Assessing the Unequal Impacts of AI on the Colombian Labor Market

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Abstract

Artificial intelligence (AI) is increasingly influential in daily life, particularly impacting the labor market. This paper assesses the level of AI exposure in the Colombian labor market and its relationship with worker characteristics and job postings. Findings indicate a relatively high level of exposure influenced by the measurement instrument used. The complementarity between AI and occupational tasks is vital for understanding its effects. Moreover, a significant positive correlation exists between AI exposure and wages, suggesting potential unequal impacts across the income distribution. Consequently, AI could affect poverty levels, potentially improving worker incomes on average.

Keywords: Artificial intelligence, labor market, job post, occupations

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1. Introduction

Artificial intelligence (AI) has disrupted multiple spheres of society (Arciénegas et al., 2024), transforming both productive systems and individual interactions. AI penetration is expected to drive labor reallocation and improve productivity (see Carbonero et al., 2023; Cave and Cammers-Goodwin, 2024). This impact 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 depends on the productive structure, suggesting that countries are likely to experience varied trajectories. Consequently, persistent lags in factors, such as innovation, technological advancement, and access to technology, make it particularly important to understand the effects of AI in the Global South.

Generally, there are forces in both directions regarding the costs and benefits of AI. AI exposure increases the risk of automation in occupations that are intensive in routine, repetitive, or physical tasks, leading to worker 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, may be less impacted by automation (Autor and Dorn, 2013). These occupations may also experience productivity increases, particularly in sectors applying 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 grow more rapidly, while occupations with low computer use experience a reduction in the average hours worked, although this does not necessarily lead to a decline in employment levels. Finally, 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 reintegration effect, in which the introduction of new AI-related tasks creates employment growth opportunities, even as other sectors experience job losses due to automation.

The labor market characteristics of developing countries, such as those in Latin America, make the study of the impacts of AI particularly relevant. Specifically, developing countries are characterized by high levels of informality, which is associated with lower exposure to AI (Cazzaniga et al., 2024). However, informal workers often have low educational levels and significant human capital misallocation, which restricts access to the education and training programs needed for transitioning into jobs created by AI adoption. Additionally, firms' low levels of technological investment in developing countries may lengthen the transition process. This slows down the rate of automation and reduces the risk of capital-labor income inequality (see Acemoglu 2024). In summary, the impact on well-being and poverty depends on the distributive effects of productivity and employment composition.

This study examines the relationship between AI exposure and job characteristics from a labor supply and demand perspective in Colombia. Specifically, it identifies the characteristics of workers and occupations associated with a 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) were used to present evidence on the relationship between AI exposure and education level, wages, and demographic composition. To complete the landscape of the labor market, data from online job postings were used to assess the penetration of AI adoption in labor demand in Colombia. Colombia is an interesting case study in this regard. On one hand, it exhibits structural labor market issues typical of developing countries, such as high levels of informality and low AI adoption. However, it has the advantage of data availability from household surveys and job posts.

The literature on the impact of AI on the labor market focuses on understanding the decomposition of the labor market. Labor demand increases through both the intensive and extensive margins. 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 lead to an increase through an intensive margin (Georgieff & 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 across various sectors (Su et al., 2021; Carbonero et al., 2023; Eloundou et al., 2023; Ernst et al., 2024; Georgieff, 2024). According to Rose (2017), occupations such as anthropologists, communication specialists, philosophers, and cultural experts are required to address the limitations of AI.

In summary, the impact of AI on the labor market is heterogeneous across occupations, depending on the combination of exposure and complementarity. Cazzaniga et al. (2024) conducted a cross-country analysis that classified occupations as high exposure and high complementarity, high exposure and low complementarity, and low exposure. The first group is likely to have increased productivity with a low risk of displacement, including occupations such as surgeons, lawyers, and judges. By contrast, the second group faces a higher risk of automation, such as call center operators (Su et al., 2021), where reallocation between formal and informal employment may occur (Cave & Cammers-Goodwin, 2024). Meanwhile, Gmyrek et al. (2024) conduct a similar cross-country study that identifies occupations with potential for automation, those with potential for growth, and a final group termed "Big unknown" where the effects of AI remain uncertain.

This paper studies the relationship between AI exposure and job characteristics from a labor supply and demand perspective for the case of Colombia. Specifically, it identifies 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 used to present evidence on the relationship between AI exposure and education level, wages, and demographic composition. To complete the landscape of the labor market, data from online job postings is used to assess the penetration of AI adoption in labor demand in Colombia. Colombia is an interesting case study. On one hand, it exhibits structural labor market issues typical of developing countries, such as high levels of informality and low AI adoption. On the other hand, it has the advantage of data availability from household surveys and job postings.

Studying the impact of AI on the labor market is the measurement of exposure to AI. Existing studies have estimated exposure indices at the occupational level, notably, those proposed by Webb (2020), Felten et al. (2021) and Pizzinelli et al. (2021), and Pizzinelli et al. (2023). The former, known as AI Occupational Exposure, relates 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. (2023) index by integrating complementarity as a factor that reduces exposure. This means that the exposure level is mitigated when the AI is complementary to 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 posts. 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.

This paper contributes to the understanding of the influence of AI on the global labor market, which is characterized by high levels of informality and a limited response to transformative changes in the labor landscape. To achieve this, we propose an analysis of both faces of the labor market. Using standardized measures of AI exposure, we compared job characteristics contained in household surveys according to their level of exposure, categorized into high and low exposure. Additionally, by examining job postings, we study the level of exposure to labor demand.

Our results indicate that the levels of AI exposure in the Colombian labor market are consistent with those observed in other countries, showing that approximately 40% of workers fall into the high-exposure category across the indices analyzed. This high exposure is associated with occupations such as business services and administration managers, finance professionals, and legal professionals, where routine, analytical tasks are predominant, making them susceptible to automation and AI integration. A relevant factor related to the level of exposure is the higher incidence of high exposure among women and formal workers, particularly in the indices developed by Felten et al. (2021) and Pizzinelli et al. (2023). AI exposure is concentrated in roles associated with higher wages, formal employment, and higher education levels, suggesting uneven distribution across demographics. This concentration could lead to income gains for high-exposure workers but also increase income inequality, indicating a need for strategies to ensure equitable economic benefits from AI integration.

Regarding job postings, our analysis reveals that AI is significantly present in the labor demand in Colombia. The AI-Col index, which assesses job vacancies based on specific AI-related skills, indicates that a substantial portion of high AI exposure vacancies are concentrated in professional and technical occupations. Notably, professionals account for 51.14% of high AI exposure vacancies, while technicians and managers follow with 23.13% and 11.27%, respectively. The mean AI-Col score for professionals is 0.13, indicating a strong integration of AI in their roles, compared to a score of 0.04 for managers and -0.01 for technicians. Additionally, Pizzinelli's index shows that 85% of the share of high AI exposure vacancies by occupation group aligns closely with the findings from our AI-Col analysis, reinforcing the trend of high AI exposure in skilled roles. Furthermore, our findings suggest that 19.2% of high-exposure positions fall into the highest AGI level (Level 3), which correlates with significant educational demands; 91.5% of these roles require advanced education. This highlights the growing importance of specialized skills in an AI-driven labor market and the need for targeted workforce development strategies to address the evolving demands of high-exposure occupations.

This paper is organized as follows. Section 2 presents data and methodology. Section 3 explores AI exposure in the labor market through 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 posts. While the former provides detailed information on employment composition by occupation, sector, and demographic characteristics, the latter offers insight into labor demand in Colombia. The household surveys, or the Gran Encuesta Integrada de Hogares (GEIH), serve as the primary instrument for measuring and monitoring the labor market in Colombia. This survey has nationwide coverage and captures relevant information, such as age, education, sex, and occupation, among others. The GEIH records occupations according to the CUOC classification, adapted for Colombia. We utilized data from 2023 which represents 22.546.259 employees, respectively.

Information about job vacancies is obtained online through web scraping from one of the websites with the highest volume of job posts. The collected data included job title, description, required education level, and salary. The description is a crucial resource that identifies both occupation and specific information regarding any requirements related to AI. The analysis considered 1,179,108 job vacancies from March 2022 to December 2023. This dataset did not include the occupation associated with each vacancy. Therefore, we implemented the imputation model proposed by Garcia-Suaza et al. (2024), which adapts the CUOC occupational classification for Colombia to the existing TFIDF-based model originally developed for ESCO (European Skills, Competences, Qualifications, and Occupations) and implemented it in the R package called labourR. The imputation was performed in two steps. In the first step, the major group (i.e., manager, professional, etc.) is assigned, and in the second step, the corresponding vacancy is matched to the occupations at the 4-digit level within the major group.

As a result, both the household survey and the job vacancy dataset include the occupation, allowing for the integration of the AI exposure indices. However, the exposure indices and Colombian data sources do not align in terms of occupational codes. For instance, proposed by Felten et al. (2021) is based on the O*NET-SOC taxonomy, while the household survey follows the Unique Classification of Occupations (CUOC), which is an adaptation of the International Standard Classification of Occupations (ISCO) tailored for Colombia. Since the occupational classifications do not match, correlational tables provided by the Bureau of Labor Statistics are used. The mapping is complex due to the "many to many" correspondences i.e., SOC occupations tend to be mapped to more than one ISCO occupation and vice versa, raising a double counting risk. To overcome this challenge, we follow the approach proposed by Causa et al. (2024). The same works for the Pizzinelli et al. (2023) index.

On the other hand, to match the Webb (2020) index and the Colombian occupation classification, a similar approach was followed, but with the difference that the data were classified under the OCC90 (Census Occupation Classification) developed by the United States Census Bureau. Consequently, the process followed to make it applicable to the Colombian context was to create a crosswalk between OCC 1990 and ISCO 88. With this input, the remaining step is to move from ISCO 88 to ISCO 08.

It is important to briefly outline the construction of the indices used in this study. To construct the Felten index (2021), known as AI Occupational Exposure (AIOE), the process begins by linking the 10 AI applications from the EFF with the 52 occupational skills of O*NET. Then, the exposure level per skill was calculated as the sum of the 10 application-skill relationship scores (x) (with data from the mTurk survey). It is important to note that for the purposes of the index, Felten (2021) assigned equal weights to all 10 applications. The exposure index is defined as follows:

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

The same works for the Pizzinelli et al. (2023) index.

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

where i indicates the AI application (EFF), j indicates the occupational skill in O*NET taxonomy, and k indicates the occupation. A_{ij}represents the skill-level exposure score. To assign an index score to each occupation, the AI exposure at the skill level is weighted by the prevalence L_{jk} and the importance I_{jk} of the skill within each occupation, by multiplying the AI skill-level exposure by the prevalence and importance scores of that skill within each occupation as defined by O*NET. These are scaled to ensure equal weighting.

For Webb (2020) index, before calculating an exposure score for each verb-noun pair, nouns from each conceptual category pair are first grouped using WordNet (Miller, 1995) database, where the pair is assigned to a higher-order hierarchy group. Now, for the calculation, tor a given technology $t \in T$, f_c^t denotes the raw count of occurrences of the aggregated verb-noun pair c extracted from the patent titles of technology t, and let C^t be the complete set of aggregated verb-noun pairs for technology t. The relative frequency rf_c^t of the aggregated verb-noun pair c in the patent titles of technology t is 1.

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

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

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.

Lastly, Pizzinelli et al. (2023) index involves a transformation of Felten et al. (2021), accounting for potential complementarity of occupation task with AI tools. The complementarity component depends on physical and social factors that assess the possibility of severe consequences from errors, as well as the level of education and training required to perform an occupation. This results in an index, called $C - AIOE$ that mitigates exposure by potential for complementarity as follows:

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

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

We classified occupations as either high or low exposure. For this, we used the position of each occupation relative to the median exposure level as the threshold. A comparative study of the characteristics of workers and job vacancies with different levels of AI exposure was conducted for both the datasets. The text contained in the job postings allows for the identification of specific terms related to AI, for which we constructed a dictionary based on the existing literature. The list of terms was obtained from Alekseeva et al. (2021) and Babashahi et al. (2024), Baruffaldi et al. (2020), Dawson (2021), Dernis et al. (2023), Gehlhaus and Mutis (2021) and Squicciarini and 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).

Moreover, although less frequently, the names of some key programming tools used in AI appear along with hard skills such as data analytics and natural language processing, which represent essential competencies in the field. Additionally, to complement the construction of this dictionary, three taxonomies were used to add relevant terms that were not referenced in the academic literature, as follows: AI Use Taxonomy (A Human-Centered Approach) by Mary Theofanos, Yee-Yin Choong, and Theodore Jensen (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 (TTC). The list of terms was reviewed and curated to minimize misleading results. The final list contains 938 terms, of which 395 are monograms and 543 are bigrams, including terms in both Spanish and English. Examples include artificial intelligence (AI), backpropagation, ChatGPT, Machine learning, and intelligent agents.

Based on the dictionary, monograms were manually assigned a level ranging from (1) low to (3) high. In contrast, the bigrams were automatically classified with a score of 4, as they needed to summarize the information to the maximum extent, whereas the monograms did not necessarily provide the same level of explanation because they may only represent individual aspects of the information rather than a comprehensive summary.

Thus, the calculated score is based on the variation in the TF-IDF calculation. In this context, the term frequency is not strictly a traditional TF; instead, each term has an already defined relevance score. We name the score AI-Col, and it is calculated using the following formula:

$$AI\text{-}Col = \sum_{t \in D} scorenum(t) \times IDF(t)$$

Where:

- D is the set of terms found in a vacancy.
- *scorenum*(t) is the value assigned to each term in the dictionary (3 for high relevance, 2 for medium, 1 for low, and 4 for bigrams).
- IDF(t) is the IDF of the term *t*, calculated as before.

This formula combines term relevance (using *scorenum*) and term rarity (using IDF), thereby increasing AI-Col, if the vacancy contains rare and highly relevant terms. Consequently, this scoring mechanism allows for a more nuanced understanding of the significance of the terms within the context of job vacancies, helping prioritize those that are most relevant and unique.

The complexity of AI tools varies, implying that the expected impacts of different AI tools also vary. Following the Artificial General Intelligence (AGI) levels in Morris et al. (2023), we constructed groups of job vacancies with varying levels of AI autonomy. Morris et al. (2023) propose six levels (0-5, where 0 represents no AI involvement, with humans performing all tasks, and 5 represents AI acting as a fully autonomous agent). We grouped these levels into three categories for analysis. Level 1, No AI, covers Level 0, which includes systems that lack autonomous artificial intelligence capabilities. This level encompasses simple software and tools requiring full human supervision and performing limited, clearly defined tasks such as calculators and basic text editing programs. Level 2, corresponding to Levels 1 and 2, includes systems with emerging and competent AI capabilities that demonstrate limited but significant generality. These systems can handle a variety of cognitive tasks with low-to-medium complexity, achieving performance levels comparable to those of average-trained humans. Although some advanced models may show proficiency in specific tasks (e.g., basic writing or analysis), they are still unable to perform a full range of tasks with high accuracy. Finally, Levels 3 to 5, group systems with advanced capabilities that meet or exceed human performance in most cognitive tasks. This level includes models that excel in specific areas with an accuracy comparable to or surpassing 99% of trained humans, as well as systems with superhuman abilities that can perform tasks at levels of complexity beyond human reach.

To study the levels of AIG, we linked terms from the dictionary to three defined levels. For this purpose, we trained ChatGPT using the full text from Morris et al. (2023) and dictionary as key inputs. This training was conducted separately for monograms and bigrams. The final set of terms was manually curated by adding specific terms to the designated levels as needed. The training process consisted of three steps. First, ChatGPT was used to characterize each AGI level described in this article using a structured approach. Next, we outlined a simplified structure by consolidating the six original levels into three, prompting ChatGPT to recharacterize these three new levels accordingly. Finally, the monograms were uploaded with pre-filled sections to clarify our objectives, allowing ChatGPT to complete any remaining fields based on the training and revised-level descriptions. The entire process was repeated for the bigrams.

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

To assess the extent to which the Colombian labor market is exposed to AI, we analyze workers and job vacancies separately and the main characteristics associated with occupations that have the highest levels of exposure. First, we analyze the workers using the GEIH. Table 1 presents the distribution of workers by level of exposure to AI. Similar to the findings reported by Cazzaniga et al. (2024), approximately 40% of workers have high exposure for both indices analyzed. This is an interesting result given that each index is constructed from a different source. While their similarities are apparent at the aggregate level, there may be differences at the occupational level. In fact, comparing Webb (2020) and Pizzinelli et al. (2023), 48% of the occupations do not coincide. In this sense, comparing indices can reveal the distinct channels through which AI impacts the labor market.

Table 1. Distribution of workers by level of exposure to AI

	Number of Workers			Percentages		
Level	**Webb (2020)**	**Felten et al. (2021)**	**Pizzinelli et al. (2023)**	**Webb (2020)**	**Felten et al. (2021)**	**Pizzinelli et al. (2023)**
Low exposure	13,719,000	13,414,802	13,196,651	60.8%	59.6%	58.5%
High exposure	8,827,260	9,105,911	9,349,608	39.2%	40.4%	41.5%
Total	22,546,259	22,520,713	22,546,259	100.0%	100.0%	100.0%

Notes: All calculations were performed using expansion factors from the 2018 census. The occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.
Source: Authors' calculations based on GEIH (2022, 2023).

In Table 2, we provide a comparison between occupations with high and low exposure to artificial intelligence can be observed, based on the indices of Webb (2020) and Pizzinelli et al. (2023). This comparison allows us to see some examples where the same category—high or low exposure—is shared, or, conversely, the same occupation is classified differently, which is useful for understanding the differences in their construction and what they ultimately capture. For cases where both indices classify an occupation as highly exposed to AI, we see professions such as business services and administration managers, finance professionals, and legal professionals. According to Webb (2020), these results correspond to exposure to specific and routine tasks with an analytical component that AI can efficiently perform, such as reporting, data analysis, and evaluation. Therefore, while these tasks may be displaced, the ability to adapt within each occupation and train in the use of these technologies may lead to heterogeneous effects. Similarly, according to Pizzinelli et al. (2023), while AI allows for the optimization of certain tasks, this does not imply the displacement of strategic human competencies.

Table 2. Comparison of AI Exposure Indices: Coincidences Between Webb (2020) and Pizzinelli et al. (2023) for Various Occupations

		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

Notes: The occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.

On the other hand, both indices agree on a low classification for occupations such as hotel and restaurant managers, sports and fitness workers, and machinery mechanics and repairers. In these cases, there are mainly manual and operational tasks, so while AI may support the monitoring of these tasks, they are not subject to being replaced by this technology. Pizzinelli et al. (2023) state that these occupations can be complemented in certain tasks, this may lead to improvements in working conditions and safety.

However, in cases where the indices do not agree with each other in classification by occupation, it is observed that when Webb (2020) classifies an occupation as high exposure, while Pizzinelli et al. (2023) classify it as low exposure, occupations such as Production managers in agriculture, forestry and fisheries, medical doctors, and manufacturing laborers are found. These discrepancies can primarily be explained by tasks that, according to Webb (2020), are performed with little room for complementarity, as in the case of medical diagnosis or health monitoring in general. On the contrary, we have occupations such as legislators and senior officials, managing directors and chief executives, university and higher education teachers. For this type of occupation, Pizzinelli et al. (2023) show a high level of complementarity since they cannot simply be replaced, requiring human skills such as judgment, creativity, and empathy, thus preserving the value of human intervention. In this way, the support provided by AI is aimed at strengthening analysis and planning in these jobs, freeing up time for workers to focus on strategic and higher-value-added activities.

Given the occupational sorting by population groups, it can be expected that AI may disproportionately affect certain population groups. For this reason, we analyze the characteristics of workers in occupations with high exposure (see Table 3). The results show that, although the proportion of highly exposed workers is similar for both indices, there are some contrasts regarding the characteristics of these workers. According to the index by Felten et al. (2021), workers in occupations with high AI exposure, in contrast to those with low exposure, are characterized by a higher representation of men, a greater share in salaried job types, and a lower proportion of informality. Workers over the age of 30 make up the majority in both AI exposure categories across all studies, given their concentration in the workforce; however, a slightly higher proportion of younger workers (under 30) appears in high-exposure roles in Pizzinelli et al. (2023). The composition of gender across occupations present remarkable differences. While Webb et al. (2020) indicates a significant male majority (72.05%), Felten et al. (2021) and Pizzinelli et al. (2023) find a higher proportion of women in such roles.

Table 3. Characteristics of workers by level of exposure to AI

Variable	Category	Webb (2020)		Felten et al. (2021)		Pizzinelli et al. (2023)	
		Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure
Age	Less than 30	25.54%	25.06%	25.54%	25.06%	24.13%	27.05%
	More than 30	74.46%	74.94%	74.46%	74.94%	75.87%	72.95%
Sex	Men	50.83%	71.46%	68.01%	45.44%	69.37%	44.13%
	Women	49.17%	28.54%	31.99%	54.56%	30.63%	55.87%
Education	No University	83.13%	71.99%	95.17%	54.55%	92.61%	59.24%
	University	16.87%	28.01%	4.83%	45.45%	7.39%	40.76%
Informality	Informal	54.86%	58.02%	69.70%	35.97%	67.60%	39.86%
	Formal	45.14%	41.98%	30.30%	64.03%	32.40%	60.14%
Employment Status	Salaried workers	51.73%	41.61%	39.20%	60.45%	37.77%	61.87%
	Self-employed / Employed	41.32%	48.68%	49.05%	36.97%	50.46%	35.37%
	Others	6.96%	9.71%	11.75%	2.58%	11.77%	2.75%

Notes: All calculations were performed using expansion factors from the 2018 census. The occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.
Source: Authors' calculations based on GEIH (2022, 2023).

Education levels also reveal a notable distinction, as the proportion of workers with university education are significantly higher in high-exposure occupation in Felten et al. (2021) and Pizzinelli et al. (2023), which report 45.42% and 40.58%, respectively. In the case of Webb et al. (2020), this is 28.01%. This indicates that education is a determining factor in the differences between the indices. According to Felten et al. (2021) and Pizzinelli et al. (2023), the status of formality is positively related to exposure to AI. In contrast, findings regarding Webb et al. (2020) show that being a formal or informal worker does not create a strong divide between occupations with high or low exposure. Finally, occupational classification shows that salaried workers are predominant in high-exposure roles. This variation in demographic and employment characteristics suggests nuanced differences in the types of roles and industries exposed to AI, highlighting that each study captures different aspects of how AI exposure has heterogeneous effects on the market and workforce.

This suggests that each index may capture different dimensions of exposure. Following the arguments in Cazzaniga et al. (2024), it can be inferred that in fact while Pizzinelli et al. (2023)) captures the dimension of complementarity between AI and human capital, Webb (2020) tends to be associated with jobs at risk of displacement by AI. Table 4 show that these findings are corroborated by the fact that workers in occupations such as professionals and technicians show the greatest differences between the two indices among high-exposure occupations. In contrast, the Felten et al. (2021) index shows low percentages of workers in occupations such as skilled agriculture, machine operators, and elementary occupations among those with high exposure levels. This result was also documented by Acemoglu et al. (2020). This would imply that, overall, the Colombian labor market may have higher levels of AI exposure than estimated when using the indices individually.

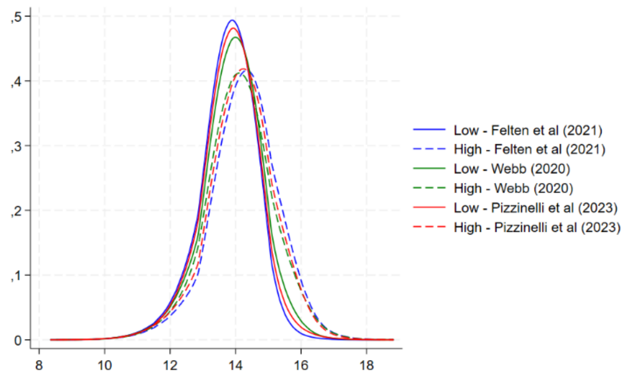
Table 4. Occupational groups by level of exposure to AI

Occupation major ISCO-08 group	Felten et al (2021)		Webb (2020)		Pizzinelli et al. (2023)	
	Low exposure	High exposure	Low exposure	High exposure	Low exposure	High exposure
Managers	0.94%	14.33%	2.08%	12.99%	5.06%	8.17%
Professionals	0.64%	26.86%	6.35%	18.81%	2.60%	23.41%
Technicians	2.94%	13.11%	5.22%	9.89%	3.09%	12.63%
Clerical Support	0.00%	14.71%	9.76%	0.00%	0.00%	14.33%
Services and Sales	16.14%	28.57%	34.75%	0.00%	12.76%	32.97%
Skilled Agricultural	9.96%	0.00%	1.00%	13.58%	10.12%	0.00%
Craft and Related Trades	16.03%	0.00%	10.52%	8.01%	13.76%	3.58%
Machine Operators	14.29%	0.00%	12.07%	2.96%	12.72%	2.56%
Elementary Occupations	39.05%	2.42%	18.26%	33.75%	39.89%	2.36%

Notes: All columns sum to 100 percent vertically, and 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.
Source: Authors' calculations based on GEIH (2022, 2023).

One of the most relevant policy questions is the impact AI may have on inequality. The labor market is perhaps the primary transmission mechanism, affecting both employment generation and wages. Therefore, we examine the wage structure for workers with high and low AI exposure. The wage distribution by level of exposure do not show significant differences between indexes, however the Figure 1 shows, according to literature, that the highest salaries correspond to occupations with higher levels of AI exposure.

Figure 1. Kernel Density Estimates of Wages for Low and High AI Exposure by Type of Exposure Index



Notes: 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.
Source: Authors' calculations based on GEIH (2022, 2023).

Error! Reference source not found. analyzes the effect of AI exposure on the logarithm of wages, using the indices of Felten et al. (2021), Webb (2020), and Pizzinelli et al. (2023), as well as control variables such as age, gender, education, informality, occupational group, and hours worked. All control variables interact with AI exposure to understand how they modify its effect on wages.

Table 5. Effects of AI Exposure on Wages by Type of Exposure Index

Variable	Felten et al (2021)			Webb (2020)			Pizzinelli et al (2023)		
Dependent: Log of salary	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Index	0.131***	0.137***		0.003**	-0.004		0.128**	3.174***	
	(0.021)	(0.025)		(0.001)	(0.003)		(0.055)	(0.893)	
Index^2		0.021			0.000**			-0.282***	
		(0.024)			(0.000)			(0.083)	
High exposure (Base: Low exposure)			0.172***			0.111*			0.081*
			(0.048)			(0.058)			(0.043)
Age									
Age	0.041***	0.040***	0.040***	0.040***	0.040***	0.040***	0.041***	0.040***	0.041***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex (Reference: Man)									
Woman	-0.281***	-0.283***	-0.286***	-0.239***	-0.245***	-0.261***	-0.282***	-0.297***	-0.278***
	(0.025)	(0.024)	(0.023)	(0.032)	(0.030)	(0.026)	(0.024)	(0.022)	(0.024)

Education (Reference: No University)									
University	0.555***	0.548***	0.601***	0.634***	0.620***	0.643***	0.642***	0.625***	0.645***
	(0.038)	(0.040)	(0.041)	(0.050)	(0.051)	(0.054)	(0.052)	(0.049)	(0.050)
Informality (Reference: Informality)									
Formality	0.398***	0.398***	0.413***	0.425***	0.425***	0.430***	0.423***	0.420***	0.429***
	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)
Occupation group (Reference: Salaried workers)									
Self-employed / Employer	0.174***	0.174***	0.174***	0.172***	0.169***	0.172***	0.179***	0.176***	0.184***
	(0.035)	(0.035)	(0.034)	(0.031)	(0.033)	(0.034)	(0.035)	(0.033)	(0.035)
Others	-0.028	-0.044	-0.098*	-0.094*	-0.115*	-0.109*	-0.096*	-0.098*	-0.091
	(0.046)	(0.050)	(0.055)	(0.054)	(0.059)	(0.055)	(0.052)	(0.051)	(0.054)
Working hours									
Weekly working hours	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls									
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.59***	12.575***	12.462***	12.36***	12.493***	12.449***	11.82***	3.642	12.437***
	(0.187)	(0.193)	(0.201)	(0.222)	(0.219)	(0.212)	(0.342)	(2.368)	(0.207)
Observations	343,175	343,175	343,175	343,629	343,629	343,629	343,629	343,629	343,629
R-squared	0.469	0.469	0.464	0.462	0.464	0.461	0.461	0.463	0.460

Clustered standard errors by occupation group in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results show that greater AI exposure is associated with higher wages, reflected in positive and significant coefficients in most models. In particular, the continuous index of AI exposure has a positive impact on wages, suggesting that, on average, workers in occupations more exposed to AI receive higher remuneration. This effect, however, is modulated by various individual and job-related characteristics.

Among the control variables, age has a quadratic effect on wages: positive coefficients for age and negative coefficients for its square indicate that the impact of AI exposure is higher for middle-aged workers but decreases with advanced age. On the other hand, women show negative and significant coefficients in their interaction with AI exposure, indicating a gender gap where women experience a smaller wage benefit from exposure to this technology compared to men. University education emerges as an important factor: workers with higher education receive greater wage increases in response to AI exposure, reflected in positive and significant interactions. This suggests that the complementary skills of workers with a university education enable them to better leverage the added value AI offers in their roles.

Regarding informality, interactions show a negative impact on wages, implying that workers in the informal sector do not benefit as much from AI exposure as those in the formal sector. Additionally, self-employed workers and business owners experience greater wage benefits from AI exposure compared to salaried workers, indicating that these groups may be better positioned to capitalize on the technology's advantages in their activities.

Finally, working hours are positively related to the effects of AI on wages, suggesting that greater hourly exposure could amplify the wage impact of AI. The model includes fixed effects by economic sector, and standard errors are clustered by occupational group, reinforcing the robustness of the results and the consistency of the observed effects. The R-squared values, ranging from 0.461 to 0.469, indicate that the model explains a considerable portion of the variation in wages, highlighting the relevance of AI exposure in the analysis of wage dynamics.

The Oaxaca-Blinder decomposition shows that there is a positive difference comparing wages between high exposed and low exposed occupations (Table 6), this difference is explained due to the fact high exposed occupations have higher wages which is a result showed by the literature. Additionally, the results show that the observed characteristics explain 42% of the difference according to Felten et Al (2021) index. On the other hand, this percentage according to Webb (2020) and Pizzinelli et al (2024) is 61% and 74%, respectively. Taking into account the observed characteristics, education explains the 24% of wage differences.

Table 6. Oaxaca-Blinder Decomposition of Wage Disparities by Occupational Exposure Level

Dependent variable Log of wages	**Felten et al (2021)**	**Webb (2020)**	**Pizzinelli et al (2023)**
High exposure	14.277***	14.131***	14.173***
	(0.002)	(0.003)	(0.002)
Low exposure	13.773***	13.914***	13.844***
	(0.002)	(0.002)	(0.002)
Difference	0.504***	0.217***	0.330***
	(0.003)	(0.003)	(0.003)
Explained	0.210***	0.133***	0.243***
	(0.003)	(0.002)	(0.002)
Unexplained	0.294***	0.084***	0.087***
	(0.003)	(0.003)	(0.003)
Observations	343,175	343,629	343,629

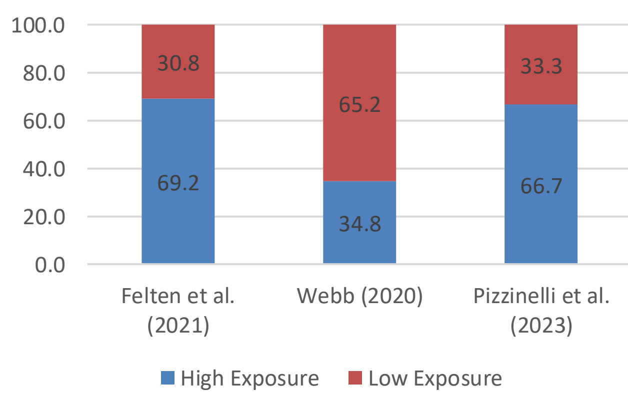
Notes: Occcupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.
Source: Authors' calculations based GEIH 2023.

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

The labor market exhibits persistent mismatches that could be exacerbated by the introduction of AI. Demand in the labor market tends to respond quickly to environmental changes, particularly to shifts in the productive sector's needs. Despite the importance of understanding these trends, detailed information on labor demand—especially regarding AI-related skills—is not commonly accessible. Analyzing the level of AI exposure in job postings provides a way to understand labor demand trends. Specifically, this approach allows us to estimate whether the demand for certain occupations aligns with their level of AI exposure. A hypothesis here is that this relationship may be non-linear: as AI becomes more pervasive, occupations at risk of automation might become less prominent, while roles that use AI to enhance productivity could gain significance.

Our second area of study is whether AI is present in labor demand. We conduct a similar analysis to correlate observable characteristics of job vacancies with the level of exposure to AI. Figure 2 presents the share of job vacancies in Colombia by AI exposure, utilizing the indices from Felten et al. (2021), Webb (2020), and Pizzinelli et al. (2023). Notably, Webb's index reveals a significant contrast, with 34.8% of Colombian job vacancies classified as having high AI exposure, while 65.2% are categorized as low exposure. In comparison, the indices from Felten et al. and Pizzinelli show similar results, with 69.2% and 66.7% of vacancies, respectively, identified as having high AI exposure. This similarity stems from Pizzinelli's construction, which builds upon Felten's framework, incorporating an element of complementarity.

Figure 2. Share of Job Vacancies by AI Exposure Across Felten et al. (2021), Webb (2020), and Pizzinelli et al. (2023) Index



Notes: The total number of vacancies is 1,179,108 and occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.
Source: Authors' calculations based on job postings database (2022, 2023).

The Table 7 shows that a significant proportion of online job vacancies is concentrated in occupations highly exposed to artificial intelligence (AI), as indicated by multiple indices. The occupational groups of "Professionals," "Technicians," and "Services and Sales," which represent

21.7%, 23.0%, and 19.3% of total vacancies, respectively, are consistently identified as highly exposed to AI across the methodologies of Felten et al. (2021), Webb (2020), and Pizzinelli et al. (2023). These groups reach high exposure levels due to the nature of their tasks, which are amenable to partial automation or AI assistance.

However, each index shows notable differences in exposure levels. For instance, the Webb (2020) index assigns a higher exposure rate to "Professionals" at 44.9%, compared to 30.8% in Felten et al. (2021) and 9.6% in Pizzinelli et al. (2023). Similarly, while "Technicians" are consistently rated as highly exposed across all indices, the specific exposure percentages vary. These discrepancies highlight differences in methodology and the classification of AI-related tasks across studies, underscoring diverse perspectives on AI's potential impact across occupational groups.

Table 7. AI Exposure by Major Occupational Groups According to Felten et al. (2021), Webb (2020), and Pizzinelli et al. (2023) Index

Occupation major ISCO-08 group	Total share	Felten et al. (2021)		Webb (2020)		Pizzinelli et al. (2023)	
		High Exposure	Low Exposure	High Exposure	Low Exposure	High Exposure	Low Exposure
Managers	7.9	11.5	0.1	20.2	1.5	9.6	4.8
Professionals	21.7	30.8	2.0	44.9	9.6	27.2	11.3
Technicians	23.0	23.6	22.0	23.0	23.2	23.3	22.9
Clerical Support	14.7	21.4	0.0	0.0	22.8	22.2	0.0
Services and Sales	19.3	12.6	34.7	0.0	29.8	16.1	26.1
Skilled Agricultural	0.7	0.0	2.2	1.4	0.3	0.0	2.0
Craft and Related Trades	5.4	0.0	15.2	4.5	4.8	1.1	11.8
Machine Operators	5.1	0.0	16.9	3.1	6.3	0.4	14.7
Elementary Occupations	2.2	0.1	7.0	2.8	1.9	0.1	6.6

Notes: The total number of vacancies is 1,179,108, all columns sum to 100 percent vertically, and occupations categorized as "High Exposure" have values exceeding the median of their respective exposure index.

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

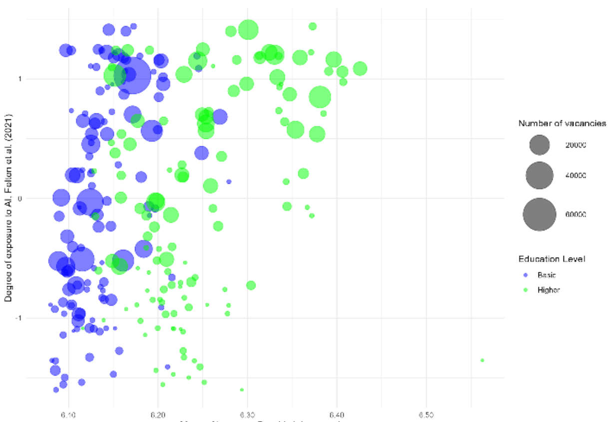
The analysis of occupational distribution by AI exposure levels shows that both the highest- and lowest-paying occupations exhibit the highest levels of exposure to AI (see Figure 3). However, the implications of AI exposure vary across the wage distribution. On the lower end, occupations with high exposure and low wages—typically requiring only basic education (shown in blue)—are likely to experience stronger displacement effects, potentially increasing unemployment rates in these roles. In contrast, on the higher end, occupations requiring higher education (in green) show a positive relationship between AI exposure and wages, suggesting that these roles are more likely to experience productivity gains rather than displacement. As a result, a widening wage gap is anticipated, especially in economies with high levels of informality, as workers with higher education and AI-related skills see income increases, while those in lower-paying, high-exposure roles face greater job insecurity.

A clear verticality in wage distribution is observed among vacancies requiring basic education, where wages remain relatively low regardless of AI exposure. In contrast, vacancies requiring higher education not only offer higher wages but also show increasing wage levels as AI exposure rises. For example, within the same occupation and exposure level, roles demanding higher educational qualifications tend to have significantly higher wages. This highlights the role of education as a buffer against the risks associated with AI exposure and as a key driver of wage differentials within the same occupation.

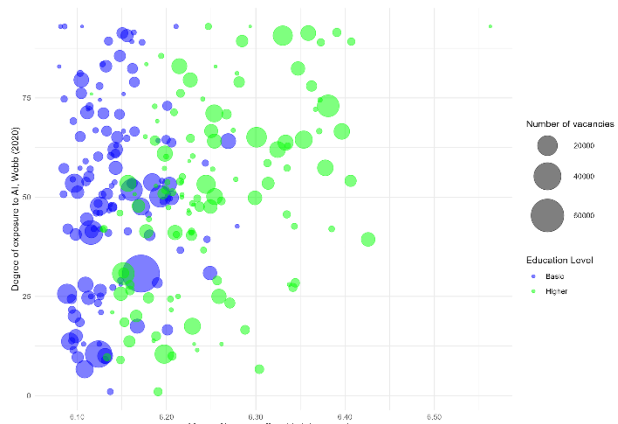
These dynamics underscore the need for targeted labor market policies. First, training and reskilling programs are essential to help workers in low-wage, high-exposure occupations transition to roles with greater stability or potential for wage growth. Second, promoting technology adoption in highly technical sectors could enhance productivity and protect workers from displacement.

One of the motivations for creating the AI-Col index is to analyze specific skills within each vacancy, as the same occupation can be exposed to AI in different ways depending on the tasks and knowledge required. The index aims to capture this variability, as AI exposure is not homogeneous across roles, even within the same occupation. By accounting for these task-based differences, the AI-Col index provides a more detailed understanding of how AI exposure interacts with skills, which may inform more effective workforce development strategies. The results of the AI-Col index are presented later in this study.

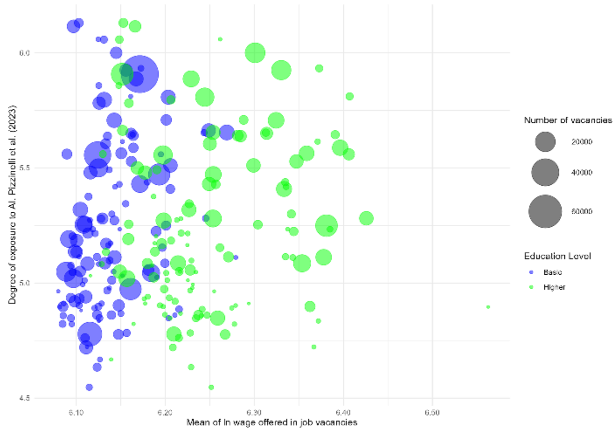
Figure 3. Distribution of AI Exposure Across Offered Wages by Education Level and Exposure Index Type



(a) Felten et al. (2021)



(b) Webb (2020)



(c) Pizzinelli et al. (2023)

Note: This figure illustrates the AI exposure measure across 271 occupation-education level 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, while different colors indicate the education level associated with each group.

The evidence in Table 7 reveals a small but statistically significant effect of AI exposure on wages, even after controlling educational attainment. For the index constructed by Felten et al. (2021), the coefficients indicate a concave relationship between AI exposure and wages, suggesting that while the initial effects of AI exposure on wages are positive, the marginal impact decreases at higher levels of exposure. This pattern may reflect a diminishing wage premium from AI as exposure intensifies, potentially due to factors like skill saturation or reduced task differentiation at higher exposure levels.

In contrast, the index by Webb (2020) shows an almost negligible effect, indicating that AI exposure has little to no impact on wages after controlling for education. This divergence could stem from methodological differences between the indices, or the nature of tasks measured in Webb's index, which may not fully capture productivity gains linked to AI exposure in highly skilled occupations.

Table 8. Effects of AI Exposure on Offered Wages in Job Advertisements, by Exposure Index Type

Variable	Felten et al (2021)			Webb (2020)			Pizzinelli et al. (2023)		
Dependent variable: Log of wage	M1	M2	M3	M4	M5	M6	M7	M8	M9
AI exposure									
Index	0.02***	0.03***		0.0001***	-0.0000		0.03***	0.03**	
	(0.0004)	(0.0005)		(0.0000)	(0.0000)		(0.001)	(0.01)	
Index^2		-0.01***			0.0000***			-0.0004	
		(0.0004)			(0.0000)			(0.001)	
High exposure (base: Low exposure)			0.02***			-0.001***			0.02***

			(0.0005)			(0.0004)			(0.0004)
Controls									
Education requested	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISCO-08 1 digit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,169,943	1,169,943	1,169,943	1,170,306	1,170,306	1,170,306	1,170,306	1,170,306	1,170,306
R-squared	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16

Clustered standard errors by ISCO-08 3 digit occupation group in parentheses

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

The exposure indicators serve as proxies for potential shifts in the labor market due to AI. However, even if a particular job is classified as affected by AI, the true impact on the worker depends on the specific tasks they perform. To gain a deeper understanding of AI's incidence in the labor market, beyond mere exposure, we conducted an analysis that assesses the alignment between job descriptions and a specially constructed AI dictionary, known as the AI-Col.

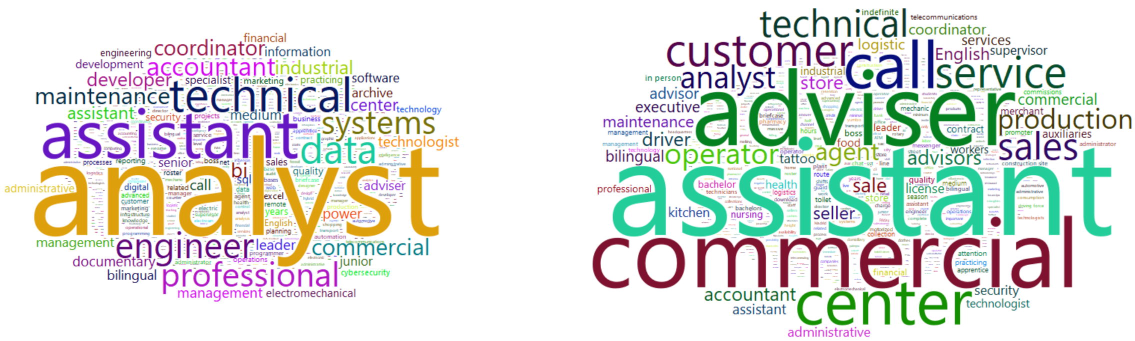
This study introduces two fundamental distinctions in the measurement of AI exposure. First, the incidence of AI varies across occupations. In other words, job postings with the same imputed occupation may exhibit different levels of AI integration. For instance, consider two job postings for systems engineers: one may pertain to tasks involving emerging technologies for service development, while the other may focus on support functions within a company's IT department. The first job posting reflects a higher AI incidence due to its emphasis on technology-driven roles.

Second, the structure of the AI dictionary aligns more closely with Felten's index, as it includes explicit terms within job descriptions that suggest the utilization of technologies often associated with advanced educational levels. This approach allows us to capture a nuanced view of AI's penetration in the labor market, emphasizing roles where AI application is more likely to demand higher skill sets and specialized knowledge.

In our analysis of high-exposure occupations, developed using the AI-Col scoring system, we generated a word cloud to highlight the most frequently occurring terms within this category (see Figure 5a: High Exposure). The word cloud reveals that the most common terms are closely linked to three primary domains: Technology, Automation, and Digitalization (e.g., "technology," "infrastructure," "reporting"); Administrative and Strategic Tasks (e.g., "director," "projects," "planning"); and Technical and Educational Specialization (e.g., "engineering," "specialist," "interns"). In summary, vacancies with high AI exposure are concentrated in technical, strategic, and digital occupations, implying that these roles generally require higher education and involve activities related to automation, data analysis, and strategic planning.

Conversely, for terms associated with low AI content, as represented in the word cloud (see Figure 5b: Lower Exposure), we identify the following categories: Operational or service-oriented roles (e.g., "assistant," "driver," "salesperson," "courier"); Customer Service and Sales (e.g., "call center," "agent," "service"); and Low-Level Technical Specialization (e.g., "bachelor," "trainee," "technician"). This pattern suggests that jobs with low AI exposure are predominantly linked to manual, operational, and customer service roles, which typically demand less specialization and fewer advanced technological skills.

Figure 4. 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).

Table 9 offers a detailed breakdown of high AI exposure vacancies by occupation group based on the AI-Col index. Professionals represent the largest share, accounting for 51.14% of high AI exposure vacancies, followed by Technicians (23.13%) and Managers (11.27%). This distribution aligns closely with Pizzinelli et al. (2023), with an 85% correlation observed between the share of high AI exposure vacancies by occupation group and the Pizzinelli index. Such alignment reinforces the finding that roles in professional and technical fields are particularly susceptible to AI exposure, reflecting a strong demand for advanced skills in technology, data analytics, and digitalization.

In terms of overall labor market impact, high AI exposure vacancies make up 1.26% of total job postings in the analyzed dataset—slightly more than half of the estimated 2% AI-exposed vacancies in the U.S., as reported by Acemoglu et al. (2021). This discrepancy may be attributed to differences in national labor market structures and sectoral demands for AI expertise. However, despite the modest share, this cross-country comparison highlights that AI exposure, while not yet widespread, is significant enough to potentially reshape certain occupation groups over time.

Notably, Managers, Professionals, and Technicians not only make up the majority of high AI exposure vacancies but also have AI-Col scores exceeding the average across occupation groups, which stands at -0.03. Specifically, Professionals exhibit a mean AI-Col of 0.13, Managers 0.04, and Technicians, though slightly lower, still above average at -0.01. This positive deviation highlights a stronger AI integration in high-skill occupations. A closer examination of associated terms further supports this, with frequent mentions of digital and technical skills. For instance, in the Professionals group, terms such as "Power BI" (1,496 mentions), "SQL Server" (847), "software" (817), and "digitalization" (320) reflect a high demand for data management and analytics capabilities. Similarly, Technicians frequently reference terms like "software" (427), "digitalization" (400), and "predictive maintenance" (204), underscoring the technical specialization required in these roles. Managers, with somewhat lower term frequencies, still show substantial mentions of "Power BI" (312), "software" (197), and "digitalization" (107), indicating their strategic involvement in managing AI-driven processes.

This concentration of technical terms within high-skill occupations aligns with the increased emphasis on digital transformation and automation in these roles. The higher frequency of advanced terms in these positions compared to lower-skill roles suggests that AI exposure is more deeply embedded in occupations requiring specialized education and expertise. This pattern not only reinforces existing wage and skill gaps across the labor market but also suggests that high-skill occupations are more likely to benefit from AI-related productivity gains, while lower-skill roles remain less affected by these technologies.

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

Occupation Major ISCO-08 Group	Proportion of High AI Exposure Vacancies by Occupation Group (%)	Proportion of High AI Exposure Vacancies Relative to Total Vacancies (%)	Mean AI-Col	Relevant Terms
Managers	11.27	0.14	0.04	power bi (312), software (197), digitalization (107), SQL server (95), google analytics (64)
Professionals	51.14	0.65	0.13	power bi (1496), SQL server (847), software (817), digitalization (320), google analytics (279)
Technicians	23.13	0.29	-0.01	software (427), digitalization (400), power bi (384), predictive maintenance (204), automation (200)
Clerical Support	7.78	0.10	-0.04	digitalization (313), software (155), power bi (146), statistical analysis (20), automation (17)
Services and Sales	3.88	0.05	-0.07	digitalization (104), software (59), cybersecurity (25), digital assistance (16), virtual assistant (16)
Skilled Agricultural	0.14	0.00	-0.06	quantitative analysis (2), digitalization (2), machine learning (2), Microsoft azure (2), power bi (2)
Craft and Related Trades	1.93	0.02	-0.06	predictive maintenance (42), automation (35), digitalization (21), power bi (17), software (16)
Machine Operators	0.52	0.01	-0.08	software (11), automation (7), digitalization (4), predictive maintenance (4), discovery (1)
Elementary Occupations	0.21	0.00	-0.08	power bi (6), statistical analysis (2), data center (2), cybersecurity (1), automation (1)
Total	100	1.26	-0.03	

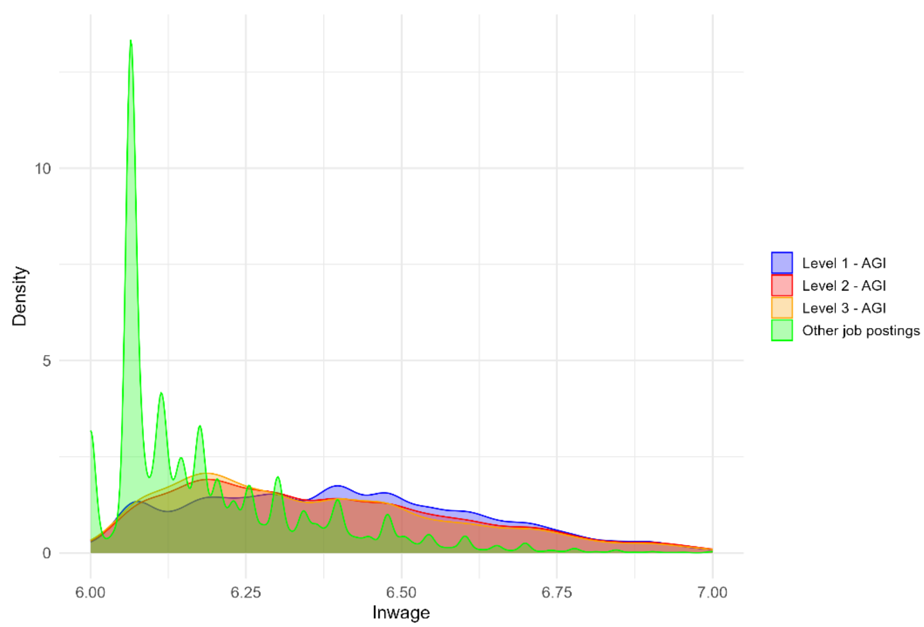
Source: Authors' calculations based on job postings database (2022, 2023).

Based on the AGI levels defined by Morris et al. (2023), as outlined in our methodology, we constructed three consolidated levels of AGI exposure among high AI exposure vacancies. Within these high-exposure roles, we found that 19.2% of the positions align with the highest AGI level, Level 3, while 40.8% fall into Level 2, and 97.9% into Level 1. This distribution reflects the nested structure of our levels, whereby a Level 3 role may also satisfy criteria for Levels 1 and 2.

A clear distinction emerges regarding educational requirements for high AGI levels: high-exposure roles at AGI Level 3 demonstrate significantly higher educational demands compared to other vacancies. While 43.65% of the broader pool of vacancies requires high education on average, this figure rises to 91.5% for Level 3 roles. This higher education requirement in Level 3 roles is associated with productivity gains and greater salary potential, indicating a direct link between AGI levels and labor market rewards.

Figure 5 further highlights this trend by illustrating the wage distribution across AGI levels. Across all AGI levels, high AI exposure vacancies exhibit higher mean salaries compared to other roles, with Levels 2 and 3 showing particularly high upper-tail wage distributions. This pattern underscores the connection between advanced AGI levels, educational requirements, and wage premiums, suggesting that the higher the AGI level in a role, the greater the economic return and demand for specialized expertise.

Figure 5. Kernel Density of log wage Across Different AGI Levels



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

5. Concluding remarks

The impact of AI on the labor market and, consequently, on well-being is not straightforward. In addition to the heterogeneity in the implications of AI use based on occupational characteristics, other factors, such as informality or the presence of active policies, can act as barriers or facilitators for anticipated productivity improvements. Based on an analysis of AI exposure among workers and labor demand in Colombia, it is evident that there is generally a high level of exposure to AI. Although this result is valid for different exposure indices, factors such as the complementarity of AI with occupational tasks are important to understand the outcome in the labor market.

Exposure in occupations with high educational requirements tends to be associated with increased productivity, in contrast to occupations with lower salaries. This suggests potential increases in inequality, which are also reflected in poverty levels. This aligns with the greater relevance of high exposure levels among workers, where those in skilled positions stand to gain more from AI integration. Conversely, lower-skilled workers may find themselves at a disadvantage, facing heightened risks of job displacement or wage stagnation.

This result is derived from the use of two exposure indices related to different dimensions of AI exposure, which can lead to either productivity improvements or increased unemployment risks. This underscores that composition and sorting within the Colombian labor market are crucial for understanding the implications for well-being and inequality. Therefore, it is necessary to implement coordinated and complementary policies, including training programs, that mitigate the effects of worker displacement and reduce access costs to technology, thereby facilitating productivity gains.

Therefore, it is necessary to implement coordinated and complementary policies, including training programs, that mitigate the effects of worker displacement and reduce access costs to technology, thereby facilitating productivity gains. Such policies should focus on upskilling and reskilling the workforce, particularly for those in vulnerable positions, to ensure they can transition into higher-value roles in an AI-enhanced economy. Additionally, fostering a supportive environment for entrepreneurship and innovation can help create new job opportunities, ultimately contributing to a more equitable distribution of the benefits of AI advancements.

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