Artificial Intelligence and Labor Market Transformations in Latin America *

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March 13, 2025

Abstract

This study examines the implications of artificial intelligence (AI) on employment, wages, and inequality in Latin America and the Caribbean (LAC). The paper identifies tasks and occupations most exposed to AI using comprehensive individual-level data alongside AI exposure indices. Unlike traditional automation, AI exposure correlates positively with higher education levels, ICT, and STEM skills. Notably, younger workers and women with high-level ICT and managerial skills face increased AI exposure, underscoring unique opportunities. A comparison of LAC with the OECD countries reveals greater impacts of AI in the former, with physical and customer-facing tasks showing divergent correlations to AI exposure. The findings indicate that while AI contributes to employment growth at the top and bottom of wage quintiles, its wage impact strongly depends on the movement of workers from the middle class to below the wage mean of the high-level quintile of wages, hence decreasing the average income of the top quintile.

*We acknowledge the outstanding research assistance from Raul Fugellie and Andres Fontaine. We thank the Strategy, Innovation, Entrepreneurship and Sustainability Group (SIES), colleagues and students from the Ph.D in Management at the School of Business at Adolfo Ibanez for their comments. We also thank Jorge Hernandez and Soledad Arellano for launching the Research with Impact Initiative, which provided us with partial funding for this research. We thank the Congreso Futuro initiative from the Chilean Senate that allows us to be the AI frontier of advances and AI legislative needs of Chile. PE is grateful for the support provided by the Centre for Social Conflict and Cohesion Studies COES (ANID/FONDAP/1523A0005) and Millennium Nucleus of The Evolution of Work MNEW (ANID/Millenium Science Initiative Program/NCS2021-033)

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JEL classifications:J23, J24, J31,O1,O33
Keywords: Artificial Intelligence, Automation, Labor Market, Developing Economies, AI Exposure, Inequality, Non Cognitive Skills, Cognitive Skills.

1 Introduction

In just over two years since the release of ChatGPT, artificial intelligence (AI) has dominated discussions about the challenges posed by AI-based automation. While numerous studies analyze the impact of robots and routine task automation, AI presents an even more significant challenge because it can perform not only routine tasks but also more complex tasks requiring a degree of cognition. This leads to a rethinking of the effects and raises the question of whether they alter the results commonly documented by traditional automation (e.g. Acemoglu and Restrepo (2011); Frey and Osborne (2013, 2017); Arntz et al. (2016); Acemoglu and Restrepo (2022, 2018); Nedelkoska and Quintini (2018); Egana-delSol et al. (2022a); Filippi et al. (2023)).[1]

Although the adoption process of Generative AI is still in the pilot stage in several industries, there have been many efforts to determine its impact on the market (Brynjolfsson et al., 2025; Brynjolfsson and Unger, 2023). These efforts have mainly focused on developed countries, with a few exceptions (Gmyrek et al., 2024; Benites and Parrado, 2024). As noted in Cazzaniga et al. (2024), unlike previous waves of automation, which had their strongest effects on middle-skilled workers, the displacement risks associated with AI extend to higher-paid workers.[2] These outcomes will depend on both the complementarity of occupations and exposure to artificial intelligence, which differ between advanced and emerging economies Cazzaniga et al. (2024).

This article explores the potential effects of artificial intelligence (AI) on the future of

[1]Prior to the advent of AI, automation has been shown to impact and exacerbate wage inequality in the United States (Acemoglu and Restrepo, 2022). Furthermore, it has influenced the distribution of tasks and skills in the labor market in OECD countries (Lassébie and Quintini, 2022). In this context, higher levels of specialization and obtaining advanced degrees can help mitigate the negative impact of automation in certain segments of the labor market (Autor, 2019). Research on developing countries, and, particularly in Latin America, indicates that the potential impacts may be even more pronounced, aligning with evidence suggesting that higher education and specialization can alleviate these effects (Egana-delSol, 2020; Egana-delSol et al., 2022a).

[2]Consistently, Webb (2020) indicates that exposure to AI is greatest among high-skilled occupations, suggesting that AI will affect a markedly different demographic group than those affected by software and robots. With this, AI may have a major impact on economies by amplifying inequalities by increasing returns to capital and with different effects for workers depending on age and educational attainment (Acemoglu and Restrepo, 2022).

work in developing countries, with a specific focus on Latin America and the Caribbean. To conduct this analysis, we utilized various data sources, including the World Bank's Skills Towards Employment and Productivity (STEP) survey, the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), and household or labor surveys from multiple countries. We implemented an expectation maximization algorithm (Ibrahim, 1990) in conjunction with AI exposure estimates from Felten et al. (2021) and Webb (2020). This approach allowed us to identify the tasks and skills that are most exposed to AI for each occupation and demographic group based on age, education, and gender.

Using both Felten et al. (2021)'s and Webb (2020)'s AI exposure indices, we estimate the degree of exposure to AI that different tasks and skills have, along with understanding the cross-country and demographic differences that may exist. Our results reveal significant gender disparities, highlighting that, for example, management skills and ICT skills exhibit notably stronger associations with AI exposure for women in several countries compared to their male counterparts. This suggests that women in these labor markets may encounter different or greater vulnerabilities to AI, especially in occupations where these skills are prevalent.

Educational attainment emerges as a critical determinant in shaping AI exposure. The coefficients for middle and high-level education are consistently positive and highly significant across countries and genders, indicating that higher educational attainment, contrary to some expectations, is associated with greater predicted exposure to AI.

As for the age variable, for young adults (18-25 years) and adults (25-40 years) they point to nuanced effects of age on AI exposure, although these effects vary by country and gender. In some cases, younger workers show lower exposure, potentially because they are in less routine or more adaptable roles.

Our results suggest that both the highly skilled and certain demographic groups, particularly women in sectors requiring ICT and managerial skills, may face disproportionately AI exposure. This interaction could point to a possible widening of inequality, where educational attainment does not uniformly protect workers but may instead concentrate exposure to AI among those expected to be more resilient in more developed economies, such as those in the OECD.

The results are consistent across both AI indices. The main differences emerge when examining tasks and skills, due to the varying considerations of these skills in constructing the indices. These results imply that AI could exacerbate existing socioeconomic inequalities in Latin America more sharply than in OECD countries, where social safety nets and labor force retraining programs could cushion similar shocks. However, the magnitude of this effect differs: the coefficients in Latin America are substantially larger than those observed in the OECD, implying that the protective effect of advanced education against AI exposure may be more pronounced (or, conversely, the exposure more acute) in Latin America. In Latin American contexts, the steeper gradients associated with education and skill levels imply that disparities in access to high-quality education and skills training could exacerbate existing inequalities, both within the region and compared to more developed economies. This is related to the recent results of Bone et al. (2025) showing that while demand for AI-related roles grew by 21%, mentions of university education requirements for these roles declined by 15%. Their causal analysis reveals that AI skills carry a wage premium of 23%, compared to 33% for university degrees up to the PhD level.

Finally, we assess how expected AI exposure (as measured by the Webb (2020) and Felten et al. (2021) methodologies) affects labor market outcomes in different quintiles of employment and across several wage ranges. The results indicate that higher exposure to AI by one index unit, as measured by the Webb (2020) methodology, is associated with a statistically significant 1.29% increase in employment growth. In contrast, the effect on wage growth is negative but not statistically significant. The results are similar when using the Felten et al. (2021) index.[3]

Regarding employment, both sets of estimations show a polarization in employment growth, with employment gains concentrated in the high and bottom quintiles of the income distribution, accompanied by a decrease in the size of the middle-income class.

Although the income of the workers entering the top quintile is growing, it is below its mean income; therefore, the average income is falling in the top quintile, but its size is growing on the lower end. These findings indicate that occupations at the higher end of the wage distribution benefit from AI exposure in terms of employment, but aggregated

[3] In fact, when using Felten et al. (2021)'s measure of AI exposure, the coefficient for employment growth is 0.656 and significant at the 5% level, while the wage effect remains small and insignificant. These findings suggest that while AI exposure appears to stimulate employment growth, the impact on wages is less clear, suggesting a complex dynamic between technology adoption, job creation and wage determination.

wage dynamics may be negatively affected, even though all workers in the top quintile might be better off.

The paper is organized as follows: In Section 2, we conduct a literature review to provide a theoretical background. Section 3 describes our data, and Section 4 our methodology. Section 5 presents our main results. Finally, Section 6 provides a discussion of our results, and Section 7 offers final remarks.

2 Literature Review IA

The relationship between automation and the labor market has been the subject of extensive research in recent years. Technological innovations, especially robotics and artificial intelligence (AI), are transforming labor structures globally. A study by (Acemoglu and Restrepo, 2022) finds that between 50% and 70% of changes in the U.S. wage structure between 1980 and 2016 can be attributed to a fall in the relative wages of workers skilled in routine tasks, particularly in industries with high exposure to automation. In Europe, the penetration of robotics has negatively impacted both wages and employment rates over the period 2006-2018 (Doorley et al., 2023).

This process of automation has led to a polarization in the labor market, with wage gains concentrated mainly at the extremes of the income and skill distribution, while workers in the middle of the distribution have seen few gains (Autor, 2015). Despite the negative effects for certain groups, automation also has the potential to complement some types of workers. Autor (2015) argues that while automation has displaced a significant portion of the workforce, it has also increased productivity, leading to an increase in labor demand, particularly in non-routine cognitive occupations.

This phenomenon can be observed in Germany, where the adoption of advanced technologies has resulted in a decrease in routine jobs and an increase in non-routine occupations, both cognitive and manual (Arntz and Zierahn-Weilage, 2024). On the other hand, less skilled workers have redirected their labor supply to the service sector, which is less susceptible to automation due to its reliance on physical skills and interpersonal interaction (Autor and Dorn, 2013).

In addition to this, there are certain empirical findings suggest that the implementation of certain technologies, such as the SCC (Control and Coordination System), reduces corporate employment in companies located in pilot cities by about 7.7% compared to those located in non-pilot cities (Cao et al., 2023). Furthermore, although the labor reduction effects due to automation have been confirmed, human capital and complementary technologies can improve the long-term employment trend (Camina and Torrent-Sellens, 2020).

In this sense, although automation presents significant challenges in terms of labor displacement, it also offers opportunities by creating new jobs and improving productivity, as observed in countries such as the United States, Japan and Germany, where the adoption of new technologies is driven by policies that favor innovation, but do not neglect the labor costs of adaptation for employees in low-skilled occupations (Heluo and Fabel, 2024). These adaptation costs fall mainly on employees with low educational attainment or professional training, thereby contributing to growing inequality in these countries.

The polarization observed in developed countries has not been replicated in developing economies. In these countries, automation has not led to a clear polarization phenomenon, although some early signs of this pattern have been detected in nations such as China (Maloney and Molina, 2016). However, automation tends to affect informal workers more acutely in developing economies. In the case of Chile, Egana-delSol et al. (2022b) found that the impact of automation on informal workers was three times greater than on formal workers, a relevant finding for countries with high levels of informality, where automation can exacerbate existing vulnerabilities.

However, the adoption of digital technologies, and in particular artificial intelligence, is marked by profound inequalities that vary not only between sectors but also between countries and demographic groups. In developed economies, access to and adoption of AI are relatively faster, creating a competitive advantage for wealthier countries, while developing economies face significant barriers due to insufficient digital infrastructure (Nations, 2024). These challenges are even more evident in sectors that rely on advanced digital skills. According to the World Bank (2024), administrative tasks, which are highly automatable, account for a large share of the most exposed occupations in low and middle-income countries, posing significant risks for workers with limited access to the digital training and resources needed to adapt to technological transformation.

A crucial aspect of the impact of automation for IA is how it affects different occupations. Cazzaniga et al. (2024) highlight that the occupations most exposed to automation are those involving repetitive and routine tasks, as in the case of administrative and clerical jobs. These occupations, which account for a large proportion of the tasks susceptible to automation, are at risk of being replaced by AI. In contrast, occupations that require a high level of knowledge and abstraction, such as professional occupations, tend to benefit from AI as a complementary tool that increases productivity, rather than completely replacing workers (Berg, 2023).

Regarding gender differences, the findings are mixed. While Muro et al. (2019) suggest that men are more exposed to the effects of automation, Egana-delSol et al. (2022a) document that, in Latin America, women are equally exposed, with 21% of them at high risk versus 19% of men, highlighting that women are more vulnerable in administrative and clerical sectors. In addition, women are overrepresented in the sectors most exposed to automation by AI, such as finance, insurance and public administration (Gmyrek et al., 2024). Many of them are in administrative roles, making them more vulnerable to being replaced by automation (Benites and Parrado, 2024). This gender vulnerability is reflected in the persistent digital divide, particularly in Latin America, where women have less access to technology compared to men. This highlights the importance of considering gender differences when analyzing the effects of automation and AI on the labor market.

The educational level of workers also plays a key role in their exposure to automation. Evidence suggests that workers with tertiary education are more likely to adapt to the changes brought about by AI, as they are better positioned to make job transitions to occupations that are not only less automatable but also benefit from technology (Gmyrek et al., 2024). In contrast, those without a college education face a higher risk of displacement, due to their lack of skills and difficulty in accessing training opportunities.

Regarding the effect of AI adoption on worker productivity, there is mixed evidence. For example, Brynjolfsson et al. (2025) provides evidence of the effect of implementing generative AI at scale in the workplace. In particular, they find that the adoption of a generative AI tool that provides conversational support to customer service agents increases agent productivity by 15%, as measured by the number of customer issues they are able to resolve per hour. Interestingly, this particular increase happens with less experienced and less skilled customer support workers, indicating that generative AI systems may be able to capture and disseminate the behaviors of the most productive agents. Furthermore, they find evidence that AI assistance leads to a slight decrease in the quality of conversations performed by the most skilled agents.

The latter is contradicted by earlier studies, such as Bresnahan et al. (2002) or Dixon et al. (2021) who find evidence of skill-biased technical change for earlier waves of computer technology and robotics and others such as Taniguchi and Yamada (2022) who, particularly in IT-focused jobs, find evidence that IT complements higher-skilled or more educated workers. Despite this, there is much literature which, while finding no detriment for more able workers, finds greater benefits for less able workers (Kanazawa et al., 2022). However, it is important to note that most of the types of jobs studied so far in AI, as opposed to previous automations, are in the customer service sector, as this is an industry with one of the highest rates of AI adoption (Chui et al., 2021).

The debate around the productivity effects of AI does not stop there. Several studies find that AI-assisted humans make worse decisions than humans or AI alone. In the case of Angelova et al. (2023) for the use of AI in judging and in the case of Agrawal et al. (2019) in medical radiology, this is shown to be true for a variety of tasks. Even Vaccaro et al. (2024) survey over 100 experimental studies and conclude that, on average, human-AI collaborations underperform both AI alone and the best human decision-makers. Despite this, it is important to keep in mind the types of work analysed and the industries that are adopting these technologies, where results may have heterogeneities.

In terms of the adoption of AI tools and their effect on productivity, this is concentrated among larger and younger firms with relatively high productivity. So far, the evidence is mixed on the effects of AI on productivity. Acemoglu and Restrepo (2019) find no detectable relationship between investments in specific AI tools and firm performance, and Babina et al. (2024) find evidence of a positive relationship between firms' AI investments and their subsequent growth and valuations.

While, as mentioned above, the effect on productivity and the level of complementarity has mixed evidence, even though the introduction of generative AI may increase the demand for lower-skilled labour within an occupation, this does not necessarily imply that in equilibrium lower-skilled workers will benefit the most, as AI assistance could lead to shifts in labour demand between occupations that benefit higher-skilled workers instead Acemoglu and Restrepo (2018) . This could also happen via the creation of new jobs that require higher skills.

Still, an interesting discussion can be had as to whether this qualification of employees is through degrees or through training and skills. Bone et al. (2025) find that the demand for AI roles grew by 21% as a proportion of all publications and simultaneously mentions of university education requirements for AI roles decreased by 15%. By doing a causal analysis, they find that AI skills have a wage value of over 23%, higher than university degrees up to PhD level (33%), and that in occupations with a high demand for AI skills, the wage value is high and the reward for degrees is relatively low. Thus, it appears that training is key to overcoming these types of gaps.

Finally, another important factor is the age of the workers. In general, older workers may be more vulnerable to the effects of automation due to their lower capacity to adapt to new technologies. In addition, they tend to have less flexibility to change occupations or relocate to roles with less exposure to automation. This is especially true for those with higher levels of education, who, being in more senior positions, face higher expectations to adapt to new technologies (Cazzaniga et al., 2024). On the other hand, younger workers tend to face a higher degree of automation in their jobs, but their greater familiarity with technology allows them to adapt more easily to change.

3 Data and Descriptive Statistics

This study utilizes multiple data sources to construct a dataset capable of estimating the exposure to AI across various skills and occupational groups in Latin America. Specifically, we rely on two key surveys to obtain worker-level information on skills and workplace tasks. The first source is the STEP survey conducted by the World Bank in Colombia and Bolivia in 2012 and El Salvador in 2014. The second source is the PIAAC survey, administered by the OECD in Chile, Ecuador, Mexico, Peru, and other OECD countries between 2011 and 2017. Both surveys provide detailed data on occupation, age, education, and other individual characteristics. Table **??** summarizes the sample by country. An expansion weight is applied for estimation purposes.

We restrict the sample to workers aged 18 to 60. Using specific survey questions, we construct ten key tasks and skills: (i) Management, (ii) Client Interaction, (iii) Self-Organization, (iv) STEM, (v) Accounting, (vi) Readiness to Learn, (vii) ICT, (viii) Physical Tasks, (ix) Autonomy and (inverse of) repetitive tasks, and (x) Critical Thinking. Details on the questions used to define each category can be found in the Appendix.

This dataset integrates skills and tasks data from the World Bank's Survey of Skills for Employment and Productivity (STEP) and the OECD's Survey of Adult Skills (PIAAC). Following the methodology of Ibrahim (1990), we estimate automation risk at the individual level, employing an expectation-maximization (EM) algorithm to iteratively refine duplication weights. This approach ensures a robust linkage between skills, tasks, and the likelihood of automation exposure (Arntz et al., 2016).

3.1 Country Surveys

We derive employment and wage data from various household surveys to examine occupational growth, decline, and wage trends over time. Table 1 outlines the primary survey sources and time frames for each country. Occupation classifications are harmonized to the ISCO-08 two-digit level for consistency. Unfortunately, data for El Salvador and Colombia were unavailable.

Table 1: Surveys Used

Country	Survey	Year 1	Year 2
Bolivia	Household Survey	2011	2019
Chile	CASEN	2011	2022
Ecuador	National Employment, Unemployment, and Underemployment Survey	2012	2023
Mexico	National Occupation and Employment Survey	2012	2023
Peru	National Household Survey	2012	2022

3.2 Skills and Tasks Across Countries

Table 2 provides a country-level overview of the key skill and task indicators utilized in the analysis. Skills such as management, client interaction, and self-organization exhibit significant heterogeneity across Latin America compared to OECD countries. STEM and ICT skills, in particular, tend to be less prevalent in Latin America, with Ecuador reporting notably low STEM intensity (0.22), while Colombia demonstrates relatively high STEM prevalence (0.62). These variations suggest differing challenges in adapting to automation within the region.

El Salvador reports the highest levels of management skills (0.58), contrasting with lower levels in Peru (0.43) and Mexico (0.45). Tasks requiring client interaction are significantly more prevalent in Latin America (e.g., 0.71 in Colombia and El Salvador) compared to OECD countries (0.26). The region's relatively low levels of STEM skills

Table 2: Average of Skills and Tasks by Country

	Bolivia	Chile	Colombia	Ecuador	El Salvador	Mexico	Peru	OECD
Managing skills (high)	0.52	0.48	0.52	0.49	0.58	0.45	0.43	0.44
Contact with Clients (high)	0.60	0.36	0.71	0.44	0.71	0.43	0.52	0.26
Self-organization (high)	0.58	0.52	0.60	0.53	0.65	0.48	0.47	0.47
Physical skills (high)	0.56	0.58	0.51	0.65	0.46	0.64	0.59	0.57
Autonomy and Repet.	0.56	0.76	0.45	0.67	0.78	0.78	0.62	0.78
STEM skills (high)	0.41	0.32	0.62	0.22	0.44	0.30	0.29	0.35
Accounting skills (high)	0.59	0.45	0.45	0.43	0.59	0.43	0.42	0.42
ICT skills (high)	0.71	0.47	0.65	0.36	0.62	0.41	0.37	0.47
Readiness to learn (high)	0.56	0.43	0.52	0.59	0.68	0.57	0.55	0.56
Critical thinking (high)	0.51	0.52	0.56	0.49	0.59	0.54	0.46	0.49

(e.g., 0.22 in Ecuador) highlight the need for targeted skill-building initiatives to prepare for future technological shifts.

3.3 Employment and Wage Growth

Table 3 presents descriptive statistics on average employment and wage levels across occupations and their changes over a decade. Bolivia shows modest employment growth, adding about 974 workers per occupation on average, while Chile and Mexico report substantial increases. Wages rise across all countries, with the largest absolute increase observed in Bolivia (609) and the smallest in Chile (230).

Table 3: Average Employment and Growth

	N	Employment			Wages		
Country		2010	2020	ΔEmp.	2010	2020	ΔWage
Bolivia	38	143692.0	144666.1	974.1	846.45	1455.36	608.91
Chile	39	175003.5	233614.4	58610.9	1395.36	1624.99	229.62
Ecuador	38	89139.63	204598.5	115278.6	1042.29	1531.96	489.68
Mexico	38	930120.4	1120962.0	190841.7	1876.36	2514.15	637.79
Peru	39	433352.0	487237.9	53885.9	807.66	995.47	187.82

In Chile, the average employment increased by 33% , while in Bolivia only grew 0,68%. Wage growth also varied, consistently Bolivia showed a notable gain of almost 72%, while Chile experienced an increase of only 16%.

Table 4: Levels of Employment and Wages with Percentual Change

Country	N	Employment			Wages		
		2010	2020	% Change	2010	2020	% Change
Bolivia	38	143692	144666	0.68%	846.45	1455.36	71.97%
Chile	39	175003	233614	33.46%	1395.36	1624.99	16.46%
Ecuador	38	89139	204598	129.37%	1042.29	1531.96	47.00%
Mexico	38	930120	1120962	20.53%	1876.36	2514.15	34.01%
Peru	39	433352	487237	12.44%	807.66	995.47	23.27%

4 Methodology

First, we pay particular attention to differences in AI exposure between age groups, gender, and education levels, emphasizing the vulnerability of young women with limited education compared to older, more educated men. Although both AI exposure measures highlight the importance of routine tasks and levels of education, gender and age, they vary in assessing the risks of specific tasks. By comparing Latin America with OECD countries, we identify notable disparities in skill composition and educational attainment levels, which influence AI exposure.

Second, using occupation-specific data from various household surveys, we explore the relationship between predicted AI exposure and changes in employment levels, wage structures, and inequality metrics over the past decade, delving deeper into potential adverse employment effects and wage polarization.

4.1 Measuring Artificial Intelligence Exposure

Following Felten et al. (2021) and Webb (2020), we use two distinct metrics for assessing artificial intelligence exposure for individuals. Using different databases and methods, these metrics differ conceptually in their automation or exposure susceptibility criteria. We examine how these two measures of exposure correlate with skills, task characteristics, education, age, and gender.

The Webb (2020) methodology gauges how exposed occupations are to a particular technology by comparing the language used in patent titles with that in job task descriptions. It identifies relevant patents through keywords, extracts key verb–noun pairs (such as “diagnose disease”), and measures their frequency. Job tasks from databases like O*NET are processed similarly, and each extracted pair is weighted by its importance within that occupation. By averaging these weights, an overall exposure score for each occupation is produced. Additionally, similar nouns are grouped using WordNet to account for varying levels of specificity, ensuring a consistent measure of technology's relative impact across different jobs.

The AI exposure score for an occupation is calculated by first determining the relative frequency of each aggregated verb–noun pair in patent titles for a given technology, then assigning these scores to the corresponding pairs from the occupation's task descriptions, and finally taking a weighted average across all tasks—where each task's weight is based on its frequency, importance, and relevance—to express the intensity of patenting activity directed toward that occupation's tasks.

On the other hand, Felten et al. (2021) method leverages two independent databases to assess the AI exposure to skills and occupations. It begins with the EFF AI Progress Measurement dataset, which tracks progress across various AI categories—such as image recognition and abstract strategy games—by aggregating and scaling multiple performance metrics sourced from academic literature, blogs, and specialized websites. In addition to this, the O*NET database offers up-to-date detailed skill content of occupations for nearly 1,000 jobs in the US labor market, highlighting 52 distinct abilities that describe the requirements of each role.

By constructing a mapping matrix—with input from computer science PhD students—the method aligns the AI categories from the EFF dataset to the corresponding O*NET abilities. It then quantifies the influence of AI on each ability, weighting this impact by its prevalence and importance within each occupation. These weighted impacts are aggregated to produce an overall effect score for each job. Although the score's absolute value is arbitrary, it provides a valuable tool for comparing the relative exposure of different occupations to AI-driven technological advances.

For each metric, we calculate the probability of AI exposure for workers in our dataset. We align these estimates with occupation data using a crosswalk that matches 6-digit Standard Occupational Classification (SOC) codes with 3-digit International Standard Classification of Occupations (ISCO) codes, based on the PIAAC and STEP surveys.

To estimate individual-level AI exposure, we model it as follows: (r_{ijo}) for worker i, in country j and occupation o using the equation:

$$r_{ijo} = \sum_{n=1}^{N} \beta_n X_{ijo} + \mu_{ijo},$$

where X_{ijo} represents worker characteristics, including skills, education, gender, and age, while β_n measures the impact of these factors on AI exposure. For workers linked to multiple risk measures, we apply weights based on the inverse number of matches, following the approach by Arntz et al. (2016).

4.2 Occupational Aggregation

In order to merge our estimates with the country surveys, the predicted AI exposure indices are aggregated at the ISCO-08 two-digit level for each country:

$$\overline{AI - Exposure}_{oj} = \frac{1}{N_{ijo}} \sum_{i \in i,j,o} \hat{r}_{ijo},$$

where j represents the country, and $\overline{AI - Exposure}_{oj}$ reflects the average automation risk for each occupation.

4.3 Linking Risk to Employment and Wages

We relate average occupational automation risks to employment and wage changes derived from household surveys. The regression model used is:

$$\Delta \ln(y_{oj}) = \beta_1 \overline{AI - Exposure}_{oj} + \gamma_j + \varepsilon_{oj},$$

where $\Delta \ln(y_{oj})$ represents changes in total employment or mean wages for occupation o in the country j. Country-specific fixed effects (γ_j) and clustered standard errors are included.

5 Marginal Effects on AI Exposure

5.1 Felten

Before presenting the detailed estimates for individual countries, Tables 5 and Table 6 summarizes the marginal effects of skills and tasks on AI exposure in five Latin American countries. The coefficients highlight how cognitive skills, physical skills, and various non-cognitive skills interact with AI exposure differently for males and females, emphasizing disparities tied to gender and education levels.

The results using Felten et al. (2021)'s methodology reveal distinct patterns in AI exposure based on gender, education, and age. The empirical evidence presented in Table 5 reveals pronounced heterogeneity in the marginal effects of various skills and tasks on the predicted exposure to artificial intelligence across five Latin American countries. The results underscore significant gender disparities, highlighting that, for example, managing skills and ICT skills exhibit notably stronger associations with AI exposure for females in several countries compared to their male counterparts. This suggests that women in these labor markets may encounter different or heightened vulnerabilities to AI, especially in occupations where such skills are prevalent.

Education level emerges as a critical determinant in shaping exposure to AI. The coefficients for medium-level and high-level education are consistently positive and highly significant across all countries and genders, indicating that higher educational attainment, contrary to some expectations, is associated with greater predicted exposure to AI. This pattern may reflect the nature of high-skilled jobs in these economies, which, despite their complexity, often involve routinizable tasks that are amenable to automation. Age-related dynamics also surface from the analysis. The variables for young adults (18-25 years) and adults (25-40 years) hint at nuanced age effects on AI exposure, though these effects vary by country and gender. In some cases, younger workers show lower exposure, potentially due to engagement in less routinized or more adaptable roles. However, inconsistencies across countries suggest that age-related vulnerabilities are complex and intersect with other factors like skill sets and industry sectors.

Inequality in exposure to AI is evident as these demographic factors—gender, education level, and age—intersect. The data implies that both high-skilled individuals and certain demographic groups, particularly women in sectors requiring ICT and managerial skills, may face disproportionately high risks of automation. This interplay signals a potential widening of inequality, where educational attainment does not uniformly shield workers but may instead concentrate AI exposure among those expected to be most resilient in more developed economies, such as the OECD.

Table 5: Marginal Effects of Skills and Tasks on Exposure to Artificial Intelligence - Felten (1)

	Bolivia		Chile		Colombia		Ecuador		El Salvador	
	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Managing skills (high)	0.050***	0.084***	0.030	0.059**	0.052***	0.102***	0.053***	0.040**	0.070***	0.019*
	(0.012)	(0.013)	(0.016)	(0.018)	(0.014)	(0.015)	(0.013)	(0.013)	(0.008)	(0.010)
Contact with Clients (high)	0.046***	0.026	0.080***	0.068***	0.042**	0.072***	0.029*	0.036**	0.003**	0.006***
	(0.011)	(0.013)	(0.014)	(0.019)	(0.013)	(0.014)	(0.013)	(0.013)	(0.001)	(0.001)
Self-organization (high)	0.003	-0.010	0.005	-0.025	-0.002	0.028*	-0.010	-0.010	-0.017	-0.051***
	(0.012)	(0.016)	(0.015)	(0.016)	(0.011)	(0.012)	(0.015)	(0.016)	(0.011)	(0.010)
Physical skills (high)	-0.091***	-0.042***	-0.103***	-0.071***	-0.093***	-0.045***	-0.042***	-0.050***	-0.048***	-0.016*
	(0.012)	(0.011)	(0.013)	(0.015)	(0.010)	(0.011)	(0.012)	(0.011)	(0.006)	(0.007)
Autonomy and Repet.	0.003	0.030*	0.020	0.016	0.007	-0.027*	0.005	-0.015	-0.019	0.004
	(0.011)	(0.014)	(0.017)	(0.021)	(0.010)	(0.012)	(0.015)	(0.017)	(0.012)	(0.012)
STEM skills (high)	0.035**	0.011	0.055***	0.057**	0.007	0.017	0.057***	0.100***	0.000	0.006
	(0.012)	(0.013)	(0.015)	(0.021)	(0.011)	(0.012)	(0.015)	(0.018)	(0.007)	(0.007)
Accounting skills (high)	0.007	0.030**	0.035*	0.092***	0.018	0.021	0.046***	0.044**	0.045***	0.073***
	(0.011)	(0.011)	(0.015)	(0.021)	(0.010)	(0.012)	(0.013)	(0.013)	(0.007)	(0.007)
ICT skills (high)	-0.009	0.043***	0.079***	0.100***	0.049***	0.031**	0.022	0.096***	0.023**	0.065***
	(0.013)	(0.012)	(0.016)	(0.017)	(0.012)	(0.011)	(0.013)	(0.016)	(0.007)	(0.008)
Readiness to learn (high)	-0.010	0.033**	-0.013	0.008	0.014	-0.006	-0.020	0.021	-0.005	0.034***
	(0.011)	(0.011)	(0.015)	(0.016)	(0.010)	(0.011)	(0.015)	(0.013)	(0.007)	(0.008)
Critical thinking tasks (high)	0.011	0.035**	0.020	0.054**	-0.003	0.027**	0.015	-0.004	0.017*	0.004
	(0.010)	(0.012)	(0.016)	(0.017)	(0.011)	(0.010)	(0.014)	(0.013)	(0.007)	(0.008)
Medium-level education	0.040***	0.034**	0.026	0.017	0.044***	0.001	0.046***	0.015	0.065***	0.088***
	(0.011)	(0.012)	(0.016)	(0.019)	(0.011)	(0.012)	(0.012)	(0.013)	(0.008)	(0.008)
High-level education	0.269***	0.193***	0.181***	0.141***	0.192***	0.185***	0.166***	0.155***	0.263***	0.226***
	(0.019)	(0.018)	(0.020)	(0.022)	(0.020)	(0.019)	(0.018)	(0.017)	(0.011)	(0.011)
Young adults (18-25 years)	-0.022	-0.008	-0.071***	-0.023	-0.037*	0.061***	-0.075***	0.002	0.052***	0.005
	(0.016)	(0.017)	(0.017)	(0.019)	(0.014)	(0.017)	(0.015)	(0.017)	(0.009)	(0.010)
Adults (25-40 years)	0.020	-0.008	-0.023	-0.007	-0.009	0.055***	-0.014	-0.016	0.011	-0.011
	(0.012)	(0.013)	(0.014)	(0.017)	(0.011)	(0.011)	(0.012)	(0.012)	(0.007)	(0.007)
N	5100	4170	3007	2446	5485	3940	3058	2141	10876	8108
Cognitive skills	0.023	0.116	0.157	0.258	0.089	0.063	0.105	0.261	0.063	0.178
	[0.231]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]
Non-Cognitive skills	0.011	0.088	0.033	0.047	0.007	0.131	0.035	0.000	-0.010	-0.038
	[0.577]	[0.000]	[0.212]	[0.127]	[0.716]	[0.000]	[0.113]	[0.999]	[0.466]	[0.005]

Robust standard errors are shown in parentheses. The coefficients are estimated using an expectation-maximization algorithm. We regress the exposure to AI, as defined by Felten, on skills, task measures, and other observable characteristics, creating a predicted value of exposure to AI at the individual level. A generalized linear model is used, weighted by the product of individual weights from the STEP and PIAAC surveys and a duplication weight, which accounts for multiple risks associated with the same worker. The expectation-maximization algorithm proposed by Ibrahim (1990) is then applied. This algorithm adjusts the duplication weights iteratively to maximize the likelihood of automation risk until the weights converge. The table presents the cumulative effects of cognitive skills (STEM, accounting, ICT, and readiness-to-learn measures) and non-cognitive skills (management, client interaction, self-organization, physical skills, and autonomy in repetitive tasks). P-values are displayed in square brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The results in both tables suggest notable gender disparities in how skills and tasks influence AI exposure. For instance, managerial skills exhibit a stronger positive marginal effect for females compared to males across all countries. This pattern is particularly pronounced in the Latin American context: the effect of high managing skills on AI exposure is almost double for females (0.084***) compared to males (0.041***), signaling that women in these regions may experience heightened exposure when possessing high managerial competencies. Similarly, client interaction skills consistently heighten AI exposure, with more substantial impacts observed for females. These gendered responses may reflect occupational roles where women engage more intensively in client-facing tasks, potentially increasing their susceptibility to AI advancements.

Educational attainment plays a critical role in shaping AI exposure. Both medium- and high-level education are associated with increased exposure across all countries studied. High-level education, in particular, produces large and statistically significant marginal effects for both genders in Mexico, Peru, OECD countries, and across the broader Latin American sample. The magnitude of these effects suggests that higher educational attainment correlates with roles more likely to encounter AI technologies. However, while the positive coefficients generally reflect increased AI exposure due to advanced skills and knowledge, they may also indicate a protective buffer against the negative employment consequences of automation, underscoring a nuanced relationship between education and inequality.

Age differentials reveal additional layers of inequality. For younger adults (18–25 years), the marginal effects on AI exposure are predominantly negative for both genders in Mexico and Peru, indicating lower exposure relative to older cohorts. Such a trend may hint at younger workers being in early career stages with less integration of AI-intensive tasks or facing barriers to entering AI-augmented sectors. In contrast, the coefficients for adults aged 25–40 years also lean negative but with diminished magnitude, suggesting a transition period where increasing experience mitigates some of the lower exposure found among the youngest workers.

Comparative analysis between Latin America and OECD countries indicates that skill impacts on AI exposure vary by geography and gender. While both groups show similar directions in marginal effects for skills such as ICT and accounting, Latin American females often experience higher coefficients than their male counterparts and their OECD peers. This divergence underscores regional disparities and hints at potential structural differences in labor markets, technological adoption, and gendered occupational segmentation. Furthermore, the aggregation of results in the LAC sample consistently mirrors these patterns, with gender gaps and education levels playing significant roles in shaping AI exposure.

5.2 Webb AI

The results presented in Table 7 offer a detailed examination of how various skills and tasks influence an individual's exposure to artificial intelligence (AI) risk across several Latin American countries using Webb (2020)'s exposure index to AI.

First, the gender-specific coefficients reveal noteworthy disparities between males and females. For example, managing skills and STEM skills generally increase AI exposure for both genders, but the magnitude and significance often differ by gender and country. In Bolivia, high-level managing skills significantly raise AI exposure for males compared to a smaller and statistically insignificant effect for females. Conversely, STEM skills exhibit a robust positive impact for both genders across most countries, with coefficients frequently significant at the 1% level. These gender-differentiated patterns highlight how men and women may face distinct AI risks based on occupational tasks and skills distribution, a nuance that is sometimes less pronounced in OECD contexts where gender disparities in technology exposure follow different trends due to varying labor market structures and educational attainment levels.

Education emerges as another critical factor shaping AI exposure. The table indicates that both medium- and high-level education are associated with increased exposure to AI across all examined countries and genders. Notably, high-level education coefficients are uniformly positive and highly significant, suggesting that advanced education correlates with greater AI exposure. This finding contrasts with some OECD evidence where higher education often mitigates risk due to increased adaptability and complex task requirements. However, in Latin America, the positive association may reflect a concentration of AI-related tasks in high-skilled occupations, or it may signal that even highly educated workers are not immune to automation pressures, potentially exacerbating educational inequalities.

Age-related effects are also evident. The coefficients for young adults (aged 18–25) and adults (25–40) vary across countries and genders. For instance, in Chile, young male adults exhibit a significant negative association with AI exposure, while young females in Colombia face a marked decrease in exposure. These patterns suggest that younger workers, particularly women in some contexts, might be less exposed to AI due to lower representation in highly automatable tasks or sectors. Nevertheless, the differential impact by age could contribute to intergenerational inequality, where certain age cohorts bear a disproportionate burden of AI risk, a dynamic that may differ from

OECD experiences due to diverse labor market entry conditions and youth employment structures.

Inequality surfaces as a recurrent theme, not only across gender and education levels but also in how these factors interact with AI exposure. The varying magnitude and significance of coefficients across different skill sets and demographic groups underscore a stratified risk landscape. This stratification implies that AI could exacerbate existing socioeconomic inequalities in Latin America more acutely than in OECD countries, where social safety nets and workforce reskilling programs might buffer similar shocks.

Table 8 presents the marginal effects of various skills and tasks on predicted exposure to artificial intelligence, as estimated using Webb (2020)'s methodology to a second group of countries and presents also LAC and OECD estimates. The analysis disaggregates results by gender across several regions—Mexico, Peru, the OECD, and the broader Latin American and Caribbean (LAC) sample—to shed light on how gender, education level, and age intersect with AI exposure and inequality. The findings reveal nuanced differences between Latin American economies and the OECD, highlighting disparities in skill returns, educational protection, and demographic vulnerabilities in the face of AI-driven change.

First, the gender dimension is pronounced. For instance, managing skills tend to increase AI exposure for males in both Mexico and Peru, whereas the effect for females is smaller and not statistically significant. This suggests that, in Latin America, male-dominated roles involving high-level management may be more susceptible to AI automation compared to similar roles held by women. In contrast, OECD data indicate a more balanced effect across genders, with both male and female workers experiencing increases in AI exposure linked to managerial competencies, though the impact is generally higher for females. Such differences point to varying occupational structures and gender distributions of tasks between regions.

Education plays a critical role in mediating AI risk. High-level education is associated with a substantial increase in predicted AI exposure across all regions and both genders, reflecting that higher educational attainment often aligns with more complex tasks that may be amenable to AI substitution. However, the magnitude of this effect differs: Latin American coefficients are typically larger than those observed in the OECD, implying that the protective effect of advanced education against AI risks may be more pronounced—or conversely, the exposure more acute—in Latin America. Medium-level education, on the other hand, shows mixed effects; it appears to reduce AI exposure for some female cohorts in Peru but exhibits less consistent patterns elsewhere, underscoring the nuanced role of mid-skill jobs in automation risk.

Age-related patterns also emerge. Young adults (18–25 years) in Latin America, especially males in Mexico and Peru, exhibit a negative association with AI exposure, suggesting that younger workers might be engaged in roles that are less vulnerable to immediate automation. The effect is less pronounced for young females, pointing towards potential gender disparities in the opportunities available to younger cohorts. Meanwhile, the impact on adults aged 25–40 is generally smaller and less significant, indicating that early career stages are a critical period for differential AI exposure risks.

These heterogeneous effects across gender, education, and age illustrate deepening inequalities. STEM and ICT skills uniformly decrease AI exposure across regions and genders, yet the distribution of these skills is uneven, contributing to wage and employment polarization. The disparities between Latin America and the OECD suggest that while advanced skills and education act as protective factors everywhere, the relative benefits and risks vary substantially. In Latin American contexts, the steeper gradients associated with education and skill levels imply that disparities in access to high-quality education and technical training could exacerbate existing inequalities, both within the region and in comparison to more developed economies.

5.3 Top Occupations by AI exposure and total employment affected

We identify a diverse range of occupations at high risk of AI-driven automation across Latin America and the Caribbean (LAC). For instance, in Mexico, the top five occupations most exposed to AI automation include science and engineering professionals, health professionals, teaching professionals, public servants, and ICT professionals. Additionally, when examining occupations with the largest number of workers at high exposure to AI, the analysis reveals some heterogeneity. For instance, the top five occupations in Mexico are sales workers, plant operators, cleaners and helpers, food processing workers, and those in mining, construction, and manufacturing. This suggests that AI-driven automation presents risks across both high-skilled and traditionally low-skilled occupations, underscoring the need for targeted policies to mitigate labor market disruptions and inequalities.

The findings presented in Figures 1 through 5 indicate a consistent trend across Latin American and Caribbean (LAC) countries. This trend reveals a shift in automation risk toward high-skilled professions, which contrasts with the traditional focus of pre-AI automation literature on routine, lower-skilled jobs (e.g., Egana-delSol et al. (2022a)).

Table 6: Marginal Effects of Skills and Tasks on Exposure to Artificial Intelligence - Felten (2)

	Mexico		Peru		OCDE		LAC sample	
	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Managing skills (high)	0.033**	0.049***	0.029**	0.049***	0.034***	0.035***	0.041***	0.084***
	(0.011)	(0.014)	(0.010)	(0.011)	(0.004)	(0.004)	(0.008)	(0.008)
Contact with Clients (high)	0.046***	0.061***	0.052***	0.092***	0.034***	0.022***	0.008**	0.011***
	(0.010)	(0.013)	(0.009)	(0.011)	(0.005)	(0.005)	(0.003)	(0.002)
Self-organization (high)	0.012	-0.021	0.011	-0.026*	0.017***	0.002	-0.006	-0.026**
	(0.011)	(0.014)	(0.011)	(0.012)	(0.004)	(0.004)	(0.007)	(0.008)
Physical skills (high)	-0.073***	-0.056***	-0.101***	-0.072***	-0.161***	-0.132***	-0.082***	-0.052***
	(0.010)	(0.012)	(0.008)	(0.009)	(0.004)	(0.004)	(0.007)	(0.007)
Autonomy and Repet.	-0.012	0.027	0.000	0.010	0.004	0.012*	0.011	0.016
	(0.012)	(0.016)	(0.011)	(0.012)	(0.005)	(0.005)	(0.007)	(0.008)
STEM skills (high)	0.013	0.069***	0.033**	0.068***	0.023***	0.058***	0.003	0.045***
	(0.011)	(0.015)	(0.010)	(0.011)	(0.004)	(0.005)	(0.007)	(0.009)
Accounting skills (high)	0.063***	0.068***	0.045***	0.046***	0.037***	0.050***	0.068***	0.061***
	(0.011)	(0.014)	(0.010)	(0.010)	(0.004)	(0.005)	(0.008)	(0.007)
ICT skills (high)	0.073***	0.065***	0.089***	0.084***	0.097***	0.112***	0.082***	0.057***
	(0.011)	(0.013)	(0.010)	(0.011)	(0.005)	(0.005)	(0.008)	(0.008)
Readiness to learn (high)	-0.012	0.003	0.005	0.010	0.008	-0.001	-0.005	-0.006
	(0.011)	(0.013)	(0.009)	(0.010)	(0.004)	(0.004)	(0.007)	(0.007)
Critical thinking tasks (high)	0.000	0.008	0.010	-0.002	-0.003	0.011*	0.006	0.009
	(0.010)	(0.013)	(0.010)	(0.011)	(0.004)	(0.004)	(0.007)	(0.008)
Medium-level education	0.065***	0.077***	0.048***	-0.007	0.010*	0.053***	0.047***	0.008
	(0.010)	(0.014)	(0.011)	(0.012)	(0.004)	(0.006)	(0.007)	(0.008)
High-level education	0.225***	0.200***	0.142***	0.103***	0.099***	0.125***	0.189***	0.177***
	(0.017)	(0.019)	(0.014)	(0.014)	(0.005)	(0.007)	(0.011)	(0.011)
Young adults (18-25 years)	-0.074***	-0.047**	-0.056***	-0.023	-0.001	-0.012*	-0.061***	0.003
	(0.012)	(0.017)	(0.012)	(0.014)	(0.005)	(0.006)	(0.008)	(0.010)
Adults (25-40 years)	-0.033**	-0.027*	-0.036***	-0.010	-0.019***	0.001	-0.028***	0.006
	(0.011)	(0.012)	(0.009)	(0.010)	(0.004)	(0.004)	(0.008)	(0.007)
N	3885	2312	5166	3433	58725	41590	36577	26550
Cognitive skills	0.137	0.205	0.173	0.209	0.164	0.218	0.148	0.157
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Non-Cognitive skills	0.007	0.061	-0.009	0.053	-0.072	-0.061	-0.028	0.032
	[0.734]	[0.010]	[0.614]	[0.002]	[0.000]	[0.000]	[0.020]	[0.018]

Robust standard errors are shown in parentheses. The coefficients are estimated using an expectation-maximization algorithm. We regress the exposure to AI, as defined by Felten, on skills, task measures, and other observable characteristics, creating a predicted value of exposure to AI at the individual level. A generalized linear model is used, weighted by the product of individual weights from the STEP and PIAAC surveys and a duplication weight, which accounts for multiple risks associated with the same worker. The expectation-maximization algorithm proposed by Ibrahim (1990) is then applied. This algorithm adjusts the duplication weights iteratively to maximize the likelihood of automation risk until the weights converge. The table presents the cumulative effects of cognitive skills (STEM, accounting, ICT, and readiness-to-learn measures) and non-cognitive skills (management, client interaction, self-organization, physical skills, and autonomy in repetitive tasks). P-values are displayed in square brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Marginal Effects of Skills and Tasks on Exposure to Artificial Intelligence - Webb (1)

	Bolivia		Chile		Colombia		Ecuador		El Salvador	
	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Managing skills (high)	0.054**	0.026	0.029	0.055*	0.030	-0.047*	0.045**	0.029	0.002	0.043***
	(0.019)	(0.016)	(0.022)	(0.027)	(0.021)	(0.022)	(0.017)	(0.019)	(0.010)	(0.011)
Contact with Clients (high)	-0.051**	-0.016	-0.044*	0.036	-0.083***	-0.005	-0.082***	0.007	-0.002	-0.006***
	(0.016)	(0.014)	(0.019)	(0.027)	(0.021)	(0.020)	(0.016)	(0.019)	(0.001)	(0.002)
Self-organization (high)	0.009	-0.030	-0.006	-0.023	0.020	-0.050*	-0.005	0.021	0.006	-0.033*
	(0.015)	(0.015)	(0.019)	(0.026)	(0.017)	(0.021)	(0.022)	(0.023)	(0.013)	(0.013)
Physical skills (high)	-0.011	-0.022	0.001	-0.065**	0.024	-0.000	0.003	-0.018	-0.009	0.004
	(0.014)	(0.012)	(0.018)	(0.023)	(0.016)	(0.016)	(0.016)	(0.016)	(0.008)	(0.008)
Autonomy and Repet.)	0.053***	-0.015	0.035	0.015	-0.015	0.032	0.014	-0.066**	0.013	-0.007
	(0.015)	(0.015)	(0.023)	(0.033)	(0.017)	(0.019)	(0.022)	(0.026)	(0.015)	(0.015)
STEM skills (high)	0.049***	0.043**	0.071***	0.035	0.078***	0.047**	0.074***	0.002	0.023*	0.045***
	(0.015)	(0.015)	(0.022)	(0.027)	(0.017)	(0.015)	(0.020)	(0.022)	(0.010)	(0.009)
Accounting skills (high)	-0.061***	0.002	-0.032	-0.012	-0.032	-0.001	-0.015	0.006	-0.032***	-0.033***
	(0.015)	(0.013)	(0.019)	(0.026)	(0.017)	(0.015)	(0.018)	(0.019)	(0.009)	(0.008)
ICT skills (high)	0.018	0.037**	0.083***	0.079**	0.039*	-0.029	-0.015	0.058**	-0.015	0.002
	(0.016)	(0.013)	(0.022)	(0.024)	(0.019)	(0.016)	(0.018)	(0.021)	(0.009)	(0.009)
Readiness to learn (high)	-0.001	0.012	0.005	-0.011	-0.003	0.022	-0.028	-0.003	0.017*	-0.006
	(0.014)	(0.013)	(0.020)	(0.025)	(0.016)	(0.016)	(0.018)	(0.020)	(0.009)	(0.009)
Critical thinking tasks (high)	0.013	-0.001	0.013	0.057*	0.030	0.057***	0.029	0.012	0.007	0.030***
	(0.014)	(0.014)	(0.022)	(0.026)	(0.018)	(0.015)	(0.018)	(0.020)	(0.008)	(0.009)
Medium-level education	0.034	0.065***	0.044*	0.044	-0.032	0.039*	-0.004	0.063**	0.030**	0.010
	(0.018)	(0.014)	(0.020)	(0.029)	(0.021)	(0.020)	(0.016)	(0.021)	(0.010)	(0.009)
High-level education	0.144***	0.191***	0.077**	0.164***	0.042	0.190***	0.061**	0.166***	0.175***	0.197***
	(0.023)	(0.019)	(0.027)	(0.031)	(0.031)	(0.034)	(0.023)	(0.024)	(0.014)	(0.013)
Young adults (18-25 years)	0.014	-0.027	-0.070**	-0.017	-0.008	-0.112***	-0.032	-0.030	-0.010	-0.007
	(0.024)	(0.019)	(0.024)	(0.033)	(0.021)	(0.022)	(0.021)	(0.026)	(0.011)	(0.012)
Adults (25-40 years)	0.030*	-0.006	-0.008	-0.034	-0.000	-0.010	0.031	0.013	-0.009	-0.019*
	(0.015)	(0.013)	(0.020)	(0.023)	(0.018)	(0.017)	(0.017)	(0.017)	(0.009)	(0.009)
N	5092	4165	3006	2445	5485	3940	3058	2141	10871	8106
Cognitive skills	0.005	0.093	0.127	0.092	0.081	0.039	0.017	0.062	-0.007	0.008
	[0.854]	[0.000]	[0.000]	[0.043]	[0.005]	[0.191]	[0.541]	[0.061]	[0.636]	[0.573]
Non-Cognitive skills	0.055	-0.057	0.015	0.018	-0.024	-0.070	-0.025	-0.028	0.010	0.001
	[0.036]	[0.029]	[0.687]	[0.666]	[0.461]	[0.039]	[0.357]	[0.343]	[0.550]	[0.953]

Robust standard errors are shown in parentheses. The coefficients are estimated using an expectation-maximization algorithm. We regress the exposure to AI, as defined by Webb, on skills, task measures, and other observable characteristics, creating a predicted value of exposure to AI at the individual level. A generalized linear model is used, weighted by the product of individual weights from the STEP and PIAAC surveys and a duplication weight, which accounts for multiple risks associated with the same worker. The expectation-maximization algorithm proposed by Ibrahim (1990) is then applied. This algorithm adjusts the duplication weights iteratively to maximize the likelihood of automation risk until the weights converge. The table presents the cumulative effects of cognitive skills (STEM, accounting, ICT, and readiness-to-learn measures) and non-cognitive skills (management, client interaction, self-organization, physical skills, and autonomy in repetitive tasks). P-values are displayed in square brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Marginal Effects of Skills and Tasks on Exposure to Artificial Intelligence - Webb (2)

	Mexico		Peru		OCDE		LAC sample	
	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Managing skills (high)	0.029*	0.023	0.049***	0.008	0.013*	0.048***	0.018	-0.004
	(0.014)	(0.017)	(0.013)	(0.016)	(0.005)	(0.007)	(0.010)	(0.010)
Contact with Clients (high)	-0.120***	-0.031	-0.079***	-0.040*	-0.080***	-0.060***	-0.035***	-0.012***
	(0.013)	(0.016)	(0.012)	(0.019)	(0.006)	(0.007)	(0.003)	(0.003)
Self-organization (high)	0.010	0.023	-0.016	0.022	0.017**	0.019**	-0.006	-0.001
	(0.014)	(0.016)	(0.017)	(0.022)	(0.005)	(0.007)	(0.010)	(0.011)
Physical skills (high)	0.005	0.026	0.003	-0.015	-0.036***	-0.031***	0.003	0.009
	(0.013)	(0.014)	(0.013)	(0.016)	(0.005)	(0.006)	(0.008)	(0.009)
Autonomy and Repet.	0.004	-0.009	0.012	-0.000	-0.007	-0.051***	0.007	-0.004
	(0.016)	(0.021)	(0.017)	(0.022)	(0.007)	(0.009)	(0.010)	(0.011)
STEM skills (high)	0.039**	0.047*	0.051***	0.007	0.065***	0.069***	0.055***	0.055***
	(0.015)	(0.018)	(0.014)	(0.015)	(0.005)	(0.008)	(0.010)	(0.010)
Accounting skills (high)	-0.024	-0.037*	0.005	0.023	-0.051***	-0.044***	-0.037***	-0.017
	(0.014)	(0.017)	(0.013)	(0.015)	(0.006)	(0.007)	(0.010)	(0.009)
ICT skills (high)	0.064***	0.059***	0.027	0.059***	0.070***	0.050***	0.050***	0.041***
	(0.014)	(0.018)	(0.014)	(0.016)	(0.006)	(0.008)	(0.010)	(0.009)
Readiness to learn (high)	0.002	0.007	0.010	0.034*	0.016**	-0.006	-0.006	0.010
	(0.013)	(0.017)	(0.015)	(0.017)	(0.005)	(0.006)	(0.009)	(0.010)
Critical thinking tasks (high)	0.024	0.035*	0.000	-0.029	-0.006	-0.001	0.017	0.026**
	(0.013)	(0.017)	(0.014)	(0.017)	(0.005)	(0.006)	(0.010)	(0.010)
Medium-level education	-0.015	0.020	-0.006	-0.060*	0.030***	0.021*	0.013	0.014
	(0.014)	(0.019)	(0.019)	(0.025)	(0.006)	(0.009)	(0.010)	(0.011)
High-level education	0.057**	0.137***	0.055*	0.064**	0.048***	0.107***	0.070***	0.137***
	(0.019)	(0.022)	(0.022)	(0.023)	(0.007)	(0.010)	(0.012)	(0.013)
Young adults (18-25 years)	-0.047**	0.022	-0.097***	-0.010	-0.063***	-0.030**	-0.062***	-0.021
	(0.017)	(0.021)	(0.017)	(0.031)	(0.007)	(0.010)	(0.011)	(0.014)
Adults (25-40 years)	-0.006	0.007	-0.043**	-0.012	-0.002	0.003	-0.016	-0.010
	(0.013)	(0.016)	(0.015)	(0.017)	(0.005)	(0.007)	(0.010)	(0.010)
N	3885	2312	5162	3432	58719	41577	36559	26541
Cognitive skills	0.081	0.076	0.093	0.123	0.099	0.068	0.061	0.089
	[0.000]	[0.009]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Non-Cognitive skills	-0.072	0.031	-0.031	-0.025	-0.092	-0.075	-0.012	-0.011
	[0.003]	[0.283]	[0.211]	[0.374]	[0.000]	[0.000]	[0.433]	[0.511]

Robust standard errors are shown in parentheses. The coefficients are estimated using an expectation-maximization algorithm. We regress the exposure to AI, as defined by Webb (2020), on skills, task measures, and other observable characteristics, creating a predicted value of exposure to AI at the individual level. A generalized linear model is used, weighted by the product of individual weights from the STEP and PIAAC surveys and a duplication weight, which accounts for multiple risks associated with the same worker. The expectation-maximization algorithm proposed by Ibrahim (1990) is then applied. This algorithm adjusts the duplication weights iteratively to maximize the likelihood of automation risk until the weights converge. The table presents the cumulative effects of cognitive skills (STEM, accounting, ICT, and readiness-to-learn measures) and non-cognitive skills (management, client interaction, self-organization, physical skills, and autonomy in repetitive tasks). P-values are displayed in square brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: The Effects of AI Exposure on Employment and Wage Growth

VARIABLES	(1) Δ ln(emp)	(2) Δ ln(wage)
Exposure to AI (Webb)	1.293***	-0.246
	(0.440)	(0.241)
Exposure to AI (Felten)	0.656**	-0.026
	(0.309)	(0.183)
r^2	0.313	0.268
N	191	191

*** p<0.01, ** p<0.05, * p<0.1

6 Delta Employment and Wage Analysis

Our updated analysis now focuses on the effects of AI exposure, rather than traditional automation risk measures, on employment and wage growth. This section presents new baseline and quantile regression results, capturing how predicted exposure to AI—measured by Webb (2020) and Felten et al. (2021) methodologies—affects labor market outcomes across different segments of the employment and wage distributions.

6.1 Average Effects of AI Exposure

Table 9 presents baseline ordinary least squares estimates of the relationship between AI exposure and subsequent changes in employment and wages. The results indicate that higher exposure to AI in one unit of the index, as measured by Webb (2020)'s methodology, is associated with a statistically significant 1.29% increase in employment growth. Conversely, the effect on wage growth is negative (-0.246) but not statistically significant. Similarly, when using Felten et al. (2021)'s measure of AI exposure, the coefficient for employment growth is 0.66% and significant at the 5% level, while the wage effect remains small and insignificant. These findings suggest that while AI exposure appears to stimulate employment growth—possibly due to the creation of new tasks or job reallocation—the impact on wages is less clear, hinting at complex dynamics between technology adoption, job creation, and wage determination.

6.2 Inequality Analysis Across Quintiles

Table 10 further examines the inequality implications of AI exposure by comparing its effects across different wage quintiles, focusing on the change in employment and wages. We estimate the heterogeneous effect in the bottom, top, and middle-wage quintiles sorted according to the wage range.

In the measure provided by Webb (2020), employment changes in both the top and bottom wage quintiles are positive. However, only the increase in employment within the top quintile is statistically significant. In contrast, the employment changes in the middle-wage quintile are negative and statistically significant. This suggests heterogeneity in how AI exposure impacts employment across different quintiles. However, the wage differences across quintiles are all negative, although in the case of the top quintile, it is not significant, implying a uniform trend in wage effects across a wide range of wages and hence workers, although not big enough in some cases, so that these effects are statistically significant.

In a similar vein, Felten et al. (2021)'s measure reveals that the impact on employment follows the same trend as Webb's estimations, although none of the results are statistically significant. However, notable differences are shown across income quintiles regarding the effects of wages. Non-significant wage increases are observed at the lower and middle segments of the income distribution, while a significant decrease in wages for the top quintile. This finding aligns with Webb's estimates and is statistically significant, suggesting that AI exposure may lead to unequal effects on wages across various levels of wage range.

It is clear that when using Webb's index, we predict an increase in wage inequality, while the Felten index predicts a decrease. Regarding employment, both sets of estimations show a polarization in employment growth by finding an increase in employment in the high and bottom quintiles of the wage range, decreasing the size of the middle-income class. One possible explanation for this result is that the increase in the number of workers in the top quintile is not enough to increase the average wage of the top quintile, which is possible if the share of employment in the bottom part of this top quintile increases more than in the top part of the distribution. What is more important is that part of the decrease in the size of the middle class moves upward in the income distribution because their wage is growing although below the mean wage of the top quintile; therefore, in the top quintile, the average wages are falling, as it is shown in

Table 10: The Effects of Automation Risk Exposure on Employment and Wage Growth - Inequality by Quintiles

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Δ ln(emp)	Δ ln(emp)	Δ ln(emp)	Δ ln(wage)	Δ ln(wage)	Δ ln(wage
Sample	<P20	P40 to P60	>P80	<P20	P40 to P60	>P80
Exposure to AI (Webb)	1.616	-3.372**	6.623*	-2.140*	-0.936**	-0.098
	(1.101)	(1.568)	(3.436)	(1.110)	(0.449)	(1.402)
r^2	0.532	0.422	0.523	0.218	0.668	0.432
N	35	33	35	35	33	35
F-test of equality		2.09			1.42	
Exposure to AI (Felten)	1.138	-1.439	2.852	0.831	0.032	-1.976*
	(0.946)	(0.851)	(4.083)	(1.039)	(0.277)	(1.046)
r^2	0.522	0.419	0.447	0.144	0.640	0.498
N	35	33	35	35	33	35
F-test of equality		0.18			3.94**	

*** p<0.01, ** p<0.05, * p<0.1

column 6 of Table 10.

7 Discussion on exposure to AI across genders, educational level and age.

Our analysis of AI exposure across Latin American countries uncovers significant insights into how gender, education, and age intersect with emerging AI exposure, contributing to understanding the secular inequality patterns in LAC. The findings resonate with and extend established economic theories of skill-biased technological change and labor market polarization (e.g., Autor and Murnane, 2003; Acemoglu and Restrepo, 2011), while highlighting region-specific dynamics not fully captured in the developed country-centric literature.

First, we find pronounced gender disparities in AI exposure. Consistent with previous evidence on gendered labor market outcomes (e.g. Fortin et al., 2019), our results show that, particularly in Latin America, women with high-level managerial and ICT skills face increased AI exposure compared to men. This observation aligns with the idea that occupations dominated by women, even at high skill levels, may involve AI routinizable tasks (see also ?). The gender differences we document extend the literature by suggesting that AI may not only affect employment but do so in a way that exacerbates existing gender inequalities, especially where occupational segregation persists.

Second, education emerges as a double-edged sword. Although traditional models argue that advanced education protects workers from automation risks (e.g., Autor and Murnane, 2003; Egana-delSol et al., 2022a, our findings reveal reversed effects for AI in Latin America: higher educational attainment correlates with greater exposure to AI. Such outcomes have profound policy implications, as they imply that simply increasing educational attainment may not suffice to shield workers against AI. This is mainly due to the fact that AI is capable of performing more nonroutine cognitive tasks.

Third, the age-related analysis indicates that younger adults, particularly those aged 18–25, generally experience lower AI exposure compared to older cohorts in several countries. This could reflect either a current mismatch between younger workers' skills and AI-susceptible tasks or differential sectoral employment patterns among youth. However, as younger workers gain experience and move into roles traditionally occupied by older cohorts, they may eventually face similar exposure, potentially reinforcing intergenerational inequalities.

Finally, the intersection of gender, education, and age with AI exposure points to deepening inequality in labor markets. Unlike the results found for both LAC and OECD countries, where higher education and advanced skills often correlate with reduced automation risk, our results suggest that in Latin America, these factors might instead concentrate AI exposure among groups traditionally seen as more resilient. This finding is consistent with skill-biased technological change and emphasizes the importance of localized policy responses. In particular, improving the quality of education, tailoring reskilling programs to address skills gaps and gender-specific vulnerabilities, and designing policies that account for age-related transitions in labor markets become paramount to mitigating exacerbated inequalities.

Regarding inequality across the extremes of the income distribution, the results are consistent with productivity increases, as employment increases at both extremes would normally have a negative impact on wages – an effect that we find to be small or null. This is, therefore, consistent with a significant productivity increase that cancels out the negative impact of increases in employment on wages.

Our results contribute to a growing body of literature that questions one-size-fits-all assumptions about AI and its distributive effects (see also Goos et al., 2007; Autor and Salomons, 2018). They highlight the need for targeted regional strategies considering the unique interaction between technology, demographic factors, and labor market institutions.

As AI continues to evolve, policymakers must heed these insights to foster inclusive growth and prevent widening inequality gaps. It is imperative to design education and training programs that go beyond mere attainment levels to emphasize adaptability, critical thinking, and non-routine skill development. Policymakers should invest in continuous reskilling initiatives, targeted particularly toward women and older workers, to mitigate the possible negative effects of AI exposure and to reap all possible benefits of AI, as increases in productivity. Strengthening institutional support for lifelong learning and fostering public-private partnerships can help bridge skill gaps and promote smoother labour market transitions across the workers' life cycle.

8 Concluding Remarks

Our analysis underscores the impact of AI exposure across genders, education, and age demographics, with pronounced implications for AI exposure in Latin American labor markets compared to OECD counterparts. The findings suggest that traditional assumptions about the protective nature of advanced education regarding traditional forms of automation do not uniformly apply to AI-driven automation. This reality calls for tailored policy interventions that address these differentiated impacts.

As mentioned, our findings on inequality at the extremes of the income distribution align with increases in productivity. We observe growth in employment at both ends of the income spectrum, which typically would negatively affect wages; however, we find this impact to be minimal or nonexistent. This suggests a substantial increase in productivity that offsets any negative effects that higher employment levels might have on wages.

Looking ahead, future research should explore longitudinal dynamics of AI exposure and labour market outcomes to capture the longer-term effects of automation on career trajectories and wage structures. Additionally, integrating firm-level AI adoption metrics could refine our understanding of the mechanisms behind AI-induced labour market shifts, informing more precise and effective policy designs.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used *Grammarly* in order to improve the writing quality. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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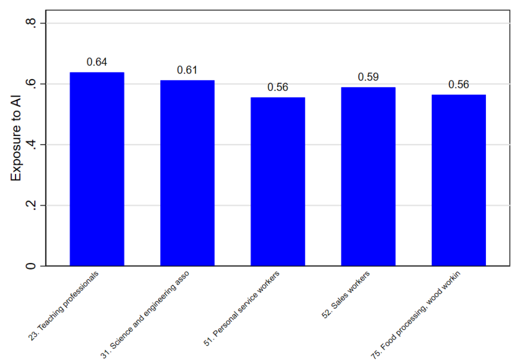
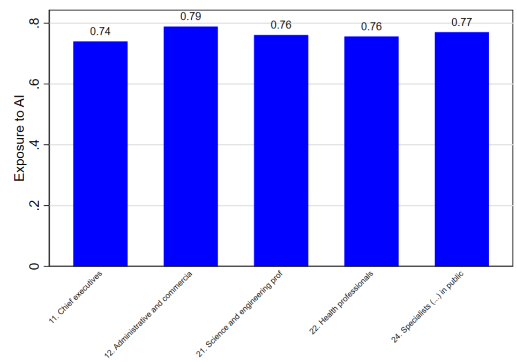
9 Graphs

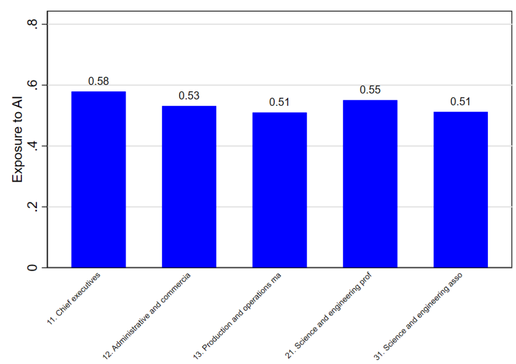
Figure 1: Bolivia



(a) Top 5 employees

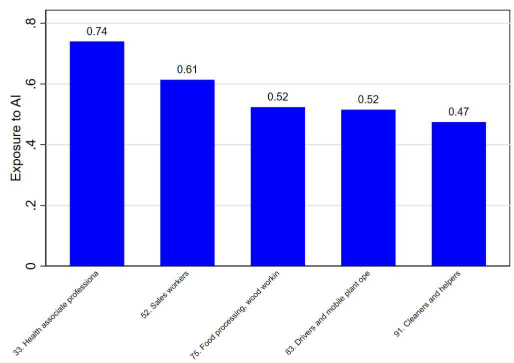


(b) Top 5 exposure to AI predicted Felten

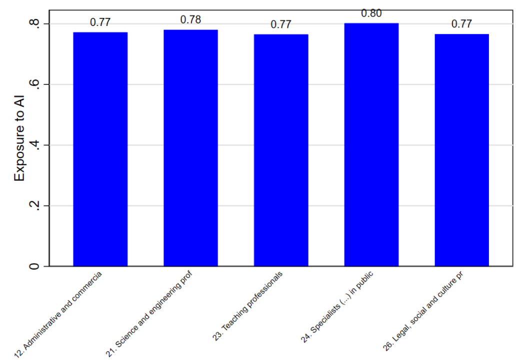


(c) Top 5 exposure to AI predicted Webb

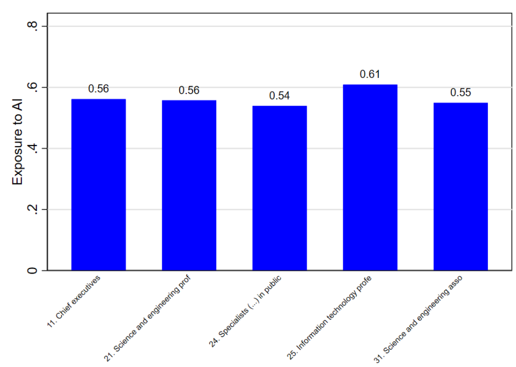
Figure 2: Chile



(a) Top 5 employees

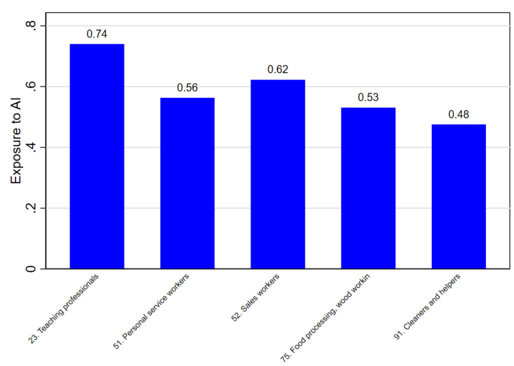


(b) Top 5 exposure to AI predicted Felten

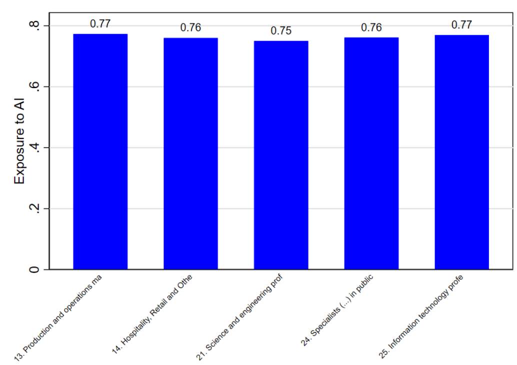


(c) Top 5 exposure to AI predicted Webb

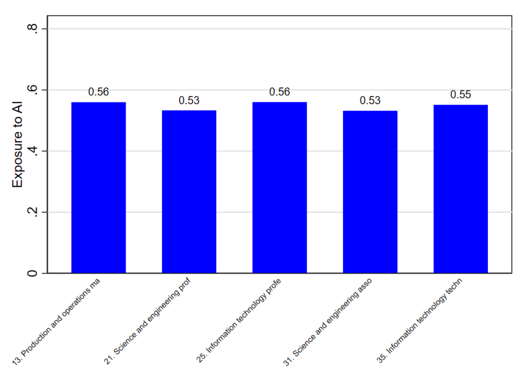
Figure 3: Ecuador



(a) Top 5 employees

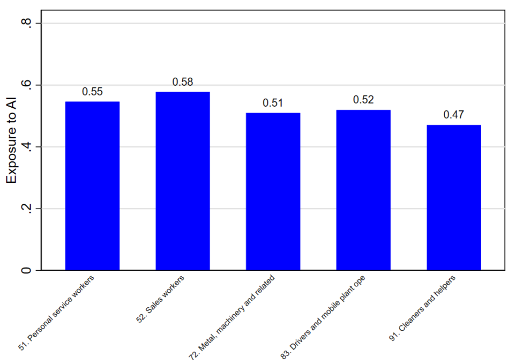


(b) Top 5 exposure to AI predicted Felten

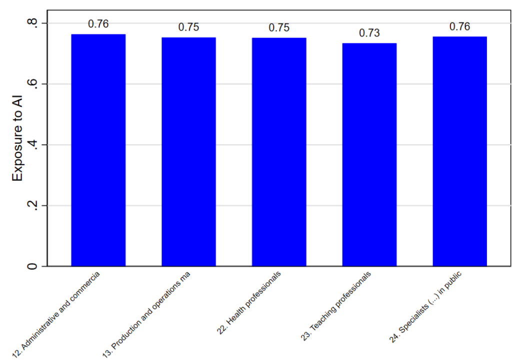


(c) Top 5 exposure to AI predicted Webb

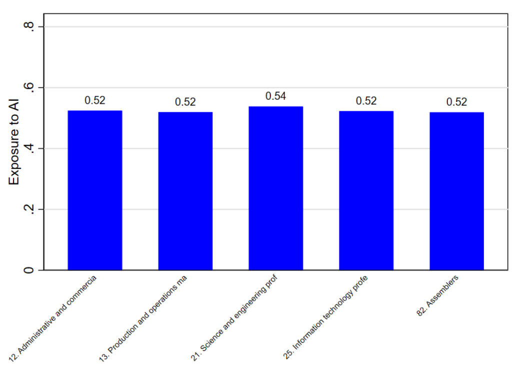
Figure 4: Peru



(a) Top 5 employees

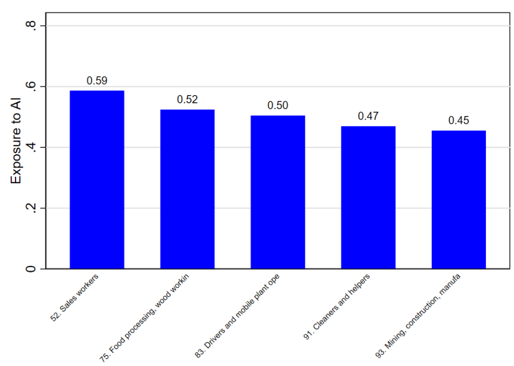


(b) Top 5 exposure to AI predicted Felten

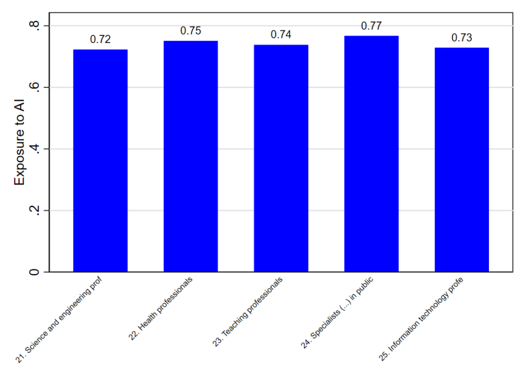


(c) Top 5 exposure to AI predicted Webb

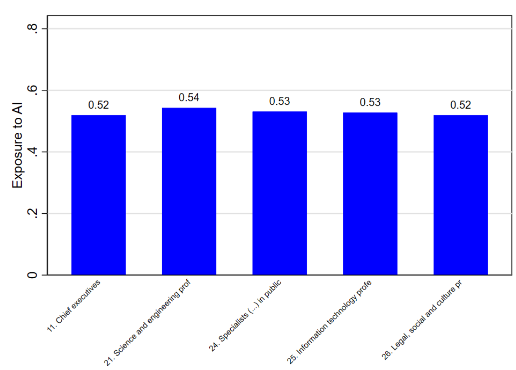
Figure 5: Mexico



(a) Top 5 employees



(b) Top 5 exposure to AI predicted Felten



(c) Top 5 exposure to AI predicted Webb