension.

In order to estimate the level of automation of occupations, Frey and Osborne (2017) used *machine learning* algorithms to predict the probability of an occupation becoming automated based on information from 70 previously classified occupations. *Machine learning* algorithms are artificial intelligence techniques that allow classification and prediction through an autonomous or semi-autonomous (supervised) learning process. These algorithms capture patterns in the data through which they can learn and modify themselves to maximise their predictive capacity by using a series of predictor variables. In this case, the variables used to predict were the set of indicators that would represent non-automatable skills. Through an iterative process, the authors trained different supervised learning algorithms. They selected the algorithm with the best performance in classifying occupations to predict the susceptibility of automation on the entire database.

Thus, in the methodology of Frey and Osborne (2017), the probability[2] of automation depends mainly on the skills deployed by each worker in their occupation, considering the technological landscape and the susceptibility of certain occupations to automation. The authors deliberately did not consider the economic aspects associated with task automation, nor did they consider political or social elements, such as possible regulations or preferences that could influence its implementation. In other words, this approach focuses exclusively on technological aspects to obtain the results. Finally, the probability of automation at the individual level was predicted using a subjective assessment of the automation potential of various occupations and based on the skills employed by workers. Using this methodology, the authors found that approximately 47% of jobs in the United States were at risk of being automated in the coming decades, with vast differences across industries and sectors of activity.

The work by Frey and Osborne (2017) has been of great importance in highlighting the relevance of labour automation in both the academic community and the public sphere in recent years. Moreover, the authors implemented innovative (subject-relevant) methods to carry out these estimates. However, their methodology has received criticism in various fields, mainly because by pre-classifying certain occupations as fully automatable or non-automatable without taking into account the diversity of tasks within each occupation, it is argued that their approach in practice is based on occupations rather than tasks, and may overestimate the risk of automation (Arntz et al., 2016; Nedelkoska and Quintini, 2018). Moreover, their study has the limitation that the results only apply to the US labour market.

D. Novel approaches to automation risk estimation

Subsequently, several studies have set out to estimate labour automation in other regions of the world. Of particular note is the paper by Arntz, Gregory and Zierahn (2016), in which they applied an approach that they called strictly task-based (and not occupation-based) and concluded that, on average, 9% of jobs are automatable for 21 countries belonging to the Organisation for Economic Co-operation and Development (OECD), far from the 47% of Frey and Osborne (2017) for the United States. Meanwhile, Nedelkoska and Quintini (2018) employed a hybrid methodology between Frey and Osborne (2017) and Arntz, Gregory and Zierahn (2016) , seeking to expand the results for all 32 OECD countries. The authors used the PIAAC (*Programme for the International Assessment of Adult Competencies*) surveys and operationalised the bottlenecks from Frey and Osborne (2017) with skill indicators available in the background questionnaire. The results of Nedelkoska and Quintini (2018) show that the average high risk of automation is 14% for OECD countries, albeit with considerable variability across countries. These findings highlight the importance of considering the variety of attributes present in the labour market in different countries and regions of the world.

It is also relevant to mention the article by Lassébie and Quintini (2022) which stands out for surveying experts to assess the degree of automation of various skills and abilities. In this study, the authors used the O*NET survey and solicited the participation of 8 artificial intelligence experts, who assessed the level of automation of 98 specific skills and abilities included in the questionnaire, whose central question was "Given current capabilities, would you say that the following skills or abilities can

[2] The authors use the term "probability" to denote the similarity of an occupation to zero (0, completely non-automatable) or to one (1, completely automatable). In other studies, other terms are also used to refer to the resulting values between 0 and 1, such as pseudo-likelihood, vote ratio, or ranking.

be automated?".[3] Although the sample of experts consulted was small, the results obtained in this survey are of great value, as they provide an up-to-date assessment of technological capabilities to date. This work contrasts with previous research by Frey and Osborne(2017), whose data dates back to 2010.

Generally speaking, the findings of Lassébie and Quintini (2022) indicate that many of the skills identified previously by Frey and Osborne (2017) as barriers to automation remain challenging to replace with technology, except for skills related to perception and manipulation. According to their results, skills such as agile object manipulation or the ability to use force dynamically and adaptively could be automatable with available technology by 2022. The authors also project that jobs with a high risk of automation will not disappear completely, as only 18-27% of the skills and abilities required in these occupations are highly susceptible to being replaced by automation in OECD countries.

Meanwhile, information on the effects of automation in developing countries, especially Latin America, is limited. Of particular note is the research by Egana-delSol (2019) which used the World Bank's STEP surveys[4] to compare the approaches of Frey and Osborne (2017), Arntz, Gregory and Zierahn (2016) and Webb (2019) in 10 countries in Africa, Asia-Pacific and Latin America. Their results suggest that developing countries face higher automation risks than countries in the global North. For the case of Latin America, the article by Egana-delSol et al. (2022) reports the effects of automation disaggregated by gender for four countries in the region (Plurinational State of Bolivia, Chile, Colombia and El Salvador) and found that women have a slightly higher automation risk than men, 21% versus 19%, respectively. These findings are consistent with those found by ILO (2021) in which they note that women in selected Latin American countries[5] perform tasks with routine content in higher proportions than men and would therefore be at higher risk of automation.

Gasparini et al. (2021) used PIAAC and household surveys to analyse the performance of routine tasks in the region, finding labour market behaviours that support the labour polarisation hypothesis. In addition, national cases in the region have been addressed, such as the article by Bravo, García and Schlechter (2019) for Chile. In the latter study, the methodology of Frey and Osborne (2017) was adapted using the PIAAC and the CASEN survey (*"Encuesta de Caracterización Socioeconómica Nacional"*), the most important household survey in the country. The authors applied machine learning algorithms in two stages: first, to predict skill use in CASEN from PIAAC survey data for Chile, and second, to predict automation using CASEN and the predicted skill variables as predictors. This paper estimates that the average probability of automation in Chile is 42.2%, while 17% of the employed would be at high risk of automation. Similarly, according to this study for Chile, middle-income workers are the most likely to be replaced by technology, and those with medium and low skill levels have a higher risk than those with high skill levels.

Likewise, ECLAC, in collaboration with the Organisation of Ibero-American States for Education, Science and Culture (OEI) , carried out a report to estimate the probability of automation in 14 countries in the region It adapted the methodology Bravo, García and Schlechter (2019), developed by applying it to household surveys in each country. This work, along with other work by Weller, Gontero and Campbell (2019), and Gontero and Novella (2021), have been particularly relevant in taking the first steps to develop a coherent estimation strategy in accordance with the reality of Latin American countries and their sources of information, and to provide a basis for addressing these issues from labour and education policies adapted to the particularities of the region.

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3 The possible answers are: "0.a - No, and it will not be possible in the near future (in the next five to 20 years); 0.b - No, but it will probably be possible in the near future (at least in certain contexts); 1 - Yes, in very few contexts; 2 - Yes, in some contexts; 3 - Yes, in many contexts; 4 - Yes, in most contexts; 5 - Yes, in all contexts".

4 Available [online] https://microdata.worldbank.org/index.php/collections/step.

5 In Chile, Ecuador, Mexico and Peru.

In summary, labour automation is an issue of great social, political, and economic relevance, which has generated a growing interest in estimating its effects. So far, most research has focused on OECD countries, where a wide variation has been observed, ranging from 9% to 47% of workers at high risk of automation. In this context, the approach to skills use in task performance in the workplace, based on the work of Frey and Osborne (2017), has been a central element in the literature and the analysis of this issue in Latin America. However, research at the regional level has been limited and has been confronted with the lack of a common strategy for estimating automatability in most countries in the region. This situation is due, in part, to the scarcity of data sources available to carry out this type of analysis.

Given this need, this report seeks to estimate and analyse the probability of labour automation in Latin America using a methodological proposal adapted to the region described in the following chapter. The proposal is based mainly on labour market data from countries in the region, minimising, where possible, the use of information from extra-regional labour structures. The methodology is presented and explained below, as well as the strategy adopted and the data processing using machine learning algorithms.

II. Methodology

The methodology used is based on the approach of Frey and Osborne (2017), with adaptations to the probability estimation strategy and analysis of the results. The 70 automatable and non-automatable occupations from the O*NET survey and the three bottlenecks established in their 2010 workshop were used as initial inputs. In addition, *machine learning* algorithms were applied to predict the probability of automation using the use of workers' non-automatable skills and socio-demographic characteristics relevant to labour market insertion in Latin American labour markets as predictor variables. This chapter details the methodological strategy used, the data sources and variables, the algorithms employed, and the use of the probability vector of automation of occupations in household surveys.

A. Estimation strategy-machine learning and unique Latin American probability vector

The estimation of the probability of automation in Latin America was carried out in two phases. In the first phase, the objective was to estimate the probability of automation at the occupation level using data obtained from the PIAAC surveys, which were available for four countries in the region during their cycle 1: Chile (2014-2015), Ecuador (2017), Mexico (2017) and Peru (2017). These PIAAC surveys provide valuable information on the competencies, skills and abilities workers in their respective countries use. Through a list of skills, each worker surveyed must indicate whether or not they use that skill and the frequency with which they use it in their job. In addition, the surveys provide relevant data on the participants' socio-demographic, employment and educational characteristics, among other important variables. Following a strategy similar to that employed by ECLAC/OEI (2020) and Bravo, García and Schlechter (2019)the three bottlenecks to automation proposed by Frey and Osborne (2017) were operationalised based on the skills indicators available in the *background questionnaire* of the PIAAC survey. As a result, a preliminary list of skill indicators not amenable to automation in the workplace was generated and used as the main predictor variables for the probability of automation.

In defining this set of indicators, special consideration was taken of the results obtained by Lassébie and Quintini (2022), who surveyed artificial intelligence experts to update the automation capability based on the technology of the year 2022. The results revealed that, according to the experts' opinion, most of the skills related to the Perception and Manipulation bottleneck could be automatable with today's technological capabilities. Based on this information, it was decided not to include the only indicator previously considered for this set of indicators ("fine manual skills"), as it would no longer be a non-automatable skill. Consequently, the relevance of the bottleneck associated with Perception and Manipulation was conceptually discarded for current technological capabilities. The list of non-automatable skills comprises 15 indicators, of which four are related to the Creative Intelligence bottleneck and 11 to the Social Intelligence bottleneck. Table 1 shows the illustrative list of non-automatable skills.

Table 1
Non-automatable skills indicators in PIAAC

Dimension	Variable	Skills
Social intelligence	F_Q01b	Cooperating with other workers
	F_Q02a	Sharing work-related information
	F_Q02b	Teaching
	F_Q02c	Presenting or making speeches
	F_Q02d	Selling
	F_Q02e	Advising
	F_Q03a	Planning your own activities
	F_Q03b	Planning activities of others
	F_Q03c	Organising your own time
	F_Q04a	Influencing
	F_Q04b	Negotiating
Creative intelligence	F_Q05a	Solving simple problems
	F_Q05b	Solving complex problems
	G_Q03h	Using advanced mathematics and statistics
	G_Q05g	Using programming languages

Source: Prepared by the authors, based on PIAAC surveys.

The estimation in this first phase also relied on a second important input: the classification of occupations in the PIAAC survey as fully automatable and fully non-automatable. Starting from the original list of 70 occupations classified a priori by Frey and Osborne (2017), a transformation and adaptation of the occupational codes according to the SOC classification of the O*NET survey was carried out to make them compatible with the ISCO-08 codes used in the PIAAC survey and most household surveys in the region. This alignment resulted in a total of 93 occupations in PIAAC according to the ISCO-08 international classifier, 47 of them as fully automatable and 46 as fully non-automatable.

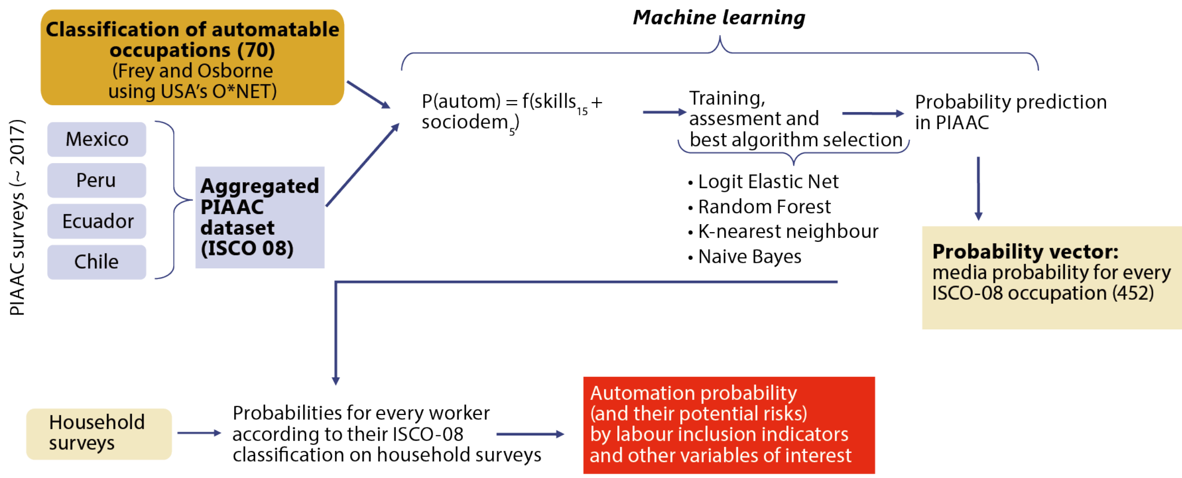
These two elements —one inherent to PIAAC surveys and the other applied to them (the classification of a subset of occupations as automatable or non-automatable)— were vital to estimating the probability of automation among workers in the four Latin American countries with PIAAC surveys. Supervised machine learning algorithms were implemented to predict the probability of automation of workers based on the pre-classification of occupations. Non-automatable skill variables worked as predictors, along with a set of socio-demographic and occupational variables. Including this additional set of socio-demographic variables sought to improve the predictive capacity of the algorithms by incorporating relevant aspects to capture task structures in their respective occupations. It was assumed that the variation in task structure in an occupation may be related not only to the skills exhibited by the worker in a particular occupation but also to differences in labour market insertion, gender, education, age and sector of activity, among other possible criteria. In this way, the algorithms were trained to learn from the data and classify all the observations on a continuum (between 0 and 1) according to the patterns and combinations they found in this set of variables.

The database used in the machine learning process combined the four PIAAC surveys for the four countries to obtain the vector of automation probabilities at the level of 4-digit occupations according to the ISCO-08 classification. The decision to combine the four PIAAC surveys has two main arguments —arising from the objective of having a uniform methodology to estimate automation in a broad group of countries in the region. First, since only four PIAAC surveys were available in Latin America, pooling the databases increased the number of observations per occupation. Increasing observations is relevant, as the sample size of these surveys individually is not ideal for making quality estimates. Secondly, unifying the databases allowed for more robust results, as not all occupations were always present in the country samples. Thus, the probability vector was composed from the data of the four countries as a whole and represents the average automation probabilities of all workers in the same occupation.

The choice of a single vector has both advantages and limitations. The main strength lies in the ability to apply this vector to Latin American countries, assuming that it is an estimate that represents to some extent the structure of skill use in the region's labour markets, albeit in an approximate way. The fact that it is a (pseudo) continuous probability also allows us to consider that automation occurs at the task level, as pointed out by Arntz, Gregory and Zierahn (2016) rather than applying to entire occupations and, therefore, such a probability could represent the proportion of automatable tasks within each occupation. Its transferability also allows its use in different contexts and incorporation into other databases, such as household surveys, to the extent that these use occupational classifiers comparable with the international ISCO-08 classifier. Moreover, their use in household surveys or other national instruments of a similar nature offers the advantage of obtaining results that reflect the distribution of occupations in each country. However, this option also has significant limitations. In order to make the vector transferable, the probabilities were aggregated at the occupation level. This implies that the vector ultimately consists of probabilities of automation of occupations common to all workers in the same occupation in any country in the region. While this assumption is necessary to carry out the strategy to obtain robust estimates, it is acknowledged to have limitations, as the task structure may vary significantly within the same occupation (Arntz et al., 2016; Autor and Handel, 2013).

The second estimation phase focuses on transferring the probability vector to the household surveys of 14 countries in the region. The quality of this transfer is mainly limited by how occupations are coded in each household survey and their compatibility with the ISCO-08 codes used in the PIAAC surveys. To carry out this transfer, we started by calculating the average probability of automation for each occupational code in the ISCO-08 classifier to four, three and two digits. By reducing the number of digits, the occupational groups are expanded (e.g., from "Information technology instructors" —code 2356—, "Other teaching professionals" —code 235—, to "Teaching professionals" —code 23—). It was necessary to estimate the probability with different levels of clustering because the information on occupations in household surveys is provided with varying disaggregations by country. Diagram 1 illustrates the estimation strategy.

Diagram 1
Flow diagram of the estimation strategy



Source: Prepared by the authors.

B. Description of algorithms and sequences of procedures and processing

Two main types of databases were used for processing. First, the PIAAC surveys of four Latin American countries in their round around 2017: Chile (2014/2015), Ecuador, Mexico and Peru. The aggregated PIAAC database is a selection of 15,886 observations corresponding to employed persons aged 15-65 not in the armed forces. Second, the fourteen household surveys of the 2019 round, which include Argentina, the Plurinational State of Bolivia, Brazil, Chile (2017), Colombia (2018), Costa Rica (2018), Ecuador, El Salvador, Honduras, Mexico (2018), Panama, Peru, the Dominican Republic (2018) and Uruguay. The aggregated household survey database included 1,006,685 observations of employed persons aged 15 years and older not in the armed forces. The selection of household surveys considered the quality of the occupational classifiers of each survey, and those that did not allow the transfer of the vector to at least two digits were discarded. Some countries have limitations in the transfer, where there is less granularity in the pasting of probabilities by occupation.[6] The rest of the countries have a four-digit probability vector in their occupational classifier.

In the first stage, PIAAC surveys were processed using variables from *the background questionnaire*. Fifteen indicators of non-automatable skill use were created by recoding variables representing intensive skill use (using the skill every day or at least once a week) or non-intensive skill use. Variables representing educational level, age groups, gender, qualification, sector of activity and country were also selected and recoded. Finally, the variable for fully automatable and non-fully automatable occupations was constructed according to the homologation of occupational codes to the ISCO-08 classifier. All predictor variables are binary, as introducing variables in continuous or ordinal form (e.g. age and educational level) does not change the results significantly in the algorithms used. Table 2 below presents some descriptive statistics for the predictor variables.

6 In Argentina and Colombia the pairing was done at two digits, and in the Plurinational State of Bolivia and Peru at three digits.

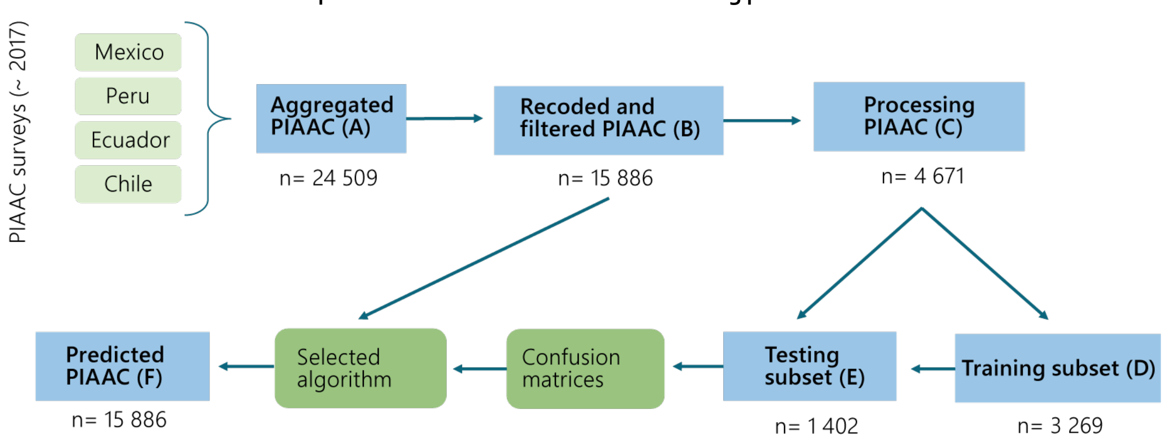
Table 2
Descriptive statistics of predictor variables

Variable	Percentages	Est. dev.	Variable	Percentages	Est. dev.
F_Q01b	40.68	0.49	Age 25–34	26.38	0.44
F_Q02a	57.52	0.49	Age 35–44	23.67	0.42
F_Q02b	31.88	0.46	Age 45–59	26.19	0.44
F_Q02c	15.66	0.36	Age 60–65	4.99	0.21
F_Q02d	42.96	0.49	Low educational level	58.64	0.49
F_Q02e	35.07	0.47	Average educational level	25.58	0.43
F_Q03a	69.87	0.45	High educational level	15.77	0.36
F_Q03b	22.93	0.42	Low rating	17.64	0.38
F_Q03c	77.29	0.41	Average rating	58.95	0.49
F_Q04a	41.78	0.49	High rating	23.42	0.42
F_Q04b	39.97	0.48	Low productivity sector	59.3	0.49
F_Q05a	47.85	0.49	Medium productivity sector	29.62	0.46
F_Q05b	28.58	0.45	High productivity sector	11.07	0.31
G_Q03h	5.76	0.23	Chile	10.81	0.31
G_Q05g	4.23	0.20	Ecuador	7.85	0.27
Men	59.58	0.49	Peru	18.91	0.39
Age 16–24	18.77	0.39	Mexico	62.43	0.48

Source: Prepared by the authors, based on PIAAC surveys Mexico (2017), Ecuador (2017), Peru (2017) and Chile (2015).
Note: Expanded results.

Predictions were made using Machine learning algorithms. These algorithms make estimations through a learning process in which they modify themselves to maximise their predictive ability from a set of instructions. These techniques benefit this study, as they allow an estimation of probabilities to many cases, with only a few observations as a reference. Diagram 2 summarises the *machine learning* procedure performed.

Diagram 2
Simplified schematic of the machine learning procedure



Source: Prepared by the authors.

The *machine learning* procedure used the recoded and selected PIAAC database (labelled "B" in diagram 2) as a starting point. Database B was derived from the aggregated PIAAC database for the four countries (labelled "A"), with some important changes: (i) filtered out only non-armed forces employed persons aged 15-65; (ii) created a binary occupational classification variable between "fully automatable" and "not fully automatable" from Frey and Osborne (2017) with information for employed persons in the sample who had any of the 93 pre-classified occupations (ISCO-08-standardised); and (iii) created and recoded the variables of interest. Then, a new processing PIAAC database (called "C") was created from database B. This database C selected only the observations of interest. Database C selected only the observations with classifications from the Frey and Osborne (2017) list, the predictor and predictor variables, and omitted missing cases of any of the variables in question. The training and testing of the algorithms, which are procedures typical of supervised learning techniques, were performed on this database. The process begins by randomly dividing the database C between training and testing —in this case, 70% of the observations in training and 30% in testing— maintaining the proportion of the variable to be predicted in both data sets. In the training dataset, through a cross-validation process in which the dataset is subdivided, the algorithms iteratively estimate using different combinations of parameters to assess whether their predictions resemble the attributes of the variable to be predicted within the same subdivision.[7]

Four algorithms were selected to perform the predictions: Logistic Regression Elastic Net (RLEN), Random Forest (RF), K-nearest Neighbours (KNN), and Naive Bayes (NB). These algorithms were selected because of their suitability for making predictions in the form of continuous probability from a binary variable to be predicted and their good performance on medium-sized databases with binary predictors. The processing and machine learning estimations were programmed using the R language (version 4.2.2) and the "caret" (*Classification and Regression Training*) package by Max Kuhn (2008 in its version 6.0.93. All random processes were seeded with the value "222". Specifically, the algorithms "glmnet", "ranger", "knn" and "nb" were chosen in the nomenclature of the "caret" package. Each algorithm was configured to perform 100 random iterations of parameters using customised search grids and five iterations of five cross-validation subdivisions, maximising the ROCAUC performance indicator. A caret upsampling option was also used during training to ensure parity in the proportion of the variable to be predicted in each subdivision in the cross-validation. This minimises prediction biases due to an imbalance in the distribution of target variable - which is especially relevant if ROCAUC is to be maximised. In cases of significant imbalances, choosing a performance indicator other than ROCAUC may be advisable due to the risk of bias. One option is to use PRAUC, or the area under the curve of the curve between Precision and Recall, although it may also incur other limitations (Carrington et al., 2020; Saito and Rehmsmeier, 2015). In this estimation, we chose to keep ROCAUC as the main indicator of predictive performance due to its widespread use in the literature, and we used resampling techniques during training to deal with potential imbalance issues during the training of the algorithms. In this way, each trained algorithm has optimised parameters to maximise the quality of predictions.

During training, the results of the predictions for each combination of parameters are stored, and the algorithm selects the version that gives the best results. Once the best-performing versions of the four algorithms are available, predictions are made on the test database, which, in this case, contains the remaining 30% of observations of workers in fully automatable or non-automatable occupations that were not used for training. From the results of this test, the algorithm with the best-performing final prediction is selected for predicting the target variable on the original dataset.

[7] For this, it is necessary to choose an indicator or criterion that establishes a better predictive quality. For this study, in training the algorithms, we chose to maximise the ROCAUC, or area under the *Receiver Operating Characteristic* curve, which corresponds to the curve of false positives and false negatives, suitable for balanced samples (the values of the response or predicted variable represent about 50% of the sample each).

The evaluation of the results of classification algorithms is performed using confusion matrices. Since, in this case, the objective is to make a binary prediction (or "classification" in data science terminology), the matrix has a dimension of 2x2 with four cells. On the horizontal axis are the binary predictions made by one of the algorithms, while on the vertical axis are the original values of the variable. The central idea behind the confusion matrix is to classify the results of the predictions in one of these cells either true positives (observations predicted as "1" that were actually "1"), false positives (observations predicted as "1" that were actually "0"), true negatives (observations predicted as "0" that were actually "1"), and false negatives (observations predicted as "0" that were actually "0"). From the confusion matrix, several predictive performance indicators emerge that serve to select the best-performing algorithm. Table 3 below details the predictive performance results of the tests of each algorithm in the test database (denoted "D" in diagram 2).

Table 3
Predictive performance of algorithms

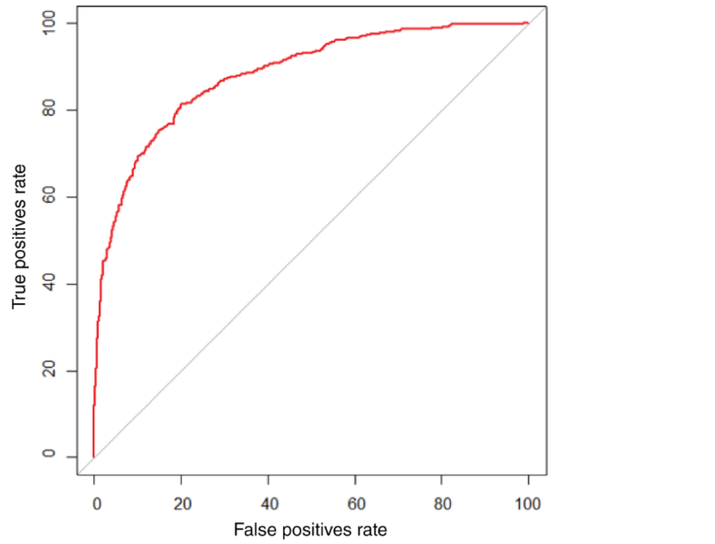
	Elastic Net Logistic Regression	Random Forest	K-Nearest Neighbours	Naive Bayes
Accuracy	0.77	0.80	0.76	0.74
Kappa	0.53	0.60	0.52	0.47
Sensitivity	0.76	0.79	0.69	0.73
Specificity	0.78	0.81	0.83	0.74
Pos. Pred. Value	0.77	0.80	0.80	0.74
Neg. Pred. Value	0.76	0.80	0.73	0.74
Precision	0.77	0.80	0.80	0.74
Recall	0.76	0.79	0.69	0.73
F1	0.76	0.80	0.74	0.73
Balanced Accuracy	0.77	0.80	0.76	0.74
ROCAUC	0.84	0.88	0.84	0.80
PRAUC	0.83	0.88	0.81	0.75

Source: Prepared by the authors.

Several indicators can help evaluate the performance of the algorithms. In this classification procedure, the ROCAUC and PRAUC indicators were especially considered. Both indicators summarise the predictive performance of binary variables by combining different metrics. In the case of ROCAUC, the metric corresponds to the area under the curve (or the integral) of the ratio between true positives and false negatives. In this sense, the higher the area under the curve, the higher the number of true positives and the lower the number of false negatives. On the other hand, the PRAUC indicator follows the same logic; only it measures the area under the curve between Precision and Recall. Precision is the ratio of true positives to the total number of observations predicted as positive. Recall measures the ratio of true positives to the sum of true positives and false negatives. For both metrics, it is observed that *Random Forest* obtains the best results compared to the rest of the algorithms (see bottom of table 3). Other relevant indicators such as F1 and Accuracy also indicate a better performance of this algorithm. Thus, due to its good performance, the optimised version of *Random Forest* was selected to perform the final predictions for the aggregated PIAAC survey.

Figure 1 shows the ROC curve resulting from testing the selected *Random Forest* algorithm. The area under the curve has a value of 0.88, i.e. it covers 88% of the total prediction area. Comparatively, if instead of using this algorithm, a random method of prediction (such as a coin toss) were used, the area under the curve would be 0.5, which is represented by the diagonal of the graph. Thus, the algorithm outperforms the baseline and shows a good prediction quality for this study.

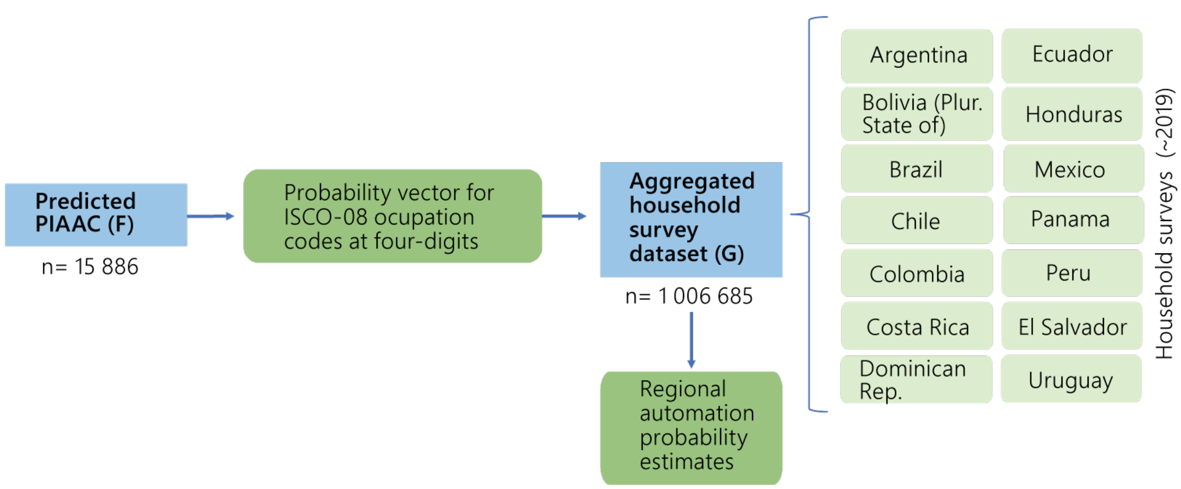
Figure 1
ROC curve of the selected *Random Forest* algorithm



Source: Prepared by the authors.

Once the algorithm was selected, it was applied to database B to predict the probability of automation for the total of 15,886 observations of employees aged 15 to 65, excluding the armed forces, including cases where occupations were already pre-classified. The algorithm estimates a continuous probability of automation at the individual level from the predictor variables that were used during training and testing. Then, two additional three-digit and two-digit average probability of automation variables were constructed. This information on average probabilities was then summarised at the level of occupations, which implies a change in the unit of analysis from employed to occupations. These variables form the probability vector of automation of occupations, which was subsequently used in household surveys. Diagram 3 below illustrates the procedure for merging and estimating the regional probability of automation.

Diagram 3
Schematic of the implementation of regional estimates of the automation probability



Source: Prepared by the authors.

Once the probability vector was included in the aggregated household survey database (denoted "G"), it was possible to make automation probability estimates for 14 countries in the region. Based on these data, the analysis results are presented in Chapter III.

C. Comparison between probability vectors

This section compares the probability vector estimated by ECLAC in this report and the probability vector of Frey and Osborne (2017). This exercise is helpful to obtain reference information on how similar or dissimilar the vectors are and to hypothesise some of the potential factors affecting their differences.

The processing necessary to achieve this comparison involved several steps. First, the occupational codes were transformed into the automation (i.e. computerisation) probability scores reported in the Frey and Osborne annexe. (2017) from the SOC-10 classification used by the O*NET surveys to the ISCO-08 classification used by the PIAAC surveys. For this purpose, we followed the methodology proposed by Acemoglu and Author (2010)) for the construction of occupational code equivalence dictionaries that have been replicated in other works, such as Hardy et al. (2018).[8] The SOC occupational codes and their resulting probabilities appear in Appendix A of Frey and Osborne (2017).

Among the occupational codes, 19 Frey and Osborne (2017) could not be automatically translated because they did not exist within the ISCO-08 international classification system. Since the table in Appendix A describes the occupation, these 19 values were imputed to the closest equivalent codes in the international system. The choice to impute was made mainly due to the benefits of having a full equivalence of both probability vectors and because several of the 19 occupations are highly analytical. A table with these occupational codes and their imputed correspondences can be found in the annexe (see table A1).

Once the equivalences of both occupational code systems were obtained, the second step was to collaps the Frey and Osborne (2017) probabilities according to the ECLAC probability vector and their respective ISCO-08 codes. This procedure is necessary because the number of occupations identified in each classifier is different. Thus, the matched database contains 343 occupations, with a variable of ISCO-08 occupational codes and two associated probability vectors, one from Frey and Osborne (2017), and another from ECLAC, estimated with the methodology used in this report.

With this data set, a *Pearson* correlation of 0.58 was obtained between the two probability variables between the two vectors. This result shows a moderate similarity between both automation probabilities, which is to be expected. If the correlation were too high, this would mean that both vectors are too similar so that a methodological adaptation to Latin American data sources would not imply a significant added value. On the other hand, if the correlation were too low, the vectors would be too dissimilar, which could be problematic since this study follows a similar approach to that of Frey and Osborne (2017), and such a scenario would suggest problems in estimation, or very different data from those collected by O*NET for the US.

Overall, thecorrelation achieved between the two vectors could point, at least partially, to the fact that Latin American and US labour markets are not entirely equivalent in the distribution of tasks and skills by occupation. For example, it is to be expected that in specific industries such as mining, a worker in the United States has more standardised tasks and, therefore, uses more potentially automatable skills than a miner in a Latin American country. This would be expected due to the lower technological penetration in the region's industries than in other labour markets, such as the US. However, this can only be taken as conjecture and with caution, as the methods of Frey and Osborne (2017) and those developed in this report are not fully comparable, although their underlying methodology served as the main inspiration to build the methodological strategy developed here.

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8 It is possible to download these dictionaries [online] https://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/.

III. Results

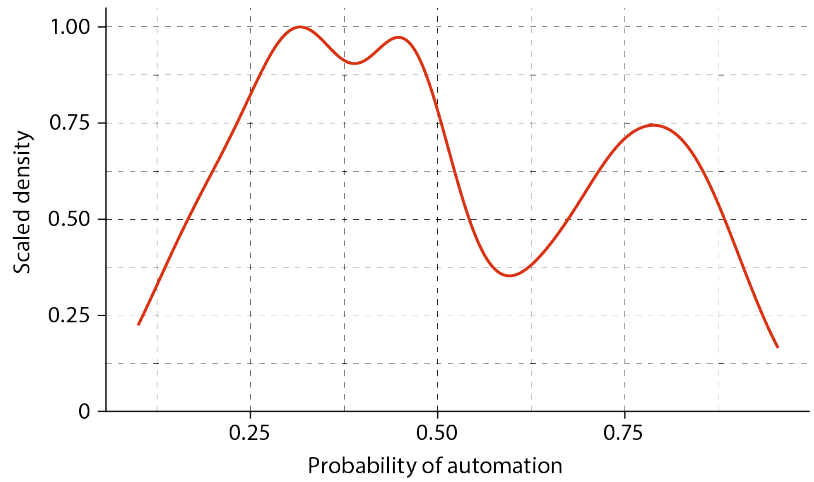
This chapter analyses the automation probability estimates obtained using the algorithm mentioned earlier, which are divided into two main parts. In the first part, the probabilities of automation are described according to various relevant criteria, such as gender, education level, sector of activity, occupation and income level, among others. The second part consists of a series of simulations that have been carried out to estimate the potential impacts of automation risk in the region. These simulations include the estimation of the number of hours and equivalent automatable employment, as well as the possible effects that partial or full automation of high-risk occupations could have in terms of income loss, increased poverty and changes in inequality.

In contrast to studies such as that of Weller, Gontero and Campbell (2019) here we chose to include all workers in the analysis of the probability of automation, including informal workers and those employed in low-productivity sectors, as well as all types of self-employed workers and employers. This criterion was guided by the objective of addressing the possible effects of technological advances in general, without making a priori distinctions by occupational categories or level of labour autonomy, so that estimates of the probability of automation of occupations primarily express the use of labour skills considered as non-automatable and their differential distribution within Latin American labour markets, in isolation from other factors that may affect the incorporation of new technologies in the labour market.

A. Descriptive analysis of automation probabilities

This section describes the probability of automation in the 14 Latin American countries and illustrates the concentration of cases at certain probability levels using density plots. The probability of automation is relatively bimodally distributed across the set of workers analysed (see figure 2). Most observations do not have a probability close to the extremes but tend to be found in two large concentrations: a "medium and low" one ranging between 0.2 and 0.5 and a "medium and high" one between 0.6 and 0.8. The number of cases between a probability of 0.5 and 0.6 decreases markedly compared to those two large clusters. The mean of the regional automation probability is 0.501, with a standard deviation of 0.229.

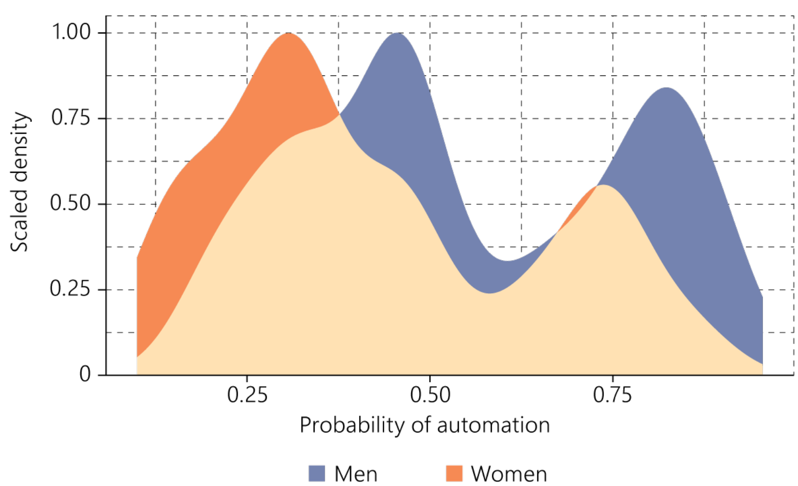
Figure 2
Latin America (14 countries):[a] automation probability density among employed persons aged 15 and over,[b] around 2019



Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of the countries. Class width for the graph is 0.05 each. The scale of the graph takes the value 1 for the highest frequency class.
[b] Excludes those engaged in the armed forces.

Figure 3 shows the differences in the probability of automation between women and men. Both distributions have a similar bimodal shape but differ in size and position. Overall, men have a mean automation probability of 0.56, whereas women have a mean of 0.43. One possible explanation for this difference is the disparity in the proportion of employees in different occupational branches by gender, which have different probabilities of automation. Men have precisely a higher share in sectors with a higher average automation probability, such as transport (male workers are 90.7%), manufacturing (62.2%), mining (86.9%) or construction (95.9%), compared to women.

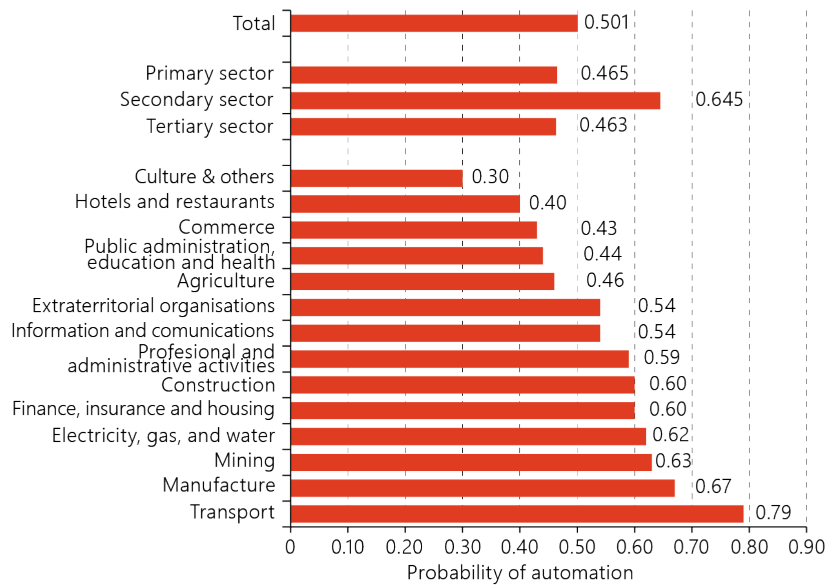
Figure 3
Latin America (14 countries):[a] density of automation probability among employed persons aged 15 and over by gender,[b] circa 2019



Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of the countries. Class width for the graph is 0.05 each. The scale of the graph takes the value 1 for the highest frequency class of each distribution.
[b] Excludes those engaged in the armed forces.

Figure 4 shows the average probability of automation in different branches of economic activity where workers perform their job functions. As noted, the transport and manufacturing sector has the highest average probability of automation, at 0.79. Around 2019, this sector employed around 12.5 million people, equivalent to 5.4% of the workers in the 14 countries of the region analysed. In contrast, the cultural, personal services and similar activities sector shows a lower probability of automation in the region, with an average of 0.30, and employs around 24.3 million workers.

Figure 4
Latin America (14 countries):[a] average probability of automation of employed persons aged 15 and over by industry,[b] around 2019
(Average)



Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of countries.
[b] Excludes those engaged in the armed forces.

Of the 14 industries, nine are in the medium probability range between 0.4 and 0.6. Furthermore, it is observed that workers in traditional or lower productivity sectors have a significantly lower probability of automation (0.41) compared to those in medium productivity sectors (0.66) and modern or higher productivity sectors (0.61).[9] Given that the probability of automation is unique for a specific occupation, these differences arise due to the different occupational structures present in the various sectors of activity. In more modern sectors and more prominent, more formal firms, jobs tend to have standardised definitions and often require workers to fill multiple positions with similar characteristics. Moreover, it is common for these occupations to concentrate on interrelated sets of tasks that take up a large part of the working day, increasing the potential for automation. In contrast, in the more traditional sectors, economic activity tends to be concentrated in micro-enterprises and, particularly, in the self-employed. Due to the nature of their roles and responsibilities, these workers tend to perform a greater variety of tasks, including different types of management. This implies that they perform fewer sets of automatable activities.

9 The traditional or lower productivity sector includes agriculture, commerce, hotels and restaurants, public administration, education and health, and culture and other services. The intermediate sector consists of manufacturing, construction, and transport and storage. Finally, the high-productivity sector includes mining, electricity, gas and water, and financial, insurance and real estate activities; information and communication; and professional and administrative activities (Infante, 2011; 2016).

On the other hand, there are also significant differences between primary, secondary and tertiary sectors. The primary sector focuses mainly on resource extraction, such as agriculture, fishing and mining. The secondary sector involves transforming raw materials into manufactured goods, including manufacturing and construction. Finally, the tertiary sector covers services provided to the population and businesses, such as trade, education, health and transport. The results show that the secondary sector has an average probability of 0.64, much higher than the primary and tertiary sectors, with a mean probability close to 0.46 in both cases.

Figure 5 groups the average probabilities of automation according to the seven occupational classes adapted by Martinez et al. (2022), the result of the first phase of the "Stratification and social mobility in middle-income countries. Challenges facing an uncertain future" project of the European Union and ECLAC. At the regional level, it is observed that among the lower occupational classes (low-skilled manual workers, including salaried workers, micro-entrepreneurs and self-employed workers), the average probability of automation was 0.45, and that of the upper occupational classes (directors, managers, administrators, and higher-level professionals and technicians) was 0.38, while in the middle classes, it was 0.58. The highest probability of automation is concentrated among skilled manual workers (0.74), followed by routine non-manual low-level workers (0.59) and to a lesser extent among routine non-manual middle-level workers (0.40). The occupational strata with the lowest probability of automation are large employers, directors and managers (0.33) and unskilled workers (0.38). They are followed by higher-level professionals (0.40), medium-skilled non-manual workers (0.41), and lower-skilled smallholders and self-employed (0.49). In the absence of adaptive and anticipatory measures to provide these workers with tools to cope with technological transformations and, at the same time, facilitate their access to social protection benefits against unemployment risks, the above results illustrate the greater vulnerability that the middle occupational classes (non-professional workers in routine non-manual activities with medium or low skills, and skilled workers in manual activities) could face in the face of the possibilities of automation.

Figure 5
Latin America (14 countries):[a] average probability of automation of employed persons aged 15 and over by occupational class,[b] around 2019
(In averages)

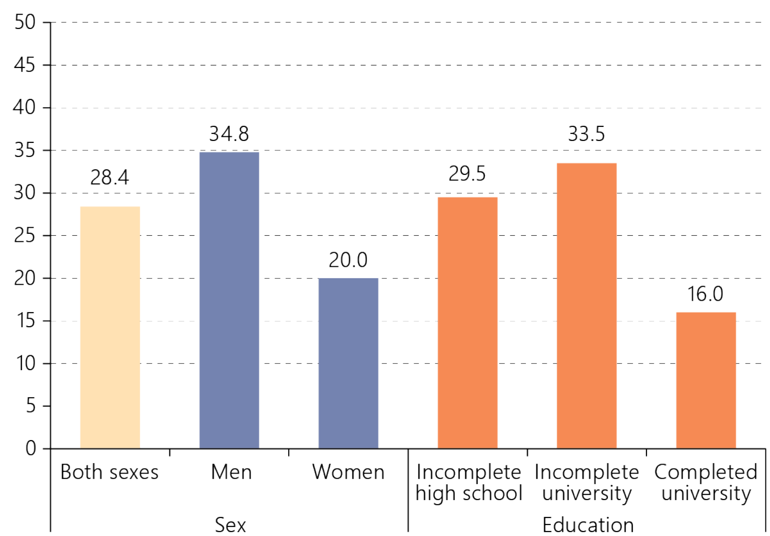
Source: Prepared by the authors on the basis of the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of countries.
[b] Excludes those engaged in the armed forces.

B. High automation risk analysis

This section analyses the profiles of workers whose jobs would have a high risk of automation according to the composition of their tasks and the skills required to perform them. In line with the literature on the subject, it was considered that those with a probability above 0.7 would face a significant risk of automation of their jobs, in contrast to those with a lower probability, among whom task adaptation is more likely to take place (Arntz, Gregory and Zierahn, 2016; Bravo, Garcia and Schlechter, 2019; Frey and Osborne, 2017). The analysis according to risk profiles is particularly relevant for designing public policies that anticipate and expand response capacity and reduce potential vulnerabilities arising from labour automation. In the following, the high risk of automation is analysed according to various analytical criteria that help to understand the main characteristics of high-risk workers and job insertions. A detailed analysis of the profiles of high-risk workers in each country to better target national and subnational public policies can be made by applying the probability vector to official databases on the characterisation and monitoring of employment developments, which is available in the annexe to this study (table A3).

Figure 6 shows the percentage of workers in jobs at high risk of automation by gender and educational level. Overall, 28.4% of workers are at high risk of automation in Latin America. Men are significantly more exposed to high automation risk, as 34.8% are in jobs whose tasks are susceptible to standardisation, while among women, only one in five is in high-risk occupations. On the other hand, workers with intermediate educational levels (in this case, workers with completed secondary education but incomplete university education or less) are positioned in occupations with a higher risk of automation (33.5%), compared to those with incomplete secondary education (29.5%), and completed university education (16.0%).

Figure 6
Latin America (14 countries):[a] workers aged 15 and over in jobs at high risk of automation by gender, educational attainment and income quintile, around 2019
(Percentages)

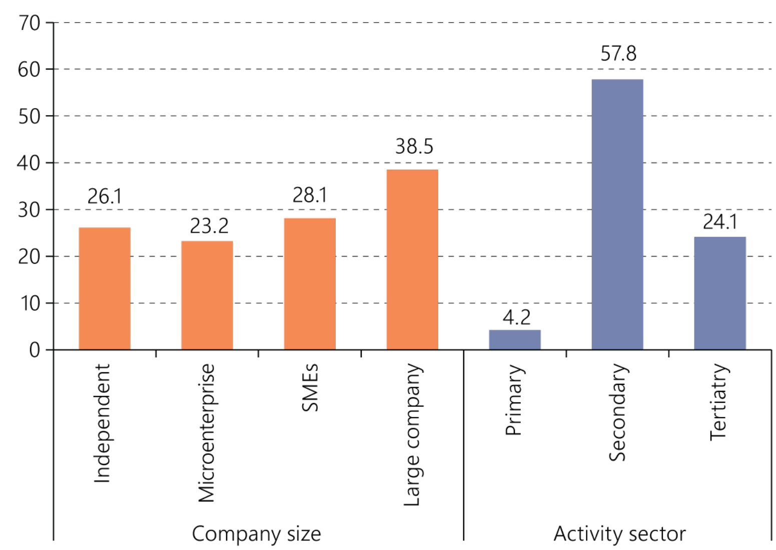


Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of countries. Excludes those employed in the armed forces.

Workers at high risk of automation according to company size and sector of activity are shown in figure 7A. Workers in larger enterprises are more exposed to the risk of automation (38.5%), in contrast to small and medium-sized enterprises (28.1%) and micro-enterprises (23.2%). This is because they concentrate a higher proportion of jobs with large sets of automatable tasks, with standardisable, protocol-driven, and potentially more routine processes. Among the self-employed, there is also a relatively low proportion of high-risk job positions, which is primarily due to the varied composition of tasks associated with self-management of work and their concentration in agricultural and service activities, and much less in industry. There is a clear difference in risk among workers in the secondary sector (57.8%) compared to the tertiary (24.1%) and primary (4.2%).[10] As mentioned above, the secondary sector concentrates workers in the manufacturing and construction industries, which include a wide range of occupations with an important set of standardisable and routine tasks (typical of mass production processes), which in the face of current technological capabilities are highly automatable.

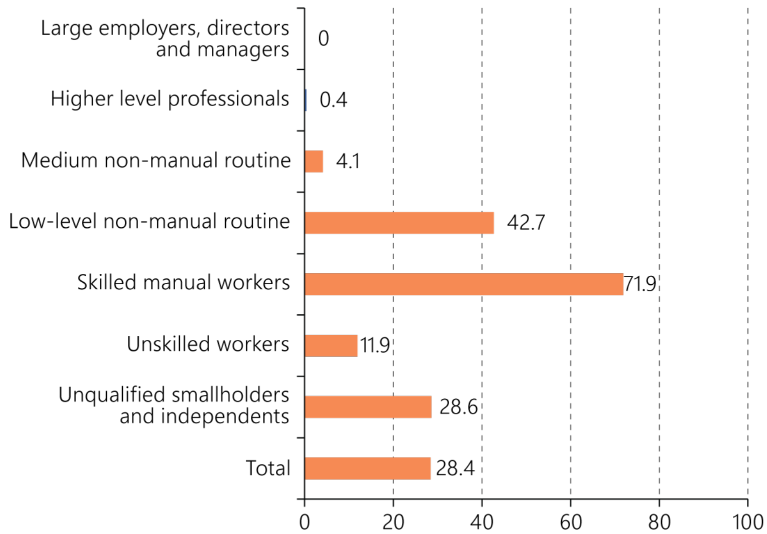
Figure 7
Latin America (14 countries):[a] workers aged 15 and over in jobs at high risk of automation by firm size, sectors of activity and occupational class, circa 2019
(Percentages)

A. According to company size and sector of activity



[10] In the mining sector, 49% of workers would be in jobs with a high risk of automation. In contrast, only 2.1 per cent of those in the agricultural sector are at high risk of automation. By 2019, agricultural employment was around 96% of primary sector employment in the 14 countries analysed.

B. According to occupational class



Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of countries. Excludes those employed in the armed forces.

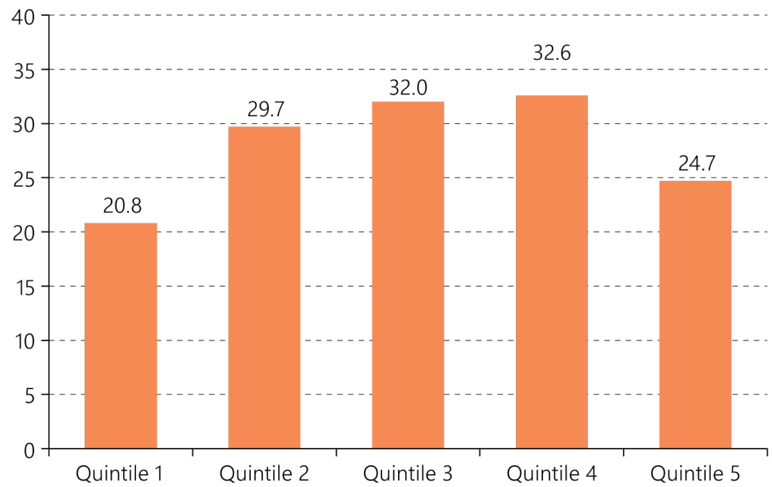
In addition, pronounced differences are observed between the percentage of high-risk workers belonging to middle and low occupational classes compared to high and low (see figure 7B). In particular, 71.9% of skilled manual workers face a high risk of automation, followed by routine non-manual workers with 42.7%. In contrast, strata that include large employers, directors and managers, along with professionals and senior managers, would not be exposed to the risk of automation in their jobs. However, some of their tasks might be susceptible to it (as shown by the average probability in figure 5). Finally, 28.6% of small owners and self-employed with lower qualifications and 11.9% of unskilled salaried workers have a high probability of automation.

On the other hand, figure 8A shows the weight of workers at high risk of automation by per capita income quintile. Workers belonging to the intermediate quintiles, particularly those in the third and fourth income quintiles, have the highest percentage of workers at high risk of automation (around 32%), and it is precisely workers in the extreme quintiles who are proportionally less affected by automation; in the first per capita income quintile this would be associated with a higher weight of low-skilled salaried and self-employed workers and in the top quintile with a higher concentration of professionals and managers.

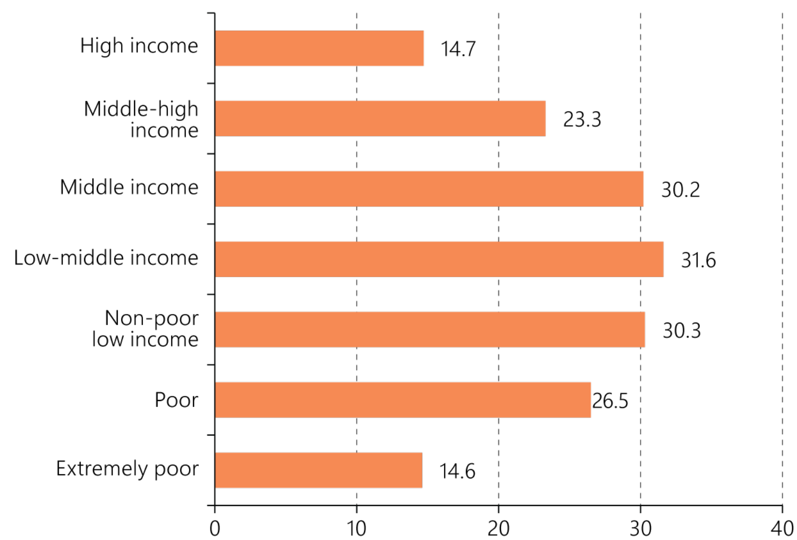
Similarly, figure 8B shows the weight of workers at high risk of automation by socio-economic strata, defined based on multiples of the poverty lines estimated by ECLAC at the national level (for more detail, see Martínez et al., 2022). These results show that workers living in poverty occupy jobs, such as salaried or self-employed workers, whose nature and composition of tasks make it difficult to fully automate, which is even more true among workers living in extreme poverty. The same is true for workers belonging to the upper-middle strata (with per capita income between 6 and 10 poverty lines per person) and high strata (10 or more poverty lines per person). These segments concentrate (to a greater extent than quintile 5 of per capita income) professionals and higher-level technicians and managers of public and private companies. In contrast, and similar to what is illustrated in figure 7B, workers in the intermediate socio-economic strata are more at risk of automation, mainly those in the lower-middle stratum.

Figure 8
Latin America (14 countries):[a] workers with high probability of automation by quintile and by per capita income strata, around 2019

A. Workers with a high probability of automation by quintiles
(Percentages)



B. Workers with high probability of automation by socio-economic strata
(Percentages)



Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of countries. Excludes those employed in the armed forces.

The above results suggest that, although the middle classes enjoy standards of living that allow for adequate labour and social inclusion, which makes these strata actors that promote economic, social and political stability in Latin American societies, they are precisely those that are most exposed to the risk of automation. Automation is generally a process that contributes to development by increasing productivity. Still, it can also be uncertain given the possibilities of job loss, reduction of labour income or the constant need to adapt and train for work, which can become a significant source of social unrest. This demands the attention of the state in terms of the design of industrial, social protection and educational and training policies that are articulated with each other and based on fiscal and social pacts that both facilitate technological innovation, increased productivity and competitiveness, and also consider workers as an active, adaptable resource that is key to these transformations.

C. Potential socio-economic impacts

This section explores the potential socio-economic impacts of labour automation in Latin America. To do so, various simulation scenarios were constructed to assess the effect on the number of hours worked, equivalent jobs, changes in income, poverty and inequality. Estimating possible socio-economic impacts is highly relevant to anticipate potential risk scenarios. The scenarios presented in this section assume partial equilibrium models to the extent that a total or partial loss of jobs for workers at high risk of automation is assumed without considering additional re-employments or job adjustments.

In this sense, and following the logic of the task approach, an occupation may be composed of tasks that require automatable or non-automatable skills and occupy different proportions of time in the working day of each occupation. In this respect, it is important to note that the PIAAC surveys measure the regularity or frequency of tasks at work rather than the extent of time they take up. Therefore, the probability of automation can be interpreted only approximately as an expression of the share of automatable hours in the total working hours of each worker.

To calculate the total sum of automatable hours, the number of hours that make up each worker's usual weekly working day was multiplied by their probability of automation. This calculation estimated how many equivalent jobs would correspond to the automatable hours by dividing by 44 hours per week, a standard working day in the region. In addition, by identifying workers at high risk of automation (probability greater than 0.7), we approximated the labour income at risk in the event of full or partial automation of their jobs.

In the 14 Latin American countries analysed, there are estimated to be just over 4.8 billion potentially automatable hours per week, equivalent to approximately 108.7 million jobs (considering a 44-hour working week). This represents 47.3% of the total jobs in the region. It is important to note that these figures refer to the maximum amount theoretically automatable given current technology. They do not consider costs, adaptation effects or other factors involved in automating tasks. Details of these estimates are presented below in table 4.

Indeed, the number of hours that can be automated in high-risk jobs is 2,265 million hours per week, equivalent to 51.5 million jobs. If all possible hours in these occupations were automated and the remaining hours were condensed into fully non-automatable jobs, almost 79% of those in high-risk occupations would have to move into new occupations. The most significant impact of automation in terms of equivalent employment would occur among skilled manual workers (21.2 million equivalent jobs, 63% of those employed in this class), low-skilled non-manual workers and lower-skilled small proprietors and independents. In contrast, large entrepreneurs, directors and managers would not experience any loss of working hours because their jobs would not have a relevant share of potentially automatable tasks. On the other hand, the secondary sector has the highest proportion of automation-equivalent employment (45% of total employment in the sector), while in the tertiary sector, this proportion is lower (19%). Still, automation, in absolute terms, could involve up to 28.7 million jobs (equivalent to 44 hours per week). It should be borne in mind that these estimates do not consider the possible adaptive efforts of workers (and employers) and other adjustments that may occur in the productive sphere and the labour market during technological innovation processes. Similarly, it is relevant to note that estimates of potential job losses assume that the replacement risk would affect the automatable portion of the working day and not the entire job (unless all tasks were automatable). In a more radical scenario in which the worker risks the loss of all working hours by having an occupation with a high risk of automation, the jobs (and employed) at risk of being replaced would be around 65.3 million.

Table 4

Latin America (14 countries):[a] employment equivalent to automatable hours and potential labour income losses in the face of partial or full automation of high-risk occupations, around 2019

(Millions of persons, in percentages and in 2011 PPP dollars)

	Total employment	Equivalent employment: By the total number of automatable hours	Equivalent employment: By automatable hours in high-risk occupations		Monthly labour income: Mean	Monthly labour income: Among high-risk occupations: Mean	Monthly labour income: Among high-risk occupations: Average potential loss due to partial automation	Potential loss of earnings relative to the mass of labour income among high-risk employed[b]: Partial automation	Potential loss of earnings relative to the mass of labour income among high-risk employed[b]: Full automation
	(Millions)		*(Millions)*	*(As a percentage of total employment)*	*(In 2011 PPP dollars)*			*(Percentages)*	
Large employers, directors and managers	5.75	1.98	-	-	2 185	-	-	-	-
Senior professionals	8.76	3.32	0.02	0.3	1 994	1 009	791	0.2	0.2
Mid-level non-manual routine	33.14	11.87	0.87	2.6	1 247	1 439	1 055	3.7	5.0
Low-level non-manual routine	36.08	20.88	11.38	31.6	708	822	616	37.1	48.5
Skilled manual workers	33.61	26.12	21.16	63.0	684	712	578	60.6	72.9
Unskilled workers	46.89	16.65	3.99	8.5	465	498	372	10.1	13.4
Unskilled self-employed and smallholders	65.60	27.88	14.06	21.4	399	533	438	31.5	37.5
Primary sector	31.52	12.75	1.11	3.5	372	925	718	8.0	9.8
Secondary sector	48.09	30.06	21.64	45.0	713	601	483	39.1	48.0
Tertiary sector	150.24	65.89	28.74	19.1	811	738	576	17.0	21.3
Total	229.84	108.70	51.50	22.4	731	684	539	20.9	26.0

Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).

[a] Weighted average of countries. Excludes those employed in the armed forces.

[b] Calculations based on income expressed in 2018 dollars. Since the exchange rate ratios between countries at 2011 PPP dollars and 2018 dollars are different, these percentages differ from what is obtained when estimating using dollars expressed in purchasing power parity.

On the other hand, we analyse the income likely to be lost with the potential loss of partial or total employment among workers with a high probability of job automation. The estimates show that for all 14 countries in the region, partial automation of all high-risk occupations would imply an average decline in monthly labour income of just under $540 per month in 2011 purchasing power parity (PPP) terms. Although this potential decline in earnings is, in absolute terms, larger as one moves up the occupational ladder (except for large employers, directors and managers), it generally ranges between 75% and 80% of these occupations' average monthly labour income. In aggregate terms, and on a par with the higher percentage of those employed in occupations at high risk of automation, the class that, in theory, would be most impacted is that of skilled manual workers since partial automation of their occupations would compromise up to 60.6% of the mass of current labour income (up to almost 73% if automation were total). Potential income loss by low-skilled non-manual workers, and lower-skilled smallholders and self-employed workers follow this.

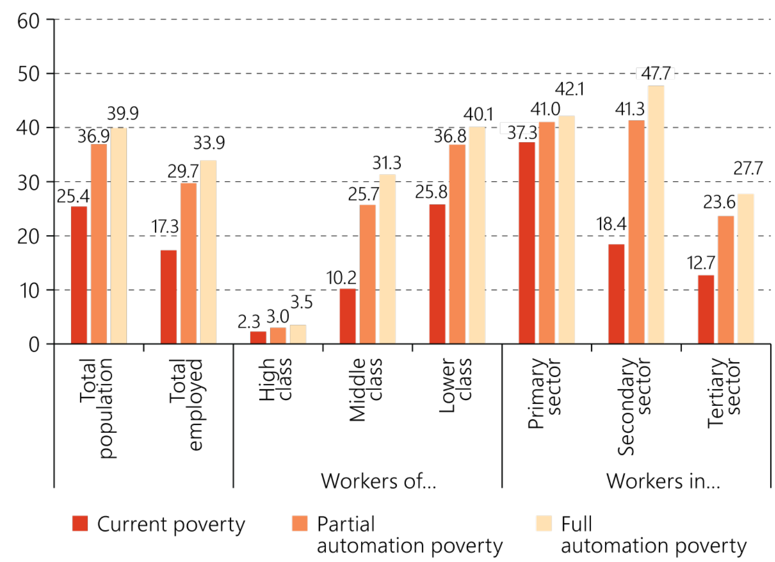
It is important to note that, except in the class of higher-level professional workers (and that of large entrepreneurs, directors and managers, with no risk of automation), workers in high-risk occupations according to occupational classes have higher labour incomes than the general average of each class, which could become an incentive to drive technological innovation processes within firms. On the other hand, the lower exposure to automation processes of higher occupational classes could change with the introduction of new generative artificial intelligence, which can significantly increase the extent to which technology can automate tasks traditionally performed by professionals and administrative staff (Felten, Raj and Seamans, 2023). However, estimates show a higher potential risk for the middle occupational classes to lose their labour income due to partial or full labour automation, as well as for workers in the manufacturing sector.

Then, to analyse the effects of potential income loss on poverty levels, occupational classes were grouped into lower classes (unskilled workers, lower-skilled smallholders and self-employed), middle classes (middle-level non-manual routine, low non-manual routine, and skilled manual workers) and upper classes (large employers, directors and managers, and higher-level professionals) (Martinez et al. 2022, p. 77). The results are presented below in figure 9. Thus, the total or partial loss of employment and respective labour income among workers in high-risk automation jobs could lead to a potential increase in poverty in the total population of up to 11.5 percentage points if automation only partially affects occupations (loss of income corresponding to automatable hours) and up to 14.5 percentage points if automation is total (high-risk occupations disappear entirely).

Given that this impact is theoretical, since in real terms, the processes of technological change and adaptation are gradual. The estimates of potential impact (in hours, equivalent employment, potential loss of income, poverty and inequality) correspond to partial equilibrium models; the potential impact on poverty in the countries analysed can be interpreted as the risk that almost 61 million non-poor people would at some point fall into poverty as a result of partial automation of the occupations of their household members in high-risk occupations. This figure would rise to 76.7 million people in the case of full automation.

On the other hand, the poverty level in the employed universe could increase by 12.4 and 16.6 percentage points (partial and full automation, respectively). The most significant potential impact in terms of the likelihood of falling into poverty is registered precisely among workers in the middle occupational classes: the risk of falling into poverty as a result of automation could potentially affect between 15.5% and 21.1% of workers in the middle occupational classes (non-manual workers with medium and low qualifications, and skilled manual workers). Workers in the secondary sector would also suffer the most from these potential automation processes, with between 23% and 29% of workers at risk of falling into poverty at some point (in addition to the 18.4% who were in poverty in 2019), if automation in the sector were partial or total, respectively (see Figure 9). Given that a gradual process of gradual introduction of automated processes is to be expected, the possibilities of adapting jobs, as well as adapting and retraining workers, suggest that these impacts could be significantly lower, provided that public policies and public-private partnerships are developed to promote this change by articulating the various sectors and actors involved.

Figure 9
Latin America (14 countries):[a] maximum potential impact of automation on poverty in scenarios of partial or total job loss among workers with a high probability of automation, by occupational class and sector of activity, around 2019
(Percentages)



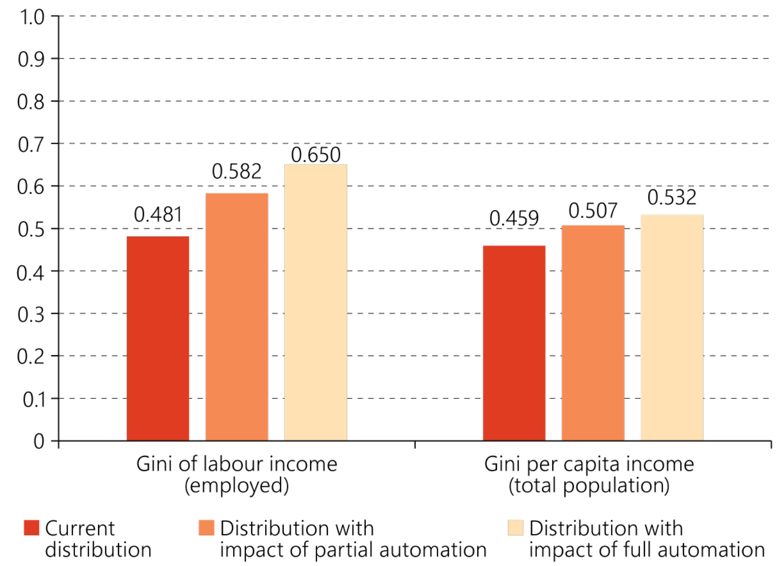
Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Weighted average of countries. Figures for employed persons exclude workers in the armed forces.

In this regard, it is crucial to take into consideration that while a significant portion of workers in the middle (and upper) occupational classes have more substantial resources and tools for retraining, training and access to job training systems in general, in the case of lower-class workers the margin for action (or response) in the face of the risk of automation is much smaller. Therefore, public policy support can be essential to minimise the adverse effects that process automation could generate.

In concordance with the poverty results, it is worth questioning the distributional effects of the loss of employment and labour income. Figure 10 shows the Gini coefficient estimates for workers' labour income and per capita household income. In the case of the labour Gini coefficient estimates, labour income is used and calculated for workers only. In that case, the estimated labour Gini coefficient corresponds to the change in income levels due to the labour income of workers with a high probability of automation who lose all or part of their jobs. This implies that for the estimated labour Gini in the total job loss scenario, the coefficient is recalculated considering that all high automation probability workers become zero-earners.[11] On the other hand, the per capita Gini coefficients consider per capita household income, and thus all individuals, and not only workers. As in the first case, the Gini per capita estimated in the case of total job loss considers that workers with a high probability of automation go on to have zero labour income.

[11] For the purposes of this redistributive effects exercise, workers who lose their jobs are left as zero-earners, which is taken into account in the calculation of the Gini coefficient. This is not a usual procedure, but is estimated in this way to show the potential effects on the labour Gini coefficient for the same set of workers as a result of the loss of income.

Figure 10
Latin America (14 countries):[a] impact of partial or full automation of high-risk occupations on labour and per capita income inequality, circa 2019
(Gini coefficients)



Source: Prepared by the authors, based on the PIAAC survey and the ECLAC household survey database (BADEHOG).
[a] Simple country average. Figures for employed persons exclude workers in the armed forces.

The results indicate that in the case of labour Gini coefficients, job loss among workers with a high probability of automation would result in a maximum increase of 0.17 points in the Gini coefficient, from 0.48 to 0.65 (full automation scenario). This sharp increase in income inequality reflects the impact of income loss in the labour market, assuming a theoretical scenario of no job adaptation or reintegration for those who lose their jobs. Similarly, in the case of the per capita Gini coefficient estimates, an increase of up to 0.07 points from 0.46 to 0.53 is observed. These changes are less abrupt but illustrate the significant impact that automation processes could have on the population as a whole, including workers, in a hypothetical scenario in which the introduction of technological change is neither gradual nor accompanied by industrial, labour, education and social protection policies.

IV. Policy implications

The results of this report have implications for several policy areas that are important to address. It is vital to recognise that automation is not necessarily a source of vulnerability but rather a potential risk that can generate vulnerability if adequate response capacity is not in place. Similarly, technological advances are an important source of productivity gains that, together with appropriate governance, can benefit countries in the region. It is, therefore, vital that policies are in place to anticipate and reduce the risks associated with automation and skills mismatch and that these measures are articulated with technological advances and their penetration into the countries' productive structures.

Skills gaps represent an inefficient use of the human resources available in society. To address this problem, developing and improving skills through vocational and continuous training, in conjunction with proactive policies, is critical. In this regard, one of the main obstacles is the lack of information in the region, both in terms of the rigorous measurement of skills and the demand for skills in the labour market, which hampers countries' ability to carry out this type of policy effectively (Gontero and Novella, 2021). Concerning anticipation and lifelong learning, different policy areas address them, such as education (primary, secondary, higher and technical), job training, labour, fiscal policy, industrial policy and social protection, often in an interrelated manner (Nedelkoska and Quintini, 2018; UNESCO, 2022).

Indeed, accelerated technological development may bring job instabilities and job losses that generate new demands for social protection, which existing policy configurations may not be prepared to satisfy (OECD & International Institute for Applied Systems Analysis, 2020). Different forms of social protection may fall within this spectrum, such as unemployment insurance, upskilling and reskilling programmes in and out of work, and individual learning accounts, which have recently gained notoriety in countries such as France and Canada (OECD, 2019a). Job losses can also pose a major challenge for pension systems, especially contributory ones, as individuals may incur lower future pensions due to prolonged or at least recurrent inactivity. The risks of automation occur in a regional context where the labour informality of adult workers is close to 47%, according to ILO (2023). Many workers will, therefore, find fewer options to retrain and adapt in their workplaces and with lower levels of protection against the risk of unemployment due to technological progress, among other potential risks. Reconfiguring this and other aspects of social protection and its interaction with other government benefits and employers is crucial to reducing the risks from automation and harnessing the benefits of technological change.

In the same vein, identifying and assessing skills mismatches is of great relevance to support the decision-making of workers, enterprises, training providers and countries in general. The availability of detailed information on occupations and skills requirements allows jobseekers to make informed decisions regarding their training and career paths. This information is also valuable for employers to design and implement training, recruitment or technology adoption policies that help mitigate the skills gap's adverse effects (Gontero and Novella, 2021). Training providers, in turn, will benefit from using this information to develop educational programmes that match existing labour demand. For its part, the public sector requires this information to identify the groups most affected by skills mismatch according to gender, age and educational level, among other relevant criteria, as well as the specific sectors or industries, such as transport, manufacturing and mining, and the areas where this problem is most prominent (ECLAC/OEI, 2020). In order to measure and address skills mismatches in an economy, it is essential to establish national skills frameworks, develop instruments to anticipate skills demand and strengthen labour information systems.

Education faces at least two crucial challenges concerning the abrupt emergence and recent development of artificial intelligence (AI). First, harnessing the benefits of AI to improve educational processes at the individual and system-wide levels; second, preparing students to acquire new skills relevant to increasingly automated economies and societies (Atchoarena, 2022; OECD, 2021b). Although AI applications are still in their early stages, the development of generative AIs open to the public shows increasing capabilities for complex problem-solving, information synthesis and adaptability to different occupational and educational needs. In this respect, many promising examples anticipate how AI could transform education and harness it to benefit students and teachers in a changing world (Giannini, 2023; OECD, 2021a, 2023b; UNESCO, 2019). In line with this challenge, given that the skills needed to enter and progress in the labour market are undergoing profound changes, with increased demand and emphasis on complex skills, education systems in several countries, especially in the OECD, have started to change their curricula and skills requirements, placing a greater emphasis on skills for innovation and citizenship in the digital age (Vincent-Lancrin and van der Vlies, 2020).

AI's ability to accelerate personalised learning and support students with special needs is highlighted in education and the classroom. At the level of the education system, promising uses are envisioned, such as predictive analytics to reduce dropout rates and assess new skills requirements (UNESCO, 2022). The growing demand for complex skills that take work to automate, such as creativity and critical thinking, is also a consequence of AI and digitalisation. To realise the full potential of AI, stakeholders must have confidence in both the technology and its use by humans. This raises new policy challenges concerning 'trusted AI', including protecting privacy and data security and preventing possible misuses that generate harmful biases towards specific individuals or groups (OECD, 2021b).

In this area, UNESCO has made progress in developing a methodology for assessing countries' artificial intelligence capabilities called RAM (*Readiness assessment methodology*). The RAM is an analysis that assesses various AI capabilities in a country, covering legal and regulatory, economic, social, cultural, scientific, educational, technical and infrastructural aspects. It also verifies whether the country's AI systems align with the values, principles and policies of UNESCO. National experts recruited by UNESCO with extensive knowledge of the local context carry out this process. The result is a comprehensive report that helps experts and policymakers identify the institutional and regulatory changes needed to harness these technologies' benefits while guarding against their potential disadvantages. Its purpose is to analyse the strengths and weaknesses of beneficiary countries concerning their ability to facilitate the ethical design, development and use of artificial intelligence (AI) and how to address these issues. For example, challenges could arise due to a need for more resources, capacity or specific policy issues, each requiring different institutional responses. These results would help UNESCO develop a valuable and unique roadmap for each country. In addition to providing detailed information on the status of individual countries, the RAM would also provide comparative information so that countries can learn from each other's experiences (UNESCO, 2023).

In a globalised world where technology is penetrating the world of work and everyday life at an ever faster pace, Latin American and Caribbean countries will need to consider similar considerations to remain competitive on a global scale. If countries in the region do not take steps to anticipate and adapt to automation, there is a risk that automation will become a severe problem. Moreover, widening productivity gaps resulting from technological innovation could further worsen the situation, affecting countries' long-term economic development and competitiveness.

V. Conclusions

This report highlights the relevance of the potential impacts of automation on the Latin American labour market. While automation is not a source of vulnerability in itself, it can be understood as a potential risk that can generate vulnerability in the absence or lack of response capacity. In this context, public policy should anticipate the risks arising from this process and take advantage of the opportunities that may arise from it. There are different policy areas to address this process, from education and job training, labour market, fiscal policy, industrial policy and social protection. The results show that it is crucial to take into account that risks are differentiated between different social groups, and that it is therefore necessary to build adapted and efficient policies that address the different needs that this process imposes.

The methodology presented in this document represents a significant step forward for estimating automation probabilities and risks in the region. It involves a unique estimation methodology, adapted to the region using available PIAAC surveys and updating current technological capabilities. The estimation procedure using *machine learning* techniques provides quality predictions that allow obtaining a probability vector easily transferable to other databases with compatible occupational classifiers, such as household surveys. The novelty of this paper is that it provides estimates of job automation based on Latin American data, including the distribution of job skills of workers in the region. The vector shows a moderate correlation with the one developed by Frey and Osborne (2017), potentially due to methodological differences and differences in skill distribution characteristics between US and Latin American occupations.

The methodological strategy has certain limitations that need to be taken into account. The main limitation stems from the assumption that each occupation has a unique probability of automation for all countries, similar to the probability vector presented by Frey and Osborne (2017) for the United States. This has been criticised by authors such as Arntz, Gregory and Zierahn (2016), who argue that automation risks may vary across workers in the same occupation due to differences in task composition. Moreover, this study focuses exclusively on the potential effects of technological capabilities on labour automation and does not address the social, economic and political factors that also influence these dynamics. Aspects such as automation costs, market preferences, taxes and regulations, and the role of trade unions and other social organisations are outside this study's scope and analytical objectives.

Unfortunately, few data sources address workers' use of job skills and types of tasks in the region. The O*NET survey has only been implemented in Uruguay, so the PIAAC surveys were considered a valuable source of information in the region for the purposes of this study. However, these surveys have a limited skill set and are not necessarily the most appropriate for conducting analyses of this type. In addition, the measures may be imprecise in specifying the uses of skills and task performance and the frequency or intensity with which they are performed. The PIAAC surveys also do not include a variable measuring the importance of a skill or task within the job, which may be an essential analytical aspect in this context, as shown by Lassébie and Quintini (2022) using the O*NET survey. Therefore, there is a need for new sources of information that respond to regional needs, as well as for improving the disaggregation of occupational classifiers in household surveys in the countries of the region, including the provision of harmonisation tables between national and international classifiers, which is essential to achieve comparable, accurate estimates that cover a more significant number of countries than those included in this study.

Concerning new sources of information and future study opportunities, in May 2023, the UNESCO Institute for Lifelong Learning (UIL) launched the e-PASS (Everyday Life Skills and Skills Survey) instrument,[12] which offers a simple, inexpensive, adaptable and effective way to assess literacy and numeracy skills, among others, for people aged 15 and over. This survey would provide reliable and comparable information, which would be valuable for policymakers at the national and international levels. The results provided by e-PASS could help skills analysis and programme planning, development and monitoring, as well as inform progress towards Sustainable Development Goal 4 of the 2030 Agenda. Indeed, novel tools such as this can help reduce the data limitations addressed in this report.

It is also important to mention that the estimates made in this study are largely based on the theoretical inputs from the workshop conducted by Frey and Osborne (2017)at Oxford University in 2010. However, this has three main limitations. First, the original conception of automatable and non-automatable occupations was made in a different technological context, without a clear vision of the future development in which various occupations and skills might become automatable due to technological advances. In recent years, there has been a breakthrough in technological capabilities that were not considered at the time (Lassébie and Quintini, 2022).Although there has been an effort to update the information on non-automatable skills in this research with new data sources and recent studies, it still relies heavily on these theoretical inputs. This poses a challenge for estimating automation risks in the short and medium term, considering the rapid technological development and increasing availability of artificial intelligence, such as the GPT or Bard series, which increases its potential use for work purposes and can potentially affect previously less exposed labour groups (Felten, Raj and Seamans, 2023).

Finally, with regard to policy implications, several key messages can be highlighted. The emergence of new technologies is presented as an opportunity to improve productivity and welfare conditions and as a risk mainly regarding job stability. Automation affects areas of labour, education and social protection policy, among others. The first major challenge is to reduce the risk of labour automation by rethinking education and adopting a culture of lifelong learning. To this end, developing and improving skills through vocational and lifelong learning and anticipatory policies that allow for early adaptation is necessary. The risks of automation are also part of the social protection needs, both in terms of prevention and protection against unemployment resulting from automation. Re-employment should be an aspect included in this policy configuration, with *upskilling* and *reskilling* modalities based on skills and competence training. Job losses can also pose a major challenge for pension systems because of the increased risk of periods of unemployment and inactivity that reduce pension contributions. Adapting and shaping these systems and benefits is crucial if countries in the region are to reap the multiple benefits of technological progress equitably, and reduce the potential risks and costs that may arise from it.

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[12] For more information see [online] https://www.uil.unesco.org/en/e-pass.

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Annex

Table A1
Frey and Osborne SOC-10 occupational codes imputed to ISCO-08

SOC-10 code not found	Description	ISCO-08 code imputed	Description
291060	Physicians and surgeons	2211	Generalist medical practitioners
291111	Registered nurses	2221	Nursing professionals
253999	Teachers and Instructors, all other	2359	Teaching professionals not elsewhere classified
251000	Postsecondary teachers	2310	University and higher education teachers
299799	Healthcare practitioners and technical workers, all other	3230	Traditional and complementary medicine associate professionals
394831	Funeral service managers, directors, morticians, and undertakers	1219	Business services and administration managers not elsewhere classified
151179	Information security analysts, web developers, and computer network architects	2529	Database and network professionals not elsewhere classified
151799	Computer occupations, all other	2529	Database and network professionals not elsewhere classified
292037	Radiologic technologists and technicians	3211	Medical imaging and therapeutic equipment technicians
131078	Human resources, training, and labour relations specialists, all other	2423	Personnel and careers professionals
292055	Surgical technologists	3259	Health associate professionals not elsewhere classified
292799	Health technologists and technicians, all other	3259	Health technologists and technicians, all other
499799	Installation, maintenance, and repair workers, all other	9622	Odd job persons
319799	Healthcare support workers, all other	3259	Health associate professionals not elsewhere classified
151150	Computer support specialists	3512	Information and communications technology user support technicians
474799	Construction and related workers, all other	7119	Building frame and related trades workers not elsewhere classified
452090	Miscellaneous agricultural workers	9212	Crop farm labourers
519399	Production workers, all other	9329	Manufacturing labourers not elsewhere classified
431041	Credit authorizers	4312	Statistical, finance and insurance clerks

Source: Prepared by the authors.

Table A2
Latin America (14 countries): probability of automation by country, age, educational attainment, sector of activity, and income quintiles
(Average)

	Argentina	Bolivia (Plurinational State of)	Brazil	Chile	Colombia	Costa Rica	Dominican Republic	Ecuador	Honduras	Mexico	Panama	Peru	El Salvador	Uruguay	Media
Media	0.51	0.53	0.51	0.49	0.52	0.50	0.51	0.48	0.49	0.50	0.51	0.49	0.48	0.53	0.50
15–24	0.48	0.52	0.52	0.49	0.51	0.52	0.52	0.48	0.48	0.49	0.50	0.52	0.47	0.51	0.51
25–34	0.51	0.56	0.51	0.48	0.52	0.51	0.53	0.50	0.50	0.50	0.53	0.52	0.49	0.53	0.51
35–44	0.51	0.55	0.50	0.49	0.52	0.49	0.50	0.48	0.50	0.50	0.52	0.49	0.48	0.52	0.50
45–54	0.51	0.52	0.50	0.50	0.52	0.49	0.50	0.48	0.49	0.50	0.50	0.48	0.47	0.53	0.50
55–64	0.52	0.51	0.50	0.50	0.51	0.50	0.50	0.47	0.48	0.49	0.51	0.47	0.46	0.53	0.49
65+	0.49	0.48	0.49	0.50	0.49	0.50	0.48	0.43	0.47	0.46	0.47	0.45	0.43	0.49	0.47
Secondary school incomplete or less	0.53	0.53	0.51	0.51	0.52	0.51	0.52	0.47	0.50	0.50	0.51	0.46	0.47	0.54	0.50
University incomplete or less	0.53	0.57	0.54	0.51	0.54	0.54	0.54	0.52	0.51	0.52	0.55	0.53	0.51	0.56	0.53
Full university education	0.44	0.44	0.43	0.41	0.43	0.41	0.42	0.42	0.40	0.43	0.44	0.48	0.44	0.41	0.43
Primary sector	0.58	0.47	0.49	0.51	0.44	0.49	0.48	0.45	0.47	0.46	0.41	0.43	0.46	0.52	0.47
Secondary sector	0.66	0.71	0.67	0.61	0.66	0.59	0.68	0.66	0.67	0.61	0.66	0.60	0.64	0.68	0.65
Tertiary sector	0.47	0.50	0.46	0.45	0.49	0.48	0.47	0.44	0.42	0.45	0.49	0.49	0.42	0.49	0.46
Quintile 1	0.49	0.50	0.47	0.50	0.49	0.47	0.48	0.45	0.47	0.46	0.44	0.46	0.45	0.50	0.47
Quintile 2	0.52	0.55	0.51	0.51	0.51	0.05	0.51	0.47	0.47	0.50	0.50	0.48	0.47	0.52	0.50
Quintile 3	0.51	0.56	0.52	0.51	0.53	0.52	0.51	0.48	0.50	0.51	0.53	0.50	0.48	0.54	0.52
Quintile 4	0.51	0.54	0.53	0.50	0.54	0.53	0.52	0.49	0.51	0.51	0.56	0.51	0.49	0.55	0.52
Quintile 5	0.49	0.50	0.48	0.45	0.50	0.48	0.51	0.49	0.49	0.48	0.49	0.49	0.48	0.51	0.48

Source: Prepared by the authors.

Table A3
Latin America (14 countries): vector probability of automation by occupational code

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
1111	Members of the legislature	0.267	0.267	0.281
1112	Senior public administration staff	0.262	0.267	0.281
1113	Heads of small towns	0.252	0.267	0.281
1114	Leaders of special interest organisations	0.292	0.267	0.281
1120	Managing Directors and General Managers	0.293	0.293	0.281
1211	Chief Financial Officers	0.315	0.303	0.345
1212	Human resources managers	0.351	0.303	0.345
1213	Policy and planning managers	0.412	0.303	0.345
1219	Administrative and service directors not elsewhere classified	0.232	0.303	0.345
1221	Sales and marketing managers	0.365	0.405	0.345
1222	Advertising and public relations managers	0.514	0.405	0.345
1223	Research and development managers	0.420	0.405	0.345
1311	Agricultural production and forestry managers	0.335	0.329	0.347
1312	Fish farming and fisheries production managers	0.200	0.329	0.347
1321	Managers of manufacturing industries	0.357	0.339	0.347
1322	Mining managers	0.339	0.339	0.347
1323	Directors of construction companies	0.342	0.339	0.347
1324	Managers of supply, distribution and related companies	0.287	0.339	0.347
1330	Managers of information and communication technology services	0.521	0.521	0.347
1341	Directors of childcare services	0.185	0.337	0.347
1342	Directors of health services	0.240	0.337	0.347
1343	Managers of elderly care services	0.337	0.337	0.347
1344	Directors of social welfare services	0.390	0.337	0.347
1345	Directors of education services	0.269	0.337	0.347
1346	Bank, financial services and insurance branch managers	0.446	0.337	0.347
1349	Directors and managers of professional services not elsewhere classified	0.506	0.337	0.347
1411	Hotel managers	0.333	0.317	0.320
1412	Restaurant managers	0.314	0.317	0.320
1420	Wholesale and retail managers	0.323	0.323	0.320
1431	Managers of sports, leisure and cultural centres	0.463	0.318	0.320
1439	Managers of services not elsewhere classified	0.282	0.318	0.320
2111	Physicists and astronomers	0.100	0.448	0.446
2112	Meteorologists	0.893	0.448	0.446
2113	Chemicals	0.421	0.448	0.446
2114	Geologists and geophysicists	0.508	0.448	0.446
2120	Mathematicians, actuaries and statisticians	0.670	0.670	0.446
2131	Biologists, botanists, botanists, zoologists and allied scientists	0.253	0.359	0.446
2132	Agronomists and related	0.380	0.359	0.446
2133	Environmental protection professionals	0.374	0.359	0.446
2141	Industrial and production engineers	0.374	0.371	0.446
2142	Civil engineers	0.296	0.371	0.446
2143	Environmental engineers	0.373	0.371	0.446
2144	Mechanical engineers	0.395	0.371	0.446

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
2145	Chemical engineers	0.375	0.371	0.446
2146	Mining, metallurgical and related engineers	0.572	0.371	0.446
2149	Engineers not elsewhere classified	0.427	0.371	0.446
2151	Electrical engineers	0.256	0.386	0.446
2152	Electronics engineers	0.444	0.386	0.446
2153	Telecommunications engineers	0.555	0.386	0.446
2161	Architects	0.539	0.576	0.446
2162	Landscape architects	0.576	0.576	0.446
2163	Product and garment designers	0.457	0.576	0.446
2164	Urban planners and traffic engineers	0.423	0.576	0.446
2165	Cartographers and surveyors	0.577	0.576	0.446
2166	Graphic and multimedia designers	0.653	0.576	0.446
2211	General practitioners	0.249	0.225	0.234
2212	Medical specialists	0.198	0.225	0.234
2221	Nursing professionals	0.207	0.188	0.234
2222	Midwifery professionals	0.112	0.188	0.234
2230	Traditional and alternative medicine practitioners	0.295	0.295	0.234
2240	Paramedic trainees	0.366	0.366	0.234
2250	Veterinarians	0.544	0.544	0.234
2261	Dentists	0.138	0.206	0.234
2262	Pharmacists	0.164	0.206	0.234
2263	Occupational and environmental health and hygiene professionals	0.603	0.206	0.234
2264	Physiotherapists	0.199	0.206	0.234
2265	Dieticians and nutritionists	0.284	0.206	0.234
2266	Audiologists and speech therapists	0.213	0.206	0.234
2267	Optometrists	0.206	0.206	0.234
2269	Health professionals not elsewhere classified	0.226	0.206	0.234
2310	University and higher education teachers	0.288	0.288	0.264
2320	Vocational teachers	0.288	0.288	0.264
2330	Secondary school teachers	0.262	0.262	0.264
2341	Primary school teachers	0.267	0.242	0.264
2342	Preschool teachers	0.173	0.242	0.264
2351	Specialists in pedagogical methods	0.257	0.298	0.264
2352	Special needs educators	0.333	0.298	0.264
2353	Other language teachers	0.255	0.298	0.264
2354	Other music teachers	0.376	0.298	0.264
2355	Other arts teachers	0.308	0.298	0.264
2356	Information technology trainers	0.194	0.298	0.264
2359	Teaching professionals not elsewhere classified	0.304	0.298	0.264
2411	Accountants	0.620	0.604	0.503
2412	Financial and investment advisors	0.525	0.604	0.503
2413	Financial analysts	0.566	0.604	0.503
2421	Management and organisational analysts	0.391	0.418	0.503
2422	Management policy specialists	0.508	0.418	0.503
2423	Specialists in personnel and related policies and services	0.379	0.418	0.503
2424	Specialists in staff training	0.452	0.418	0.503

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
2431	Advertising and marketing professionals	0.466	0.464	0.503
2432	Public relations professionals	0.451	0.464	0.503
2433	Technical and medical sales professionals (excluding ICT)	0.436	0.464	0.503
2434	Information and communications technology sales professionals	0.512	0.464	0.503
2511	Systems analysts	0.489	0.505	0.481
2512	Software developers	0.542	0.505	0.481
2513	Web and multimedia developers	0.746	0.505	0.481
2514	Application programmers	0.309	0.505	0.481
2519	Software and multimedia developers and analysts, and analysts not elsewhere classified	0.476	0.505	0.481
2521	Database designers and administrators	0.469	0.428	0.481
2522	System administrators	0.368	0.428	0.481
2523	Computer network professionals	0.443	0.428	0.481
2529	Database and computer network specialists not elsewhere classified	0.424	0.428	0.481
2611	Lawyers	0.308	0.337	0.349
2612	Judges	0.155	0.337	0.349
2619	Legal professionals not elsewhere classified	0.581	0.337	0.349
2621	Archivists and museum curators	0.489	0.519	0.349
2622	Librarians, documentalists and related professionals	0.565	0.519	0.349
2631	Economists	0.371	0.241	0.349
2632	Sociologists, anthropologists and related	0.288	0.241	0.349
2633	Philosophers, historians and political scientists	0.287	0.241	0.349
2634	Psychologists	0.293	0.241	0.349
2635	Social work professionals	0.170	0.241	0.349
2636	Religious professionals	0.189	0.241	0.349
2641	Authors and other writers	0.629	0.593	0.349
2642	Journalists	0.646	0.593	0.349
2643	Translators, interpreters and linguists	0.219	0.593	0.349
2651	Artists of visual arts	0.417	0.392	0.349
2652	Musicians, singers and composers	0.390	0.392	0.349
2653	Dancers and choreographers	0.327	0.392	0.349
2654	Film, theatre and related directors	0.253	0.392	0.349
2655	Actors	0.511	0.392	0.349
2656	Radio, television and other media broadcasters	0.556	0.392	0.349
2659	Creative and performing artists not elsewhere classified	0.351	0.392	0.349
3111	Physical and chemical science technicians	0.362	0.526	0.454
3112	Civil engineering technicians	0.649	0.526	0.454
3113	Electrotechnicians	0.423	0.526	0.454
3114	Electronics technicians	0.473	0.526	0.454
3115	Mechanical engineering technicians	0.455	0.526	0.454
3116	Industrial chemistry technicians	0.402	0.526	0.454
3117	Mining engineering and metallurgy technicians	0.842	0.526	0.454
3118	Draughtsmen and technical draughtsmen	0.802	0.526	0.454
3119	Physical science and engineering technicians not elsewhere classified	0.500	0.526	0.454
3121	Supervisors in mining engineering	0.603	0.407	0.454
3122	Supervisors in manufacturing industries	0.432	0.407	0.454
3123	Construction supervisors	0.336	0.407	0.454

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
3131	Operators of energy production facilities	0.909	0.487	0.454
3132	Operators of incinerators, water treatment plants and related facilities	0.635	0.487	0.454
3133	Controllers of chemical processing facilities	0.590	0.487	0.454
3134	Operators of oil and natural gas refining installations	0.304	0.487	0.454
3135	Metal production process controllers	0.171	0.487	0.454
3139	Process control technicians not elsewhere classified	0.454	0.487	0.454
3141	Life science technicians (excluding medicine)	0.574	0.355	0.454
3142	Agricultural technicians	0.321	0.355	0.454
3143	Forestry technicians	0.498	0.355	0.454
3151	Engineer officers in navigation	0.518	0.421	0.454
3152	Captains, deck officers and pilots	0.364	0.421	0.454
3153	Aviation and related pilots	0.421	0.421	0.454
3154	Air traffic controllers	0.419	0.421	0.454
3155	Aviation safety technicians	0.421	0.421	0.454
3211	Medical diagnostic and treatment equipment technicians	0.397	0.400	0.437
3212	Medical laboratory technicians	0.442	0.400	0.437
3213	Pharmacy technicians and assistants	0.330	0.400	0.437
3214	Medical and dental prosthesis technicians	0.374	0.400	0.437
3221	Mid-level nursing professionals	0.463	0.463	0.437
3222	Mid-level midwifery professionals	0.463	0.463	0.437
3230	Mid-level practitioners of traditional and alternative medicine	0.158	0.158	0.437
3240	Veterinary technicians and assistants	0.633	0.633	0.437
3251	Dental assistants and dental assistants	0.525	0.426	0.437
3252	Health documentation technicians	0.426	0.426	0.437
3253	Community health workers	0.358	0.426	0.437
3254	Optometric technicians and opticians	0.404	0.426	0.437
3255	Physiotherapist technicians and assistants	0.317	0.426	0.437
3256	Trainees and medical assistants	0.377	0.426	0.437
3257	Occupational, environmental and related health inspectors	0.492	0.426	0.437
3258	Ambulance attendants	0.519	0.426	0.437
3259	Mid-level health professionals not elsewhere classified	0.177	0.426	0.437
3311	Brokers, foreign exchange and other financial services	0.698	0.694	0.535
3312	Loan and credit officers	0.761	0.694	0.535
3313	Bookkeepers	0.646	0.694	0.535
3314	Mid-level statistical, mathematical and related service professionals	0.491	0.694	0.535
3315	Valuers	0.862	0.694	0.535
3321	Insurance agents	0.747	0.440	0.535
3322	Sales representatives	0.406	0.440	0.535
3323	Purchasing agents	0.432	0.440	0.535
3324	Purchasing agents and consignees	0.512	0.440	0.535
3331	Customs declarants or managers	0.518	0.546	0.535
3332	Conference and event organisers	0.399	0.546	0.535
3333	Employment agents and labour contractors	0.704	0.546	0.535
3334	Real estate agents	0.658	0.546	0.535
3339	Commercial services agents not elsewhere classified	0.649	0.546	0.535
3341	Secretarial supervisors	0.417	0.644	0.535

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
3342	Legal secretaries	0.575	0.644	0.535
3343	Administrative and executive secretaries	0.707	0.644	0.535
3344	Medical secretaries	0.622	0.644	0.535
3351	Customs officers and border inspectors	0.188	0.472	0.535
3352	Tax administration agents	0.524	0.472	0.535
3353	Agents of social security services	0.410	0.472	0.535
3354	Licensing and permit issuing services agents	0.763	0.472	0.535
3355	Police inspectors and detectives	0.279	0.472	0.535
3359	Law enforcement and related public administration agents not elsewhere classified	0.524	0.472	0.535
3411	Mid-level legal, legal services and related professionals	0.710	0.585	0.465
3412	Mid-level social workers and social workers	0.369	0.585	0.465
3413	Lay auxiliaries of religions	0.322	0.585	0.465
3421	Athletes and sportsmen	0.432	0.333	0.465
3422	Coaches, instructors and referees of sporting activities	0.349	0.333	0.465
3423	Instructors of physical education and recreational activities	0.295	0.333	0.465
3431	Photographers	0.712	0.449	0.465
3432	Interior designers and decorators	0.434	0.449	0.465
3433	Technicians in art galleries, museums and libraries	0.276	0.449	0.465
3434	Chefs	0.349	0.449	0.465
3435	Other mid-level professionals in cultural and artistic activities	0.409	0.449	0.465
3511	Information and Communications Technology Operations Technicians	0.639	0.595	0.595
3512	Information and Communications Technology User Support Technicians	0.554	0.595	0.595
3513	Network and computer systems technicians	0.593	0.595	0.595
3514	Web Technicians	0.638	0.595	0.595
3521	Broadcasting and audio-visual recording technicians	0.558	0.592	0.595
3522	Telecommunications engineering technicians	0.695	0.592	0.595
4110	General clerks	0.747	0.747	0.755
4120	Secretaries (general)	0.749	0.749	0.755
4131	Word-processing machine operators and typists	0.848	0.799	0.755
4132	Data recorders	0.787	0.799	0.755
4211	Bank tellers and related staff	0.590	0.644	0.659
4212	Betting and betting-related receivers	0.614	0.644	0.659
4213	Moneylenders	0.888	0.644	0.659
4214	Collectors and related	0.716	0.644	0.659
4221	Travel agency employees	0.770	0.670	0.659
4222	Call centre employees	0.754	0.670	0.659
4223	Telephone operators	0.837	0.670	0.659
4224	Hotel receptionists	0.366	0.670	0.659
4225	Information desk employees	0.685	0.670	0.659
4226	Receptionists (general)	0.678	0.670	0.659
4227	Survey and market research interviewers	0.720	0.670	0.659
4229	Customer information services employees not elsewhere classified	0.763	0.670	0.659
4311	Accounting and costing clerks	0.707	0.719	0.697
4312	Statistical, financial and insurance services employees	0.884	0.719	0.697
4313	Payroll clerks	0.684	0.719	0.697

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
4321	Supply and inventory control clerks	0.661	0.684	0.697
4322	Production support services employees	0.781	0.684	0.697
4323	Transport service employees	0.811	0.684	0.697
4411	Library staff	0.724	0.766	0.766
4412	Postal service employees	0.862	0.766	0.766
4413	Data encoders, proof-readers and related	0.662	0.766	0.766
4414	Notaries public and related	0.914	0.766	0.766
4415	Archive employees	0.773	0.766	0.766
4416	Employees of the personnel service	0.713	0.766	0.766
4419	Administrative support staff not elsewhere classified	0.772	0.766	0.766
5111	On-board service assistants	0.572	0.833	0.282
5112	Public transport inspectors and ticket collectors	0.867	0.833	0.282
5113	Tourist guides	0.762	0.833	0.282
5120	Cooks	0.197	0.197	0.282
5131	Waiters and waitresses	0.279	0.287	0.282
5132	Bar waiters	0.365	0.287	0.282
5141	Hairdressers	0.179	0.179	0.282
5142	Specialists in beauty and related treatments	0.179	0.179	0.282
5151	Maintenance and cleaning supervisors in offices, hotels and other establishments	0.611	0.489	0.282
5152	Bursars and domestic stewards	0.352	0.489	0.282
5153	Caretakers	0.441	0.489	0.282
5161	Astrologers, fortune tellers and the like	0.269	0.269	0.282
5162	Accompanists and valets	0.181	0.269	0.282
5163	Morticians and embalmers	0.599	0.269	0.282
5164	Animal carers	0.389	0.269	0.282
5165	Driving instructors	0.315	0.269	0.282
5169	Personal service workers not elsewhere classified	0.321	0.269	0.282
5211	Kiosk and market stall vendors	0.232	0.215	0.322
5212	Street vendors selling food products	0.186	0.215	0.322
5221	Shopkeepers	0.261	0.327	0.322
5222	Shop and warehouse supervisors	0.444	0.327	0.322
5223	Shop and store sales assistants	0.353	0.327	0.322
5230	Cash dispensers and ticket dispensers	0.630	0.630	0.322
5241	Fashion, art and advertising models	0.566	0.330	0.322
5242	Shop demonstrators	0.460	0.330	0.322
5243	Door-to-door salesmen	0.184	0.330	0.322
5244	Telemarketers	0.533	0.330	0.322
5245	Petrol station forecourts	0.377	0.330	0.322
5246	Counter food vendors	0.298	0.330	0.322
5249	Salespersons not elsewhere classified	0.326	0.330	0.322
5311	Childminders	0.176	0.334	0.336
5312	Teacher assistants	0.545	0.334	0.336
5321	Personal care workers in institutions	0.473	0.343	0.336
5322	Personal home care workers	0.290	0.343	0.336
5329	Personal care workers in health services, not elsewhere classified	0.474	0.343	0.336
5411	Firefighters	0.556	0.773	0.773

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
5412	Police	0.617	0.773	0.773
5413	Prison guards	0.768	0.773	0.773
5414	Protective guards	0.816	0.773	0.773
5419	Protective services personnel not elsewhere classified	0.706	0.773	0.773
6111	Farmers and skilled field crop workers	0.445	0.457	0.444
6112	Farmers and skilled tree and shrub plantation workers	0.481	0.457	0.444
6113	Farmers and skilled orchard, greenhouse, nursery and garden workers	0.463	0.457	0.444
6114	Mixed crop farmers and skilled workers	0.451	0.457	0.444
6121	Livestock breeders	0.450	0.431	0.444
6122	Poultry farmers and skilled poultry workers	0.310	0.431	0.444
6123	Beekeepers and sericulturists and skilled beekeeping and sericulture workers	0.444	0.431	0.444
6129	Breeders and skilled animal handlers engaged in the rearing of livestock not elsewhere classified	0.481	0.431	0.444
6130	Producers and skilled workers of mixed agricultural holdings whose production is destined for the market	0.341	0.341	0.444
6210	Skilled forestry and related workers	0.662	0.662	0.487
6221	Aquaculture farm workers	0.573	0.444	0.487
6222	Freshwater and coastal water fishermen	0.380	0.444	0.487
6223	Deep-sea fishermen	0.520	0.444	0.487
6224	Hunters and trappers	0.444	0.444	0.487
6310	Subsistence agricultural workers	0.355	0.355	0.317
6320	Subsistence livestock workers	0.243	0.243	0.317
6330	Subsistence agricultural workers	0.198	0.198	0.317
6340	Subsistence fishermen, hunters, trappers, and gatherers	0.328	0.328	0.317
7111	Home builders	0.818	0.836	0.801
7112	Bricklayers	0.840	0.836	0.801
7113	Stone masons, stone cutters, stone cutters and engravers	0.896	0.836	0.801
7114	Reinforced concrete workers, plasterers and related workers	0.766	0.836	0.801
7115	Carpenters and carpentry work	0.840	0.836	0.801
7119	Building and related trades workers (rough construction) and related trades workers not elsewhere classified	0.820	0.836	0.801
7121	Roofers	0.775	0.676	0.801
7122	Floor layers and floor layers	0.873	0.676	0.801
7123	Revocators	0.816	0.676	0.801
7124	Installers of insulation and soundproofing materials	0.812	0.676	0.801
7125	Glaziers	0.735	0.676	0.801
7126	Plumbers and pipe fitters	0.563	0.676	0.801
7127	Refrigeration and air-conditioning installation mechanics-assemblers	0.647	0.676	0.801
7131	Painters and wallpaperers	0.854	0.774	0.801
7132	Varnishers and related	0.495	0.774	0.801
7133	Facade cleaners and chimney sweeps	0.755	0.774	0.801
7211	Moulders and moulders	0.864	0.815	0.682
7212	Welders and flame cutters	0.814	0.815	0.682
7213	Sheet metal workers and boilermakers	0.875	0.815	0.682
7214	Metal structure fitters	0.789	0.815	0.682
7215	Riggers and cable splicers	0.770	0.815	0.682
7221	Blacksmiths and smiths	0.869	0.820	0.682

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
7222	Toolmakers and allied trades	0.785	0.820	0.682
7223	Controllers and machine tool operators	0.790	0.820	0.682
7224	Metal polishers and tool sharpeners	0.757	0.820	0.682
7231	Motor vehicle mechanics and repairers	0.491	0.557	0.682
7232	Aircraft engine mechanics and repairers	0.475	0.557	0.682
7233	Agricultural and industrial machinery mechanics and repairers	0.763	0.557	0.682
7234	Bicycle and related repairers	0.356	0.557	0.682
7311	Precision instrument mechanics and repairers	0.566	0.762	0.779
7312	Musical instrument manufacturers and tuners	0.283	0.762	0.779
7313	Jewellers, goldsmiths and silversmiths	0.888	0.762	0.779
7314	Potters and related trades (earthenware, clay and abrasives)	0.830	0.762	0.779
7315	Glass blowers, shapers, laminators, cutters and polishers	0.600	0.762	0.779
7316	Poster designers, decorative painters and engravers	0.670	0.762	0.779
7317	Craftsmen in wood, basketry and similar materials	0.861	0.762	0.779
7318	Craftsmen of textiles, leather and similar materials	0.784	0.762	0.779
7319	Crafts and skilled trades not elsewhere classified	0.734	0.762	0.779
7321	Cashiers, typesetters and related workers	0.849	0.851	0.779
7322	Printers	0.850	0.851	0.779
7323	Bookbinders and related trades	0.858	0.851	0.779
7411	Site electricians and related tradesmen	0.836	0.790	0.712
7412	Electrical mechanics and fitters	0.696	0.790	0.712
7413	Electrical line installers and repairers	0.753	0.790	0.712
7421	Mechanics and repairers in electronics	0.542	0.576	0.712
7422	Information and communications technology installers and repairers	0.629	0.576	0.712
7511	Butchers, fishmongers and related workers	0.566	0.685	0.724
7512	Bakers, confectioners and bakers' workshops	0.707	0.685	0.724
7513	Dairy processing operators	0.857	0.685	0.724
7514	Fruit, vegetables and related products preservation workers	0.678	0.685	0.724
7515	Food and beverage tasters and graders	0.602	0.685	0.724
7516	Preparers and manufacturers of tobacco and tobacco products	0.621	0.685	0.724
7521	Wood processing operators	0.803	0.844	0.724
7522	Cabinetmakers and related trades	0.867	0.844	0.724
7523	Controllers and operators of woodworking machines	0.840	0.844	0.724
7531	Tailors, dressmakers, furriers, hatters and milliners	0.823	0.731	0.724
7532	Pattern makers and fabric and related cutters	0.832	0.731	0.724
7533	Seamstresses, embroiderers and related workers	0.701	0.731	0.724
7534	Upholsterers, upholsterers, mattressers and allied workers	0.619	0.731	0.724
7535	Furskinners, leatherworkers and tanners	0.731	0.731	0.724
7536	Shoemakers and related trades	0.767	0.731	0.724
7541	Divers	0.559	0.626	0.724
7542	Money changers and gluers	0.676	0.626	0.724
7543	Product graders and testers (excluding food and beverages)	0.626	0.626	0.724
7544	Fumigators and other pest and weed controllers	0.538	0.626	0.724
7549	Journeymen, journeymen and craftsmen in the mechanical and other crafts and trades not elsewhere classified	0.758	0.626	0.724
8111	Miners and operators of mining installations	0.840	0.849	0.800
8112	Operators of mineral and rock processing installations	0.883	0.849	0.800

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
8113	Drillers and drillers of wells and related fields	0.804	0.849	0.800
8114	Operators of machines for the manufacture of cement and other mineral products	0.885	0.849	0.800
8121	Metal processing plant operators	0.871	0.875	0.800
8122	Metal polishing, galvanising and coating machine operators	0.909	0.875	0.800
8131	Chemical plant and machine operators	0.834	0.834	0.800
8132	Operators of machines for manufacturing photographic products	0.834	0.834	0.800
8141	Operators of machines for the manufacture of rubber products	0.733	0.761	0.800
8142	Operators of machines for the manufacture of plastic products	0.824	0.761	0.800
8143	Operators of machines for the production of paper products	0.699	0.761	0.800
8151	Operators of fibre preparation, spinning and winding machines	0.808	0.751	0.800
8152	Operators of looms and other weaving machines	0.808	0.751	0.800
8153	Sewing machine operators	0.880	0.751	0.800
8154	Bleaching, dyeing and fabric cleaning machine operators	0.783	0.751	0.800
8155	Hide and skin processing machine operators	0.822	0.751	0.800
8156	Operators of machines for the manufacture of footwear and related industries	0.864	0.751	0.800
8157	Washing machine operators	0.215	0.751	0.800
8159	Operators of machinery for the manufacture of textile products and fur and leather articles not elsewhere classified	0.825	0.751	0.800
8160	Food and allied product processing machine operators	0.821	0.821	0.800
8171	Operators of pulp and paper pulp preparation facilities	0.892	0.883	0.800
8172	Wood processing plant operators	0.879	0.883	0.800
8181	Glaziers and ceramics plant operators	0.829	0.788	0.800
8182	Steam engine and boiler operators	0.904	0.788	0.800
8183	Packaging, bottling and labelling machine operators	0.766	0.788	0.800
8189	Operators of machinery and fixed installations not elsewhere classified	0.775	0.788	0.800
8211	Mechanical machinery assemblers	0.858	0.882	0.882
8212	Assemblers of electrical and electronic equipment	0.892	0.882	0.882
8219	Assemblers not elsewhere classified	0.882	0.882	0.882
8311	Locomotive drivers	0.809	0.802	0.879
8312	Brakemen, switchmen and shunting agents	0.788	0.802	0.879
8321	Motorbike drivers	0.955	0.923	0.879
8322	Car, taxi and van drivers	0.908	0.923	0.879
8331	Bus and tram drivers	0.902	0.851	0.879
8332	Heavy truck drivers	0.812	0.851	0.879
8341	Operators of mobile agricultural and forestry machinery	0.642	0.767	0.879
8342	Operators of earthmoving and related machines	0.791	0.767	0.879
8343	Crane, hoist and related equipment operators	0.785	0.767	0.879
8344	Forklift operators	0.863	0.767	0.879
8350	Deckhands and related seafarers	0.760	0.760	0.879
9111	Cleaners and domestic helpers	0.121	0.310	0.356
9112	Cleaners and assistants in offices, hotels and other establishments	0.742	0.310	0.356
9121	Manual washers and ironers	0.224	0.612	0.356
9122	Vehicle washers	0.704	0.612	0.356
9123	Window washers	0.612	0.612	0.356
9129	Other cleaning staff	0.747	0.612	0.356
9211	Farm labourers	0.484	0.486	0.486

ISCO-08 Code	Occupation	Likelihood of automation		
		to 4 digits	to 3 digits	to 2 digits
9212	Livestock farm labourers	0.438	0.486	0.486
9213	Mixed crop and livestock farm labourers	0.521	0.486	0.486
9214	Garden and horticultural workers	0.578	0.486	0.486
9215	Forestry labourers	0.515	0.486	0.486
9216	Fishery and aquaculture workers	0.460	0.486	0.486
9311	Mine and quarry labourers	0.851	0.273	0.403
9312	Public works and maintenance workers	0.516	0.273	0.403
9313	Building construction labourers	0.210	0.273	0.403
9321	Hand packers	0.520	0.507	0.403
9329	Labourers in manufacturing industry not elsewhere classified	0.496	0.507	0.403
9331	Drivers of pedal- and arm-operated vehicles	0.410	0.479	0.403
9332	Drivers of animal-drawn vehicles and machinery	0.479	0.479	0.403
9333	Loading labourers	0.439	0.479	0.403
9334	Shelf stockers	0.640	0.479	0.403
9411	Fast food cooks	0.328	0.385	0.385
9412	Kitchen assistants	0.433	0.385	0.385
9510	Mobile service and related workers	0.507	0.507	0.369
9520	Street vendors (excluding food vendors)	0.363	0.363	0.369
9611	Refuse and recyclable material collectors	0.724	0.617	0.636
9612	Waste sorters	0.703	0.617	0.636
9613	Street sweepers and related workers	0.488	0.617	0.636
9621	Messengers, errand boys, porters and delivery drivers	0.723	0.643	0.636
9622	Persons performing miscellaneous work	0.515	0.643	0.636
9623	Cash pickers at vending machines and meter readers	0.899	0.643	0.636
9624	Water carriers and firewood collectors	0.643	0.643	0.636
9629	Elementary occupations not elsewhere classified	0.510	0.643	0.636

Source: Prepared by the authors, based on PIAAC surveys.

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