Universidad del Rosario | Facultad de Economía

SERIE DOCUMENTOS DE TRABAJO

No. 324

21 de abril de 2025

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Unequal Impacts of AI on Colombia's Labor Market: An Analysis of AI Exposure, Wages, and Job Dynamics

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Abstract

The rapid advancements in the domain of artificial intelligence (AI) have exerted a considerable influence on the labor market, thereby engendering alterations in the demand for specific skills and the structure of employment. This study aims to evaluate the extent of exposure to AI within the Colombian labor market and its relation with workforce characteristics and available job openings. To this end, we built a specific AI exposure index or Colombia based on skill demand in job posts. Our findings indicate that 33.8% of workers are highly exposed to AI, with variations observed depending on the measurement method employed. Furthermore, it is revealed a positive and significant correlation between AI exposure and wages, i.e., highly exposed to AI earn a wage premium of 21.8%. On the demand side, only 2.5% of job openings explicitly mention AI-related skills. These findings imply that international indices may underestimate the wage premium associated with AI exposure in Colombia and underscore the potential unequal effects on wages distribution among different demographic groups.

Keywords: Artificial intelligence, labor market, job posts, occupations, skills, Colombia.
JEL code: E24, J23, J24, O33.

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We would like to express our gratitude to The Future of Life Institute for funding this paper through the grant titled "Evaluating the Impact of AI on Poverty, Health, Energy, and Climate SDGs". We thank to Carlo Pizzinelli and his co-authors for sharing with us their complementarity index and C-AIOE estimates.

1. Introduction

Artificial intelligence (AI) has disrupted multiple spheres of society, transforming both productive systems and individual interactions (CAF, 2024). The increasing adoption of AI is expected to drive labor reallocation and improve productivity (see Carbonero et al., 2023; Cave and Cammers-Goodwin, 2024). This transformative phenomenon has already been observed in the labor market, and its influence is expected to grow significantly. In this context, the ability of labor markets to adapt to new technologies and leverage the benefits of AI has become a global priority. However, the transition of labor markets is linked to the structure of production, suggesting that countries are likely to experience varied trajectories. Consequently, persistent disparities in factors, such as innovation, technological advancement, and access to technology highlight the need to understand the effects of AI in the Global South.

There are generally competing forces influencing the costs and benefits of AI. On one hand, AI exposure increases the risk of automation in occupations defined by routine, repetitive, or physical tasks, which may result in job displacement (Brynjolfsson et al., 2018; Acemoglu and Restrepo, 2019; Green, 2024). In contrast, jobs that rely on cognitive skills, such as critical thinking, creativity, and problem solving, tend to be less impacted by automation (Autor and Dorn, 2013). These occupations may also experience productivity increases, particularly in sectors that integrate advanced technologies such as agritech or fintech (see, for example, Mhlanga, 2021; Alonso et al., 2022). Georgieff and Hyee (2022) and Alonso et al. (2022) show that occupations involving computer use tend to grow more rapidly, while occupations with low computer use experience a reduction in the average hours worked. Moreover, new occupations have emerged in industries such as software, data analytics, and creative sectors as a consequence of AI adoption. Acemoglu and Restrepo (2019) and Carbonero et al. (2023) argue that there is a sort of *reintegration effect*, in which the introduction of new AI-related tasks creates employment growth opportunities, even as automation leads job losses in other sectors.

The labor market characteristics of developing countries, such as those in Latin America, remark the importance of studying the impacts of AI. Specifically, developing countries are characterized by high levels of informality, which correlates with lower exposure to AI (Cazzaniga et al., 2024). However, informal workers are less educated and face significant human capital misallocation. Additionally, low levels of technological investment by firms in developing countries may prolong AI adoption. This delays automation and reduces the risk of capital-labor income inequality (see Acemoglu 2024). Nonetheless, some evidence suggests that digital skill acquisition has accelerated in response to technological changes following the COVID-19 pandemic. For instance, Sarango-Iturralde et al., (2021) reports a 3-percentage point increase in the demand for digital competencies in Colombia.

This study examines the relationship between AI exposure and job characteristics from the perspectives of both labor supply and demand in Colombia. Specifically, we aim to identify the characteristics of workers and occupations associated with higher exposure to AI. To achieve this, occupation-level exposure indices to AI proposed by Webb (2020), Felten et al. (2021), and Pizzinelli et al. (2023) are employed to provide evidence on the relationship between AI exposure and education level, wages, and demographic composition. Additionally, data from online job postings are analyzed to assess the penetration of AI adoption in labor demand in Colombia and construct an exposure index (named AI-Col). The construction of this index involved two stages: first, the development of a dictionary of AI-related terms, and second, the application of a TF-IDF methodology to job titles and descriptions. Colombia is an interesting case study in this regard. On the one hand, it exhibits structural labor market issues typical of developing countries, such as high levels of informality and low AI adoption. In addition, Colombia also has the advantage of data availability from household surveys and job posts.

The literature on the impact of AI on the labor market has focused on understanding the changes in the composition of the labor market. Existing evidence shows that occupations with a high probability of being automated will not necessarily experience a reduction in employment, as partial automation by AI can enhance productivity and stimulate growth through an intensive margin (Georgieff and Hyee, 2022; Su et al., 2021). On the other hand, the complementarity between human capital and AI contributes to an increase in the extensive margin of employment across various sectors (Su et al., 2021; Carbonero et al., 2023; Eloundou et al., 2023; Ernst et al., 2024; Georgieff, 2024).

The impact of AI on the labor market is heterogeneous across occupations, depending on the interplay of exposure and complementarity. Cazzaniga et al. (2024) conducted a cross-country analysis and classify occupations into three categories: high exposure and high complementarity, high exposure and low complementarity, and low exposure. The first category is likely to have increased productivity with a low risk of displacement, including occupations such as surgeons, lawyers, and judges. By contrast, the second category faces a higher risk of automation (Su et al., 2021). These types of occupation, e.g. call center operators, are more likely to experiencing reallocation between formal and informal jobs (Cave & Cammers-Goodwin, 2024). Gmyrek et al. (2024) conduct a similar cross-country study that categorizes occupations into three groups: those with potential for automation, those with potential for growth, and a final group termed *Big unknown* where the effects of AI remain uncertain. While these studies focus on cross-national dynamics our paper contributes to this literature by analyzing not only the supply side but also incorporating the demand side.

Studying the impact of AI on the labor market involves measuring exposure to AI. Webb (2020), Felten et al. (2021) and Pizzinelli et al. (2023) have estimated exposure indices at the occupation level. For instance, Felten et al. (2021) propose an index known as AI Occupational Exposure which links information on skills associated with ten AI applications described by the Electronic Frontier Foundation using Amazon's Mechanical Turk service to the skills outlined in ONET. Similarly, Webb (2020) quantified exposure to AI by combining text from AI-related patents obtained from Google Patents with job descriptions from ONET. Pizzinelli et al. (2023) expand the Felten et al. (2021) index by integrating complementarity as a factor that mitigates exposure. This means that the exposure level is reduced when the AI is complementary to the tasks performed in a particular occupation. Our study compares the results using these three indices while also constructing a dictionary of terms that allows for the measurement of AI incidence in job postings.[1]

[1] Other alternatives, such as Gmyrek et al. (2023) and Georgieff et al. (2024), have employed the ISCO-08 occupational classification along with GPT-4 to determine the level of task exposure to automation.

Therefore, this study contributes to the understanding of AI's impact on the labor market, particularly in economies characterized by high informality and structural barriers to AI adoption. To do so, we propose a dual approach that examines both labor supply and demand. Using standardized AI exposure indices, we assess worker characteristics from household surveys, identifying disparities between highly and minimally exposed occupations. Simultaneously, we analyze job postings to measure the extent and nature of AI-related labor demand. A key contribution of our study is the development of AI-Col index, a country-specific AI exposure index tailored to the Colombian labor market.AI-Col index captures skill requirements and industry trends that international indices may overlook, providing a more precise measure of AI penetration in the workforce. This approach allows for a nuanced comparison with existing global indices, shedding light on the distinct dynamics of AI adoption in emerging economies.

Our analysis of AI exposure in the Colombian labor market reveals that 33.8% of workers have high exposure to AI, according to the AI-Col index. This index closely matches international measurements but differs in key aspects. In comparison to indices such as Pizzinelli et al. (2023) the AI-Col index reflects a balanced distribution between workers with and without higher education (50%-50%), while indices in the UK assign greater exposure to non-university workers. Wage differentials further reinforce this pattern, with highly exposed workers receiving a 21.8% wage premium, consistent with estimates from advanced economies. Oaxaca-Blinder decompositions indicate that this premium is only partially explained by observed characteristics, suggesting that AI-related skills are valued in the labor market beyond traditional qualifications.

In terms of labor demand, our analysis of over one million job postings reveals that only 2.5% explicitly mention AI-related skills, a figure that is lower than in developed economies. In contrast, AI exposure in Colombia is primarily associated with applied AI, where the technology complements, rather than replaces, human labor. Moreover, AI-related job postings offer a comparable 11% wage premium. However, differences in terminology make more complex direct comparisons. Unlike international markets, where specific AI skills are clearly defined, job postings in Colombia often integrate AI capabilities within broader digital competencies. This highlights the need for a standardized framework to better understand how companies integrate AI into their hiring processes in a developing country.

This paper is organized as follows. Section 2 outlines the data sources and methodology. Section 3 explores AI exposure in the labor market, drawing insights from household surveys. Section 4 analyzes AI exposure in the labor market based on job postings. Finally, Section 5 provides concluding remarks.

2. Data and methodology

The two main sources of information for the proposed analysis are the household survey and a set of job postings. The household surveys provide comprehensive information on employment composition by occupation, sector, and demographic characteristics, while the job postings offer insights into labor demand in Colombia. The *Gran Encuesta Integrada de Hogares* (GEIH) is the primary instrument for measuring and monitoring Colombia's labor market. This nationwide household survey collects detailed information on key demographic and labor market variables, including age, education, gender, and occupation. Occupations in the GEIH are classified according to the *Clasificación Única de Ocupaciones para Colombia* (CUOC) at the four-digit level, a classification system specifically adapted to the Colombian context. For this analysis, we used data from 2023, representing a total of 22,520,713 employees.

Job vacancy information was obtained through web scraping from one of the platforms with the highest volume of job postings. The collected data includes job title, job description, required education level, and salary. The job description is a key input for identifying the occupation and extracting specific information related to AI. The analysis considered a total of 1,169,943 job vacancies posted between March 2022 and December 2023. This dataset did not include the occupational code associated with each vacancy. To address this limitation, we implemented the occupational imputation model proposed by García-Suaza et al. (2025), which adapts the CUOC to the methodology of the R package labouR, developed by Kouretsis et al. (2020) that employs a term frequency–inverse document frequency (TF-IDF) approach, originally designed under the ESCO (European Skills, Competences, Qualifications, and Occupations) occupational classification.

Availability of occupation codes, enabling the integration of the AI exposure indices. However, the exposure indices and Colombian data sources do not coincide perfectly in terms of taxonomy of occupational codes. For instance, the index proposed by Felten et al. (2021) is based on the O*NET-SOC taxonomy, while the GEIH follows the CUOC, which is an adaptation of the International Standard Classification of Occupations (ISCO-08) for Colombia. Due to this mismatch in occupational classifications, correlational tables provided by the Bureau of Labor Statistics[2] were utilized to merge the datasets. The mapping is complex due to the "many to many" correspondences. For instance, a single SOC occupation may map to multiple ISCO occupations and vice versa, raising the risk of double counting. To overcome this challenge, we adopted the approach proposed by Scholl (2023) using averages to aggregate categories. In the case of the Webb (2020) index, occupations are classified according to the OCC90 (Census Occupation Classification) developed by the United States Census Bureau. Therefore, we constructed a crosswalk between OCC 1990 and ISCO 88, and subsequently with ISCO 08, in order to adapt the occupation codes to the CUOC.

The first index we consider, the Felten index (2021), known as AI Occupational Exposure (AIOE), links the 10 AI applications identified by the Electronic Frontier Foundation with the 52 occupational skills listed in O*NET. Then, the exposure level per skill was calculated as the sum of the 10 application-skill relationship scores (x) derived from data collected through the mTurk survey. Notably, Felten et al. (2021) assigned equal weights to all 10 applications. The Webb (2020) index introduces a method to assess AI exposure through the analysis of verb-noun pairs, a linguistic construct representing actions (verbs) and the objects or entities they act upon (nouns). These pairs capture functional relationships relevant to technological advancements. Before calculating an exposure score for each verb-noun pair, nouns are grouped into conceptual categories using the WordNet database (Miller, 1995). Lastly, the Pizzinelli et al. (2023) index builds upon the Felten et al. (2021) framework by introducing a transformation that accounts for the

[2] The tables are available at: https://www.bls.gov/soc/isco_soc_crosswalk.xls

potential complementarity of occupation task with AI tools. A detailed description of the indexes is provided in Appendix A.

For our analysis, we classified occupations into two categories: high exposure or low exposure, using the median value of each exposure level index as the threshold following the approach of (Cazzaniga et al., 2024). To refine this analysis, an index was developed, which is referred to as AI-Col. This index was specifically tailored to the Colombian labor market and enables a comparative analysis of our findings with those derived from indices designed for developed economies. The construction of this index involved two stages: first, the development of a dictionary of AI-related terms, and second, the application of a TF-IDF methodology to job titles and descriptions from job advertisements. The list of terms was compiled from Alekseeva et al., (2021); Babashahi et al., (2024); Baruffaldi et al., (2020); Dawson et al., (2021); Dernis et al., (2023); Gehlhaus & Mutis, (2021) and Squicciarini & Nachtigall, (2021). In general, these terms refer to techniques related to AI, ranging from general concepts, such as Machine Learning, to more specific ones associated with algorithms and models, e.g., decision trees, KNN, and neural networks[3].

Moreover, although less frequently, key programming tools are mentioned, along with hard skills such as data analytics and natural language processing, which are essential competencies in the field. Additionally, to enhance the construction of this dictionary, three taxonomies were used to add relevant terms that were not referenced in the academic literature. These include AI Use Taxonomy (A Human-Centered Approach) by Theofanos et al. (2024); Creation of a Taxonomy for the European AI Ecosystem by the European Institute of Innovation and Technology community (2021); and the second edition of EU-US Terminology and Taxonomy for Artificial Intelligence 2024 by AI experts from the EU-US Trade and Technology Council (2024). The list of terms was reviewed and curated to minimize misleading results[4]. The final list contains 847 terms, including monograms and bigrams, with terms in both Spanish and English. Examples include AI, backpropagation, ChatGPT, Machine learning, and intelligent agents.

The AI-Col score for each job vacancy is calculated by summing the Inverse Document Frequency (IDF) values of the relevant terms found in the vacancy's text. The process is as follows. First, a text cleaning and tokenization step is carried out, which involves preprocessing the text of each job vacancy, including both the title and description. This includes by removing unnecessary characters such as punctuation, numbers, and stop words. The cleaned text is then tokenized, breaking it down into individual terms (tokens) that carry meaningful information. Second, each term in the predefined dictionary is systematically checked against the text of each job posting. To allow for minor variations in spelling or formatting, flexible string matching is applied using similarity metrics such as the Jaro-Winkler distance, with a maximum threshold of 0.05. This mapping process identifies the presence of dictionary terms in each vacancy and serves as

[3] The dictionary used to classify AI exposure is available upon request.

[4] Among these terms were "Development," which could refer to business development or interpersonal development—areas that are not our focus. Similarly, "Information" is a broad term that could yield irrelevant results, such as “vacancy information”. Additionally, "CV" is often associated with computer vision in the technology field, whereas in the context of job vacancies, it refers to a résumé.

the basis for the subsequent IDF-based scoring. For each identified term, the Inverse Document Frequency (IDF) is calculated as follows:

$$IDF(t) = log\left(\frac{T}{v(t) + 1}\right) + 1$$

Where $IDF(t)$ refers to the Inverse Document Frequency of the term t, , which downweights commonly occurring terms by accounting for their distribution across the full job vacancy documents. T is the total job vacancies in the dataset, and $v(t)$ is the number of vacancies in which the term t appears.

In turn, The AI-Col Index for the job vacancy j is calculated as the sum of the IDF values corresponding to all relevant terms identified in the text of each job vacancy. This is expressed as:

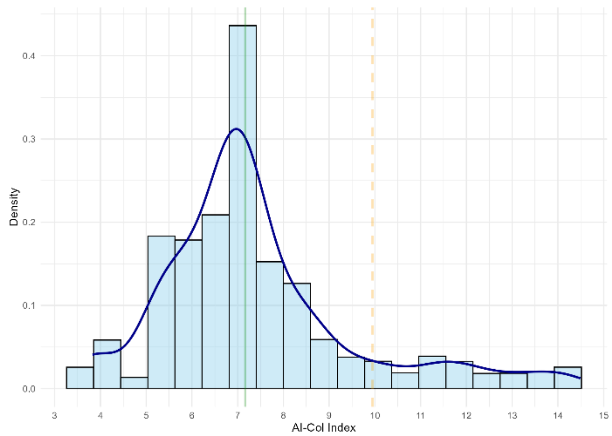
$$AI - Col_j = \sum_{i=1}^{n_j} IDF_j(i)$$

with n_j the total number of terms found in the vacancy's text. In cases where no terms from the proposed dictionary are found in a job vacancy, the corresponding AI-Col value will be set to zero. The fundamental significance of the AI-Col index lies in its foundation on local labor market information. In contrast to indices generated from occupation-based external data, this approach can capture the specific characteristics of the labor market, avoiding potential biases stemming from structural differences in occupations across countries. Furthermore, by calculating AI exposure based on the terms used in the vacancies, it allows for greater granularity within the same occupation, reflecting more accurately the differences in skill requirements. The text-based methodology employed ensures that the index adapts to changes in demand conditions by applying directly to each job posting. In other words, if new job postings within a particular occupation increasingly emphasize AI-related skills, the AI-Col index adjusts accordingly.

A preliminary analysis of the proposed index reveals that the distribution is highly skewed. Most vacancies show no mention of AI-related terms, with only 2.5% of postings registering a non-zero value. Among those exposed, most vacancies cluster around relatively low index values, the median is 7.17 (see Figure 1.). A small number of highly specialized postings, however, show much higher levels of AI-related content, pushing the maximum observed value to 126.38 and raising the overall mean to 9.95. This distribution suggests that while direct references to AI remain rare, the intensity of exposure varies widely across the few vacancies where such terms are present.

In light of these considerations, and as a preliminary step toward the labor supply and demand analyses to be undertaken in subsequent sections, we propose two distinct approaches for operationalizing the AI-Col index. For the analysis of labor supply, we compute an aggregated AI-Col index at the three-digit ISCO-08 level, defined as the average score of all vacancies classified within each occupational group. To distinguish between occupations exposed and not exposed to AI, we then use the median value of this aggregated distribution as a threshold. For the analysis of labor demand, we leverage the granularity of the vacancy-level data and employ the AI-Col index directly as a measure of exposure to AI. In this framework, vacancies with a non-zero AI-Col index are classified as exposed, that is, those in which at least one term from the AI dictionary is identified.

Figure 1. Distribution of the AI-Col Index across job vacancies



Source: Authors' calculations based on job postings database (2022, 2023). The green solid line represents the median of the distribution, while the orange dashed line marks the mean. Outlier observations were excluded from the graph.

3. AI Exposure in the Labor Market: Insights from Household Survey

To assess the extent of AI exposure in the Colombian labor market, we separately analyze workers characteristics and job vacancies. In the analysis based on the household survey, we calculate the proportion of workers who, according to their occupation, are employed in jobs with high and low exposure (see Table 1). Low exposure corresponds to occupations where the index level is below the median, while high exposure applies to those where the index is above the median. Consistent with the findings of Pizzinelli et al. (2023), who studied Brazil, Colombia, and South Africa, nearly 40% of workers in these countries are in high-exposure occupations. Our results indicate that all four indices show a higher proportion (60%) of workers in low-exposure jobs, with the AI-Col index reporting the highest share of workers in high-exposure occupations (66.2%), followed by Pizzinelli et al. (2023) (58.5%), Felten et al. (2021) (59.6%), and Webb (2020) (60.8%).

These results are interesting given that each index, using different inputs, may capture distinct aspects of AI exposure. While their similarities are apparent at the aggregate level, there may be differences at the occupational level. In fact, a comparison of Webb (2020) and Pizzinelli et al. (2023) show that 48% of the occupations do not coincide in the AI exposure level. Comparing the indexes of Webb (2020) and AI-Col, 58% coincide while for Pizzinelli et al (2023) and AI-Col the percentage of coincidence is 70%. In this sense, comparing indices can reveal the distinct channels through which AI impacts the labor market. The percentage of coincidence comparing Pizzinelli et al. (2023) and AI-Col shows that high exposure occupations are mostly highly skilled and professional or technical level jobs, many of these occupations require analytical skills, creativity, decision making or interaction with data and technology (mathematicians, architects, engineers among others) while in low exposure occupations are manual, operation and services occupations (veterinarians, painters, facade cleaners, among others).

Table 1. Distribution of workers by level of AI exposure

	Quantity				Percentages			
Level	Webb (2020)	Felten et al (2021)	Pizzinelli et al (2023)	AI-COL Index	Webb (2020)	Felten et al (2021)	Pizzinelli et al (2023)	AI-Col Index
Low exposure	13,693,453	13,414,802	13,171,105	14,904,285	60.8%	59.6%	58.5%	66.2%
High exposure	8,827,260	9,105,911	9,349,608	7,616,428	39.2%	40.4%	41.5%	33.8%
Total	22,520,713	22,520,713	22,520,713	22,520,713	100.0%	100.0%	100.0%	100.0%

Source: Authors' calculations based on GEIH (2023). All calculations were performed using sample weights. The occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.

As another example, Table 2 we present a comparison of occupations with high and low AI exposure, based on the indices of Webb (2020) and Pizzinelli et al. (2023). This is useful for understanding what the indices are ultimately capturing. For instances where both indices classify an occupation as highly exposed to AI, we observe occupations such as business services and administration managers, finance professionals, and legal professionals. According to Webb (2020), these results correspond to exposure to routine tasks with an analytical component that AI can efficiently perform (e.g., reporting, data analysis, and evaluation).

Table 2. Comparison of AI Exposure Indices: Coincidences between Webb (2020) and Pizzinelli et al. (2023)

		Pizzinelli et al. (2023) index	
		High Exposure	Low Exposure
Webb (2020) index	High Exposure	• Business Services and Administration Managers • Sales, Marketing and Development Managers • Finance Professionals • Legal Professionals • Medical and Pharmaceutical Technicians	• Production Managers in Agriculture, Forestry and Fisheries • Medical Doctors • Mining, Manufacturing and Construction Supervisors • Subsistence Crop Farmers • Manufacturing Laborers
	Low Exposure	• Legislators and Senior Officials • Managing Directors and Chief Executives • University and Higher Education Teachers • Creative and Performing Artists • Secretaries (general)	• Hotel and Restaurant Managers • Sports and Fitness Workers • Personal Care Workers in Health Services • Machinery Mechanics and Repairers • Food Processing and Related Trades Workers

Source: Prepared by the authors. The occupations categorized as "High Exposure" have values exceeding the median in the Pizzinelli et al (2023) and Webb (2020) indices, respectively.

On the other hand, both indices classify occupations such as hotel and restaurant managers, sports and fitness workers, and machinery mechanics and repairers as having low AI exposure. These occupations are primarily manual and operational. AI may support in monitoring these tasks but are not subject to being replaced. Pizzinelli et al. (2023) state that these occupations can be complemented in a certain manner, potentially leading to improvements in working conditions. However, in cases where the indices classify occupations differently, key discrepancies emerge regarding the role of AI complementarity. These differences stem from Webb's methodology, which focuses on task automation potential rather than AI complementarity. In contrast, Pizzinelli et al. (2023) assigns high exposure to occupations such as legislators, senior officials, and university professors—not because they are at risk of automation, but because AI can enhance cognitive and decision-making tasks central to these professions. Thus, while Webb (2020) emphasizes displacement risk based on task routineness, Pizzinelli et al. (2023) captures exposure through augmentation, where AI acts as a productivity-enhancing tool.

To explore the differences between workers in high-exposure jobs and those in low-exposure jobs, we analyze socioeconomic characteristics and job features for each group. The results presented in Table 3 show that there is occupational sorting based on AI exposure. That is, it can be expected that AI may disproportionately affect certain workers groups. In turn, analyzing the main characteristics of workers in occupations with high AI exposure, according to the Felten et al. (2021) index and the AI-Col index, these are workers predominantly in salaried jobs, and a lower level of informality. Regarding age, the majority of workers are under 30 years old, and their distribution is similar regardless of the level of AI exposure. A striking difference is observed when comparing the indices of Felten et al. (2021) and Pizzinelli et al. (2023), where a relatively lower proportion of young workers is found in highly exposed occupations. In terms of gender composition, although nearly 60% of workers are men overall, Pizzinelli et al. (2023) shows a higher proportion of men among those with low exposure. However, this result is reversed when analyzing the Webb (2020) index.

Table 3. Characteristics of workers by AI exposure level

Variable	Category	Webb (2020)		Felten et al (2021)		Pizzinelli et al (2023)		AI-Col Index		Total
		Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure	
Age	More than 30	73.94%	75.77%	74.46%	74.94%	75.86%	72.95%	73.76%	76.41%	74.65%
	Less than 30	26.06%	24.23%	25.54%	25.06%	24.14%	27.05%	26.24%	23.59%	25.35%
Sex	Men	50.77%	71.46%	68.01%	45.44%	69.35%	44.13%	60.71%	55.31%	58.88%
	Women	49.23%	28.54%	31.99%	54.56%	30.65%	55.87%	39.29%	44.69%	41.12%
Education	No University	83.11%	71.99%	95.17%	54.55%	92.60%	59.24%	93.40%	50.09%	78.75%
	University	16.89%	28.01%	4.83%	45.45%	7.40%	40.76%	6.60%	49.91%	21.25%
Informality	Informal	54.79%	58.02%	69.70%	35.97%	67.56%	39.86%	67.01%	34.63%	56.06%
	Formal	45.21%	41.98%	30.30%	64.03%	32.44%	60.14%	32.99%	65.37%	43.94%
Employment status	Salaried workers	51.78%	41.61%	39.20%	60.45%	37.80%	61.87%	39.90%	63.25%	47.79%
	Self-employed / Employed	41.26%	48.68%	49.05%	36.97%	50.41%	35.37%	48.40%	35.89%	44.17%
	Others	6.97%	9.71%	11.75%	2.58%	11.79%	2.75%	11.71%	0.87%	8.04%

Source: Authors' calculations based on GEIH (2023). All calculations were performed using sample weights. The occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.

Informality is a significant characteristic of Colombia's labor market. The results reveal differences in the level of exposure of informal workers when comparing international indices. According to the Webb (2020) index, the share of informal workers among those with high exposure is similar to the overall average. However, for the rest of the indices, including AI-Col, workers with high exposure are predominantly formal, ranging between 60.14% and 65.37%. This could suggest that AI adoption has been concentrated in sectors with higher formalization rates, which tend to have greater market access. It may also indicate that AI penetration is higher among large firms, which are generally more formal.

These differences in what each index captures are evident when analyzing the occupational groups based on AI exposure levels. Table 4 shows that, according to the Webb (2020) index, the largest proportion of high-exposure workers is concentrated in elementary occupations, while the other indices assign higher exposure to more technical and professional occupations. Similar findings have been documented by Acemoglu et al. (2020), who highlight that AI exposure measures can diverge significantly depending on whether they prioritize task automation or task augmentation. The Webb (2020) index, which primarily focuses on automation potential, tends to classify lower-wage, routine-intensive occupations as highly exposed. In contrast, indices such as Felten et al. (2021) and Pizzinelli et al. (2023) emphasize the integration of AI into high-skilled professions. The AI-Col index, in particular, presents the majority of high-exposure workers in the Professionals category, followed by Technicians and Managers, which suggests that this index emphasizes occupations requiring specialized AI-related knowledge and advanced technical skills.

Table 4. Employment share by occupational groups and level of exposure to AI

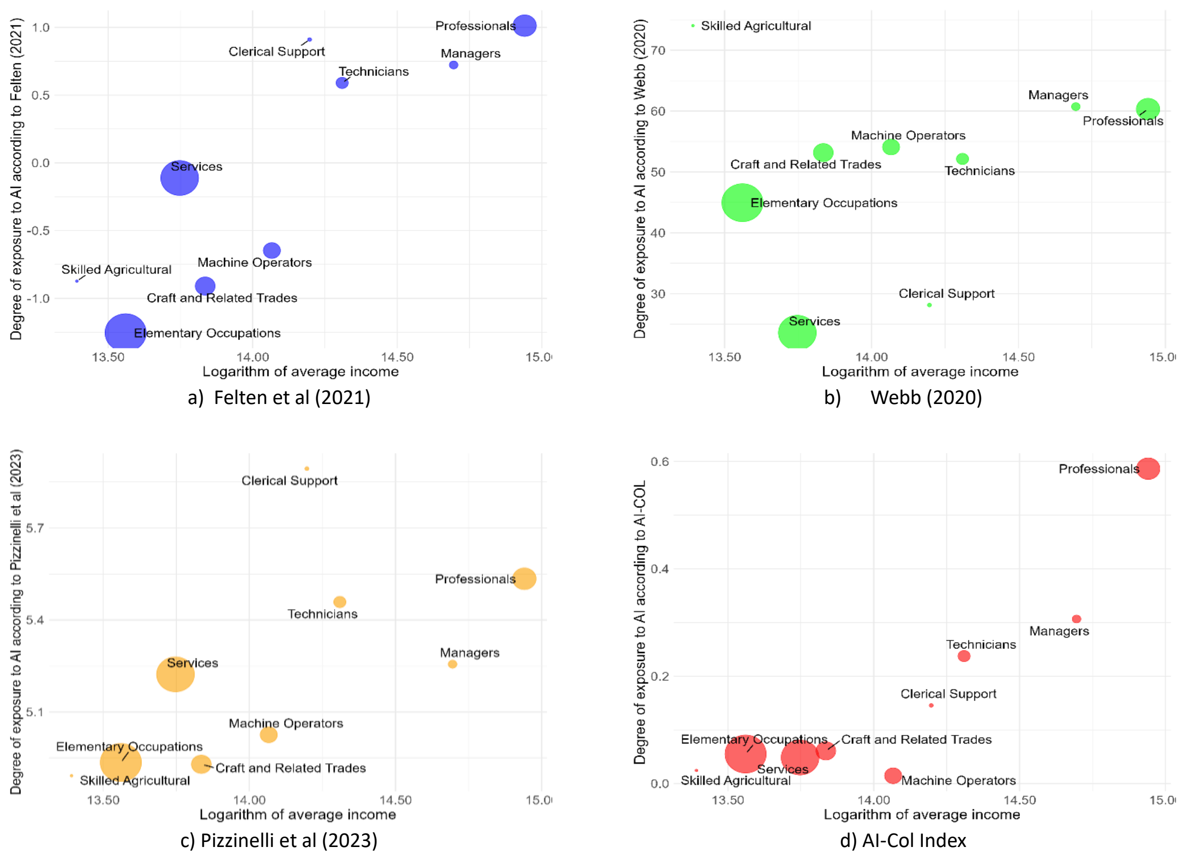
Occupation ISCO-08 major group	Webb (2020)		Felten et al (2021)		Pizzinelli et al (2023)		AI-Col Index		Total
	Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure	
Managers	2.08%	12.99%	0.94%	14.33%	5.07%	8.17%	0.00%	18.80%	6.36%
Professionals	6.36%	18.81%	0.64%	26.86%	2.61%	23.41%	0.41%	32.44%	11.24%
Technicians	5.23%	9.89%	2.94%	13.11%	3.10%	12.63%	1.01%	18.89%	7.05%
Clerical Support	9.78%	0.00%	0.00%	14.71%	0.00%	14.33%	4.26%	9.25%	5.95%
Services and Sales	34.81%	0.00%	16.14%	28.57%	12.79%	32.97%	31.72%	0.52%	21.17%
Skilled Agricultural	1.00%	13.58%	9.96%	0.00%	10.14%	0.00%	8.96%	0.00%	5.93%
Craft and Related Trades	10.54%	8.01%	16.03%	0.00%	13.78%	3.58%	11.69%	5.35%	9.55%
Machine Operators	12.09%	2.96%	14.29%	0.00%	12.74%	2.56%	12.87%	0.00%	8.51%
Elementary Occupations	18.11%	33.75%	39.05%	2.42%	39.78%	2.36%	29.09%	14.76%	24.24%

Source: Authors' calculations based on GEIH (2023). All columns sum to 100 percent, and occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.

One of the most relevant policy questions is the impact that AI may have on inequality, particularly because the labor market serves as a key driver influencing employment status and wages. Therefore, we extend our analysis to explore the relationship between wages and AI exposure. Despite the differences in demographic and employment characteristics, there are notable similarities in the wage distribution across AI exposure indices (see Appendix B). But, a positive relationship is observed between wages and the level of AI exposure.

This relationship is further explored in Figure 2, which disaggregates the data by occupational groups, offering a more detailed perspective on this pattern. For instance, consistent with the previous findings from the Felten et al. (2021), Pizzinelli et al. (2023) and AI-Col indexes, occupational groups such as managers, professionals and technicians exhibit both higher AI exposure and higher wages. This suggests that the integration of AI technologies may be enhancing productivity. In contrast, occupational groups such as elementary occupations, skilled agricultural workers, and craft and related trades demonstrate the opposite trend, with lower AI exposure and lower average wages. This indicates that AI exposure might shape wage disparities across different segments of the labor market, highlighting the potential challenges for less-affected occupations in adapting to an increasingly AI-driven economy.

Figure 2. Relation between AI Exposure and wages by occupational groups



Source: Authors' calculations based on GEIH (2023). This figure illustrates the AI exposure measure across 9 occupation groups. Marker sizes correspond to the proportion of workers for each group.

To analyze the relationship between AI exposure and wages, conditional on observable characteristics, we use linear regression models under the following specification:

$$\log(w_i) = \alpha + \theta high\ exposure_i + \boldsymbol{X}_i\beta\ + \varepsilon_i \qquad (1)$$

Where $\log(w_i)$ is the logarithm of wage, $high\ exposure_i$ is a dummy variable equal to 1 for occupations with high exposure to AI and 0 for those with low exposure, $\boldsymbol{X}_i$ is a set of variables with: age, gender, education, informality status, occupational group, and hours worked as well as department (or state) and sector fixed effects. In alternative specifications, each index is included in both its continuous and quadratic form in the analysis.

The results presented in Table 5 reveal a positive correlation between AI exposure and wages. The first two columns corresponding to the model including index level and its quadratic form, respectively, while the third column includes the dummy variable for occupations with high exposure. Estimated coefficients suggest that a 1-point increase in AI exposure is associated with an approximate 13.1% increase in wages in the Felten et al. (2021) index and a 12.7% in the Pizzinelli et al. (2023) index. In contrast, the Webb index (2020) demonstrates a positive effect, albeit of a smaller magnitude (0.3%). The AI-Col index also exhibits a positive relationship with wages, with the estimated coefficient indicating that a 1-point increase in AI exposure is associated with an increase of approximately 23.9% in wages.

The analysis of AI exposure categories reveals that higher exposure is associated with higher wages, with coefficients ranging from 8.1% to 21.8%. A comparison of these effects across indexes shows that the coefficient of the Pizzinelli et al. (2023) index is approximately half that obtained with the Felten et al. (2021) index (8.1% vs. 17.2%). This outcome aligns with the Pizzinelli et al. (2023) index's methodology, which adjusts for complementarity, signifying those occupations with higher human capital and reduced exposure to AI result in a lower average wage for jobs with high exposure.

The differences in results between AI-Col and the other indices may highlight the need for measurements adapted to local labor market contexts. In fact, the comparison suggests that international indices may be underestimating the wage premium associated with AI exposure in Colombia. In advanced economies, the wage premium for AI skills is estimated to be between 23% and 25%, according to Bone (2025) and PwC (2024) AI Jobs Barometer. It is noteworthy that while the indices developed in advanced economies are applicable to Colombia, the AI-Col reveals a wage premium comparable to that of these economies.

Table 5. Effects of AI Exposure on wages

Variable	Webb (2020)			Felten et al (2021)			Pizzinelli et al (2023)			AI-Col		
$AI\ Index$	0.003**	-0.004		0.131***	0.137***		0.127**	3.176***		0.239*	0.598***	
	(0.001)	(0.003)		(0.021)	(0.025)		(0.056)	(0.893)		(0.131)	(0.138)	
$AI\ Index^2$		0.000**			0.021			-0.282***			-0.073***	
		(0.000)			(0.024)			(0.083)			(0.019)	
High exposure			0.111*			0.172***			0.081*			0.218***
			(0.058)			(0.048)			(0.043)			(0.043)
Constant	12.694***	12.805***	12.769***	12.961***	12.929***	12.777***	12.148***	3.960	12.775***	12.799***	12.801***	12.822***
	(0.224)	(0.218)	(0.213)	(0.187)	(0.199)	(0.205)	(0.352)	(2.369)	(0.209)	(0.209)	(0.203)	(0.200)
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	343,175	343,175	343,175	343,175	343,175	343,175	343,175	343,175	343,175	343,175	343,175	343,175
R-squared	0.463	0.464	0.462	0.469	0.469	0.464	0.461	0.463	0.460	0.463	0.469	0.469

Source: Authors' calculations based GEIH 2023. Clustered standard errors by occupation group in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index. In addition to including sector and department fixed effects, the estimates include variables such as age, gender, education, informality status, occupational group and hours worked.

These results indicate that there is a significant wage difference based on AI exposure, even after accounting for differences in worker characteristics. To gain a deeper understanding of the sources of these wage disparities, we implement Oaxaca-Blinder decompositions (Oaxaca, 1973; Blinder, 1973) following the specification:

$$\bar{w}_H - \bar{w}_L = (\bar{X}_H - \bar{X}_L)\hat{\beta}_H + \bar{X}_L(\hat{\beta}_H - \hat{\beta}_L)$$

where $\bar{w}_H$ and $\bar{w}_L$ represent the mean of log wages for high and low exposure occupations, respectively, $\bar{X}_H$ and $\bar{X}_L$ are the mean values of the explanatory variables, and $\hat{\beta}_H$ and $\hat{\beta}_L$ the estimated coefficients. This decomposition involves separating the observed difference in a variable into two components: one that depends on observable characteristics such as: age, sex, educational attainment, informality status, occupational category, working hours, and sector, known as the explained component (the first term in the right-hand side) and in the second term a residual component or the unexplained component that reflects differences in coefficients or wage premiums across AI exposure groups.

Table 6 presents the raw wage differences as well as the estimates of the two components. Both components are statistically significant across the AI exposure indices. While the smallest wage differential is observed with the Webb (2020) index, the largest is found with the AI-Col index. Interestingly, in all four indices analyzed, the unexplained component accounts for most of the wage difference. This suggests that even if workers in high and low AI exposure jobs were identical in their observable characteristics, statistically significant wage differences would still be observed. That is, if workers in both AI exposure groups had the same characteristics, workers in high exposure jobs would earn 50.4% more according to the Felten et al. (2021) index. These estimates are 32.9% for the Pizzinelli et al. (2023) index and 64.3% for the AI Col. index.

The magnitude of wage premiums associated with AI exposure exhibits considerable variation when contingent on the utilized index. Specifically, the wage differential ascertained through the Pizzinelli et al. (2023) index is 17.5 percentage points lower than that of Felten et al. (2021). This discrepancy could be attributed to the fact that the Pizzinelli et al. (2023) index incorporates complementarity as a differentiating element, thereby isolating the net impact of AI exposure on wages more effectively. In contrast, the Felten et al. (2021) index does not explicitly control for this factor, which might explain its higher wage premium.

In contrast, the AI-Col index demonstrates a 31.4 percentage points higher wage premium compared to that reported by Pizzinelli et al. (2023). This discrepancy is primarily attributable to the unexplained component (See Appendix B). This finding indicates that the AI-Col index captures unique factors inherent to the Colombian labor market. The index is derived from local job vacancies and offers greater granularity in reflecting skill requirement disparities within the same occupation.

In summary, Table 6 shows that although factors such as education and employment type play a key role in explaining the wage gap associated with AI exposure, a significant unexplained disparity remains. This result underscores the need to delve deeper into structural and systemic factors that perpetuate inequalities in the Colombian labor market, particularly in the context of technological changes driven by AI.

Table 6. Oaxaca-Blinder Decomposition of wage disparities by occupational exposure level

	Webb (2020)	Felten et al (2021)	Pizzinelli et al (2023)	AI COL
High exposure	14.131***	14.277***	14.173***	14.404***
	(0.003)	(0.002)	(0.002)	(0.003)
Low exposure	13.915***	13.773***	13.845***	13.761***
	(0.002)	(0.002)	(0.002)	(0.002)
Difference	0.216***	0.504***	0.329***	0.643***
	(0.003)	(0.003)	(0.003)	(0.003)
Explained	0.098***	0.243***	0.239***	0.315***
	(0.003)	(0.003)	(0.003)	(0.003)
Unexplained	0.118***	0.262***	0.090***	0.328***
	(0.004)	(0.004)	(0.003)	(0.003)
Explained				
Age	0.002***	0.001***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.045***	-0.050***	-0.059***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.000)
University	0.070***	0.117***	0.169***	0.137***
	(0.001)	(0.002)	(0.002)	(0.002)
Formal	-0.003***	0.138***	0.117***	0.128***
	(0.001)	(0.001)	(0.001)	(0.001)
Salaried workers	-0.020***	0.013***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Self-employed / Employer	0.027***	-0.025***	-0.034***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
Weekly working hours	-0.006***	-0.002**	-0.022***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Unexplained				
Age	-0.005	0.205***	0.130***	0.368***
	(0.007)	(0.007)	(0.007)	(0.007)
Woman	-0.014***	-0.030***	-0.014***	0.004
	(0.002)	(0.003)	(0.003)	(0.002)
University	0.091***	0.146***	0.031***	0.151***
	(0.002)	(0.003)	(0.003)	(0.003)
Formal	-0.001	0.054***	0.037***	0.044***
	(0.003)	(0.004)	(0.004)	(0.004)
Salaried workers	-0.127***	0.243***	0.203***	0.104***
	(0.005)	(0.014)	(0.014)	(0.028)
Self-employed / Employer	-0.124***	0.164***	0.101***	0.096***
	(0.006)	(0.010)	(0.009)	(0.018)
Weekly working hours	0.071***	-0.288***	-0.151***	-0.159***
	(0.008)	(0.007)	(0.007)	(0.007)
Constant	0.801**	0.707*	0.547	0.660
	(0.336)	(0.388)	(0.339)	(0.415)
Economic Sector	Yes	Yes	Yes	Yes
Observations	343,175	343,175	343,175	343,175

Source: Authors' calculations based GEIH 2023. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.

4. AI Exposure in the Labor Market: Analysis of Job Postings

The labor market exhibits persistent mismatches that have the potential to be exacerbated by the introduction of AI. Labor demand has been observed to respond rapidly to these changes, particularly in response to the evolving needs of the productive sector. However, detailed information on labor demand is not usually available, especially in relation to AI-associated skills. We address this gap by utilizing online vacancy information to measure the AI content of labor demand. By examining the extent of AI exposure in job vacancies, we can identify labor demand trends and assess the correlation between demand for specific occupations and AI tools. To do so, we construct the AI-Col index, a metric that quantifies both the presence and the intensity of AI-related terms in job postings. This index enables us to detect the heterogeneous results of AI across occupations providing a granular view of how AI-related skills are being integrated into the labor market.

We find that only 2.5% of the 1,169,943 job vacancies contain at least one AI-related term, thus being classified as highly exposed to AI (see Table 7). This figure could represent an upper bound, as the AI-Col dictionary covers a broad set of terms; however, the literature consistently classifies these terms as AI-related. For instance, terms such as "machine learning" or "neural networks" are central to AI, while others, such as "data analytics" or "automation," are essential to AI but also widely used in other domains, such as business intelligence or industrial process optimization. This overlap may lead to an overestimation of the specific demand for AI, although it aligns with the broad conceptualization of AI-related work found in existing research.

We impute the occupational codes to each vacancy in the dataset, we employed the occupational imputation model developed by Garcia-Suaza et al. (2025), which adapts the the R package labouR methodology (Kouretsis et al., 2020) to the CUOC. As shown in Table 7, the Webb (2020) index classifies 34.9 percent of vacancies as highly exposed to AI. The figures are even higher when using the indices proposed by Felten et al. (2021) and Pizzinelli et al. (2023), which identify 69.2 percent and 66.7 percent of vacancies, respectively, as highly exposed. In contrast, the AI-Col index, which relies on the presence of AI-related terms in the actual job descriptions, identifies only 2.5 percent of vacancies as highly exposed.

This marked difference stems from the underlying methodological approaches. International indices assign fixed exposure scores to occupations and apply them uniformly to all related vacancies, assuming that jobs within the same occupational category involve similar tasks and exposure levels. The AI-Col index follows a different logic. Instead of assigning exposure based on occupational codes alone, it draws on the textual content of each vacancy to detect explicit references to AI technologies or skills. This allows for a more fine-grained analysis that captures variation within occupations and provides a clearer view of the specific demands expressed by employers.

Table 7. Distribution of job vacancies by level of AI exposure

	Number of vacancies				Percentages			
Level of exposure	**Webb (2020)**	**Felten et al (2021)**	**Pizzinelli et al (2023)**	**AI-Col Index**	**Webb (2020)**	**Felten et al (2021)**	**Pizzinelli et al (2023)**	**AI-Col Index**
Low exposure	762,111	359,911	389,758	1,140,614	65.1%	30.8%	33.3%	97.5%
High exposure	407,832	810,032	780,185	29,329	34.9%	69.2%	66.7%	2.5%
Total	1,169,943	1,169,943	1,169,943	1,169,943	100%	100%	100%	100%

Source: Authors' calculations based on job postings database (2022, 2023). The total number of vacancies is 1,169,943 and the occupations categorized as "High exposure" have values above the median of their respective exposure index, except for the AI-Col index which takes as High exposure all vacancies where at least one AI dictionary term has been found.

Table 8 shows there are differences in distribution of high and low-exposure job postings by occupational groups across indices. Professionals represent the category with the highest proportion of high-exposure postings in all indices, reaching 49.3% in AI-Col, 44.9% in Webb, 30.7% in Felten, and 27.2% in Pizzinelli. This finding suggests that professionals are the most sought-after for AI-related skills, irrespective of the index used. In contrast, technicians exhibited a balanced distribution between high and low exposure across all indices, with values close to 23%.

Meanwhile, significant differences across indices were observed in the case of Clerical Support Workers and Service and Sales Workers. While the Webb (2020) index and AI-Col index categorize the majority of these postings as low exposure, the Felten and Pizzinelli indices designate a substantial proportion as high exposure. This discrepancy may be attributable to variations in the methodologies employed to identify AI-related terms. In the context of elementary occupations and machine operators, the proportion of high-exposure postings is negligible in AI-Col, contrasting with indices from advanced economies, which allocate a comparatively higher AI exposure in these sectors. This lends further credence to the notion that the application of indices from advanced economies to a developing economy may result in overestimations within specific segments of the labor market. The extent of AI exposure exhibits significant variability, contingent on the specific occupation and the index employed, thereby underscoring the necessity for a metric that is customized to the particularities of each country's labor market.

Table 8. Distribution of vacancies by occupational groups and level of exposure to AI

Occupation ISCO-08 major group	Webb (2020)		Felten et al. (2021)		Pizzinelli et al. (2023)		AI-Col index		Total share of vacancies
	Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure	
Managers	1.46%	20.22%	0.11%	11.50%	4.79%	9.60%	7.89%	12.17%	8.00%
Professionals	9.57%	44.93%	1.96%	30.75%	11.31%	27.18%	21.19%	49.30%	21.89%
Technicians	23.19%	23.03%	21.98%	23.64%	22.87%	23.26%	23.15%	22.27%	23.13%
Clerical Support Workers	22.76%	0.00%	0.00%	21.41%	0.00%	22.23%	15.01%	7.80%	14.83%
Services and Sales Workers	29.79%	0.00%	34.67%	12.62%	26.08%	16.07%	19.74%	6.23%	19.40%
Skilled Agricultural Workers	0.29%	1.37%	2.15%	0.00%	1.99%	0.00%	0.67%	0.17%	0.66%
Craft and Related Trades Workers	4.78%	4.52%	15.25%	0.00%	11.78%	1.15%	4.78%	1.20%	4.69%
Machine Operators	6.29%	3.12%	16.86%	0.00%	14.69%	0.44%	5.31%	0.44%	5.19%
Elementary Occupations	1.88%	2.81%	7.02%	0.06%	6.48%	0.07%	2.25%	0.43%	2.20%

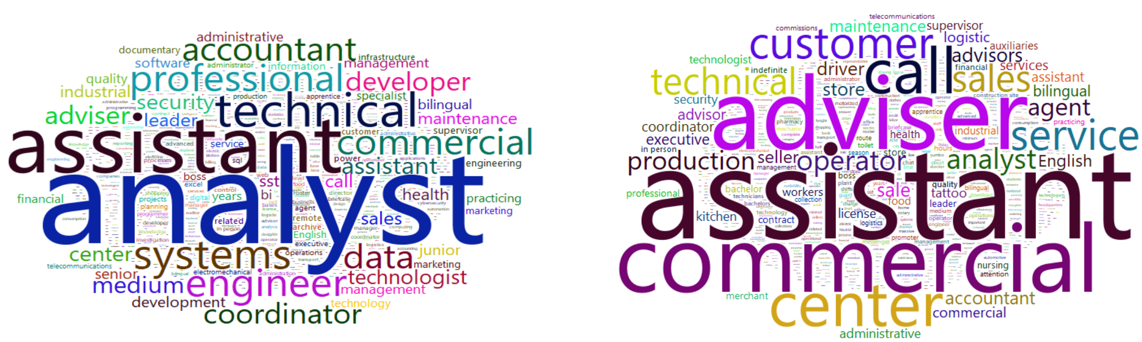
Source: Authors' calculations based on job postings database (2022, 2023). The total number of vacancies is 1,169,943 and the occupations categorized as "High exposure" have values above the median of their respective exposure index, except for the AI-Col index which takes as High exposure all vacancies where at least one AI dictionary term has been found.

By classifying job vacancies into high- and low-exposure categories, we explore whether certain terms characterize each category. To do so, we construct a word cloud using the most frequent terms found in job descriptions and group these terms according to the ESCO (European Skills, Competences, Qualifications, and Occupations)[5] classification to provide a structured analysis. This classification enables a more systematic understanding of the content and emphasis of each group of vacancies.

For high-exposure vacancies (see Figure 3), the most common terms are closely linked to three main domains: Information and Communication Technology Skills (S5 - working with computers, 06 - ICTs), including terms such as "technology," "infrastructure," and "reporting" Management and Administrative Skills (S4 - management skills, 04 - business, administration , and law), reflected in words like "director," "projects," and "planning"; and Technical and Educational Specialization (07 - engineering, manufacturing and construction, 01 - education), with terms such as "engineering," "specialist," and "interns". Conversely, low-exposure vacancies tend to feature terms related to Manual and Operational Skills (T5 - physical and manual skills and competences, S6 - handling and moving, 10 - services), such as "assistant," "driver," "salesperson," and "courier"; Customer Service and Sales (S1 - communication , collaboration, and creativity, 04 - business, administration, and law), including words like "call center," "agent," and "service"; and Low-Level Technical Specialization (T1 - core skills and competences, 00 - generic programs and qualifications), with terms like "bachelor," "trainee," and "technician."

This pattern suggests that low-exposure jobs are predominantly linked to manual, operational, and customer service tasks, while high-exposure jobs are associated with digital skills, strategic management, and specialized technical knowledge.

Figure 3. Word Clouds of Job Titles by Level of AI Exposure



a) High exposure

b) Low exposure

Source: Authors' calculations based on job postings database (2022, 2023).

[5] In the ESCO classification, *S* refers to "Skills"; *T* to "Transversal Skills and Competences"; K "Knowledge"; *K* "Language skills and knowledge". The numeric codes (e.g., S1, T5) correspond to specific skill groups or fields of education and training. This dual classification provides both a skill-based and a disciplinary lens. For example, S5: Working with computers includes digital and programming skills, while T5: Physical and manual skills encloses hands-on abilities such as lifting, operating machinery, or performing routine manual tasks. For more information, see the ESCO classification system: https://esco.ec.europa.eu/en/classification/skill_main.

Table 9 presents the average AI-CoI index across major occupational groups, based on the first digit of the ISCO-08 classification. This analysis focuses on the 2.5 percent of job vacancies identified as exposed to AI, that is, those that include at least one AI-related term. The results reveal a clear pattern: higher-level occupations tend to exhibit significantly higher AI-CoI scores. Specifically, Professionals reach an average index of 0.65, Managers 0.35, and Technicians 0.20, compared to an overall average of 0.17. A closer look at the relationship between the AI-CoI index and the most salient terms within each occupational group highlights a strong concentration of digital and analytical competencies in these segments.

To facilitate a more systematic interpretation of these results, the terms have been grouped within the ESCO classification system, which organizes skills into structured categories. This framework helps identify the types of competences most in demand within each segment of the labor market. Initially, occupations with the greatest exposure to AI are associated with computing and data analysis skills, corresponding to ESCO categories related to working with digital technologies and managing information. For instance, the most prevalent terms found in Managers and Professionals occupational groups, such as SQL, Power BI, IT, Software, Cloud, Linux, and Python, reflect a high demand for knowledge in database management, digital infrastructure, and software development. These tools are essential for automating processes and optimizing data-driven decision-making.

Second, the importance of automation and digitalization skills is evident in intermediate-level occupations, especially in the Technicians group. Terms such as "digitalization," "automation," and "forecasting" suggest that these occupations require adaptation to digitalized environments, although to a lesser extent than in the case of Professionals. In the case of occupations such as Machine Operators and Craft Workers, the presence of terms such as "automation" and "digitalization" is less frequent but suggests a gradual process of AI integration in these sectors.

Table 9. Composition of High AI Exposure Vacancies by Occupation Group According to AI-CoI

Occupation Major ISCO-08 Group	Mean AI-CoI	Relevant Terms
Managers	0.35	Power BI (409), IT (361), SQL (338), Software (279), Statistics (228), Cloud (171), Linux (152), Digitalization (141), SQL Server (134), Forecasting (116)
Professionals	0.65	SQL (3207), Power BI (2093), IT (1379), Software (1156), SQL Server (1147), Statistics (1117), Java (1043), Python (1001), Cloud (957), Linux (836)
Technicians	0.20	IT (915), Software (581), Digitalization (533), Power BI (492), SQL (489), Linux (478), Automation (468), Statistics (372), Cloud (210), Forecasting (136)
Clerical Support	0.10	IT (557), Digitalization (445), Software (215), Power BI (191), Statistics (126), SQL (125), Cloud (90), Forecasting (67), Automation (48), Statistical Analysis (32)
Services and Sales	0.06	IT (584), Digitalization (148), Software (81), Cloud (63), Statistics (58), Cybersecurity (49), Forecasting (33), QlikView (30), Linux (28), Digital Assistance (26)
Skilled Agricultural	0.05	Cloud (6), Statistics (5), IT (5), Digitalization (3), Machine Learning (3), Microsoft Azure (3), Pipeline (3), Power BI (3), Quantitative Analysis (2), Big Data (1)
Craft and Related Trades	0.05	Automation (68), Statistics (35), IT (31), Digitalization (23), Software (21), Power BI (18), SQL (12), Google Analytics (9), Java (6), SQL Server (6)
Machine Operators	0.02	IT (48), Automation (16), Software (15), Digitalization (7), Pandas (5), Linux (3), Cloud (3), Forecasting (3), SQL (2), Autonomous Vehicle (2)
Elementary Occupations	0.03	IT (23), Statistics (6), Power BI (6), SQL (6), Software (4), Statistical Analysis (2), Data Center (2), Digitalization (2), Pipeline (2), Automation (1)
Average AI-CoI index	**0.17**	

Source: Authors' calculations based on job postings database (2022, 2023). The frequency of each term in each occupational group is shown in parentheses.

In the Managers group, a relationship with management and strategy skills is observed within the administration and business category in ESCO, suggesting that AI is used in strategic planning functions and in the optimization of administrative processes, as evidenced by the presence of terms such as Forecasting, Planning, and Projects. Less frequently, terms related to data science and cybersecurity are identified in several occupational groups, linked to the information technology and mathematical sciences categories in ESCO. The presence of terms such as Cybersecurity, Big Data, and Quantitative Analysis indicates a growing specialization in these areas within the labor market.

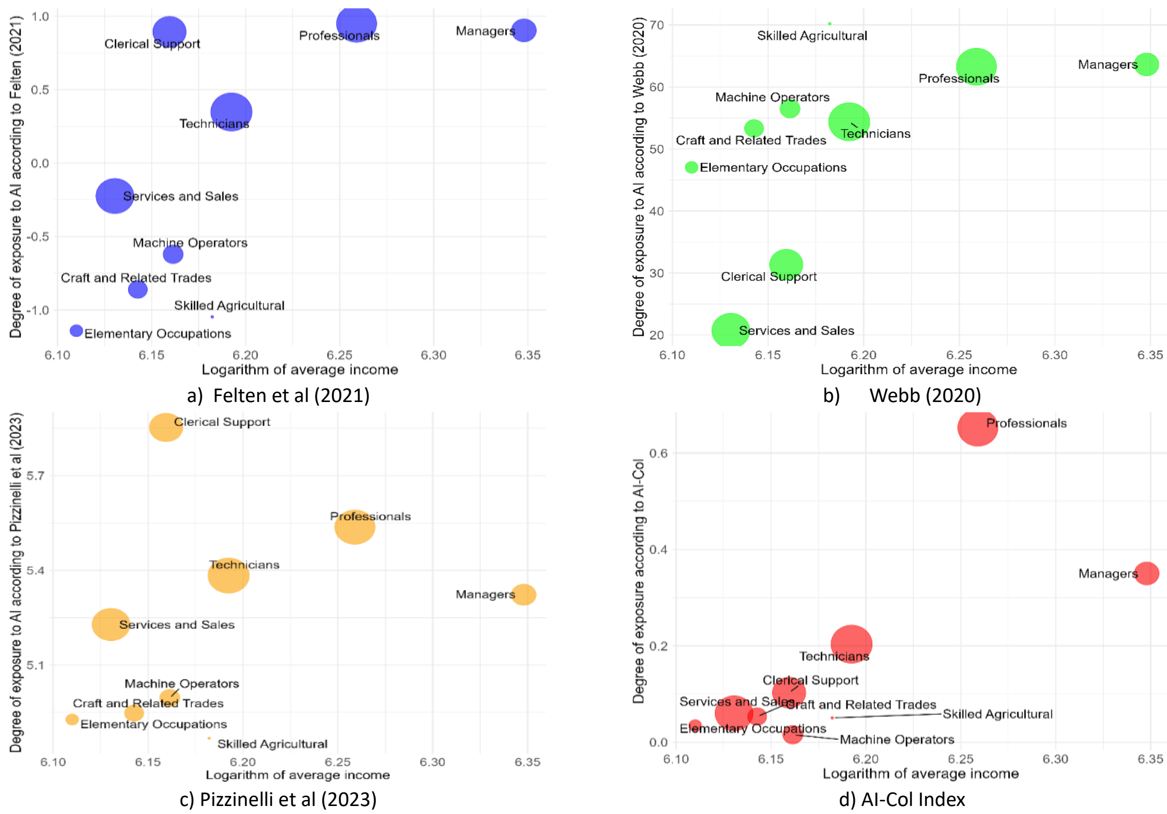
In contrast, occupations exhibiting a below-average AI-Col index include Clerical Support (0.10), Services and Sales (0.06), Skilled Agricultural Workers (0.05), Craft and Related Trades (0.05), Machine Operators (0.02), and Elementary Occupations (0.03). Within these occupations, the implementation of digital technologies and automation remains limited, with a reduced presence of terms associated with AI. However, some of these occupations have begun to incorporate digital tools to a lesser extent, with terms such as "Automation," "Digitalization," and "Cloud," although not as intensely as those observed in the occupations with greater exposure. In these cases, the predominant skills are more aligned with the ESCO categories of communication, collaboration, and creativity, as well as customer support and service, suggesting that the impact of AI in these sectors is focused on optimizing administrative processes and improving customer interaction.

A taxonomic analysis of the terms reveals that the presence of AI in the labor market is not homogeneous, and the demand for related skills varies according to the degree of specialization of each occupation. While occupations with high exposure require advanced knowledge in information technology and data analysis, those with less exposure tend to integrate AI indirectly, through digital tools for information management and operational support.

Figure 4 depicts a comparison of the different AI exposure indices, including the AI-Col, and reveals a correlation between AI exposure and wages. Across all indices examined, occupations requiring higher levels of skill and expertise, such as Professionals and Managers, exhibit the most significant exposure to AI. Beyond the correlation with automation, the examination of mean wages in diverse occupations suggests an association between exposure to AI and the offered wage, as indicated by the logarithmic average wage on the horizontal axis. The graphs reveal a positive correlation between occupations with greater exposure to AI and higher wages. This finding suggests that Professionals and Managers, who are well-positioned in terms of AI exposure, also occupy the upper end of the wage distribution. This observation lends further support to the notion that advanced digital skills are increasingly linked to better job prospects and higher earnings.

In contrast, occupations with less exposure to AI, such as Elementary Occupations, Machine Operators, and Craft and Related Trades, not only exhibit low integration of digital tools but are also concentrated at the bottom of the wage distribution. This finding suggests that the digital transformation of the labor market could be widening wage gaps, favoring workers with greater digital skills.

Figure 4. Relation between AI Exposure and offered wages by *occupational* groups



Source: Authors' calculations based on job postings database (2022, 2023). This figure illustrates the AI exposure measure across 1-digit ISCO occupation groups. The horizontal axis represents the logarithm of the wages offered for each group. Marker sizes correspond to the number of job postings for each group.

The findings indicate a consistent pattern across both dimensions of labor market. The occupational groups with the highest salaries, such as Professionals and Managers, are also those most exposed to AI in both supply and demand-side. Conversely, groups such as Elementary Occupations and Craft and Related Trades consistently exhibit low levels of AI exposure and are positioned at the lower end of the wage distribution. To examine the association between AI exposure and the wages offered in job vacancies, conditional on observable characteristics, we estimate a series of linear regression models based on the specification in Equation (1). In this model, $\boldsymbol{X}$ is a vector of control variables, including required education level and the first digit of the ISCO-08 occupational classification. In alternative specifications, each exposure index is also introduced in both its linear and quadratic forms to capture potential nonlinearities.

The results, displayed in Table 10 demonstrate a positive correlation between AI exposure and offered wages in job postings. However, the magnitude and statistical significance of this relationship exhibit variation across indices. The indices developed by Felten et al. (2021) and Pizzinelli et al. (2023) consistently demonstrate a positive and significant effect, with a 1-point increase in AI exposure correlating to an approximate 2% and 3% increase in wages, respectively. These estimates are consistent with prior findings from labor force data, thereby reinforcing the notion that occupations involving AI tend to offer higher wages. In contrast, the Webb (2020) index exhibits a much smaller effect, with coefficients close to zero and in some specifications, not statistically significant.

This discrepancy suggests that the Webb (2020) index may capture different occupational dimensions compared to Felten et al. (2021) and Pizzinelli et al. (2023), potentially emphasizing automation risk rather than wage premiums associated with AI-related skills. The AI-Col index also shows a positive relationship between AI exposure and wages in job postings. The estimated coefficients indicate that a 1-point increase in exposure is associated with a wage increase of approximately 1%, though with slightly lower magnitudes compared to Felten et al. (2021) and Pizzinelli et al. (2023). Notably, when incorporating a quadratic term, the estimates reveal a concave relationship, suggesting diminishing returns to AI exposure beyond a certain threshold.

The analysis of AI exposure categories corroborates this pattern, with high-exposure occupations offering wage premiums across most indices. The estimated coefficients for high-exposure occupations range between 2% and 11%, with the largest effect observed in the AI-COL index. Control variables exhibit stable effects across models, with education requirements and occupational categories accounting for a significant portion of wage variation.

These findings highlight the necessity of employing multiple AI exposure indices to capture the nuances of AI's impact on labor demand. While international indices offer valuable benchmarks, the AI-Col index unveils distinct patterns specific to Colombia's labor market. Notably, the positive and significant coefficients observed in AI-Col suggest that AI-intensive occupations lead wage premiums comparable to those in developed economies, further emphasizing the mounting demand for AI-related skills in the country.

Table 10. Effects of AI Exposure on offered wages

Variable	Webb (2020)			Felten et al (2021)			Pizzinelli et al (2023)			AI-Col		
$AI\ Index$	0.0001***	-0.0000		0.02***	0.03***		0.03***	0.03**		0.01***	0.01***	
	(0.0000)	(0.0000)		(0.0004)	(0.0005)		(0.001)	(0.01)		(0.0001)	(0.0001)	
$AI\ Index^2$		0.0000***			-0.01***			-0.0003			-0.0001***	
		(0.0000)			(0.0004)			(0.001)			(0.0000)	
High exposure			-0.001***			0.02***			0.02***			0.11***
			(0.0004)			(0.0005)			(0.0004)			(0.001)
Education requested	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISCO-08 1 digit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943	1,169,943
R-squared	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16

Source: Authors' calculations based on job postings database (2022, 2023). Clustered standard errors by occupation group in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5. Concluding remarks

This study offers a comprehensive perspective on the prevalence of AI in the Colombian labor market. To achieve this, a comparative analysis was conducted between international indices that are frequently utilized in the extant literature and a novel index derived from job vacancies in Colombia. From the labor supply perspective, we identified the profile of workers most exposed to AI, while from the demand perspective, we analyzed employers' specific requirements, as well as the wage differentials and premiums associated with these skills. The findings reveal key trends and disparities in the workforce exposed to AI, providing valuable insights for policymakers, employers, and workers.

The labor supply analysis indicates that between 33.8% and 41.5% of workers in Colombia are highly exposed to AI, with a higher prevalence among those over 30 years of age. While a wage premium is observed for occupations with high exposure to AI, similar to developed economies, formal education continues to play a determining role in hiring in Colombia. The AI-Col index shows a 50/50 balance between workers with and without higher education. Conversely, indices developed in the UK reflect a lower proportion of university-educated workers, suggesting that AI adoption in Colombia is more closely tied to formal education, potentially due to more traditional hiring structures or less reliance on alternative certifications and self-directed learning. Analysis of AI exposure indices also suggests that international indices may be underestimating the wage premium associated with AI skills in Colombia. The AI-Col index indicates a wage premium is 21.8%, a value comparable to that observed in advanced economies 23% for UK and 25% for US (Bone et al., 2025; PwC, 2024). This suggests that, despite differences in labor market structure, the appreciation of AI skills in Colombia is analogous to that observed in developed countries.

From a demand-side perspective, an analysis of over one million job openings reveals a greater alignment between job requirements in Colombia and the management of applied AI as opposed to the development of generative AI. This observation suggests that AI exposure in the country serves as a complement to human labor rather than a substitute. In terms of magnitude, only 2.5% of job openings explicitly mention AI skills, a proportion that is lower than that observed in advanced economies, where demand has grown most significantly for roles linked to generative AI. This observation indicates that, while AI adoption is evident, its implementation in Colombia remains predominantly focused on practical applications within traditional sectors, as opposed to the creation of new, highly specialized roles in emerging technologies. The accurate forecasting of skills demand is imperative to facilitate a proactive approach to identifying novel jobs and the requisite competencies. The availability of precise data on changes in job openings would empower key stakeholders—government, employers, and workers—to make informed decisions and efficiently adapt training and reskilling strategies.

As this study has demonstrated, online vacancy data offers detailed insights into job openings and can serve as a valuable tool for anticipating labor market trends. Consequently, it is imperative that both the public and private sectors ensure that the workforce acquires the necessary skills to address technological advancements. Given the disparate rates of evolution between education and industry, the imposition of specific educational prerequisites can result in the exclusion of individuals who have acquired skills through self-directed learning, online courses, or work experience. In emerging sectors, such as AI, where talent shortages persistently emerge, the adoption of skills-based hiring over academic credentials could potentially broaden the talent pool and mitigate the skills gap.

The 2023 Colombia Talent Shortage Survey, administered by ManpowerGroup, revealed that 64% of companies in the nation are encountering challenges in identifying qualified personnel, marking an increase from the 61% observed in the 2022 survey. The study identified the following skills as being in high demand: customer service (25%), marketing and sales (23%), and information and data technologies

(21%). This underscores the mounting necessity for professionals possessing digital and technological competencies. In this context, the AI-Col index offers valuable insights for the formulation of labor policies and business strategies.

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Appendix

Appendix A. Indexes calculations

- **Felten (2021) index:**

The exposure index is defined as follows:

$$A_{ij} = \sum_{i=1}^{10} x_{ij}.$$

$$AIOE_k = \frac{\sum_{j=1}^{52} A_{ij} L_{jk} I_{jk}}{\sum_{j=1}^{52} L_{jk} I_{jk}}$$

In this formula, i represents an AI application (EFF), j corresponds to an occupational skill from the O*NET taxonomy, and k refers to the specific occupation. The term A_{ij} denotes the skill-level exposure score, which measures the extent to which skill j is impacted by AI application i. To calculate the exposure score for each occupation, Aij is weighted by two occupation-specific factors: the prevalence L_{jk} , which indicates how commonly skill j is used in occupation k, and the importance I_{jk}, which reflects the criticality of skill j to that occupation. By multiplying the skill-level exposure with these weights and summing across all 52 skills, the index captures the cumulative AI exposure for an occupation. The denominator ensures proper scaling, resulting in a normalized measure that represents the average weighted exposure of each occupation to AI. This approach provides a comprehensive framework to link AI advancements to occupational skill structures, highlighting the nuanced impact of technology on the labor market.

- **Webb (2020)**

This process assigns each pair to a higher-order hierarchical group, facilitating a more structured and interpretable analysis. To calculate the index, consider a given technology $t \in T$. Let f_c^t denotes the raw count of occurrences of the aggregated verb-noun pair c as extracted from the patent titles associated with. The set of all aggregated verb-noun pairs for technology t is denoted as C^t . The relative frequency rf_c^t of a specific verb-noun pair c within the patent titles for technology t is then calculated to reflect the prominence of that functional relationship. This methodology provides a systematic way to link technological innovations to their underlying functions and applications.

$$rf_c^t = \frac{f_c^t}{\sum_{c \in Ct} f_c^t}$$

$$Exposure_{i,t} = \frac{\sum_{k \in k_t} \left[w_{k,i} * \sum_{c \in S_k} rf_c^t \right]}{\sum_{k \in k_t} \left[w_{k,t} * [\![c : c \in S_k]\!] \right]}$$

Thus, in the $Exposure$ index, K_i is the set of tasks in occupation i , and S_k is the set of verb-noun pairs extracted from task $k \in K$. Finally, $w_{k,i}$, the weight of task k within occupation i , is an average of the frequency, importance, and relevance of task k for occupation i, as specified in the O*NET database, with weights scaled to sum to 1.

- **Pizzinelli (2023)**

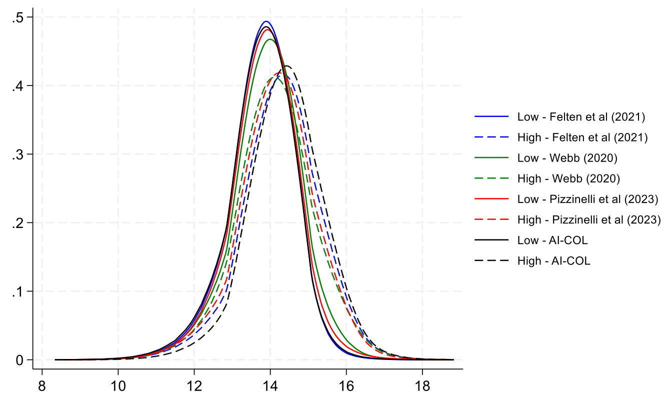
The complementarity component incorporates physical and social factors that assess the possibility of severe consequences from errors, alongside the level of education and training required to perform a given occupation. The resulting index, called $C - AIOE$ is defined as follows:

$$C - AIOE_k = AIOE_k\big(1 - (\theta_i - \theta_{min})\big)$$

Where θ is the complementarity index. This means that as the level of complementarity increases, the penalty on exposure also increases.

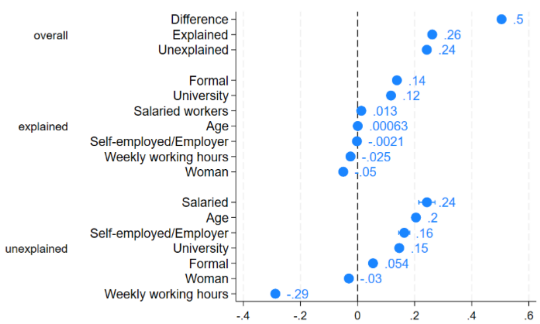
Appendix B. Figures

Figure 5. Wage distribution by AI Exposure

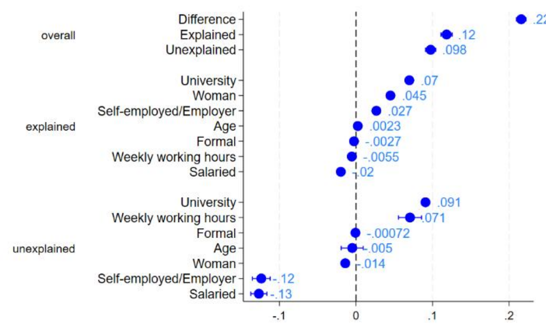


Source: Authors' calculations based on GEIH (2023). The occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index. All calculations were performed using expansion factors from the 2018 census.

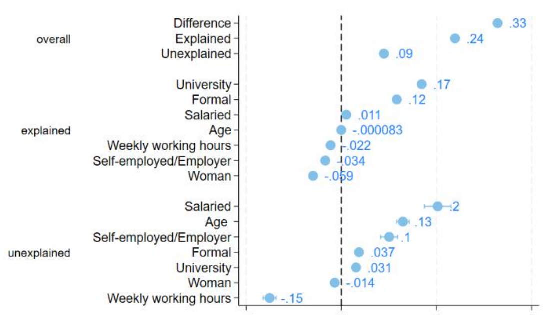
Figure 6. Oaxaca-Blinder decomposition for the wage difference by AI exposure category



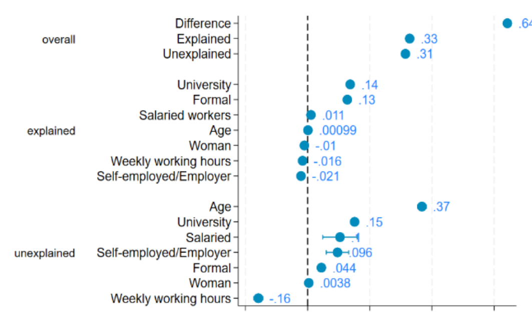
a) Felten et al. (2021)



b) Webb (2020)



c) Pizzinelli et al (2023)



d) AI-Col

Source: Authors' calculations based GEIH 2023. Occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index. The estimates include sector fixed effects.