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Digitalization and artificial intelligence in Latin America: employer demand for AI, technical and soft skills

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Digitalization and artificial intelligence in Latin America: employer demand for AI, technical and soft skills

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Abstract

The rapid diffusion of automation and the application of artificial intelligence (AI) to production have boosted productivity and economic growth while also posing significant challenges for labor markets. These technological transformations reshape the tasks performed within occupations and, consequently, the skills that employers demand from workers—with potentially disparate effects across groups of workers depending on their exposure to automation and their ability to adapt to new skill requirements. Despite the growing international literature, empirical evidence for Latin America remains scarce. Given the region's structural specificities, directly extrapolating results from other contexts may be misleading. This paper seeks to help close this gap by providing a robust, evidence-based understanding of the demand for soft, AI-related and non-AI digital skills in four Latin American countries—Argentina, Brazil, Colombia and Mexico—drawing on a novel regional taxonomy and more than one million of online job postings. The results show that employers overwhelmingly demand multidimensional and highly complementary skill profiles, with technical non-AI and soft skills appearing—jointly, in most cases—in the vast majority of postings. In contrast, explicit demand for AI-related skills remains limited, accounting for less than 3% of postings in all four countries. This aggregate result, however, masks substantial heterogeneity: AI-related requirements are concentrated in professional and technical occupations and take qualitatively different forms depending on the specific tasks each occupation involves. Freelance and traditional job portals exhibit different skill profiles, and employers value educational credentials and work experience as complements rather than substitutes. These findings suggest that, despite growing expectations regarding AI-driven transformations, conventional technical and interpersonal competencies still account for the vast majority of employers' skill requirements in Latin America.

JEL codes: J23, J24, O33, O54

Keywords: artificial intelligence, Latin America, skills, online job postings

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Digitalización e inteligencia artificial en América Latina: la demanda empresarial de habilidades de IA, técnicas y blandas

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Abstract

La rápida difusión de la automatización y la aplicación de la inteligencia artificial (IA) a la producción han impulsado la productividad y el crecimiento económico, al tiempo que plantean desafíos significativos para los mercados laborales. Estas transformaciones tecnológicas reconfiguran las tareas que se realizan dentro de las ocupaciones y, en consecuencia, las habilidades que los empleadores demandan de los trabajadores—esto genera efectos potencialmente dispares entre los distintos grupos de trabajadores según su exposición a la automatización y su capacidad para adaptarse a los nuevos requisitos de habilidades. A pesar de la creciente literatura internacional, la evidencia empírica para América Latina sigue siendo escasa. Dadas las especificidades estructurales de la región, extrapolar directamente los resultados de otros contextos puede resultar engañoso. Este documento busca contribuir a cerrar esta brecha mediante la provisión de una comprensión sólida y basada en evidencia sobre la demanda de habilidades blandas, digitales no vinculadas a la IA y relacionadas con la IA en cuatro países latinoamericanos—Argentina, Brasil, Colombia y México—, a partir de una novedosa taxonomía regional y de más de un millón de ofertas de empleo en línea. Los resultados muestran que los empleadores demandan de manera abrumadora perfiles de habilidades multidimensionales y altamente complementarios, donde las habilidades técnicas no vinculadas a la IA y las habilidades blandas aparecen—en la mayoría de los casos, de forma conjunta—en la gran mayoría de los avisos. En contraste, la demanda explícita de habilidades relacionadas con la IA sigue siendo limitada y representa menos del 3 % de las ofertas de empleo en los cuatro países. Este resultado agregado, sin embargo, oculta una heterogeneidad sustancial: los requisitos relacionados con la IA se concentran en ocupaciones profesionales y técnicas, y adoptan formas cualitativamente diferentes según las tareas específicas que implica cada ocupación. Los portales de empleo tradicionales y de trabajo independiente (*freelance*) exhiben perfiles de habilidades diferentes, y los empleadores valoran las credenciales educativas y la experiencia laboral como complementos en lugar de sustitutos. Estos hallazgos sugieren que, a pesar de las crecientes expectativas respecto a las transformaciones impulsadas por la IA, las competencias técnicas e interpersonales convencionales todavía explican la gran mayoría de los requisitos de habilidades de los empleadores en América Latina.

JEL codes: J23, J24, O33, O54

Keywords: inteligencia artificial, América Latina, habilidades, avisos de empleo en línea

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1 | INTRODUCTION

Technological transformations have very significant economic, social and environmental impacts. These are reflected, among other dimensions, in the quantity and quality of employment, productivity, required skills, and population wellbeing. The links between innovation and these dimensions are multiple and are shaped by institutions, regulatory and organizational frameworks— particularly those related to labor relations—as well as by the structure of relative prices, among other factors.

Over recent decades, a rapid transformation of economic and social life has taken place worldwide, driven by the widespread diffusion of digital technologies. This has been reflected in the emergence of new technological, productive and organizational paradigms across key sectors of activity, such as Industry 4.0, precision agriculture (or agtech), fintech and e-commerce, among others. It is also evident in the dynamism of sectors known as knowledge-based services (KBS). However, the effects of digital transformation can be observed, with varying intensity, across different sectors of activity and occupations.

The COVID-19 pandemic intensified global trends towards greater digitalization, and there is broad agreement that the influence of digital technologies will be even greater in the future than in the past (Economic Commission for Latin America and the Caribbean (ECLAC), 2021). This process has unfolded in a context of high uncertainty, reconfiguring productive structures and accelerating the adoption of digital tools across firms of very different sizes and sectors. Although there is little doubt about the significant impacts that new technologies have had—and will continue to have—across multiple dimensions of societal wellbeing, the pace and depth of this transformation still vary considerably across countries and productive structures. The transformative potential of new technologies becomes even more evident with the emergence of artificial intelligence (AI). Advances in data processing and machine learning have enabled the development of increasingly sophisticated and autonomous systems and applications, extending AI's influence to almost all economic sectors and generating both unique opportunities and challenges.

From a labor market perspective, the acceleration of technological advances in recent decades has mainly manifested itself through increased automation in the tasks carried out within different occupations. Increasingly, "robots" can be programmed to perform routine tasks that can be codified and automated. In this new context, the relevant object of analysis is no longer the worker or the occupation per se, but rather the tasks and activities performed. This shift from an "occupation-based approach" to a "task-based approach" allows for the assessment not only of overall employment creation and destruction, but also of differential effects across groups of workers performing tasks with varying degrees of complementarity, resilience or substitutability vis-à-vis technological change. In addition, the growing expansion of artificial intelligence is expected to significantly reconfigure labor markets, with substantial impacts on efficiency and productivity, affecting a broader range of occupations and tasks. This, in turn, may generate both employment opportunities in emerging sectors and challenges related to worker training and adaptation. In this context, distributive impacts may be significant.

Although these issues have gained increasing relevance worldwide, studies on this topic in Latin America remain scarce. This is particularly concerning, as it cannot be assumed that the impacts of automation observed in more developed countries will be similar in the region, given different starting points in terms of productive and occupational structures, relative prices, task content and the position of occupations within the wage distribution, among other factors. For this reason, the region's agenda regarding digital transformation and its labor market impacts is both necessary and demanding, requiring intensive public policy efforts. Such policies must ensure that these transformations foster the creation of more and better jobs in the future and contribute to reducing labor gaps and the high levels of inequality that characterize the region. Consequently, it is highly relevant—both from an academic perspective and, especially, for policy design—to advance a thorough study of these new processes in Latin America.

At the heart of this transformation is a fundamental shift in the capabilities required by the workforce. While technology drives change, its impact is mediated by how the demand for specific competencies evolves within the local productive structure. Understanding these shifts requires looking beyond broad employment categories and into the granular evolution of the skills that define modern work—not only the traditionally-defined digital skills associated with earlier waves of automation, but also the soft skills that complement them and the emerging set of skills specifically tied to the adoption of artificial intelligence.

This paper seeks to help close this gap by providing a robust, evidence-based understanding of the demand for soft, AI-related and non-AI digital skills across occupations in four Latin American countries—Argentina, Brazil, Colombia and Mexico—over the past nine years.

The paper makes several contributions to the literature on this topic. On the one hand, from a methodological perspective, it proposes a robust approach to analyze novel and little-explored sources of information for this type of study. On the other hand, it generates new knowledge on the demand for soft, AI-related and non-AI digital skills among workers in four Latin American countries. Finally, the study provides evidence directly relevant to policy design by analyzing how digitalization and AI are transforming occupations and tasks in the region. By mapping the demand for these three categories of skills across occupations and countries, this paper offers insights into the interaction between technological adoption and workforce dynamics. This evidence can inform policies aimed at fostering inclusive and resilient labor markets and supporting workers' adaptation to technological change.

The remainder of the paper is organized as follows. Section 2 reviews the literature on technological change, tasks, and skill demand, situating the analysis within both the global evidence on technical, soft, and AI-related skills and the emerging evidence for Latin America. Section 3 describes the data sources and data collection strategy used to construct the online job postings database for the four countries under study. Section 4 outlines the methodology and key definitions, including the development and validation of the skills taxonomy. Section 5 presents the main findings on the demand for different types of skills. Section 6 examines how these patterns vary across occupations, while Section 7 analyzes skill demand by educational attainment and work experience requirements. Finally, Section 8 concludes.

2 | LITERATURE REVIEW

The relationship between technological change and labor markets has been extensively studied over the last decades. The increasing adoption of automation, robotics, digital technologies and artificial intelligence has generated profound transformations in occupational structures, work organization and the demand for skills. While these developments can foster productivity growth and economic expansion, they may also generate disruptive effects on employment, wages and income distribution, while simultaneously reshaping the competencies required in the labor market.

An important strand of the literature developed around the Skill-Biased Technological Change (SBTC) hypothesis, according to which technological progress increases the relative productivity of highly skilled workers, thereby raising their demand and contributing to widening wage and employment differentials. Within this framework, technological advances complement workers with higher levels of education and analytical capabilities while substituting for less-skilled labor, thereby increasing the relative demand for skilled workers. This mechanism has been used to explain the simultaneous expansion of employment in skill-intensive occupations and the widening of wage inequality observed in several advanced economies during the last decades of the twentieth century. The empirical evidence also highlights the central role of educational attainment in explaining differences in labor demand and wage premia associated with technological change, reinforcing the importance of human capital in workers' adaptation to evolving production technologies (Autor et al., 1998; Acemoglu, 2002; Goldin and Katz, 2008; Acemoglu and Autor, 2011).

However, subsequent research questioned the ability of the SBTC framework to explain the heterogeneous effects of technological change across occupations with similar educational requirements. In particular, the observation that some middle-skilled occupations experienced substantial employment declines while others remained relatively unaffected suggested that education alone could not account for workers' exposure to technological change (Autor et al., 2003; Acemoglu and Autor, 2011).

To address these limitations, the literature evolved toward the Task-Based Technological Change (TBTC) framework. Autor et al. (2003) and Acemoglu and Autor (2011) argue that technology does not substitute entire occupations but rather specific tasks within occupations. In particular, digital technologies tend to replace routine tasks—whether manual or cognitive—that can be codified through explicit rules, while complementing non-routine activities involving problem solving, analytical reasoning, creativity and interpersonal interaction.

This perspective highlights that the effects of technological change depend on the task composition of jobs. Workers engaged primarily in non-routine tasks are more likely to benefit from technological advances through higher productivity and stronger labor demand, whereas workers performing routine activities face greater risks of substitution. Consequently, the impact of technological change depends less on occupational titles than on the underlying task content of jobs (Autor et al., 2003; Acemoglu and Autor, 2011). This represented an important conceptual change, shifting the focus from workers' educational attainment to the tasks they perform.

The overall employment effects of technological change remain ambiguous. While automation may displace certain tasks and workers, technological innovations can also generate productivity gains and cost reductions that expand output and increase labor demand through scale effects. The net employment impact therefore depends on the balance between displacement and productivity-enhancing mechanisms (Autor, 2015; Acemoglu and Restrepo, 2018, 2019).

This framework has been widely used to explain occupational polarization in advanced economies. Autor and Dorn (2013) document a decline in middle-skill occupations alongside the expansion of both highly skilled jobs and low-paid service occupations in the United States. Similar patterns have been identified in Europe by Goos and Manning (2007) and Goos et al. (2014). In these contexts, workers at the top of the wage distribution tend to perform complex cognitive tasks, workers at the bottom are concentrated in non-routine manual service activities, whereas middle-income workers are more likely to perform routine tasks susceptible to automation.

However, evidence from Latin America presents a more nuanced picture. Maurizio and Monsalvo (2023) emphasize that the effects of technological change depend on the interaction between technological adoption and country-specific structural conditions, including occupational structures, productive specialization, technology absorptive capacity, macroeconomic conditions, and labor market institutions.

Using census data from 21 developing countries, Maloney and Molina (2016) find little evidence of occupational polarization, although they identify a relative decline in operator occupations in Brazil and Mexico. Messina and Oviedo (2016) analyze occupational changes in Brazil, Chile, Mexico, and Peru during the 2000s and find limited support for the polarization hypothesis, except in Chile. Based on this evidence, Messina and Silva (2018) argue that the slower diffusion of digital technologies may have delayed the emergence of polarization patterns in the region. Maurizio and Monsalvo (2023) find that labor demand in Argentina, Chile, and Mexico shifted away from occupations located at the bottom of the earnings distribution toward middle- and upper-income occupations, while lower-paid occupations experienced the largest wage gains.

Evidence from individual countries also challenges the polarization hypothesis. For Zapata-Román (2021) finds no statistically significant evidence of occupational or income polarization and instead identifies an inverted U-shaped pattern in earnings. For Ballón and Dávalos (2020) show that declining inequality between 2004 and 2011 was associated with the expansion of medium-skilled employment at the expense of low-skilled jobs. Focusing on Maurizio and Monsalvo (2023) also find that changes in employment composition did not replicate the polarization pattern observed in advanced economies. Instead, they document a relocation from low-paying and, to a lesser extent, high-paying occupations toward middle-paying occupations, while earnings dynamics followed a different pattern.

Beyond occupational polarization, some studies have documented important shifts in the task composition of employment. Using occupational information from O*Apella and Zunino (2017) show that cognitive tasks increased while manual tasks declined in Argentina and Uruguay between the mid-1990s and 2015. Extending the analysis to nine countries in Latin America and the Apella and Zunino (2022) report a similar increase in the relative importance of cognitive tasks across the region. These findings suggest that the absence of occupational polarization does not imply that technological change has been limited in the region, but rather that its effects may operate through changes in the content of jobs and the skills required to perform them.

Gasparini et al. (2021) show that occupations characterized by a high content of routine tasks experienced slower employment growth—or even declining employment shares—during the first two decades of the twenty-first century, while occupations with lower routinization expanded. For Brambilla and Tortarolo (2018) find that the adoption of information and communication technologies increases productivity and wages, particularly in highly productive firms employing skilled workers, while also stimulating job creation across all skill groups.

The literature also highlights substantial heterogeneity in workers' exposure to automation. Exposure to technological change is not evenly distributed across workers, as it depends on the tasks they perform and their position within the labor market. Maurizio and Monsalvo (2023) show that workers differ substantially in their exposure to automation according to their occupational tasks and socio-demographic characteristics. In particular, informal workers and those with lower skill levels and lower incomes are more likely to perform routine tasks and therefore face greater potential exposure to automation. Brambilla et al. (2022) show that the risks associated with automation are asymmetrically distributed across workers in Latin America, with unskilled and semi-skilled workers bearing a disproportionate share of potential adjustment costs. These findings suggest that technological change may reinforce existing labor market inequalities if workers differ in their ability to adapt to changing skill requirements.

More recently, the emergence of generative artificial intelligence (GenAI) has renewed concerns regarding the future of work. Unlike previous waves of automation, which primarily affected routine manual and cognitive tasks, GenAI systems are capable of performing increasingly sophisticated non-routine cognitive activities, including natural language processing, content generation, information retrieval, coding, translation, and analytical reasoning. As a result, occupations previously considered relatively insulated from automation may also experience substantial changes in their task composition and skill requirements (Eloundou et al., 2023; Brynjolfsson, Li, and Raymond, 2023; OECD, 2023; ILO, 2023).

While the task-based perspective remains highly relevant, recent studies suggest that GenAI expands the scope of technological change beyond the routine–non-routine distinction. Rather than affecting only codifiable tasks, these technologies increasingly interact with activities that require judgment, communication, creativity, and knowledge-intensive problem solving. At the same time, their impact is unlikely to be uniform across occupations, as exposure depends on the specific bundle of tasks performed by workers and the extent to which AI complements or substitutes their capabilities (Eloundou et al., 2023; Autor et al., 2024; Brynjolfsson et al., 2023).

Consequently, the literature has increasingly shifted its attention from occupations and tasks toward the skills required to perform them. Recent research emphasizes that the adoption of GenAI is reshaping the demand for both digital and soft skills, while increasing the importance of workers' ability to interact effectively with AI systems, adapt to evolving technologies, and perform complementary tasks that remain difficult to automate. Using detailed information from online job vacancies in the United Alekseeva et al. (2024) document a rapid expansion in the demand for AI-related skills across a wide range of industries and occupations during the 2010s. They also find that jobs requiring AI skills offer significant wage premiums, suggesting that these competencies have become increasingly valuable in the labor market.

Acemoglu et al. (2022) use online vacancy data from the United States to show a rapid increase in AI-related hiring between 2010 and 2018. They find that firms adopting AI reduce hiring for non-AI positions while simultaneously changing the skill requirements of remaining vacancies, indicating that AI reshapes labor demand within firms. However, these effects remain detectable only at the establishment level, with no measurable impacts on aggregate employment or wage growth during the period analyzed.

Analyses conducted by Burning Glass Technologies and, more recently, Lightcast show that competencies related to programming, data analytics, cloud computing, artificial intelligence, and cybersecurity are increasingly demanded not only in information technology occupations but also across a broad range of traditionally non-technical jobs. Drawing on hundreds of millions of job postings between 2015 and 2021, Burning Glass Institute and Wiley (2022) find that one in eight U.S. job postings already required at least one of the four fastest-growing and most rapidly spreading skill sets—artificial intelligence/machine learning, cloud computing, product management, and social media—with demand for these skills growing almost seven times faster than the job market overall. Crucially, this diffusion extends well beyond the technology sector: one in five manufacturing-sector postings and one in ten government job openings already required at least one of these skills, illustrating how digitalization is reshaping skill requirements throughout the economy rather than within a limited set of sectors.

International organizations such as the OECD increasingly rely on online vacancies to construct indicators of skill shortages and surpluses, identify labor market bottlenecks and support evidence-based education and training policies. The OECD's Skills for Jobs Database, first introduced in Getting Skills Right: Skills for Jobs Indicators (OECD, 2017), constructs occupation-level shortage and surplus indicators from signals including wage growth, employment growth, hours worked, unemployment and under-qualification, benchmarked against economy-wide trends. Its 2022 update incorporated a new methodology for calculating the importance of skills in occupations based directly on online job vacancies, extending coverage to 43 countries and adding more detailed information on digital skill requirements—illustrating the growing convergence between vacancy-based and survey-based approaches to measuring skill imbalances at the international level.

Vacancy data have also been used to analyze occupational mobility and labor market transitions. This approach builds on an older strand of labor economics that measures the "distance" between occupations based on their skill or task content. Gathmann and Schönberg (2010), using German survey data on tasks performed across occupations, propose the concept of task-specific human capital and show that individuals tend to move into occupations with similar task requirements, with the distance of such moves declining as workers accumulate labor market experience—and that this task-specific human capital accounts for up to 52% of individual wage growth. Alabdulkareem et al. (2018) laid the groundwork for this approach, using O*NET skill data together with U.S. occupational transition records to construct a network-based "skill space," showing that skills cluster into two broad groups—social-cognitive and sensory-physical—and that this skill topology is closely linked to occupational wage polarization.

Building on this framework, Dawson et al. (2021) combine real-time online job advertisement data with longitudinal household survey data for Australia to build a recommender system that predicts optimal occupational transition pathways based on skill similarity. Their results also show that the difficulty of moving between occupations is asymmetric—it is easier to transition in one direction than the reverse—and they construct an early-warning indicator based on the adoption of new technologies, using artificial intelligence as a case study, identifying it as a significant driver of rising occupational transitions.

Beyond the demand for AI-specific skills, a substantial body of literature has focused specifically on the growing labor market value of soft skills. Given that this paper analyzes both dimensions jointly with technical skills more broadly, it is useful to situate the analysis within this global evidence before turning to the Latin American context.

Using online job vacancies posted in the United States between 2010 and 2015, Deming and Kahn (2018) show that more productive firms demand higher levels of both cognitive and social skills. Their results indicate that the combination of these two types of skills is particularly strongly associated with wages, providing evidence of increasing complementarity between cognitive and social skills. Moreover, they find that differences in firms' demand for these skills explain a non-negligible share of wage differentials and productivity differences across firms.

Moving from stated requirements to directly measured ability, Weidmann and Deming (2021) provide experimental evidence that social skills—defined as a latent factor combining social intelligence with an individual's measured contribution to team output—improve team performance by roughly as much as cognitive ability (IQ), formally establishing social skill as a productive input in its own right rather than a secondary trait.

Using Swedish administrative data spanning two decades, Edin et al. (2022) document a secular increase in the labor market return to non-cognitive skill between 1992 and 2013, concentrated at the top of the wage distribution and in the private sector, and driven in part by workers with high non-cognitive skill increasingly sorting into abstract, non-routine, social and non-automatable occupations. Synthesizing this broader body of work, Deming (2022) concludes, among four stylized facts about human capital, that higher-order skills such as problem-solving and teamwork have become increasingly valuable in the labor market, even as the technology for teaching and measuring them remains comparatively underdeveloped relative to foundational skills like literacy and numeracy.

Evidence from Latin America remains limited but points to substantial heterogeneity across countries and workers. Busso et al. (2012), combine multiple employer and household surveys across several Latin American countries to examine the relationship between schooling, skills and employment outcomes, distinguishing explicitly between technical, cognitive and socio-emotional skills demanded by firms. Their results show that employers value socio-emotional skills as highly as, technical skills when hiring—yet the region's education systems remain primarily oriented toward the transmission of technical and cognitive content, generating a "disconnect" between what schools teach and what employers actually seek.

Ciaschi and Ramirez-Leira (2025) show that exposure to AI technologies varies considerably across 14 Latin American countries due to differences in occupational structures. Countries with a larger share of professional, clerical, and service occupations tend to exhibit greater exposure to AI-related transformations. However, estimated risks depend critically on whether analyses account for potential complementarities between workers and AI technologies, and, in the absence of complementary labor market policies, AI-driven displacement could increase both inequality and poverty.

Gmyrek et al. (2024) analyze the potential effects of GenAI on employment in Latin America and argue that exposure should not be equated with job displacement, as AI is expected to complement rather than replace workers in many occupations. They also emphasize that the extent to which countries benefit from AI depends on workers' digital capabilities and access to digital technologies, highlighting the importance of the region's persistent digital divide.

Using real-time online job vacancies from Argentina, Chile, and Vezza et al. (2025) document a growing demand for digital, cognitive, technical, and socioemotional skills across occupations. Their findings also show that employers increasingly seek combinations of complementary skills.

Bennett et al. (2022) show that online vacancies in Uruguay are concentrated in medium- and high-skill occupations and are associated with higher educational and skill requirements.

Using a complementary approach that combines vacancy postings with job applicants' data for Escudero et al. (2024) show that cognitive skills, customer service, people management and social skills are among the five most frequently identified competencies on the applicant (labor supply) side, while character skills feature prominently on the vacancy (labor demand) side.

Overall, the literature suggests that technological change affects labor markets primarily through transformations in the task content of jobs and the skills demanded by employers. This shift from occupations to tasks—and increasingly from tasks to skills, particularly digital capabilities—has motivated a growing body of research aimed at identifying, measuring, and monitoring skill demand through new data sources such as online job vacancies.

3 | DATA SOURCES AND COLLECTION STRATEGY

Measuring employers' demand for emerging skills poses important challenges because traditional labor market data rarely contain detailed information on the competencies required for individual jobs. Household surveys primarily describe workers' characteristics, while administrative records capture realized employment relationships rather than employers' hiring requirements. The digitalization of recruitment has fundamentally expanded the information available for labor market analysis. Online job portals provide a unique source of information on employers' hiring requirements, allowing researchers to observe the skills, qualifications, and experience sought at the moment of recruitment.

This paper takes advantage of this new data source through the systematic scraping and analysis of online job postings. Compared with traditional labor market data sources, online job postings offer several important advantages. First, they provide job-level information on employers' skill requirements, including competencies, educational qualifications, work experience, certifications, and other job-specific qualifications. Second, they are available with very short publication lags, allowing researchers and policymakers to monitor changes in labor demand almost in real time. This is particularly important when studying rapidly evolving technologies such as artificial intelligence, where skill requirements can change over relatively short periods. Third, they are generated at a very large scale, providing extensive coverage across occupations, industries, firms, and regions. Their granularity also makes it possible to analyze variation in hiring requirements within occupations and across employers. Together, their scale, granularity, and timeliness make online job postings a unique source for analyzing employers' skill demand, occupational change, and labor market adjustment processes.

As a result, online job postings have become one of the principal empirical sources for studying how technological change reshapes employers' demand for digital, AI-related, and other emerging skills. An important limitation of these data, however, is their overrepresentation of formal employment. This bias arises largely because posting a vacancy on a digital platform is itself indicative of a more formalized recruitment process: employers relying on informal hiring channels, personal networks, referrals, or word of mouth, rarely use online job portals. The bias is further reinforced by firm size, as informality in the region is strongly correlated with small and micro enterprises, which are also the least likely to recruit through digital platforms. While this is a well-recognized caveat in international literature, its practical relevance depends largely on the size of the informal sector in the economy under study. In most developed countries, where informality accounts for roughly 10% or less of total employment, this limitation is relatively modest. In Latin America, by contrast, informality rates in urban areas range from about 32% in Brazil, 43% in Argentina, 46% in Colombia and over 48% in Mexico. As a result, vacancy-based estimates of skill demand may fail to capture the characteristics and skill requirements of a significant share of the workforce. The evidence presented in this paper should therefore be interpreted as reflecting employers' demand as expressed through formal online recruitment channels rather than the labor market as a whole. In addition, because the unit of analysis is the individual job posting, repeated advertisements of the same vacancy may appear multiple times in the dataset (as explained later). Therefore, the reported frequencies characterize the prevalence of skills in online job postings rather than in unique job vacancies.

Despite this limitation, there is broad agreement that online job vacancies constitute one of the most valuable sources for studying contemporary transformations in labor demand. Although they do not fully represent the labor market, they provide an exceptionally rich and timely picture of how employers adjust hiring requirements in response to technological change. For this reason, online job posting data have become an essential source for monitoring the diffusion of digital and AI-related skills and for analyzing the evolution of labor demand across occupations, industries, and countries.

3.1 | Current online job vacancy data

To obtain a granular dataset across the region, we collected data from the largest online job portals operating in the four Latin American countries under study: Argentina, Brazil, Colombia and Mexico. The selection of countries was based on two criteria. First, they represent diverse labor markets that together account for approximately 76% of total employment in Latin America. Second, the presence of well-established online job platforms enabled the construction of a large and comparable dataset suitable for cross-country analysis.

The selection of portals was guided by the following criteria: breadth of occupational coverage within each national market, cross-country comparability, and the practical feasibility of data extraction. While several additional job platforms operate across the region, many are technically protected against automated data collection, making systematic scraping unfeasible. The final set of portals therefore consists of those satisfying both substantive and technical requirements. Table 1 presents the portals used for each country.

TABLE 1 Job portals for four Latin American countries

Country	Traditional Portals	Nontraditional Portal
Argentina (AR)	ZonaJobs / Computrabajo	Workana Arg
Brazil (BR)	Catho / InfoJobs	Workana Br
Colombia (CO)	Computrabajo	Workana Co
Mexico (MX)	Computrabajo	Workana Mx

Source: Authors' calculation based on data from job portals.

The portal selection follows a dual-track logic that mirrors the formal and emerging structures of these labor markets. On the one hand, traditional job portals: ZonaJobs and Computrabajo in Argentina, InfoJobs and Catho in Brazil, Computrabajo in Colombia, and Computrabajo in Mexico, serve as the primary data source for understanding formal labor demand across all types of employment categories, from industrial and operational sectors to administrative and mid-level management positions. These portals capture employers' demand across a broad spectrum of occupations, industries, and skill levels through the standard recruitment channels of the formal labor market.

In addition, we incorporate data from Workana, a leading freelance platform operating across the four countries. Unlike traditional job portals, freelance platforms capture project-based demand, which tends to respond rapidly to technological change and the emergence of new digital tools. As a result, they provide a valuable complement to standard job postings by offering early signals of evolving skill requirements. Monitoring Workana therefore provides valuable information on the early diffusion of new digital skills and their subsequent incorporation into more traditional labor markets.

An additional advantage of Workana is that it operates under a common technological infrastructure and taxonomy across all four countries. This reduces cross-country differences arising from platform-specific taxonomies and classification systems, thereby improving comparability. However, the number of postings is considerably smaller than in traditional portals (Table 2), so Workana is primarily used to characterize the gig economy rather than to quantify cross-country differences.

Across all sources and time periods, we capture the full text of each job posting. These raw textual data form the basis for extracting detailed information on employers' hiring requirements, including job titles, demanded hard and soft skills (technical proficiencies and interpersonal competencies required for task execution), required educational qualifications, and prior work experience requirements. Further, the textual descriptions may be used to infer the tasks associated with each position. The extraction of these attributes relies on a combination of complementary text-mining techniques, described in detail in the following section.

The final analytical dataset comprises 1,225,017 job postings collected from the online job platforms described above between late December 2025 and the end of June 2026 across the four countries included in the analysis. The postings are distributed as follows: 64,088 in Argentina, 464,335 in Brazil, 340,879 in Colombia, and 355,715 in Mexico.

3.2 | Historical online job vacancy data

To complement the analysis of current labor demand with a historical dimension, we incorporate archival job vacancy data retrieved from the Internet Archive (archive.org), which preserves timestamped snapshots of major job boards, including Computrabajo and InfoJobs. These snapshots make it possible to reconstruct longitudinal series of vacancy postings reaching well beyond the coverage window of live scraping.

This historical layer is essential for contextualizing current trends: by comparing the skill content of job posting over time, the analysis can identify not only which competencies are being demanded today, but at what pace and in which occupational segments the composition of skill demand is shifting in response to digital transformation.

Data availability varied by country, so we selected one portal per country and built a sample covering 2017-2022: Computrabajo for Argentina and Mexico, InfoJobs for Brazil, and El Empleo for Colombia. Across the four countries, this historical sample comprises 83,692 job postings.

4 | METHODOLOGY AND DEFINITIONS

The central methodological challenge of this study is to transform heterogeneous, multilingual, and unstructured online job postings into a harmonized analytical database that can be consistently compared across countries. Each component of the methodology addresses one dimension of this transformation, including skill identification, educational requirements, and occupational classification.

4.1 | Taxonomy construction and validation

This section presents the methodological framework developed to transform heterogeneous, multilingual, and unstructured online job postings into a harmonized analytical database that can be consistently compared across countries. The methodology consists of four sequential components: (i) the construction of a regional skills taxonomy, (ii) data preprocessing and skill extraction, (iii) extraction of educational requirements and work experience requirement, and (iv) occupational classification. Together, these components provide a reproducible framework for measuring employers' demand for skills across Latin American labor markets.

The development of labor market intelligence systems requires taxonomies capable of consistently organizing and classifying skills, knowledge, competencies and occupations. These classification systems provide a common language that allows information extracted from online job vacancies and other labor market sources to be standardized, compared and analyzed across sectors, occupations and countries. Given the central objective of this paper -to measure employers' demand for digital, AI-related, and soft skills across Latin America- the construction of a robust and regionally adapted skills taxonomy constitutes a critical methodological step. Indeed, the construction of this taxonomy represents one of the principal methodological contributions of this study.

As a starting point, we rely on the Lightcast Skills Taxonomy (formerly Burning Glass Technologies), one of the most comprehensive and widely used skill classification systems currently available. The taxonomy contains more than 33,000 standardized skills derived from millions of online job postings, resumes, and professional profiles, and is continuously updated to reflect changes in labor demand. Its broad coverage and hierarchical organization make it an appropriate foundation for large-scale analyses of skill demand.

However, directly applying the original Lightcast taxonomy to Latin American job postings would lead to substantial losses in coverage and classification accuracy. Beyond the obvious language difference—Lightcast is developed in English while the postings analyzed here are written in Spanish and Portuguese—regional labor markets use country-specific terminology, abbreviations, idiomatic expressions, and alternative names for many technical and professional skills. Moreover, interpersonal and organizational competencies frequently demanded by employers are only partially represented in internationally developed taxonomies.

Importantly, the challenge extended beyond translation. The same technical competency is often described using different expressions across Argentina, Brazil, Colombia, and Mexico, requiring the incorporation of regional terminology, country-specific variants, and locally used professional expressions into the taxonomy. Rather than translating the original taxonomy, we therefore constructed a regionalized skills taxonomy specifically adapted to the linguistic and occupational characteristics of Latin American labor markets.

We developed a regionally adapted taxonomy through a multi-stage process of linguistic expansion, regional adaptation, and expert validation. We first extracted the complete Lightcast taxonomy through its API. Each skill was then processed individually through a large language model instructed to act as a regional labor-market taxonomy expert, generating, for every skill, the full set of Spanish and Portuguese terms used in regional job postings—including main translations, country-level variants, abbreviations, and, where relevant, English terms kept as-is when that is the industry convention in the region (see Appendix A.1). This expansion was carried out in batches using Google Vertex AI. Because each skill was expanded independently of the others, the same term occasionally emerged as a valid expression for more than one skill, generating collisions in the resulting dictionary. These collisions were resolved through a manual disambiguation process assisted by a language model, and in some cases required reassigning terms between closely related Lightcast skills as part of the broader iterative validation described below. The resulting dictionary then underwent an extensive cleaning process to remove ambiguous, generic, and low-information terms likely to generate false positives. Subsequently, the expanded vocabulary was manually validated, complemented with a bottom-up soft skills lexicon derived from Latin American job postings, and finally integrated into a unified regional taxonomy.

Validation constituted one of the most demanding stages of taxonomy construction. Automatically generated translations and semantic expansions frequently produced ambiguous expressions, regional variants with different meanings across countries, and generic terms that would have generated high rates of false positives when matched against vacancy texts. Beyond resolving the skill-to-skill collisions identified during expansion stage, the validation process focused on eliminating these additional sources of ambiguity. To address this, the cleaning stage removed single-character entries, generic expressions, common abbreviations, and terms whose meaning in Latin American job postings differed from their intended technical referent in the original taxonomy. The remaining vocabulary was then manually reviewed in an iterative process—rather than a single post-processing step—consolidating synonyms and verifying that each retained term accurately represented its intended skill within the linguistic context of the four countries, with particular attention to regional terminology. Multiple rounds of refinement were carried out until the taxonomy achieved satisfactory coverage and precision across Argentina, Brazil, Colombia, and Mexico.

An additional limitation of international taxonomies concerns their relatively limited representation of soft skills demanded by employers in Latin American labor markets. To address this issue, we constructed a complementary soft skills lexicon through the systematic analysis of a representative sample of job postings collected from ZonaJobs (Argentina) during October and November 2025. Frequently occurring interpersonal, communicative, and organizational competencies were identified, manually reviewed, harmonized across countries, and incorporated into the taxonomy. This bottom-up procedure complements the top-down Lightcast taxonomy by adapting it to the linguistic and occupational realities of Latin American labor markets. Rather than relying exclusively on the Anglo-American conventions embedded in international skill taxonomies, the resulting taxonomy reflects the terminology actually used by employers across the region.

The integration of these top-down and bottom-up approaches produced a unified regional taxonomy comprising approximately 36,000 validated terms in Spanish and Portuguese, which serves as the reference framework for all subsequent stages of skill extraction and classification.

For the empirical analysis, the final taxonomy is organized into three mutually exclusive analytical categories according to the type of competency represented: soft skills, AI-related skills, and technical non-AI skills. Skills categorized as soft encompass transversal competencies often linked to emotional and social intelligence. The technical non-AI category comprises specialized knowledge in specific fields, including computational skills outside the AI domain. Finally, AI-related skills refer to competencies associated with the development and application of artificial intelligence technologies. This classification allows the same unified taxonomy to be consistently applied across all job postings while supporting differentiated analyses of the three skill dimensions examined in this paper.

Because artificial intelligence constitutes one of the central dimensions of the empirical analysis, AI-related skills are further classified following the OECD (2021, 2023) AI Skills Taxonomy. Specifically, AI-related skills are divided into two broad groups: generic AI skills and specific AI skills. Generic AI skills include competencies that appear across a broad range of occupations beyond those directly involved in AI development, such as machine learning, artificial intelligence, computer vision, and machine translation. Specific AI skills, by contrast, comprise more specialized competencies closely associated with AI-related occupations, including gradient boosting, natural language processing, convolutional neural networks, and deep learning. This additional level of disaggregation provides a more nuanced picture of how artificial intelligence is reshaping skill requirements and occupational profiles in labor markets.

Beyond these analytical categories, all skills are also assigned to taxonomic clusters (hereafter, clusters) that group conceptually related competencies. For technical and soft skills, the clustering follows the subcategory structure of the original Lightcast taxonomy, which was preserved throughout the regional adaptation process and subsequently refined through the same iterative validation and cleaning procedures described above. AI-related skills follow a different organization. Rather than relying on the original Lightcast subcategories, they are grouped according to the topical classification proposed by the Stanford Human-Centered Artificial Intelligence (HAI) Institute, which distinguishes major areas of AI knowledge and application. As with the rest of the taxonomy, these clusters were reviewed, adapted where necessary, and validated to ensure consistency with the terminology and occupational practices observed in Latin American job postings. The resulting clustering framework enables analyses not only of overall AI skill demand but also of the technological domains in which this demand is concentrated (Figure 1).

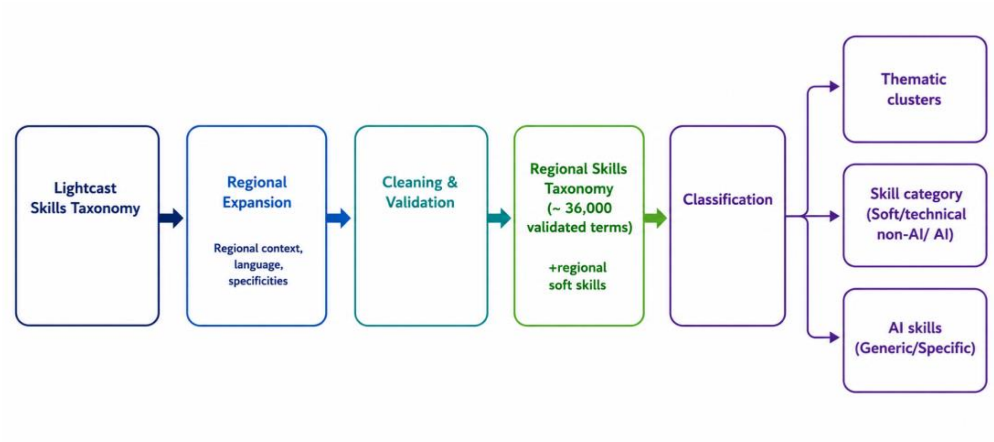

FIGURE 1 A multi-stage regionally adapted taxonomy process of linguistic expansion. *Notes:* The figure summarises the sequence followed to build the regional skills taxonomy: the Lightcast Skills Taxonomy is expanded to regional terminology, cleaned and validated, and the resulting taxonomy (approximately 36,000 validated terms, plus a bottom-up regional soft skills lexicon) is then classified into thematic clusters, skill categories (soft, technical non-AI, AI) and, for AI, generic versus specific skills. *Source:* Authors' elaboration.

4.2 | Data preprocessing and skill extraction

Online job postings constitute an exceptionally rich source of information on labor demand, but they also present important methodological challenges. Unlike structured administrative databases, job advertisements are unstructured textual documents whose content, organization, and level of detail vary substantially across employers, industries, job portals, and countries. The same information may appear in different sections of the posting, be expressed using different terminology, or be omitted altogether. Consequently, extracting comparable information from multilingual vacancy corpora requires a reproducible processing framework capable of handling substantial linguistic and structural heterogeneity while maintaining consistent extraction criteria across countries and platforms.

To address these challenges, we developed an integrated data processing pipeline that combines automated data collection, corpus preprocessing, and taxonomy-based skill extraction. Rather than relying on portal-specific or country-specific extraction rules, the pipeline was designed as a unified framework capable of processing heterogeneous job postings while ensuring that the same extraction criteria are applied consistently across all four countries included in the analysis.

We developed an automated scraping infrastructure capable of continuously collecting job postings from multiple online job portals across Argentina, Brazil, Colombia, and Mexico. The collection process extracts portal-specific formats during acquisition and stores the retrieved data directly in a centralized cloud repository, facilitating continuous updates, reproducibility, and version control throughout the data collection process.

Prior to analysis, all collected postings undergo a standardized preprocessing pipeline. Raw data from each portal are normalized to a common schema by harmonizing field names, character encodings, date formats, and metadata across sources. The resulting country-specific datasets are then integrated into a unified master database, where additional preprocessing removes textual noise and prepares the corpus for subsequent information extraction.

Duplicate postings associated with the same URL are removed during the construction of the master dataset. However, job portals may contain multiple postings corresponding to the same underlying vacancy, particularly when recruitment agencies publish identical advertisements under different URLs or across multiple categories within the platform. As these postings cannot be reliably distinguished from independent advertisements using URL identifiers alone, they are retained in the dataset as independent observations. As we noted earlier, this paper treats the individual job posting, not the unique vacancy, as its unit of analysis. Worth restating here because it's the point where that choice starts to matter mechanically: from this point on, every frequency, share, and count reported in the paper refers to postings, not vacancies. Repeated postings for the same underlying position enter the counts as separate observations, so a vacancy advertised repeatedly carries more weight in the results than one posted once — a bias to keep in mind when reading the frequencies that follow.

The extraction of skills presents an additional methodological challenge. Employers rarely report competencies in standardized sections. Instead, skills are typically embedded within free-text descriptions together with job tasks, educational requirements, work experience, software names, and organizational information. Furthermore, the structure and wording of job advertisements differ considerably across countries and recruitment platforms, making robust large-scale extraction substantially more complex than conventional keyword searches. An equally important consideration concerns the validity of the underlying taxonomy. The quality of any extraction algorithm depends directly on the quality of the vocabulary being matched. International taxonomies frequently include expressions that, in Latin American job postings, correspond to tasks, activities, or generic terms rather than genuine skills. Consequently, the regional taxonomy developed in Section 4.1 constitutes a fundamental component of the extraction framework, substantially reducing the risk of misclassifying tasks or generic expressions as skills.

Building on this regional taxonomy, prior to matching it was further refined through a hierarchical system of exclusions applied at the level of categories, subcategories, skills, and individual terms, removing entries that were retained in the taxonomy for completeness but were unsuitable for direct text matching—such as the "Physical Abilities" subcategory and a set of specific skills and terms with high false-positive rates in Latin American postings (Appendix A.2 reports the details). Skill detection is performed using FlashText, a multi-pattern search algorithm based on a prefix tree (trie) that scans each posting's text once, in linear time regardless of dictionary size—an important property given a taxonomy of tens of thousands of terms, since the cost of a regular-expression-based search grows with the number of patterns while FlashText's does not. The algorithm identifies only complete word-level matches, discarding occurrences of a term as a substring of another, and retains the longest match when terms overlap (e.g., "machine learning" prevails over "learning"). Because the corpus is multilingual, spanning Spanish and Portuguese text with different accentuation conventions, all text was normalized and accented characters were explicitly treated as word characters, preventing terms such as "diseño" or "gestão" from being truncated at the accent (Appendix A.2 provides further implementation details).

For each posting, all available textual fields—title, body, requirements, and portal-specific auxiliary fields—are concatenated and matched against the taxonomy. A skill is counted at most once per posting regardless of how many times it appears. For every detected match, the corresponding term and a five-word surrounding context window are retained, enabling manual review of any doubtful match.

Each matched skill is subsequently linked to the regional taxonomy presented in Section 4.1, allowing every identified expression to be assigned to its corresponding analytical category (soft skills, AI-related skills, or technical non-AI skills). The resulting structured database associates each job posting with the complete set of matched skills identified in its text and constitutes the foundation for the empirical analyses presented in the following sections. In addition, matched AI-related skills are further classified into generic or specific, following the taxonomy detailed in Section 4.1.

Taken together, the preprocessing, taxonomy, and matching procedures constitute a unified and reproducible extraction framework that can be readily extended to additional countries or online job portals.

4.3 | Educational level and experience requirements extraction

Beyond the technical, soft, and AI-related skills discussed above, job postings also convey information on the educational credentials and prior work experience employers require. To capture this dimension, we extract two additional variables for each posting: the minimum educational level required and whether the posting requires prior work experience.

Educational level. Educational requirements constitute one of the most important dimensions of labor demand. However, unlike structured survey data, online job postings do not report educational qualifications using standardized categories. Employers refer to educational requirements using heterogeneous terminology that varies across countries, occupations, and firms, ranging from formal degree names to generic expressions such as "university studies," "professional degree," or "student."

Extracting educational requirements in a comparable way across four countries poses a challenge that goes beyond linguistic heterogeneity. This linguistic variability makes direct comparison difficult, particularly across countries where educational systems and professional titles differ substantially: the same nominal degree does not represent the same educational attainment across countries. A bachelor's-type qualification in Argentina, Colombia, Brazil, and Mexico corresponds to different program structures, durations, and institutional traditions, and postings often refer to specific degree titles — a named engineering degree, a technical certification, a professional registration — rather than to a generic educational level. Establishing comparability therefore required a dedicated prior effort to catalog university and technical degree titles across the four countries and map them onto a common scale.

To address this challenge, we developed a standardized educational extraction pipeline that identifies educational references from the full text of job postings and maps them onto a harmonized set of educational levels. This mapping produced a harmonized classification of eleven educational categories: doctorate, master, postgraduate, bachelor, undergraduate, tertiary, technical, secondary, and primary, following the ISCED 2011 framework, plus two residual categories—none, for postings that explicitly state no educational requirement, and unknown, for postings containing insufficient information to determine a level, consistent with the general principle of not inferring information that is not stated in the posting. These categories are treated as an ordinal scale (doctorate > master > postgraduate > bachelor > undergraduate > tertiary > technical > secondary > primary > none > unknown), which underlies the rule, described below, of assigning the minimum required level when a posting mentions more than one.

The categories reflect meaningful institutional distinctions across countries, and required a set of explicit methodological decisions to keep them consistent. Postgraduate and master are kept as separate, ordinally ranked categories to distinguish shorter specialization degrees from a completed master's, even though both are advanced degrees beyond a bachelor's. Undergraduate is reserved for postings that explicitly accept students still pursuing a degree rather than requiring its completion, and is placed below tertiary in the ordinal scale as a conservative choice, reflecting the last level of education the applicant can be assumed to have actually completed. Technical is restricted to short-cycle post-secondary vocational training, distinct from technical or vocational tracks completed at the secondary-school level, which are coded as secondary. Tertiary captures university-level short-cycle programs distinct from a full bachelor's degree, a category that takes markedly different institutional forms across the four countries. Appendix A.3 details the full category scheme, the underlying rationale for each distinction, and the country-specific degree titles mapped onto each category.

Once this harmonized scheme was in place, educational level was extracted for each posting following a three-step sequential procedure. When the portal provides a structured field explicitly reporting the required educational level, this field is used directly and mapped onto the harmonized categories; this is the case for Computrabajo in Argentina, Colombia, and Mexico, and for InfoJobs in Brazil, which together account for the majority of postings. The specific vocabulary mapped in this step, and its correspondence to the harmonized categories, differs substantially by portal and country, and is documented in Appendix A.3.

When no structured field is available—as with Zonajobs in Argentina and Catho in Brazil—the free text of the posting is searched for language- and country-specific patterns associated with each educational category, using a purpose-built vocabulary of educational terms, degree titles, and contextual markers. This step applies a set of complementary rules: it identifies the minimum required level when multiple levels are mentioned, treats requirements marked as desirable or a plus as non-binding and infers the level below as the effective minimum, and disambiguates between homonyms (such as "técnico" as an adjective versus as a degree title). For the small share of postings in which neither step yields an unambiguous classification, a supervised text classifier trained on the postings already classified through the two previous steps is applied, subject to a minimum confidence threshold; cases that do not meet this threshold are coded as unknown rather than assigned a default category.

Experience requirements. The extraction of experience requirements follows a different logic. Job postings are highly heterogeneous in whether and how they specify prior work experience: postings differ in whether experience is mentioned at all, in which section it appears, and in how it is phrased, and there is no consistent convention across portals or countries for reporting a minimum number of years or a particular type of experience. Given this heterogeneity, we adopt a binary criterion: each posting is classified according to whether prior work experience is explicitly required or not, rather than attempting to extract a quantity or type of experience that could not be reliably compared across postings. Postings containing no identifiable information on experience requirements are left unclassified.

The resulting database contains standardized educational requirements that are directly comparable across countries and occupations.

4.4 | Matching of Job Titles to ISCO

Occupation constitutes the principal unit for analyzing labor market structure. However, online job portals do not employ standardized occupational classifications. Instead, employers freely define vacancy titles, generating hundreds of thousands of heterogeneous occupational descriptions that cannot be directly compared across firms, countries, or platforms.

Assigning job postings to occupational categories constitutes a fundamental step for analyzing the structure of labor demand across countries. Online job advertisements, however, present another well-known challenge for occupational classification: titles are highly heterogeneous, vary substantially across portals and countries, and are frequently accompanied by location references, salary information, scheduling details, and other contextual noise that is irrelevant for occupational identification. Differences in terminology, abbreviations, seniority labels, and country-specific naming conventions make direct mapping to international occupational classifications particularly challenging.

To address these issues, we developed a two-stage classification procedure that maps heterogeneous vacancy titles onto standardized ISCO-08 occupations. The first stage consists of a standardized title cleaning pipeline; the second applies a matching algorithm against a curated occupational dictionary.

Prior to occupation matching, all job titles undergo a standardized preprocessing procedure designed to remove non-informative content while preserving the occupational denomination of each posting. This process includes the elimination of recruitment phrases, company names, location references, administrative qualifiers, contractual information, salary references, and other portal-specific elements that do not contribute to occupational identification. In addition, titles are normalized to reduce linguistic variation, including the standardization of gendered expressions and other formatting inconsistencies. The resulting cleaned titles provide a concise and consistent representation of the occupation, improving the accuracy and comparability of the subsequent matching process.

Occupational classification is performed by matching each standardized short title against a curated dictionary of occupational terms organized by ISCO-08 sub-major groups. Rather than relying on the complete 43-category ISCO-08 hierarchy, we focused on a reduced set of 21 sub-major groups corresponding to the occupations most frequently observed in Latin American online job postings. For each group, the dictionary contains a set of occupational terms and expressions drawn from the actual vocabulary observed in the four countries' postings, including morphological variants (masculine, feminine, singular, and plural forms) and country-specific equivalents in Spanish and Portuguese.

Occupation matching is performed by applying regular expressions to the standardized job titles using the occupation dictionary described above. Multi-word expressions are matched before single-word terms to prioritize more specific occupational denominations, while word-boundary matching prevents spurious partial matches. Titles that cannot be matched are assigned to a residual category and subsequently reviewed to identify missing occupational terms, supporting the iterative expansion of the dictionary.

This procedure yields, for each job posting, the assigned ISCO sub-major group and the specific term that triggered the match, enabling transparent auditing of classification decisions.

4.5 | Measuring occupational exposure to AI

A question that follows naturally from analysing the skills demanded by employers - particularly those related to AI- is whether certain occupations are at risk of being replaced by these new technologies. Several indexes have been developed to quantify this exposure, and two of them inform the analysis below.

The first is the C-AIOE index, introduced by Pizzinelli et al. (2023), as an extension of the AIOE index. Where AIOE measures the overlap between the skills required for an occupation and the capabilities of the main AI applications available, C-AIOE adds a complementarity term: an occupation may exhibit high exposure to AI and still be largely unaffected, or even strengthened, if the technology complements rather than substitutes for what occupation does, resulting in productivity gains. Conversely, occupations characterized by high AI exposure, but low complementarity may face significantly higher risk of substitution.

The second is the GENOE index, developed by Benítez and Parrado (2024). This index shifts the focus to a task-level analysis, suggesting that AI substitution occurs at the level of specific tasks, rather than at an occupational level. To construct this metric, the authors conducted "synthetic surveys" asking large language models (LLMs)to evaluate these technologies' capacity to perform these tasks while weighing social and ethical factors considerations alongside the purely technical ones. This methodology provides a more objective assessment of an occupation's AI exposure, and by utilizing LLMs, trained on recent data, the index inherently incorporates the latest technological capabilities and trends into its analysis.

Both indexes rely on O*NET as their primary data source. However, their methodological approaches differ: while the C-AIOE focuses on the abilities required for each occupation, GENOE evaluates individual tasks and subsequently aggregates their findings at occupational level. Lastly, although the C-AIOE takes values between 0 and 10 and GENOE values range from 0 to 1, their interpretation is similar: higher index values represent a greater relative risk of AI exposure.

5 | RESULTS I: AGGREGATE SKILL DEMAND BY TYPE

As previously mentioned, the analysis of job postings distinguishes between two types of platforms throughout this section: Workana, a platform more dedicated to freelance vacancies, and the four traditional labor marketplaces—Catho, Computrabajo, InfoJobs, and ZonaJobs (hereafter collectively referred to as "non-Workana" portals).

Most of what follows draws on the current sample, hereafter referred as 2026. But at several points the analysis also brings in the historical sample described in Section 3.2, covering 2017-2022, to see how skill demand has moved over time. Because that historical sample was built entirely from non-Workana portals, every comparison against it is restricted to the non-Workana segment of the current data as well—Workana enters only the sections that describe the present moment on its own.

This split matters because the composition of job postings differs substantially between these two types of platforms. To capture that, we constructed "employment areas" based on the classifications provided by the job portals themselves (see Appendix B.1). As detailed in Table B.1 of Appendix B.1, Workana exhibits a highly concentrated sectoral distribution, with all postings classified into only seven categories. In contrast, non-Workana portals display a much broader distribution, covering between 17 and 24 categories, depending on the country.

The analysis of the composition of postings within each platform reveals several relevant patterns. Across all countries in our sample, the relative share of postings in "Design, Arts & Architecture" and "Translation, Languages & Content" is considerably higher on Workana than on non-Workana platforms. This pattern reflects the fact that a large proportion of Workana postings correspond to creative and digitally oriented occupations. Conversely, although "Sales, Commercial & Marketing" roles are also present on Workana, their relative importance is substantially lower than on traditional job portals. Finally, the "Administration, Accounting & Finance" category shows cross-country heterogeneity: its share of postings on Workana exceeds that observed on non-Workana portals in Argentina, Colombia, and Mexico, but is comparatively lower in Brazil.

5.1 | Distribution of job postings by skill type

Table 2 reports, for each country and job portal, the raw number of job postings collected between February and the end of June 2026, the number and percentage of postings requiring at least one skill, and the average of skills requested per posting.

TABLE 2 Summary of skill extraction results by country and portal. 2026

ARGENTINA				
Metrics	**Computrabajo**	**ZonaJobs**	**Workana**	**Total**
N° of raw job postings	31,239	25,511	7,338	64,088
N° of postings with ⩾1 skill identified	28,514	24,388	7,197	60,099
% with ⩾1 skill	91	96	98	94
Average skills per posting	6.4	7.5	7.3	7.0
BRAZIL				
Metrics	**Catho**	**InfoJobs**	**Workana**	**Total**
N° of raw job postings	217,085	231,779	15,471	464,335
N° of postings with ⩾1 skill identified	198,110	203,400	15,305	416,815
% with ⩾1 skill	91	88	99	90
Average skills per posting	5.5	5.0	8.1	5.3

COLOMBIA			
Metrics	**Computrabajo**	**Workana**	**Total**
N° of raw job postings	334,081	6,798	340,879
N° of postings with ⩾1 skill identified	291,953	6,708	298,661
% with ⩾1 skill	87	99	88
Average skills per posting	4.5	7.3	4.5
MEXICO			
N° of raw job postings	349,995	6,66	335,715
Metrics	**Computrabajo**	**Workana**	**Total**
N° of postings with ⩾1 skill identified	304,995	6,540	311,535
% with ⩾1 skill	87	98	88
Average skills per posting	4.4	7.7	4.5

Source: Authors' calculation based on data from job portals.

Computrabajo is the leading source in Argentina, Colombia, and Mexico, although ZonaJobs also accounts for a substantial share of postings in Argentina. In Brazil, the dataset is drawn primarily from Catho and InfoJobs. Workana contributes a smaller share of postings across all four countries. Nevertheless, it plays a key methodological role in the analysis. As the only platform operating in all four countries, it provides a common basis for cross-country comparisons. As discussed above, Workana is particularly oriented towards digital, technology-intensive, and frontier occupations, making it especially well-suited for analyzing emerging skill demands associated with digitalization and artificial intelligence.

There are substantial differences in the volume of postings across countries. Argentina records around 64,000 postings, compared with approximately 350,000 in Colombia and Mexico and nearly 465,000 in Brazil. As discussed previously, these figures should not be interpreted as fully representative of the size or structure of national labor markets, rather they represent a specific proportion of the entry rate for each country, representing

6-7% of new employment (three months of tenure or less) in Argentina and Brazil, and around 15% in Colombia and Mexico. Informality alone does not explain the gap alone. The high incidence of informality in Latin America, together with other market-specific factors, implies that online job vacancies capture only part of labor demand. However, differences in informality alone cannot account for the observed variation across countries. For example, Argentina records substantially fewer online vacancies than Colombia and Mexico despite having lower levels of labor informality. This suggests that country-specific differences in recruitment practices, the penetration of online job portals, and the use of alternative hiring channels—both formal and informal—are also likely to influence the number of vacancies observed in each market.

Despite these differences, several findings are remarkably consistent across the four countries. First, the importance of skill requirements is evident not only at the extensive margin—around 90% of job postings require at least one skill from the three categories considered—but also at the intensive margin. Employers request, on average, between five and seven different skills per posting, suggesting that labor demand is increasingly oriented towards multidimensional skill profiles rather than individual competencies. These numbers are also high by international standards and are broadly consistent with the evidence reported for European countries in recent OECD studies (Schmidt et al., 2024).

Second, Workana consistently stands out across all four countries, exhibiting both the highest proportion of postings requiring at least one skill and the highest average number of skills requested among those postings. In fact, almost all Workana postings require at least one skill, and employers request, on average, between seven and eight different skills per posting. Several complementary explanations may account for this pattern. First, a composition effect: Workana skews towards technical, digital and creative occupations, which naturally require the enumeration of specific tools and technologies to convey the scope of work; traditional portals, by contrast, span a much wider occupational range—including operational and manual roles—for which few describable "skills" exist beyond the job title itself, pulling down the overall average. Second, a difference in the nature of the listing itself: a Workana posting describes a discrete, bounded project, requiring the client to specify the full scope of deliverables and tools needed; a traditional job posting describes an ongoing role, and tends to rely on more generic requirement language (e.g., completed secondary education, years of experience) rather than an exhaustive task-by-task account. Third, the absence of a subsequent interview stage: in traditional employment, much of the skill verification happens after the posting, during the interview process; on freelance platforms, hiring decisions rely almost entirely on what is written in the posting itself, giving clients a stronger incentive to front-load as much detail as possible into the text.

Third, as shown in Table 3,[1]1 technical non-AI skills are by far the most frequently requested skill category across all four countries. Between 85% and 92% of job postings require at least one technical non-AI skill. Soft skills rank second in importance and are also highly prevalent, appearing in around 70% or more of all postings. By contrast, AI-related skills are requested in only a very small share of postings, ranging from about 1% in Brazil, Colombia, and Mexico to around 3% in Argentina. This finding suggests that, while AI has attracted considerable attention in public debate, its direct adoption in hiring requirements remains limited. At present, employers place much greater emphasis on conventional technical skills and soft skills than on AI-specific competencies.

[1]The figures reported in this table correspond to the total number of job postings across all job portals in each country and represent the percentage of postings requiring each type of skill among all postings that require at least one skill.

TABLE 3 Distribution of job postings by skill type and country. 2026

Skill type	Argentina	Brazil	Colombia	Mexico
Technical non AI	92.1	85.6	86.1	84.9
Soft	74.1	77.6	67.3	72.6
AI	3.1	1.1	0.7	0.6
Skills combinations	**Argentina**	**Brazil**	**Colombia**	**Mexico**
Technical non-AI + Soft	63.9	62.3	52.9	57.1
Only Technical non- AI	25.1	22.1	32.5	27.3
Only Soft	7.8	14.4	13.9	15.1
Technical non-AI + Soft + AI	2.3	0.9	0.5	0.5
Technical non-AI + AI	0.8	0.3	0.2	0.1
Soft + AI	0.0	0.0	0.0	0.0
Only AI	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0
Total	100.0	100.0	100.0	100.0

Source: Authors' calculation based on data from job portals.

This low incidence of explicit AI-skill requirements should not be read as contradicting evidence on the region's broader occupational exposure to AI (Ciaschi and Ramirez-Leira, 2025; Gmyrek et al., 2024). Exposure and explicit demand are conceptually distinct: an occupation's tasks may be highly exposed to AI-driven automation or augmentation without employers yet requiring specific AI competencies in job postings, likely reflecting the fact that the everyday adoption of these tools within workplaces still lags behind their broader disruptive potential. Nor is this pattern unique to Latin America, nor is the low share observed here particularly low by international standards. In the United Alekseeva et al. (2021) find that AI-related postings accounted for just 0.6% of all vacancies in 2019, while the Stanford AI Stanford Institute for Human-Centered Artificial Intelligence (2021) documents that, between 2013 and 2020, machine learning postings grew from 0.1% to 0.5% of total US vacancies, and artificial intelligence postings from 0.03% to 0.3%. Comparable patterns have been documented in Canada, Singapore and the United Kingdom (Squicciarini and Nachtigall, 2021). More strikingly, Green (2024), analyzing vacancy data across ten OECD countries, finds that most workers in occupations highly exposed to AI will not need—and are not currently asked to have—specialized AI skills such as machine learning or natural language processing; instead, what increases in these occupations is demand for complementary management, business and digital skills.

A further interpretive caveat concerns the nature of vacancy data itself. Online postings capture the flow of new hiring rather than the stock of existing employment. Where AI fully substitutes for a given task or role, this would not necessarily manifest as a vacancy explicitly requiring AI skills, but rather as the corresponding vacancy failing to be posted at all—a form of displacement that vacancy-based indicators are not designed to detect directly. Consistent with the OECD evidence just described, much of the labor-market adjustment to AI appears to occur "behind the scenes," through employers' internal adoption of AI tools that reshape existing workers' task composition, rather than through the explicit hiring of workers possessing AI skills. The low incidence of explicit AI-skill requirements documented here should therefore be interpreted as evidence about the terms of new, ongoing hiring, rather than as a comprehensive measure of AI's aggregate labor-displacing effect—though, as shown below, this aggregate figure also masks substantial heterogeneity across job portals.

Fourth, technical non-AI skills are most frequently demanded in combination with soft skills rather than in isolation, pointing to a high degree of complementarity between the two. Across the four countries, the combination of technical and soft skills accounts for the majority of job postings, ranging from 53% in Colombia to 64% in Argentina. This finding suggests that employers seek workers who combine occupation-specific technical expertise with socio-emotional and interpersonal competencies, rather than relying on either type of skill alone. These findings are consistent with recent evidence highlighting the growing complementarity between technical and social skills in other labor markets (e.g., Deming, 2017; Deming & Kahn, 2018).

Fifth, while the ranking of skill combinations is remarkably stable across countries—technical-plus-soft combinations always rank first, followed by technical skills alone, and then soft skills alone— two differences emerge between countries. On the one hand, in Argentina, soft skills alone are the least likely to be demanded on their own, suggesting that, when Argentine employers value soft skills, they almost always do so alongside a specific technical requirement, whereas in the other three countries there is a somewhat larger pool of postings that demand soft skills without any accompanying technical competency. On the other hand, Colombia and Mexico exhibit the highest shares of postings requiring technical skills in isolation (32.5% and 27.3%, respectively), indicating a somewhat more compartmentalized skill demand compared to Argentina and Brazil.

Sixth, as noted above, AI-related skills represent a very small share of overall postings across the four countries. Interestingly, however, the same complementarity pattern documented for technical and soft skills more broadly also holds for AI specifically: AI skills are not requested in isolation and are instead almost always demanded in combination with other skill types. Moreover, when AI is involved, the most frequent combination is not simply technical-plus-AI, but the full combination of technical, soft, and AI skills together. This suggests that, even in its still-limited presence in job postings, AI does not appear to be displacing the demand for interpersonal and socio-emotional competencies—if anything, the postings that do require AI skills tend to be among the most comprehensive in terms of overall skill demand, reinforcing the broader pattern of skill complementarity discussed above rather than contradicting it.

Seventh, as shown in Table B.5 in Appendix B.2, there are systematic differences between Workana and the remaining, more traditional portals. In all four countries, Workana postings are more likely to require technical non-AI skills (99.1%-99.4%, compared to 84.6%-91.2% in the remaining portals) and AI skills (6.4%-9.9%, compared to just 0.5%-2.6% elsewhere), and less likely to require soft skills (52.7%-54.7%, compared to 67.6%-78.5% elsewhere). This seems to be consistent with Workana's occupational composition, concentrated largely in technical, digital and creative freelance work, relative to the broader occupational spectrum covered by traditional portals, which include administrative, operational and customer-facing roles as well. These differences also shape the internal ranking of skill combinations: while the technical-plus-soft combination remains the most common in both types of portals, and technical skills alone remain the second most common, the third-ranked combination differs between them—the full technical-soft-AI bundle in Workana, versus soft skills alone in the remaining portals, in all four countries. Taken together, these results seem to be consistent with the structural differences between a freelance, technology-oriented platform and traditional job portals spanning a broader range of occupations. In addition, because non-Workana postings account for the vast majority of the sample in every country, the aggregate ranking reported for the full sample effectively reflects the non-Workana pattern.

Eighth, Table 4 compares the share of postings with at least one identified skill between the historical sub-period (2017-2022) and the current period, restricting the comparison to non-Workana portals, since the historical data do not include Workana. At the extensive margin, the results are mixed: coverage rose in Argentina (from 89% to 93.2%) and Brazil (from 84% to 89.5%), fell in Colombia (from 92% to 87.4%), and remained essentially unchanged in Mexico (87% to 87.4%). At the intensive margin—the average number of skills identified per posting—the pattern is more consistent. Argentina shows a slight increase, from 5.6 skills per postings in 2017-2022 to 6.9 today, while the other three countries show no significant change between the two periods. Brazil and Mexico edge up slightly, from 4.9 to 5.2 and from 4.1 to 4.4 respectively, while Colombia edges down, from 4.8 to 4.5. None of these three moves far enough to call it a trend.

This lack of a consistent cross-country pattern is not entirely surprising. While one might expect the overall richness of skill requirements in job postings to increase over time—both at the extensive and intensive margins—as a reflection of AI's growing role in the economy, some considerations complicate this a priori expectation. As AI tools become more accessible and user-friendly over time, the level of specialized skill required to use them may decline even as adoption rises, consistent with OECD evidence that most workers exposed to AI do not require specialized AI skills (Green, 2024). In addition, much of AI adoption may occur through the retraining of incumbent workers rather than external hiring, a channel that vacancy data cannot capture. Finally, general-purpose technologies have historically diffused into measurable labor market outcomes only after a considerable lag, as complementary investments in data infrastructure and organizational adaptation take hold. Beyond these economic mechanisms, differences in data extraction quality between archived historical postings and current, live-scraped postings may also contribute to the country-specific patterns observed, and cannot be fully ruled out given the data available.

Ninth, Table 5 compares the composition of skill demand between the 2017-2022 sub-period and the current period, restricting the comparison to non-Workana platforms to ensure greater comparability over time. The most striking pattern is the substantial and consistent increase in the incidence of soft skills across all four countries: from 60% to 77% in Argentina, from 46% to 79% in Brazil, from 46% to 68% in Colombia, and from 57% to 73% in Mexico. This increase is observed not only in postings requiring soft skills alone (with the exception of Argentina), but also—and more importantly—in combination with technical non-AI skills. By contrast, the overall share of postings requiring technical skills declined over the period, although this reduction is entirely explained by the decrease in postings demanding technical skills in isolation. Indeed, postings requiring both technical and soft skills increased markedly in all four countries, rising by between 11 and 25 percentage points. The growth of this combination is substantially larger than that observed for any other individual skill category or skill combination. These results suggest that the complementarity between technical and soft skills documented in the previous section is not simply a characteristic of the current labor market but rather reflects a broader trend that has strengthened over time across the region.

By contrast, the evolution of AI-related skills is far less uniform. Argentina exhibits the clearest increase, with the share of postings requiring AI-related skills rising from 0.6% to 2.6% and the combination of technical, soft, and AI skills increasing from 0.4% to 2.0%. In the other three countries, however, the incidence of AI-related skills remains relatively stable over time.

Finally, as above-mentioned these temporal comparisons should be interpreted with caution. Although the historical and current datasets were harmonized to maximize comparability, differences in data sources, platform coverage, and other characteristics may affect the observed changes. Consequently, the results should be viewed as indicative of broad trends rather than as precise estimates of changes in skill demand over time.

TABLE 4 Summary of skill extraction results by country and subperiod. 2017–2022 / 2026

ARGENTINA & BRAZIL				
	ARGENTINA		**BRAZIL**	
Metrics	2017-2022	2026	2017-2022	2026
N° of raw job postings	5,970	56,750	43,019	448,864
N° of postings with ⩾1 skill identified	5,342	52,902	36,116	401,510
% with ⩾1 skill	89	93	84	89
Average skills per posting	5.6	6.9	4.9	5.2
COLOMBIA & MEXICO				
	COLOMBIA		**MEXICO**	
Metrics	2017-2022	2026	2017-2022	2026
N° of raw job postings	7,718	334,081	26,985	349,052
N° of postings with ⩾1 skill identified	7,074	291,953	23,437	304,995
% with ⩾1 skill	92	87	87	87
Average skills per posting	4.8	4.5	4.1	4.4

Source: Authors' calculation based on data from job portals.

TABLE 5 Distribution of job postings by skill type and country. 2017–2022 / 2026

	ARGENTINA		**BRAZIL**	
Skill type	2017-2022	2026	2017-2022	2026
Technical non-AI	90.3	91.2	91.8	85.0
Soft	59.9	76.9	46.3	78.5
AI	0.6	2.6	0.6	0.8
Skill combinations	2017-2022	2026	2017-2022	2026
Technical non-AI + Soft	49.9	66.1	53.4	62.8
Only Technical non-AI	39.9	22.6	37.9	21.4
Only Soft	9.6	8.8	8.1	14.9
Technical non-AI + Soft + AI	0.4	2.0	0.2	0.7
Technical non-AI + AI	0.1	0.5	0.3	0.1
Soft + AI	0.0	0.0	0.0	0.0
Only AI	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0
	COLOMBIA		**MEXICO**	
Skill type	2017-2022	2026	2017-2022	2026
Technical non-AI	95.7	85.8	90.2	84.6
Soft	45.6	67.6	56.5	73.0
AI	0.9	0.5	0.3	0.5
Skill combinations	2017-2022	2026	2017-2022	2026
Technical non-AI + Soft	54.2	53.0	46.4	57.2
Only Technical non- AI	40.6	32.2	43.4	26.9
Only Soft	4.3	14.2	9.8	15.4
Technical non-AI + Soft + AI	0.7	0.4	0.1	0.4
Technical non-AI + AI	0.2	0.1	0.3	0.1
Soft + AI	0.0	0.0	0.0	0.0
Only AI	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0

Source: Authors' calculation based on data from job portals.

Having provided an overview of the demand for the different skill categories, the following three sections turn to the requested competencies in each category: technical non-AI skills, soft skills, and AI-related skills. In particular, we examine the ten most frequently requested skill clusters and the twenty most demanded individual skills within each category. Consistent with the approach adopted throughout the paper, the analysis distinguishes between Workana and the remaining job portals, given their different coverage and labor market orientation.

5.2 | Technical non-AI skills

Table 6 presents the ten most frequently requested technical non-AI skill clusters for each country, separately for non-Workana and Workana portals. Despite some country-specific differences, the results reveal a remarkably consistent pattern across the four countries. In traditional job portals, the most frequently requested clusters can be grouped into four broad categories. The first comprises administrative and business-related competencies, including Office and Productivity Equipment and Technology—which ranks first in all four countries—together with Business Operations, Billing and Invoicing, and Business Management (particularly in Colombia). The second includes operational and production-related skills, such as Machinery and Quality Assurance and Control. A third group encompasses sales and commercial competencies, including General Sales Practices, Marketing Strategy and Techniques, and Customer Relationship Management (particularly in Brazil). Finally, Occupational Health and Safety emerges as an important cluster associated with regulatory compliance, ranking second in Brazil and Colombia, third in Mexico, and seventh in Argentina.

Only a few clusters depart from this predominantly administrative and operational profile. Software Development (fourth in Argentina) and Data Science (sixth in Brazil) are the only explicitly technology-oriented clusters to appear among the ten most frequently requested skills in traditional job portals, and they do so in only two of the four countries. Project Management, meanwhile, appears near the bottom of the top ten in Argentina and Mexico, reflecting a more transversal coordination function than a purely administrative competency.

Although the composition of the leading clusters is highly similar across countries, demand for technical non-AI skills is far from concentrated. Even the most frequently requested cluster—Office and Productivity Equipment and Technology—accounts for less than 10% of all technical skill mentions, ranging from 7.6% in Colombia to 9.3% in Mexico. This indicates a high degree of granularity in employers' technical skill requirements, with demand distributed across a broad set of specialized competencies rather than concentrated in a small number of clusters.

TABLE 6 Distribution of top ten technical non-AI clusters by portal and country. 2026

ARGENTINA			
Workana	**%**	**Non-Workana**	**%**
Writing and Editing	5.7%	Office and Productivity Equipment and Technology	8.2%
Office and Productivity Equipment and Technology	5.7%	Business Operations	2.6%
Graphic and Visual Design	4.4%	Machinery	2.4%
Digital Marketing	4.2%	Software Development	2.0%
Marketing Strategy and Techniques	3.7%	Quality Assurance and Control	1.8%
Graphic and Visual Design Software	3.3%	General Sales Practices	1.7%
Scripting Languages	3.3%	Project Management	1.7%
Web Design and Development	2.9%	Billing and Invoicing	1.7%
Photo/Video Production and Technology	2.7%	Occupational Health and Safety	1.6%
Animation and Game Design	2.2%	Marketing Strategy and Techniques	1.6%
BRAZIL			
Workana	**%**	**Non-Workana**	**%**
Graphic and Visual Design	6.0%	Office and Productivity Equipment and Technology	9.1%
Graphic and Visual Design Software	5.2%	Occupational Health and Safety	3.3%
Scripting Languages	4.7%	Machinery	2.3%
Web Design and Development	3.9%	Business Operations	2.1%
Writing and Editing	3.8%	General Sales Practices	2.0%
Digital Marketing	3.6%	Data Science	2.0%
Photo/Video Production and Technology	3.5%	Marketing Strategy and Techniques	1.9%
Animation and Game Design	3.1%	Language Competency	1.8%
Marketing Strategy and Techniques	3.1%	Food and Beverage	1.7%
Social Media	2.2%	Customer Relationship Management (CRM)	1.6%
COLOMBIA			
Workana	**%**	**Non-Workana**	**%**
Office and Productivity Equipment and Technology	6.1%	Office and Productivity Equipment and Technology	7.6%
Writing and Editing	5.6%	Occupational Health and Safety	2.9%
Graphic and Visual Design	4.5%	Machinery	2.9%
Digital Marketing	3.9%	Quality Assurance and Control	2.3%
Scripting Languages	3.4%	Billing and Invoicing	2.2%
Graphic and Visual Design Software	3.3%	General Sales Practices	2.0%
Marketing Strategy and Techniques	3.3%	Business Management	1.6%
Web Design and Development	3.2%	Telecommunications	1.6%
Photo/Video Production and Technology	2.4%	Food and Beverage	1.4%
Animation and Game Design	2.1%	Business Operations	1.4%
MEXICO			
Workana	**%**	**Non-Workana**	**%**
Writing and Editing	6.1%	Office and Productivity Equipment and Technology	9.2%
Office and Productivity Equipment and Technology	5.3%	General Sales Practices	3.2%
Graphic and Visual Design	4.8%	Occupational Health and Safety	2.4%
Digital Marketing	4.2%	Billing and Invoicing	1.9%
Graphic and Visual Design Software	3.6%	Business Operations	1.6%
Scripting Languages	3.4%	Quality Assurance and Control	1.6%
Marketing Strategy and Techniques	3.4%	Machinery	1.5%
Web Design and Development	3.2%	Project Management	1.3%
Photo/Video Production and Technology	2.3%	Marketing Strategy and Techniques	1.3%
Online Advertising	2.3%	Cash Management	1.3%

Source: Authors' calculation based on data from job portals.

Workana exhibits an equally strong degree of regional consistency. Eight of the ten most frequently requested technical clusters are virtually identical across the four countries, differing only in their ranking. Writing and Editing, Graphic and Visual Design (together with its associated software), Digital Marketing, Marketing Strategy and Techniques, Scripting Languages, Web Design and Development, and Photo and Video Production and Technology all appear among the top ten clusters in every country. Overall, these patterns point to a more digital and creative skill profile than that observed in traditional job portals, where administrative and operational competencies predominate. This difference seems to be consistent with the distinct occupational composition and labor market orientation of Workana.

However, Workana's skill profile is not entirely distinct from that observed in traditional job portals. Two of its most frequently requested clusters—Office and Productivity Equipment and Technology and Marketing Strategy and Techniques—also rank consistently among the leading technical competencies in non-Workana platforms. In Colombia, Office and Productivity Equipment and Technology is, in fact, the most frequently requested technical cluster in both segments. Thus, the contrast between a predominantly digital and creative profile (Workana) and a more administrative and operational profile (traditional job portals) should not be interpreted as a complete separation. Rather, both segments share a common foundation of office productivity and commercial competencies, upon which each develops its own distinctive set of technical requirements.

Finally, Workana also displays a high degree of granularity in technical skill demand. As in traditional job portals, even the most frequently requested cluster accounts for only about 6% of all technical skill mentions in each country, indicating that demand is spread across a wide range of specialized competencies rather than concentrated in a handful of dominant skills.

Examining individual skills (Tables 7 through 10) helps explain the composition of the leading clusters identified above. In traditional job portals, Microsoft Excel and Microsoft Office (which may or may not explicitly include Excel) are by far the most frequently requested technical skills in all four countries. Both belong to the Office and Productivity Equipment and Technology cluster, explaining why this cluster consistently ranks first across countries.

Finally, as mentioned above, among traditional job portals, the "Software Development" cluster appears in Argentina, while the "Data Science" cluster emerges in Brazil. However, in the case of Argentina, this result is driven by the aggregation of several specific skills within this category, each of which accounts for a relatively small share of postings. Consequently, none of these individual skills ranks among the twenty most frequently requested competencies. In Brazil, by contrast, "Informatics" ranks third among individual skills, explaining the relative importance of the "Data Science" cluster. This is the only case across the four countries in which an informatics- or systems-related skill appears among the top non-AI technical skills demanded on non-traditional portals.

Interestingly, Microsoft Excel also ranks among the top three skills in Workana (except in Brazil), indicating that it represents a cross-cutting skill across different types of job platforms. Marketing is another highly demanded non-AI technical skill on this platform in all four countries. In fact, when considered individually, it ranks first in Argentina and Mexico, even though the broader cluster to which it belongs—"Marketing Strategy and Techniques"—does not appear among the top four clusters. Closely related to this, "Social Media Marketing" (part of the "Digital Marketing" cluster) also shows a substantial presence.

The relevance of the "Graphic and Visual Design" cluster, in turn, is largely driven by the high prevalence of individual skills such as "Graphic Design", which ranks first in Brazil, second in Mexico, and third in Argentina and Colombia, in Workana. Related skills also contribute to the importance of this cluster, particularly "Adobe Illustrator" and "Adobe Photoshop", both belonging to the "Graphic and Visual Design Software" cluster. Finally, "Editing" is another relevant individual skill, ranking fourth in all countries except Brazil (where it still appears among the twenty most demanded skills), which contributes to the prominence of the "Writing and Editing" cluster.

Overall, the analysis of technical non-AI skills reveals clear differences in the type of competencies demanded across platform types, while also highlighting important areas of overlap. Traditional job portals are characterized by a strong demand for administrative, operational, and commercial skills, with office productivity tools, particularly Microsoft Office and Excel, occupying a central role across countries. In contrast, Workana exhibits a more digital and creative-oriented profile within the non-AI technical skill domain, with greater relevance of competencies related to graphic design, digital marketing, web development, and content production. Nevertheless, these two segments are not fully separated, as they share a common foundation of transversal skills, particularly those related to productivity tools and marketing. Finally, the relatively low concentration of demand across skill clusters in both types of platforms indicates that employers' technical requirements are highly diverse, suggesting that jobs rely on combinations of complementary skills rather than on a single dominant competency.

5.3 | Soft skills

The second most important skill category, as discussed above, corresponds to soft skills. As in the previous section, Table 11 presents the ten most frequently requested soft skill clusters, while Table 12 reports the most demanded individual skills within this category.

Compared with technical non-AI skills, the distribution of soft skills is considerably less dispersed, with the leading clusters accounting for a much larger share of total soft skill mentions. This concentration is particularly pronounced in Workana, where demand is more heavily concentrated than in traditional job portals.

A striking finding is the overwhelming importance of the Personal Attributes cluster, which ranks first in every country and across both types of platforms. In non-Workana portals, this cluster accounts for between 27% and nearly 47.4% of all requested soft skills, while in Workana its share rises even further, ranging from approximately 47 % to 56%.

Despite this common dominance, the specific competencies underlying the Personal Attributes cluster differ systematically across platform types. In Workana, employers place greater emphasis on attributes associated with autonomous and project-based work, including organizational skills, the ability to work quickly, attention to detail, creativity, preparedness, professionalism, trustworthiness, the ability to follow directions, mental agility, and the capacity to work without supervision. By contrast, although organizational skills, attention to detail, mental agility, professionalism, and trustworthiness also rank highly in traditional job portals, greater importance is assigned to attributes such as a strong work ethic, willingness to learn, hospitality, politeness, and sales acumen.

These differences are consistent with the distinct nature of work performed through each type of platform. The prominence of creativity, preparedness, and the ability to work independently in Workana reflects the characteristics of freelance, project-based work, where workers are expected to organize their own activities, meet deadlines, and deliver outputs with limited supervision while adapting to clients' requirements. In contrast, the stronger emphasis on work ethic, willingness to learn, hospitality, politeness, and sales-related abilities in traditional job portals suggests greater importance of competencies that facilitate integration into organizational settings and interactions with colleagues and customers.

TABLE 7 Distribution of top 20 technical non-AI skills by portal and country. 2026

ARGENTINA — Workana			ARGENTINA — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Marketing	Marketing Strategy and Techniques	2.8%	Microsoft Excel	Office and Productivity Equipment and Technology	3.8%
Microsoft Excel	Office and Productivity Equipment and Technology	2.8%	Microsoft Office	Office and Productivity Equipment and Technology	2.9%
Graphic Design	Graphic and Visual Design	2.3%	Billing	Billing and Invoicing	1.6%
Editing	Writing and Editing	1.9%	Management Systems	Business Operations	1.4%
Language Translation	Language Interpretation, Translation, and Studies	1.6%	Marketing	Marketing Strategy and Techniques	1.3%
Social Media Marketing	Digital Marketing	1.6%	Customer Relationship Management	Customer Relationship Management (CRM)	1.2%
JavaScript (Programming Language)	Scripting Languages	1.4%	Machinery	Machinery	1.1%
Adobe Photoshop	Graphic and Visual Design Software	1.4%	Quality Policy	Quality Assurance and Control	1.0%
Video Editing	Photo/Video Production and Technology	1.3%	Electricity	Basic Electrical Systems	0.8%
Transcribing	Dictation	1.2%	Blueprint Reading	Drafting and Engineering Design	0.7%
Adobe Illustrator	Graphic and Visual Design Software	1.1%	Safety Standards	Occupational Health and Safety	0.7%
HyperText Markup Language (HTML)	Web Design and Development	1.1%	Enterprise Resource Planning	Business Operations	0.7%
Lead Generation	Prospecting and Qualification	1.1%	Liquidation	Specialized Accounting	0.6%
Facebook	Social Media	1.0%	SAP Applications	Business Solutions	0.6%
Financial Analysis	Financial Analysis	1.0%	E-Tools	Project Management	0.6%
Microsoft Word	Office and Productivity Equipment and Technology	1.0%	Closing (Sales)	General Sales Practices	0.5%
AutoCAD	Engineering Software	1.0%	Commercial Management	Business Management	0.5%
PHP (Scripting Language)	Scripting Languages	0.9%	Microsoft Word	Office and Productivity Equipment and Technology	0.5%
Branding	Brand Management	0.9%	Plumbing	Plumbing	0.5%
Facebook Advertising	Online Advertising	0.9%	Electromechanics	Electromechanical Engineering	0.5%

Source: Authors' calculation based on data from job portals.

TABLE 8 Distribution of top 20 technical non-AI skills by portal and country. 2026 (continued)

BRAZIL — Workana			BRAZIL — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Graphic Design	Graphic and Visual Design	3.4%	Microsoft Office	Office and Productivity Equipment and Technology	3.8%
Adobe Photoshop	Graphic and Visual Design Software	2.3%	Microsoft Excel	Office and Productivity Equipment and Technology	3.6%
Marketing	Marketing Strategy and Techniques	2.2%	Informatics	Data Science	1.8%
JavaScript (Programming Language)	Scripting Languages	2.0%	Safety Standards	Occupational Health and Safety	1.6%
Adobe Illustrator	Graphic and Visual Design Software	1.9%	English Language	Language Competency	1.4%
Video Editing	Photo/Video Production and Technology	1.7%	Customer Relationship Management	Customer Relationship Management (CRM)	1.2%
HyperText Markup Language (HTML)	Web Design and Development	1.4%	Marketing	Marketing Strategy and Techniques	1.2%
Social Media Marketing	Digital Marketing	1.3%	Machinery	Machinery	1.0%
PHP (Scripting Language)	Scripting Languages	1.3%	Enterprise Resource Planning	Business Operations	1.0%
Motion Graphics	Animation and Game Design	1.2%	Quality Policy	Quality Assurance and Control	0.7%
Python (Programming Language)	Scripting Languages	1.2%	Microsoft Word	Office and Productivity Equipment and Technology	0.6%
MySQL	Databases	1.1%	Management Systems	Business Operations	0.6%
Lead Generation	Prospecting and Qualification	1.0%	Food Security	Food and Beverage	0.5%
Adobe After Effects	Animation and Game Design	1.0%	Workforce Management	People Management	0.5%
Video Production	Photo/Video Production and Technology	0.9%	Analytics	Data Analysis	0.4%
Responsive Web Design	Web Design and Development	0.9%	Housekeeping	Cleaning and Janitorial Services	0.4%
Editing	Writing and Editing	0.9%	SAP Applications	Business Solutions	0.4%
Facebook	Social Media	0.8%	Plumbing	Plumbing	0.4%
Microsoft Excel	Office and Productivity Equipment and Technology	0.8%	Closing (Sales)	General Sales Practices	0.4%
Facebook Advertising	Online Advertising	0.8%	Cashier Balancing	Cash Register Operation	0.4%

Source: Authors' calculation based on data from job portals.

TABLE 9 Distribution of top 20 technical non-AI skills by portal and country. 2026 (continued)

COLOMBIA — Workana			COLOMBIA — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Microsoft Excel	Office and Productivity Equipment and Technology	3.0%	Microsoft Excel	Office and Productivity Equipment and Technology	4.4%
Marketing	Marketing Strategy and Techniques	2.4%	Billing	Billing and Invoicing	1.9%
Graphic Design	Graphic and Visual Design	2.4%	Microsoft Office	Office and Productivity Equipment and Technology	1.6%
Editing	Writing and Editing	1.8%	Machinery	Machinery	1.4%
Language Translation	Language Interpretation, Translation, and Studies	1.6%	Telecommunications	Telecommunications	1.4%
JavaScript (Programming Language)	Scripting Languages	1.5%	Quality Policy	Quality Assurance and Control	1.3%
Transcribing	Dictation	1.4%	Safety Standards	Occupational Health and Safety	1.0%
Adobe Photoshop	Graphic and Visual Design Software	1.4%	Commercial Management	Business Management	1.0%
Social Media Marketing	Digital Marketing	1.3%	Electricity	Basic Electrical Systems	0.8%
Adobe Illustrator	Graphic and Visual Design Software	1.3%	Call Center Experience	Customer Service	0.8%
AutoCAD	Engineering Software	1.2%	Occupational Safety and Health	Occupational Health and Safety	0.7%
Financial Analysis	Financial Analysis	1.1%	Cashiering	Cash Register Operation	0.7%
HyperText Markup Language (HTML)	Web Design and Development	1.1%	Customer Relationship Management	Customer Relationship Management (CRM)	0.7%
Video Editing	Photo/Video Production and Technology	1.1%	Microsoft Word	Office and Productivity Equipment and Technology	0.7%
Facebook	Social Media	1.1%	Closing (Sales)	General Sales Practices	0.7%
Microsoft Word	Office and Productivity Equipment and Technology	1.1%	SAP Applications	Business Solutions	0.6%
Typing	Basic Technical Knowledge	1.0%	Marketing	Marketing Strategy and Techniques	0.5%
PHP (Scripting Language)	Scripting Languages	0.9%	Enterprise Resource Planning	Business Operations	0.5%
Lead Generation	Prospecting and Qualification	0.9%	Analytics	Data Analysis	0.5%
Python (Programming Language)	Scripting Languages	0.8%	Sales Management	Sales Management	0.5%

Source: Authors' calculation based on data from job portals.

TABLE 10 Distribution of top 20 technical non-AI skills by portal and country. 2026 (continued)

MEXICO — Workana			MEXICO — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Marketing	Marketing Strategy and Techniques	2.5%	Microsoft Excel	Office and Productivity Equipment and Technology	4.4%
Graphic Design	Graphic and Visual Design	2.4%	Microsoft Office	Office and Productivity Equipment and Technology	3.3%
Microsoft Excel	Office and Productivity Equipment and Technology	2.3%	Closing (Sales)	General Sales Practices	1.8%
Editing	Writing and Editing	1.9%	Billing	Billing and Invoicing	1.7%
JavaScript (Programming Language)	Scripting Languages	1.6%	Safety Standards	Occupational Health and Safety	1.2%
Adobe Photoshop	Graphic and Visual Design Software	1.5%	Marketing	Marketing Strategy and Techniques	1.0%
Social Media Marketing	Digital Marketing	1.4%	Customer Relationship Management	Customer Relationship Management (CRM)	1.0%
Microsoft Word	Office and Productivity Equipment and Technology	1.4%	Cash Handling	Cash Management	1.0%
Adobe Illustrator	Graphic and Visual Design Software	1.3%	Telecommunications	Telecommunications	0.9%
Language Translation	Language Interpretation, Translation, and Studies	1.3%	Enterprise Resource Planning	Business Operations	0.9%
Transcribing	Dictation	1.3%	Quality Policy	Quality Assurance and Control	0.8%
HyperText Markup Language (HTML)	Web Design and Development	1.1%	SAP Applications	Business Solutions	0.8%
Lead Generation	Prospecting and Qualification	1.1%	Electricity	Basic Electrical Systems	0.7%
Facebook	Social Media	1.1%	Machinery	Machinery	0.7%
Video Editing	Photo/Video Production and Technology	1.1%	Microsoft Word	Office and Productivity Equipment and Technology	0.6%
Typing	Basic Technical Knowledge	1.1%	Financial Services	General Finance	0.6%
PHP (Scripting Language)	Scripting Languages	1.0%	Workforce Management	People Management	0.6%
Facebook Advertising	Online Advertising	0.9%	KPI Reporting	Business Analysis	0.6%
MySQL	Databases	0.9%	Talent Attraction	Recruitment	0.6%
Digital Marketing	Digital Marketing	0.8%	Overcoming Objections	Company, Product, and Service Knowledge	0.6%

Source: Authors' calculation based on data from job portals.

TABLE 11 Distribution of top ten soft skill clusters by portal and country. 2026

ARGENTINA			
Workana	**%**	**Non-Workana**	**%**
Personal Attributes	47.0%	Personal Attributes	30.0%
Initiative and Leadership	19.8%	Initiative and Leadership	23.8%
Communication	18.7%	Communication	16.5%
Customer Service	6.4%	Social Skills	10.9%
Critical Thinking and Problem Solving	3.1%	Critical Thinking and Problem Solving	6.4%
Labor Compliance	1.4%	Contract Management	4.3%
Contract Management	0.8%	People Management	2.8%
Quality Assurance and Control	0.8%	Customer Service	1.9%
Social Skills	0.5%	Business Intelligence	1.8%
People Management	0.4%	Labor Compliance	0.5%
BRAZIL			
Workana	**%**	**Non-Workana**	**%**
Personal Attributes	56.0%	Personal Attributes	47.4%
Communication	17.8%	Initiative and Leadership	18.6%
Initiative and Leadership	14.4%	Communication	16.8%
Critical Thinking and Problem Solving	4.3%	Social Skills	6.0%
Customer Service	3.2%	Contract Management	3.9%
Contract Management	1.1%	Critical Thinking and Problem Solving	2.8%
Social Skills	0.8%	People Management	1.3%
People Management	0.6%	Customer Service	0.8%
Labor Compliance	0.6%	Process Improvement and Optimization	0.6%
Project Management	0.2%	Labor Compliance	0.4%
COLOMBIA			
Workana	**%**	**Non-Workana**	**%**
Personal Attributes	47.0%	Personal Attributes	26.9%
Initiative and Leadership	18.9%	Initiative and Leadership	20.3%
Communication	17.4%	Communication	16.1%
Customer Service	7.5%	Customer Service	12.3%
Critical Thinking and Problem Solving	3.3%	Social Skills	10.4%
Labor Compliance	1.6%	Critical Thinking and Problem Solving	5.1%
Contract Management	0.9%	Contract Management	3.4%
Social Skills	0.9%	People Management	2.4%
People Management	0.6%	Business Intelligence	1.5%
Teaching and Training	0.6%	Labor Compliance	0.6%
MEXICO			
Workana	**%**	**Non-Workana**	**%**
Personal Attributes	50.7%	Personal Attributes	26.6%
Communication	18.3%	Initiative and Leadership	26.3%
Initiative and Leadership	18.0%	Communication	16.2%
Customer Service	5.4%	Social Skills	9.7%
Critical Thinking and Problem Solving	2.6%	Customer Service	5.5%
Labor Compliance	1.5%	Contract Management	5.2%
Contract Management	0.9%	Critical Thinking and Problem Solving	4.5%
Quality Assurance and Control	0.7%	People Management	3.1%
Social Skills	0.5%	Business Intelligence	1.1%
People Management	0.4%	Labor Compliance	0.7%

Source: Authors' calculation based on data from job portals.

The Initiative and Leadership cluster ranks second in non-Workana portals across all four countries and also occupies a prominent position in Workana, ranking second in

Argentina and Colombia and third in Brazil and Mexico. As with the Personal Attributes cluster, some differences emerge in the underlying competencies, although they are less pronounced. In both types of platforms, employers consistently value proactive behavior, accountability, goal orientation, decision-making, and punctuality, suggesting that these competencies are broadly valued regardless of the employment arrangement. However, Workana places relatively greater emphasis on time management and entrepreneurship, reflecting the importance of self-management and the ability to independently organize work in freelance settings. By contrast, traditional job portals assign somewhat greater importance to leadership and planning, competencies that are more closely associated with coordination and career development within organizational structures.

The Communication cluster ranks among the three most frequently requested soft skill clusters in both Workana and non-Workana portals across all four countries. In particular, effective communication consistently ranks among the most frequently requested individual soft skills, suggesting that it is a cross-cutting competency valued across occupations and labor market segments, regardless of the type of job platform.

Another noteworthy difference concerns the Social Skills cluster, which ranks fourth among the most demanded soft skill clusters in non-Workana portals but occupies a considerably lower position in Workana. This pattern is consistent with the different work arrangements typically associated with each type of platform. Jobs advertised in traditional portals are more likely to involve continuous interaction with colleagues, supervisors, and customers within organizational settings, making interpersonal competencies particularly valuable. Accordingly, the prominence of this cluster in non-Workana portals is driven by skills such as teamwork, friendliness, and rapport building, all of which appear among the twenty most frequently requested individual soft skills. In contrast, these competencies do not rank among the top twenty individual skills in Workana, reflecting their comparatively lower demand.

A similar pattern emerges for the People Management cluster, which consistently ranks higher in non-Workana portals than in Workana, where it occupies the bottom positions of the top ten clusters. This difference is largely explained by the prominence of team management, which is more frequently requested in traditional job portals. The result is consistent with the fact that such competencies are less frequently required in Workana, where work is generally organized around individual tasks or project-based assignments rather than the management of permanent work teams.

The opposite pattern is observed for the Critical Thinking and Problem Solving cluster, which is more prominent in Workana than in non-Workana portals. In Workana, this cluster is primarily driven by strategic planning and analytical thinking, which rank among the most frequently requested individual skills. By contrast, in traditional job portals the cluster is mainly represented by analytical thinking and problem solving, although with a comparatively lower relative importance. This pattern suggests that postings in Workana place greater emphasis on higher-order cognitive competencies associated with independently analyzing problems, developing solutions, and planning tasks, whereas such competencies, while still valued in traditional job portals, play a less prominent role within the overall profile of requested soft skills.

More broadly, these results suggest that the distinction between Workana and non-Workana job portals extends beyond differences in technical skill requirements and also shapes the type of soft skills employers seek. While some competencies—particularly Personal Attributes, Initiative and Leadership, and Communication—are consistently valued across both types of platforms, important differences emerge in the specific dimensions that employers emphasize. Traditional job portals place greater importance on competencies that facilitate integration into organizational settings and interactions with colleagues and customers, including teamwork, people management, hospitality, politeness, and other interpersonal skills. By contrast, Workana places relatively greater emphasis on competencies associated with autonomy, self-management, creativity, strategic planning, and analytical thinking, reflecting the importance of independently organizing work, managing tasks, and delivering outputs. Overall, the evidence indicates that, although a common core of soft skills is valued across labor market segments, each type of platform places additional emphasis on those competencies that are most closely aligned with its predominant work organization and job requirements. Consequently, differences in soft skill demand seem to reflect not only differences in occupational composition but also the distinct ways in which work is organized across labor market segments.

5.4 | AI-related skills

As documented above, AI-related skills represent a very small share of total postings across the four countries (between 0.5% and 2.6% in the current period). Within this generally low incidence, Workana systematically shows a higher share than traditional portals—approximately 2.8 times higher in Argentina, and between 12 and 14 times higher in Brazil, Colombia and Mexico.

At the cluster level (see Table 16), the composition of AI demand is remarkably homogeneous, both across countries and across portal types. In Workana, the generic Artificial Intelligence cluster ranks first in all four countries without exception, followed by AI Agents, Machine Learning, Natural Language Processing and Generative AI—the latter two occupying positions 4 and 5, identical across all four countries. In non-Workana portals, four of these five clusters dominate the top 5-6, although with greater variation in internal ordering: Argentina is the only country where Machine Learning surpasses the generic Artificial Intelligence cluster for first place, whereas in the other three countries that generic cluster leads. In both portal types, and in all four countries without exception, the clusters AI Ethics, Governance, and Regulations and Robotics/Autonomous driving occupy the lowest positions in the ranking.

Unlike what is observed for technical non-AI skills and soft skills, where Workana and non-Workana portals exhibit clearly differentiated sets of clusters, in the case of AI both portal types share essentially the same set of dominant clusters, with only minor variation in internal ordering— suggesting that, at the level of aggregate clusters, there is no substantive difference across platforms in the type of AI demanded.

TABLE 12 Distribution of top 20 soft skills by portal and country. 2026

ARGENTINA — Workana			ARGENTINA — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Effective Communication	Communication	13.5%	Effective Communication	Communication	12.2%
Detail Oriented	Personal Attributes	13.0%	Teamwork	Social Skills	6.6%
Working Quickly	Personal Attributes	12.0%	Proactivity	Initiative and Leadership	6.3%
Proactivity	Initiative and Leadership	7.6%	Accountability	Initiative and Leadership	4.8%
Organizational Skills	Personal Attributes	6.9%	Bargaining	Contract Management	4.3%
Customer Service	Customer Service	6.4%	Organizational Skills	Personal Attributes	4.1%
Creativity	Personal Attributes	4.8%	Leadership	Initiative and Leadership	4.0%
Collaboration	Communication	4.4%	Unsupervised Work	Personal Attributes	3.9%
Time Management	Initiative and Leadership	4.3%	Sales Acumen	Personal Attributes	3.6%
Trustworthiness	Personal Attributes	1.8%	Collaboration	Communication	3.2%
Punctuality	Initiative and Leadership	1.7%	Working Quickly	Personal Attributes	3.2%
Confidentiality	Labor Compliance	1.4%	Analytical Thinking	Critical Thinking and Problem Solving	3.1%
Entrepreneurship	Initiative and Leadership	1.3%	Detail Oriented	Personal Attributes	3.1%
Strategic Planning	Critical Thinking and Problem Solving	1.2%	Goal-Oriented	Initiative and Leadership	2.2%
Accountability	Initiative and Leadership	1.2%	Problem Solving	Critical Thinking and Problem Solving	2.1%
Unsupervised Work	Personal Attributes	1.1%	Decision Making	Initiative and Leadership	2.0%
Mental Agility	Personal Attributes	1.0%	Customer Service	Customer Service	1.8%
Analytical Thinking	Critical Thinking and Problem Solving	0.9%	Customer Centricity	Business Intelligence	1.8%
Professionalism	Personal Attributes	0.9%	Rapport Building	Social Skills	1.5%
Bargaining	Contract Management	0.8%	Team Management	People Management	1.3%

Source: Authors' calculation based on data from job portals.

TABLE 13 Distribution of top 20 soft skills by portal and country. 2026 (continued)

BRAZIL — Workana			BRAZIL — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Effective Communication	Communication	14.2%	Organizational Skills	Personal Attributes	20.9%
Organizational Skills	Personal Attributes	12.8%	Effective Communication	Communication	13.9%
Working Quickly	Personal Attributes	12.4%	Accountability	Initiative and Leadership	4.0%
Detail Oriented	Personal Attributes	8.5%	Mental Agility	Personal Attributes	4.0%
Creativity	Personal Attributes	4.9%	Detail Oriented	Personal Attributes	4.0%
Proactivity	Initiative and Leadership	3.9%	Proactivity	Initiative and Leadership	3.9%
Mental Agility	Personal Attributes	3.3%	Bargaining	Contract Management	3.9%
Preparedness	Personal Attributes	3.3%	Leadership	Initiative and Leadership	3.1%
Customer Service	Customer Service	3.2%	Strong Work Ethic	Personal Attributes	3.1%
Collaboration	Communication	2.6%	Working Quickly	Personal Attributes	2.7%
Strategic Planning	Critical Thinking and Problem Solving	2.4%	Teamwork	Social Skills	2.7%
Time Management	Initiative and Leadership	2.3%	Goal-Oriented	Initiative and Leadership	2.6%
Professionalism	Personal Attributes	2.2%	Collaboration	Communication	2.3%
Accountability	Initiative and Leadership	1.7%	Willingness To Learn	Personal Attributes	2.0%
Trustworthiness	Personal Attributes	1.7%	Friendliness	Social Skills	1.9%
Goal-Oriented	Initiative and Leadership	1.5%	Trustworthiness	Personal Attributes	1.7%
Punctuality	Initiative and Leadership	1.4%	Professionalism	Personal Attributes	1.3%
Bargaining	Contract Management	1.1%	Analytical Thinking	Critical Thinking and Problem Solving	1.1%
Analytical Thinking	Critical Thinking and Problem Solving	1.0%	Punctuality	Initiative and Leadership	1.1%
Visionary	Initiative and Leadership	1.0%	Unsupervised Work	Personal Attributes	1.0%

Source: Authors' calculation based on data from job portals.

TABLE 14 Distribution of top 20 soft skills by portal and country. 2026 (continued)

COLOMBIA — Workana			COLOMBIA — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Detail Oriented	Personal Attributes	12.9%	Effective Communication	Communication	12.6%
Effective Communication	Communication	12.6%	Customer Service	Customer Service	12.3%
Working Quickly	Personal Attributes	12.5%	Teamwork	Social Skills	7.8%
Customer Service	Customer Service	7.5%	Detail Oriented	Personal Attributes	4.5%
Proactivity	Initiative and Leadership	7.2%	Leadership	Initiative and Leadership	4.0%
Organizational Skills	Personal Attributes	6.5%	Accountability	Initiative and Leadership	3.9%
Creativity	Personal Attributes	4.4%	Goal-Oriented	Initiative and Leadership	3.8%
Time Management	Initiative and Leadership	4.0%	Bargaining	Contract Management	3.4%
Collaboration	Communication	3.8%	Working Quickly	Personal Attributes	3.3%
Trustworthiness	Personal Attributes	2.1%	Proactivity	Initiative and Leadership	2.8%
Punctuality	Initiative and Leadership	1.7%	Sales Acumen	Personal Attributes	2.7%
Confidentiality	Labor Compliance	1.6%	Hospitality	Personal Attributes	2.4%
Accountability	Initiative and Leadership	1.1%	Analytical Thinking	Critical Thinking and Problem Solving	2.3%
Strategic Planning	Critical Thinking and Problem Solving	1.0%	Collaboration	Communication	1.9%
Professionalism	Personal Attributes	1.0%	Willingness To Learn	Personal Attributes	1.7%
Analytical Thinking	Critical Thinking and Problem Solving	0.9%	Decision Making	Initiative and Leadership	1.6%
Entrepreneurship	Initiative and Leadership	0.9%	Team Management	People Management	1.5%
Decision Making	Initiative and Leadership	0.9%	Customer Centricity	Business Intelligence	1.5%
Bargaining	Contract Management	0.9%	Planning	Initiative and Leadership	1.5%
Mental Agility	Personal Attributes	0.9%	Mental Agility	Personal Attributes	1.5%

Source: Authors' calculation based on data from job portals.

TABLE 15 Distribution of top 20 soft skills by portal and country. 2026 (continued)

MEXICO — Workana			MEXICO — Non-Workana		
Skill	**Cluster**	**%**	**Skill**	**Cluster**	**%**
Detail Oriented	Personal Attributes	15.4%	Effective Communication	Communication	13.0%
Working Quickly	Personal Attributes	13.1%	Teamwork	Social Skills	7.6%
Effective Communication	Communication	12.8%	Punctuality	Initiative and Leadership	6.4%
Organizational Skills	Personal Attributes	6.4%	Customer Service	Customer Service	5.5%
Proactivity	Initiative and Leadership	6.3%	Bargaining	Contract Management	5.2%
Customer Service	Customer Service	5.4%	Accountability	Initiative and Leadership	4.8%
Creativity	Personal Attributes	5.1%	Hospitality	Personal Attributes	4.7%
Collaboration	Communication	4.5%	Proactivity	Initiative and Leadership	3.9%
Time Management	Initiative and Leadership	4.1%	Leadership	Initiative and Leadership	3.7%
Punctuality	Initiative and Leadership	2.3%	Working Quickly	Personal Attributes	3.5%
Trustworthiness	Personal Attributes	2.1%	Goal-Oriented	Initiative and Leadership	3.4%
Confidentiality	Labor Compliance	1.5%	Detail Oriented	Personal Attributes	2.5%
Professionalism	Personal Attributes	1.2%	Collaboration	Communication	2.5%
Accountability	Initiative and Leadership	1.1%	Problem Solving	Critical Thinking and Problem Solving	2.0%
Bargaining	Contract Management	0.9%	Team Management	People Management	2.0%
Decision Making	Initiative and Leadership	0.9%	Organizational Skills	Personal Attributes	1.9%
Strategic Planning	Critical Thinking and Problem Solving	0.9%	Analytical Thinking	Critical Thinking and Problem Solving	1.6%
Following Directions	Personal Attributes	0.8%	Decision Making	Initiative and Leadership	1.6%
Analytical Thinking	Critical Thinking and Problem Solving	0.8%	Willingness To Learn	Personal Attributes	1.5%
Quality Driven	Quality Assurance and Control	0.7%	Politeness	Personal Attributes	1.4%

Source: Authors' calculation based on data from job portals.

TABLE 16 Distribution of top ten AI skill clusters by portal and country. 2026

ARGENTINA			
Workana	**%**	**Non-Workana**	**%**
Artificial Intelligence	41.1%	Machine Learning	27.5%
AI Agents	21.9%	AI Agents	22.5%
Machine Learning	18.7%	Artificial Intelligence	18.9%
Natural Language Processing	10.4%	Generative AI	16.3%
Generative AI	5.2%	Neural Networks	10.2%
Neural Networks	1.1%	Natural Language Processing	3.5%
Visual Image Recognition	0.9%	Visual Image Recognition	0.4%
Autonomous driving	0.6%	Robotics	0.3%
AI Ethics, Governance, and Regulations	0.1%	Autonomous driving	0.2%
		AI Ethics, Governance, and Regulations	0.2%
BRAZIL			
Workana	**%**	**Non-Workana**	**%**
Artificial Intelligence	37.3%	Artificial Intelligence	41.7%
Machine Learning	21.0%	Machine Learning	22.6%
AI Agents	20.9%	AI Agents	16.0%
Natural Language Processing	14.5%	Generative AI	12.1%
Generative AI	4.6%	Visual Image Recognition	2.3%
Neural Networks	0.5%	Natural Language Processing	2.1%
Autonomous driving	0.5%	Neural Networks	1.9%
Visual Image Recognition	0.5%	Autonomous driving	0.7%
Robotics	0.1%	Robotics	0.5%
AI Ethics, Governance, and Regulations	0.1%	AI Ethics, Governance, and Regulations	0.1%
COLOMBIA			
Workana	**%**	**Non-Workana**	**%**
Artificial Intelligence	39.0%	Artificial Intelligence	44.1%
AI Agents	21.7%	Machine Learning	16.7%
Machine Learning	21.5%	Generative AI	15.0%
Natural Language Processing	10.1%	AI Agents	14.8%
Generative AI	4.5%	Neural Networks	3.8%
Visual Image Recognition	1.1%	Natural Language Processing	2.6%
Autonomous driving	1.0%	Autonomous driving	1.9%
Neural Networks	0.8%	Visual Image Recognition	0.8%
Robotics	0.3%	Robotics	0.2%
		AI Ethics, Governance, and Regulations	0.1%
MEXICO			
Workana	**%**	**Non-Workana**	**%**
Artificial Intelligence	37.5%	Artificial Intelligence	46.8%
AI Agents	23.5%	Machine Learning	17.3%
Machine Learning	18.4%	AI Agents	12.9%
Natural Language Processing	11.2%	Generative AI	12.7%
Generative AI	6.4%	Autonomous driving	3.1%
Visual Image Recognition	1.4%	Natural Language Processing	3.1%
Neural Networks	0.6%	Visual Image Recognition	2.0%
Autonomous driving	0.4%	Neural Networks	1.0%
AI Ethics, Governance, and Regulations	0.4%	Robotics	0.9%
Robotics	0.2%	AI Ethics, Governance, and Regulations	0.4%

Source: Authors' calculation based on data from job portals.

A second distinctive feature of AI-related skills is their much higher degree of concentration. Unlike what is observed for technical non-AI skills—where even the leading cluster accounted for a relatively small share of the total (8%-9%), reflecting highly granular demand distributed across numerous specific clusters—AI demand is, similarly to soft skills, considerably more concentrated: the top four clusters (Artificial Intelligence, AI Agents, Machine Learning and Natural Language Processing/Generative AI, depending on each country's ordering) jointly account for more than 90% of all AI-related mentions. This suggests that, while demand for technical non-AI skills is spread across a wide diversity of specific categories, both soft skills and AI skills are concentrated in a narrow core of clusters that is broadly shared across countries and portals.

Additionally, in Workana, the top 5-6 AI skills are dominated, across all four countries, by a set of broad, generic terms (Artificial Intelligence, Machine Learning, Chatbot, Natural Language Processing, and ChatGPT). In non-Workana portals, the remainder of the top 20—beyond these generic competencies—includes a wider variety of specific technical tools, such as TensorFlow, Deep Learning, Retrieval-Augmented Generation, MLOps, LangChain, Prompt Engineering, Scikit-Learn, and Google Gemini, together with country-specific cases such as LangGraph, CrewAI, AutoGen, PineCone, and Weaviate in Argentina, or GitHub Copilot in Mexico (see Table 17).

Overall, these findings suggest that AI-related skill demand is characterized not only by its limited incidence but also by a relatively low degree of specialization. Most requested AI skills correspond to broad AI competencies rather than specific tools or frameworks. In Workana, only between four and six of the twenty most frequently requested AI skills refer to specific technologies, while in non-Workana portals the corresponding number ranges between seven and ten. Thus, even among the relatively small number of postings requiring AI-related skills, demand remains concentrated primarily on general AI competencies rather than on specialized technical applications.

6 | RESULTS II: SKILL DEMAND BY TYPE AND OCCUPATION

The previous section documented broad patterns in skill demand across countries and skill categories. This section examines whether these patterns are shared across occupations or instead reflect occupation-specific skill requirements. The analysis is restricted to the two-digit ISCO-08 occupational groups that account for the largest shares of employment in the four countries under study. Rather than providing a comprehensive description of occupational skill demand, the objective is to assess the extent to which the aggregate findings discussed above remain consistent across occupations or are driven by specific occupational groups. To facilitate cross-country comparisons, the discussion focuses on the five most frequently requested skills within each skill category—technical non-AI, soft and AI-related skills—for each occupational group. Table 21 summarizes the results. Additionally, a brief analysis of each occupational group's possible exposure to AI replacement is provided.

| Management and professional occupations (ISCO 11, 21-26)

A first striking result is the extent to which technical non-AI skills closely align with the functional content traditionally associated with each occupational group. Managers (ISCO 11) are characterized by business-oriented technical competencies, including Marketing, Management Systems and Microsoft Excel, reflecting the analytical, organizational and commercial dimensions of managerial work. Science and engineering professionals (ISCO 21) display engineering-specific skills including AutoCAD, Civil Engineering, Electromechanics and Mechatronics. Health professionals (ISCO 22) are associated with Medical Records, Clinical Auditing, Therapeutic Ultrasound and Basic Life Support; teaching pro-

TABLE 17 Distribution of top 20 AI skills by portal and country. 2026

ARGENTINA — Workana				ARGENTINA — Non-Workana			
Skill	**Cluster**	**Type**	**%**	**Skill**	**Cluster**	**Type**	**%**
Artificial Intelligence	Artificial Intelligence	Generic	38.7%	Artificial Intelligence	Artificial Intelligence	Generic	10.3%
Machine Learning	Machine Learning	Generic	16.0%	Langgraph	AI Agents	Specific	7.9%
Chatbot	AI Agents	Generic	13.2%	TensorFlow	Neural Networks	Specific	7.6%
Natural Language Processing (NLP)	Natural Language Processing	Generic	6.4%	LangChain	AI Agents	Specific	6.7%
ChatGPT	AI Agents	Generic	5.5%	Deep Learning	Neural Networks	Specific	6.6%
TensorFlow	Neural Networks	Specific	1.9%	Generative Artificial Intelligence	Generative AI	Generic	6.2%
Optical Character Recognition (OCR)	Natural Language Processing	Generic	1.7%	Keras (Neural Network Library)	Neural Networks	Specific	6.2%
AI Agents	AI Agents	Generic	1.4%	Retrieval Augmented Generation	Generative AI	Specific	5.4%
Adobe Sensei	Generative AI	Generic	1.1%	PyTorch (Machine Learning Library)	Machine Learning	Specific	3.9%
Retrieval Augmented Generation	Generative AI	Specific	1.1%	MLOps (Machine Learning Operations)	Machine Learning	Specific	3.7%
Google Gemini	Generative AI	Specific	0.8%	CrewAI	AI Agents	Specific	3.2%
Generative Artificial Intelligence	Generative AI	Generic	0.7%	AutoGen	Machine Learning	Specific	3.2%
Language Models	Natural Language Processing	Generic	0.7%	Language Models	Natural Language Processing	Generic	2.9%
Conversational AI	AI Agents	Generic	0.7%	Machine Learning	Machine Learning	Generic	2.4%
OpenCV	Autonomous driving	Specific	0.6%	PineCone	Artificial Intelligence	Specific	2.2%
Computer Vision	Visual Image Recognition	Generic	0.6%	Weaviate	Artificial Intelligence	Specific	2.2%
Large Language Modeling	Generative AI	Generic	0.5%	Artificial Intelligence Systems	Artificial Intelligence	Generic	1.8%
Machine Translation	Natural Language Processing	Generic	0.4%	Google Gemini	Generative AI	Specific	1.5%
Automation Systems	Artificial Intelligence	Generic	0.4%	Text to Speech (TTS)	Generative AI	Specific	1.4%
Artificial Intelligence Development	Artificial Intelligence	Generic	0.4%	ChatGPT	AI Agents	Generic	1.3%

Source: Authors' calculation based on data from job portals.

TABLE 18 Distribution of top 20 AI skills by portal and country. 2026 (continued)

BRAZIL — Workana				BRAZIL — Non-Workana			
Skill	**Cluster**	**Type**	**%**	**Skill**	**Cluster**	**Type**	**%**
Artificial Intelligence	Artificial Intelligence	Generic	34.3%	Artificial Intelligence	Artificial Intelligence	Generic	28.7%
Machine Learning	Machine Learning	Generic	19.5%	Automation Systems	Artificial Intelligence	Generic	10.3%
Chatbot	AI Agents	Generic	15.3%	Machine Learning	Machine Learning	Generic	10.0%
Natural Language Processing (NLP)	Natural Language Processing	Generic	11.4%	ChatGPT	AI Agents	Generic	6.1%
ChatGPT	AI Agents	Generic	3.1%	Generative Artificial Intelligence	Generative AI	Generic	4.2%
Artificial Intelligence Development	Artificial Intelligence	Generic	1.4%	Chatbot	AI Agents	Generic	3.1%
Optical Character Recognition (OCR)	Natural Language Processing	Generic	1.1%	Google Gemini	Generative AI	Specific	3.1%
AI Agents	AI Agents	Generic	1.1%	Apache Spark	Machine Learning	Generic	2.1%
Google Gemini	Generative AI	Specific	1.0%	AI Agents	AI Agents	Generic	2.1%
TensorFlow	Neural Networks	Specific	1.0%	TensorFlow	Neural Networks	Specific	1.8%
Language Models	Natural Language Processing	Generic	0.9%	Deep Learning	Neural Networks	Specific	1.8%
Generative Artificial Intelligence	Generative AI	Generic	0.7%	Retrieval Augmented Generation	Generative AI	Specific	1.6%
Adobe Sensei	Generative AI	Generic	0.6%	Microsoft Copilot	AI Agents	Generic	1.5%
Intelligent Automation	Artificial Intelligence	Generic	0.5%	MLOps (Machine Learning Operations)	Machine Learning	Specific	1.3%
AI Algorithms	Artificial Intelligence	Generic	0.5%	LangChain	AI Agents	Specific	1.2%
Retrieval Augmented Generation	Generative AI	Specific	0.5%	Prompt Engineering	Generative AI	Specific	1.2%
Natural Language Understanding	Natural Language Processing	Specific	0.4%	Scikit-Learn (Python Package)	Machine Learning	Specific	1.1%
OpenCV	Autonomous driving	Specific	0.4%	Facial Recognition	Visual Image Recognition	Generic	1.0%
Claude Code	Generative AI	Specific	0.4%	Predictive Modeling	Machine Learning	Generic	0.9%
Conversational AI	AI Agents	Generic	0.3%	Large Language Modeling	Generative AI	Generic	0.9%

Source: Authors' calculation based on data from job portals.

TABLE 19 Distribution of top 20 AI skills by portal and country. 2026 (continued)

COLOMBIA — Workana				COLOMBIA — Non-Workana			
Skill	**Cluster**	**Type**	**%**	**Skill**	**Cluster**	**Type**	**%**
Artificial Intelligence	Artificial Intelligence	Generic	36.6%	Artificial Intelligence	Artificial Intelligence	Generic	35.6%
Machine Learning	Machine Learning	Generic	17.3%	Generative Artificial Intelligence	Generative AI	Generic	5.0%
Chatbot	AI Agents	Generic	12.7%	ChatGPT	AI Agents	Generic	4.6%
Natural Language Processing (NLP)	Natural Language Processing	Generic	6.7%	Machine Learning	Machine Learning	Generic	4.6%
ChatGPT	AI Agents	Generic	5.3%	Automation Systems	Artificial Intelligence	Generic	3.9%
AI Agents	AI Agents	Generic	2.1%	Retrieval Augmented Generation	Generative AI	Specific	3.1%
TensorFlow	Neural Networks	Specific	1.5%	TensorFlow	Neural Networks	Specific	3.0%
Optical Character Recognition (OCR)	Natural Language Processing	Generic	1.3%	Deep Learning	Neural Networks	Specific	2.8%
Google Gemini	Generative AI	Specific	1.1%	LangChain	AI Agents	Specific	2.6%
Language Models	Natural Language Processing	Generic	1.0%	Google Gemini	Generative AI	Specific	2.3%
OpenCV	Autonomous driving	Specific	0.9%	Langgraph	AI Agents	Specific	2.2%
Generative Artificial Intelligence	Generative AI	Generic	0.7%	Keras (Neural Network Library)	Neural Networks	Specific	1.7%
Artificial Intelligence Development	Artificial Intelligence	Generic	0.7%	Microsoft Copilot	AI Agents	Generic	1.6%
Adobe Sensei	Generative AI	Generic	0.7%	MLOps (Machine Learning Operations)	Machine Learning	Specific	1.5%
Retrieval Augmented Generation	Generative AI	Specific	0.5%	Language Models	Natural Language Processing	Generic	1.5%
PyTorch (Machine Learning Library)	Machine Learning	Specific	0.5%	Prompt Engineering	Generative AI	Specific	1.4%
Computer Vision	Visual Image Recognition	Generic	0.5%	Apache Spark	Machine Learning	Generic	1.3%
Conversational AI	AI Agents	Generic	0.5%	PyTorch (Machine Learning Library)	Machine Learning	Specific	1.3%
Microsoft Copilot	AI Agents	Generic	0.4%	Path Analysis	Autonomous driving	Generic	1.2%
Scikit-Learn (Python Package)	Machine Learning	Specific	0.4%	Chatbot	AI Agents	Generic	1.1%

Source: Authors' calculation based on data from job portals.

TABLE 20 Distribution of top 20 AI skills by portal and country. 2026 (continued)

MEXICO — Workana				MEXICO — Non-Workana			
Skill	**Cluster**	**Type**	**%**	**Skill**	**Cluster**	**Type**	**%**
Artificial Intelligence	Artificial Intelligence	Generic	33.8%	Artificial Intelligence	Artificial Intelligence	Generic	38.3%
Machine Learning	Machine Learning	Generic	16.7%	ChatGPT	AI Agents	Generic	6.0%
Chatbot	AI Agents	Generic	12.8%	Machine Learning	Machine Learning	Generic	4.9%
Natural Language Processing (NLP)	Natural Language Processing	Generic	7.2%	Apache Spark	Machine Learning	Generic	4.1%
ChatGPT	AI Agents	Generic	6.0%	Google Gemini	Generative AI	Specific	4.0%
Optical Character Recognition (OCR)	Natural Language Processing	Generic	1.9%	Generative Artificial Intelligence	Generative AI	Generic	3.7%
Google Gemini	Generative AI	Specific	1.9%	Applications Of Artificial Intelligence	Artificial Intelligence	Generic	3.5%
AI Agents	AI Agents	Generic	1.5%	Automation Systems	Artificial Intelligence	Generic	3.5%
Language Models	Natural Language Processing	Generic	1.1%	Path Analysis	Autonomous driving	Generic	2.6%
Conversational AI	AI Agents	Generic	1.0%	Microsoft Copilot	AI Agents	Generic	2.3%
Generative Artificial Intelligence	Generative AI	Generic	0.8%	Retrieval Augmented Generation	Generative AI	Specific	1.6%
Large Language Modeling	Generative AI	Generic	0.8%	AI Agents	AI Agents	Generic	1.5%
Automation Systems	Artificial Intelligence	Generic	0.8%	Optical Character Recognition (OCR)	Natural Language Processing	Generic	1.4%
Adobe Sensei	Generative AI	Generic	0.7%	TensorFlow	Neural Networks	Specific	1.3%
Computer Vision	Visual Image Recognition	Generic	0.7%	MLOps (Machine Learning Operations)	Machine Learning	Specific	1.3%
Microsoft Copilot	AI Agents	Generic	0.7%	Prompt Engineering	Generative AI	Specific	1.0%
AI Algorithms	Artificial Intelligence	Generic	0.6%	Scikit-Learn (Python Package)	Machine Learning	Specific	0.9%
Recommender Systems	Machine Learning	Specific	0.5%	Chatbot	AI Agents	Generic	0.9%
Deep Learning	Neural Networks	Specific	0.5%	GitHub Copilot	Generative AI	Specific	0.9%
TensorFlow	Neural Networks	Specific	0.5%	Language Models	Natural Language Processing	Generic	0.8%

Source: Authors' calculation based on data from job portals.

TABLE 21 Top skills and C-AIOE & GENOE indexes by ISCO occupation group. 2026

			TECHNICAL NON-AI SKILLS			
ISCO	**C-AIOE**	**GENOE**	**Argentina**	**Brazil**	**Colombia**	**Mexico**
11	4.08	0.17	Quality Policy; Marketing; Management Systems; Microsoft Excel; Enterprise Resource Planning	Workforce Management; Marketing; Microsoft Excel; Microsoft Office; Inventory Management	Microsoft Excel; Commercial Management; Marketing; Customer Relationship Management; Quality Policy	Microsoft Excel; Microsoft Office; Marketing; KPI Reporting; Workforce Management
21	4.64	0.22	AutoCAD; Microsoft Office; Microsoft Excel; Electromechanics; Quality Policy	Civil Engineering; English Language; AutoCAD; Microsoft Excel; Microsoft Office	Microsoft Excel; AutoCAD; Telecommunications; Quality Policy; Project Management	AutoCAD; Microsoft Office; Microsoft Excel; Mechatronics; Telecommunications
22	3.85	0.14	Medical Records; Clinical Auditing; Internal Medicine; Auditing; Digital Media	Case Report Forms; Customer Relationship Management; Informatics; Microsoft Excel; Sign Languages	Basic Life Support (BLS) Certification; Auditing; Medical Records; Patient Safety; Hepatitis B	Therapeutic Ultrasound; Microsoft Office; Quality Policy; Disease Prevention; First Aid
23	4.44	0.17	Physical Education; Dictation; Machinery; Informatics; Ongoing Reliability Tests	Physical Education; English Language; Weight Training; Informatics; K-12 Education	Mathematics; Instructional Strategies; Biology; POCO (C++ Library); Social Sciences	E-Tools; Microsoft Office; Blackboard Learning Systems; Mathematics; Educational Software
24	4.93	0.33	Microsoft Excel; Billing; Liquidation; Microsoft Office; Account Analysis	Microsoft Excel; Book Closure; Accounting Journal Entries; Accounting Regulations; Financial Statements	Microsoft Excel; Billing; Financial Statements; International Financial Reporting Standards; Liquidation	Billing; Microsoft Excel; Financial Statements; Microsoft Office; Enterprise Resource Planning
25	5.22	0.28	Back End (Software Engineering); Git (Version Control System); React.js (Javascript Library); RESTful Web Services; Front End (Software Engineering)	English Language; Git (Version Control System); JavaScript (Programming Language); RESTful Web Services; React.js (Javascript Library)	JavaScript (Programming Language); Back End (Software Engineering); Software Development; Python (Programming Language); Git	Java (Programming Language); Git (Version Control System); JavaScript (Programming Language); RESTful Web Services; Back End (Software Engineering)
26	4.59	0.22	Labor Law; Microsoft Office; Legal Pleadings	Legal Pleadings; Legal Writing; Microsoft Office; Court Proceedings; Labor Law	Labor Law; Regulatory Compliance; Court Proceedings; Business Law; Legal Writing	Microsoft Office; Electronic Document Management; Zoom (Video Conferencing Tool)
33	4.82	0.36	Customer Relationship Management; Marketing; Consultative Selling; Microsoft Office; Closing (Sales)	Customer Relationship Management; Microsoft Office; Consultative Selling; Closing (Sales); Marketing	Telecommunications; Commercial Management; Closing (Sales); Sales Management; Customer Relationship Management	Closing (Sales); Customer Relationship Management; Microsoft Office; Marketing; Microsoft Excel
41	5.55	0.68	Microsoft Excel; Billing; Microsoft Office; Management Systems; Administrative Support	Microsoft Office; Microsoft Excel; Informatics; Administrative Support; Microsoft Word	Microsoft Excel; Billing; Microsoft Office; Administrative Support; Microsoft Word	Microsoft Excel; Microsoft Office; Billing; Administrative Support; Microsoft Word
42	5.29	0.52	Microsoft Office; Microsoft Excel; Cashiering; Billing; Phone Support	Informatics; Microsoft Office; Phone Support; Administrative Support; Telemarketing	Call Center Experience; Microsoft Excel; Billing; Phone Support; Microsoft Office	Microsoft Office; Microsoft Excel; Phone Support; Billing; Tournaments
43	5.2	0.63	Microsoft Excel; Management Systems; Microsoft Office; Enterprise Resource Planning; Order Picking	Informatics; Microsoft Office; Microsoft Excel; Safety Standards; Inventory Management	Microsoft Excel; Management Systems; SAP Applications; Microsoft Office; Stock Management	—
51	4.35	0.2	Housekeeping; Quality Policy; Mise En Place; Bartending; Grilling	Food Security; Food Preparation; Quality Policy; Housekeeping; Cooking	Food Preparation; Quality Policy; Bartending; Housekeeping; Mise En Place	Food Preparation; Quality Policy; Housekeeping; Bartending; Progress Chef (Software)
52	4.94	0.41	Customer Relationship Management; Microsoft Office; Closing (Sales); Microsoft Excel; Reactivity	Customer Relationship Management; Microsoft Office; Closing (Sales); Informatics; Consultative Selling	Cashiering; Presales; Closing (Sales); Commercial Management; Sales Management	Closing (Sales); Microsoft Office; Motorcycles; Microsoft Excel; Billing
53	4.3	0.15	Vital Signs; Adult Care; Emotional Support; Psychopathology; Activities Of Daily Living (ADLs)	Personal Care; First Aid; Activities Of Daily Living (ADLs); Emotional Support; Drug Administration	Elderly Care; Vital Signs; First Aid; Hepatitis B; Physical Therapy	First Aid; Drug Administration; Vital Signs; Food Preparation; Elderly Care
71	3.94	0.16	Plumbing; Occupational Safety And Health; Painting; Masonry; Liners	Masonry; Safety Standards; Plastering; Liners; Plumbing	Painting; Safety Standards; Quality Policy; Automotive Paint; Plumbing	Plumbing; Dewatering; Painting; Valves (Piping); Safety Standards
72	4.21	0.3	Blueprint Reading; Machinery; Electricity; Soldering Iron; Metal Inert Gas (MIG) Welding	Machinery; Safety Standards; Refrigeration; Drawing Interpretation; Brakes	Machinery; Soldering Iron; Blueprint Reading; Safety Standards; Electricity	Brakes; Machinery; Diesel Engines; Tires; Engine Repair
74	3.95	0.17	Electricity; Blueprint Reading; Machinery; Electromechanics; Electrical Systems	Electrical Systems; Safety Standards; Electrical System Installation; Machinery; Electrical Diagrams	Electricity; Electrical Systems; Electromechanics; Machinery; Electrical System Installation	Electricity; Electromechanics; Electrical System Installation; Switchgear; Machinery
81	4.6	0.53	Machinery; Production Line; Personnel Selection; Hand Tools; Assembly Lines	Machinery; Safety Standards; Machine Operation; Production Line; Quality Policy	Machinery; Caulking; Quality Policy; Machine Operation; Safety Standards	Machinery; Safety Standards; Machine Operation; Wastewater Treatment Plant; Personal Protective Equipment
83	4.13	0.3	Safety Standards; Truck Driving; Traffic Laws; Chassis; Automobile Handling	Safety Standards; Traffic Regulations; Traffic Laws; Defensive Driving; Truck Driving	Traffic Laws; Passenger Transport; Safety Standards; Safe Driving; Tires	Automobile Handling; Cash Handling; Product Delivery; Motor Vehicle Operation; Liquidation
91	4.5	0.27	Machinery; Housekeeping; Pressure Washer; Cleaning Products; Rotary Printing Press	Cleaning Products; Housekeeping; Safety Standards; Disinfecting; Garbage Collection (Computer Science)	Machinery; Hepatitis; Hazardous Waste Management; Biomedical Waste; Influenza	Cleaning Products; Disinfecting; Housekeeping; Scaling And Root Planing; Sanitization
93	4.11	0.33	Order Picking; Associate Certified Electronics Technician; Mobile Apps; Safety Standards; Microsoft Excel	Safety Standards; Manifold; Material Handling; Management Systems; Warehouse Management Systems	Order Picking; Radio Frequency; Office Automation; Quality Policy; Billing	Personal Protective Equipment; Work Order; Sanitation; Cashiering; Hairstyling

Notes: Panel: Technical Non-Ai Skills. *Source:* Authors' calculation based on data from job portals. C-AIOE index taken from Pizzinelli et al. (2023) and GENOE index taken from Benítez and Parrado (2024).

TABLE 22 Top skills and C-AIOE & GENOE indexes by ISCO occupation group. 2026 (continued)

			SOFT SKILLS			
ISCO	**C-AIOE**	**GENOE**	**Argentina**	**Brazil**	**Colombia**	**Mexico**
11	4.08	0.17	Leadership; Effective Communication; Bargaining; Decision Making; Visionary	Leadership; Organizational Skills; Effective Communication; Goal-Oriented; Team Management	Leadership; Effective Communication; Bargaining; Team Management; Goal-Oriented	Leadership; Effective Communication; Team Management; Goal-Oriented; Bargaining
21	4.64	0.22	Effective Communication; Teamwork; Analytical Thinking; Leadership; Proactivity	Organizational Skills; Effective Communication; Leadership; Analytical Thinking; Ability To Meet Deadlines	Effective Communication; Teamwork; Leadership; Analytical Thinking; Problem Solving	Effective Communication; Problem Solving; Teamwork; Analytical Thinking; Working Quickly
22	3.85	0.14	Effective Communication; Teamwork; Leadership; Accountability; Collaboration	Organizational Skills; Effective Communication; Accountability; Leadership; Trustworthiness	Effective Communication; Teamwork; Accountability; Leadership; Collaboration	Effective Communication; Teamwork; Punctuality; Leadership; Proactivity
23	4.44	0.17	Effective Communication; Accountability; Collaboration; Teamwork; Proactivity	Effective Communication; Organizational Skills; Creativity; Accountability; Leadership	Effective Communication; Teamwork; Leadership; Planning; Creativity	Effective Communication; Planning; Leadership; Collaboration; Creativity
24	4.93	0.33	Effective Communication; Teamwork; Analytical Thinking; Organizational Skills; Detail Oriented	Organizational Skills; Effective Communication; Detail Oriented; Analytical Thinking; Accountability	Leadership; Customer Service; Effective Communication; Detail Oriented; Teamwork	Effective Communication; Detail Oriented; Analytical Thinking; Teamwork; Accountability
25	5.22	0.28	Effective Communication; Collaboration; Teamwork; Analytical Thinking; Problem Solving	Effective Communication; Coaching; Organizational Skills; Problem Solving; Collaboration	Effective Communication; Teamwork; Analytical Thinking; Bargaining; Collaboration	Effective Communication; Teamwork; Collaboration; Problem Solving; Working Quickly
26	4.59	0.22	Effective Communication; Teamwork; Proactivity; Detail Oriented; Unsupervised Work	Organizational Skills; Effective Communication; Accountability; Analytical Thinking; Proactivity	Effective Communication; Analytical Thinking; Bargaining; Detail Oriented; Decision Making	Bargaining; Effective Communication; Detail Oriented; Analytical Thinking; Teamwork
33	4.82	0.36	Effective Communication; Bargaining; Sales Acumen; Proactivity; Unsupervised Work	Effective Communication; Organizational Skills; Bargaining; Goal-Oriented; Proactivity	Effective Communication; Customer Service; Goal- Oriented; Bargaining; Sales Acumen	Effective Communication; Bargaining; Goal-Oriented; Customer Service; Proactivity
41	5.55	0.68	Effective Communication; Organizational Skills; Proactivity; Detail Oriented; Teamwork	Organizational Skills; Effective Communication; Detail Oriented; Accountability; Proactivity	Effective Communication; Customer Service; Detail Oriented; Teamwork; Working Quickly	Effective Communication; Detail Oriented; Teamwork; Punctuality; Accountability
42	5.29	0.52	Effective Communication; Customer Service; Proactivity; Organizational Skills; Friendliness	Organizational Skills; Effective Communication; Friendliness; Professionalism; Mental Agility	Customer Service; Effective Communication; Empathy; Hospitality; Working Quickly	Effective Communication; Customer Service; Hospitality; Punctuality; Accountability
43	5.2	0.63	Organizational Skills; Leadership; Proactivity; Accountability; Teamwork	Organizational Skills; Detail Oriented; Effective Communication; Mental Agility; Accountability	Teamwork; Organizational Skills; Accountability; Detail Oriented; Effective Communication	—
51	4.35	0.2	Teamwork; Working Quickly; Accountability; Effective Communication; Proactivity	Organizational Skills; Mental Agility; Friendliness; Effective Communication; Willingness To Learn	Teamwork; Customer Service; Hospitality; Detail Oriented; Working Quickly	Teamwork; Hospitality; Customer Service; Working Quickly; Punctuality
52	4.94	0.41	Effective Communication; Sales Acumen; Bargaining; Proactivity; Unsupervised Work	Effective Communication; Organizational Skills; Bargaining; Goal-Oriented; Proactivity	Customer Service; Effective Communication; Goal- Oriented; Sales Acumen; Bargaining	Effective Communication; Customer Service; Bargaining; Punctuality; Hospitality
53	4.3	0.15	Empathy; Accountability; Effective Communication; Patience; Unsupervised Work	Organizational Skills; Empathy; Effective Communication; Accountability; Unsupervised Work	Accountability; Effective Communication; Teamwork; Patience; Empathy	Patience; Effective Communication; Accountability; Hospitality; Positivity
71	3.94	0.16	Accountability; Teamwork; Detail Oriented; Proactivity; Collaboration	Organizational Skills; Strong Work Ethic; Detail Oriented; Accountability; Teamwork	Teamwork; Detail Oriented; Accountability; Team Management; Proactivity	Punctuality; Teamwork; Accountability; Detail Oriented; Collaboration
72	4.21	0.3	Teamwork; Accountability; Proactivity; Detail Oriented; Effective Communication	Organizational Skills; Strong Work Ethic; Accountability; Detail Oriented; Teamwork	Teamwork; Detail Oriented; Accountability; Working Quickly; Effective Communication	Teamwork; Punctuality; Accountability; Proactivity; Problem Solving
74	3.95	0.17	Teamwork; Proactivity; Accountability; Problem Solving; Collaboration	Organizational Skills; Teamwork; Accountability; Effective Communication; Strong Work Ethic	Teamwork; Accountability; Effective Communication; Working Quickly; Problem Solving	Punctuality; Teamwork; Accountability; Hospitality; Effective Communication
81	4.6	0.53	Teamwork; Accountability; Proactivity; Collaboration; Detail Oriented	Organizational Skills; Strong Work Ethic; Detail Oriented; Accountability; Proactivity	Teamwork; Detail Oriented; Accountability; Willingness To Learn; Working Quickly	Accountability; Punctuality; Teamwork; Working Quickly; Proactivity
83	4.13	0.3	Accountability; Punctuality; Working Quickly; Teamwork; Effective Communication	Organizational Skills; Accountability; Effective Communication; Punctuality; Trustworthiness	Punctuality; Accountability; Effective Communication; Working Quickly; Customer Service	Punctuality; Hospitality; Accountability; Teamwork; Effective Communication
91	4.5	0.27	Accountability; Punctuality; Detail Oriented; Teamwork; Organizational Skills	Organizational Skills; Detail Oriented; Strong Work Ethic; Accountability; Proactivity	Accountability; Teamwork; Hospitality; Punctuality; Detail Oriented	Punctuality; Accountability; Detail Oriented; Hospitality; Teamwork
93	4.11	0.33	Teamwork; Accountability; Proactivity; Organizational Skills; Working Quickly	Organizational Skills; Mental Agility; Strong Work Ethic; Teamwork; Detail Oriented	Teamwork; Customer Service; Proactivity; Punctuality; Mental Agility	Detail Oriented; Working Quickly; Customer Service; Punctuality; Accountability

Notes: Panel: Soft Skills. *Source:* Authors' calculation based on data from job portals. C-AIOE index taken from Pizzinelli et al. (2023) and GENOE index taken from Benítez and Parrado (2024).

TABLE 23 Top skills and C-AIOE & GENOE indexes by ISCO occupation group. 2026 (continued)

			AI SKILLS			
ISCO	**C-AIOE**	**GENOE**	**Argentina**	**Brazil**	**Colombia**	**Mexico**
11	4.08	0.17	Artificial Intelligence; Artificial Intelligence Systems; Reinforcement Learning from Human Feedback (RLHF); Machine Learning; Ethical AI	Artificial Intelligence; Google Colaboratory; Boosting; Chatbot; Apache Spark	Artificial Intelligence; ChatGPT; Intelligent Automation; TensorFlow; Prompt Engineering	Artificial Intelligence; Machine Learning; Generative Artificial Intelligence; Applications Of Artificial Intelligence; Google Gemini
21	4.64	0.22	Artificial Intelligence; Machine Learning; Microsoft Copilot; Retrieval Augmented Generation; Deep Learning	Apache Spark; Artificial Intelligence; Machine Learning; Automation Systems; Retrieval Augmented Generation	Artificial Intelligence; Retrieval Augmented Generation; Machine Learning; Automation Systems; Apache Spark	Artificial Intelligence; Automation Systems; Apache Spark; ChatGPT; Language Models
22	3.85	0.14	Artificial Intelligence; Artificial Intelligence Systems	Image Analysis	—	Artificial Intelligence; Image Analysis
23	4.44	0.17	Artificial Intelligence; Generative Artificial Intelligence; Artificial Intelligence Systems; Language Models	Artificial Intelligence; Machine Learning; Google Gemini; Deep Learning; Generative Artificial Intelligence	Artificial Intelligence; Machine Learning; Deep Learning; Scikit-Learn (Python Package); Prompt Engineering	Artificial Intelligence; Generative Artificial Intelligence; Digital Twin Technology; Motion Analysis; Deep Learning
24	4.93	0.33	Artificial Intelligence; Google Gemini; ChatGPT; Artificial Intelligence Systems	Artificial Intelligence; Automation Systems; Microsoft Copilot; Knowledge-Based Systems	Artificial Intelligence; Machine Learning; Google Gemini	Artificial Intelligence
25	5.22	0.28	LangChain; Language Models; Langgraph; AI Agents; PineCone	Artificial Intelligence; Machine Learning; AI Agents; Generative Artificial Intelligence; ChatGPT	Artificial Intelligence; Machine Learning; Generative Artificial Intelligence; GitHub Copilot; Google Gemini	Artificial Intelligence; Machine Learning; Microsoft Copilot; Google Gemini; GitHub Copilot
26	4.59	0.22	Artificial Intelligence Systems; Language Models; Artificial Intelligence; Semantic Analysis; Speech Recognition	Artificial Intelligence; ChatGPT; Google Gemini; Generative Artificial Intelligence	Artificial Intelligence; Generative Artificial Intelligence	Artificial Intelligence; Microsoft Copilot; Applications Of Artificial Intelligence; Machine Translation; ChatGPT
33	4.82	0.36	Artificial Intelligence; Generative Artificial Intelligence; Applications Of Artificial Intelligence; Chatbot; ChatGPT	Artificial Intelligence; Amazon Alexa; ChatGPT; Boosting; Automation Systems	Artificial Intelligence; ChatGPT; Digital Twin Technology; Automation Systems; Advanced Driver Assistance Systems	Artificial Intelligence; ChatGPT; Chatbot; Automation Systems
41	5.55	0.68	Applications Of Artificial Intelligence; Artificial Intelligence; ChatGPT; Google Gemini; Artificial Intelligence Systems	Artificial Intelligence; ChatGPT; Chatbot; Automation Systems; Google Gemini	Artificial Intelligence; ChatGPT; Chatbot; Applications Of Artificial Intelligence; Intelligent Control	Artificial Intelligence; ChatGPT; Machine Learning; Google Gemini; Applications Of Artificial Intelligence
42	5.29	0.52	—	Artificial Intelligence; Chatbot; ChatGPT; Google Gemini; Microsoft Copilot	Artificial Intelligence; Boosting	Artificial Intelligence; Chatbot
43	5.2	0.63	—	Chatbot	—	—
51	4.35	0.2	—	Apache Spark; K-Nearest Neighbors Algorithm	—	—
52	4.94	0.41	Google Gemini; ChatGPT; Artificial Intelligence	Artificial Intelligence; ChatGPT; Chatbot; Amazon Alexa; Automation Systems	Artificial Intelligence; Automation Systems	Applications Of Artificial Intelligence; Artificial Intelligence; ChatGPT
53	4.3	0.15	—	—	—	—
71	3.94	0.16	—	—	—	—
72	4.21	0.3	Automation Systems	Automation Systems; Artificial Intelligence	—	Automation Systems; Machine Vision
74	3.95	0.17	Automation Systems; Advanced Driver Assistance Systems	Automation Systems; Thermal Imaging Analysis; Amazon Alexa	Automation Systems	Artificial Intelligence; Automation Systems
81	4.6	0.53	—	—	—	—
83	4.13	0.3	Artificial Intelligence; Path Analysis	Chatbot; Advanced Driver Assistance Systems	—	Path Analysis
91	4.5	0.27	—	—	—	—
93	4.11	0.33	—	—	—	—

Notes: Panel: Ai Skills. *Source:* Authors' calculation based on data from job portals. C-AIOE index taken from Pizzinelli et al. (2023) and GENOE index taken from Benítez and Parrado (2024).

fessionals (ISCO 23) with subject-specific competencies such as Mathematics, Biology and Physical Education; business and administration professionals (ISCO 24) with accounting and finance skills; ICT professionals (ISCO 25) with programming languages and software development tools; and legal professionals (ISCO 26) with Labor Law, Legal Writing and Court Proceedings.

Alongside these occupation-specific competencies, a small set of digital office skills —particularly Microsoft Excel and Microsoft Office— appears repeatedly across several professional occupations. Their widespread presence suggests that these tools constitute a layer of transversal digital literacy embedded across occupations, complementing rather than replacing occupation-specific technical knowledge.

Compared with technical skills, soft skills display a much more stable pattern across professional occupations. Effective Communication consistently emerges among the most frequently requested competencies across professional occupations, complemented by Analytical Thinking, Teamwork, Collaboration and Organizational Skills. Managers differ from other professional occupations in that Leadership is consistently the leading soft skill across countries, reflecting the coordinating and supervisory nature of managerial work.

Unlike technical non-AI skills, which are largely tied to occupational content, AI-related skills combine a small set of highly transversal competencies with a more specialized layer of technologies that varies substantially across occupations. Across most occupations, broad AI-related concepts— such as Artificial Intelligence, Machine Learning, ChatGPT and Generative Artificial Intelligence— account for a large share of AI-related demand. More specialized competencies—such as LangChain, AI Agents, Retrieval-Augmented Generation, Automation Systems or Machine Vision—appear only in particular occupational groups, reflecting differences in how AI technologies are integrated into work activities.

In terms of the risk of AI substitution, these occupational groups exhibit rather low indexes, which aligns with the findings on the top soft skills: as Pizzinelli et al. (2023) note, even as continued advances in AI capabilities affect communication as we know it, most occupations still require skills involving personal relationships with coworkers and public speaking.

Professional occupations such as those related to business and administration (ISCO 24) and ICT (ISCO 25) show the largest C-AIOE and GENOE indexes within this subgroup, which is consistent with the current ability of most AI applications to perform some of the technical non-AI skills mentioned above, particularly programming and accounting software management.

| Business and administration associate professionals (ISCO 33)

Business and administration associate professionals (ISCO 33) occupy a position characterized by the application and coordination of business processes, combining specialized knowledge with operational responsibilities. Consistent with this role, their technical non-AI skill profiles combine commercial competencies, customer-management capabilities and transversal digital tools. Across countries, Customer Relationship Management consistently emerges as a core competency, complemented by sales-oriented skills such as Consultative Selling, Closing, Sales Management and Commercial Management. Microsoft Office and Microsoft Excel also appear repeatedly, highlighting the role of basic digital tools as transversal competencies within business-related occupations. Compared with business and administration professionals (ISCO 24), whose profiles are more closely associated with specialized functions such as accounting, finance or analysis, ISCO 33 occupations appear more strongly oriented toward the operational implementation of commercial processes and customer-facing activities.

Soft skills display a highly consistent pattern across countries, centered on communication, negotiation and performance-oriented competencies. As in professional occupations, Effective Communication is consistently among the most frequently requested soft skills across countries. However, in ISCO 33 it is accompanied by competencies more directly related to commercial interaction and performance, including Bargaining, Customer Service, Goal-Oriented behavior, Sales Acumen and Proactivity. This pattern reflects the client-oriented and coordination-intensive nature of associate professional roles.

AI-related skills further illustrate the diffusion of artificial intelligence beyond occupations directly involved in technology development. Across countries, demand is dominated by broad AI concepts—particularly Artificial Intelligence and ChatGPT—alongside application-oriented technologies such as Generative Artificial Intelligence, Chatbots and Automation Systems. More specialized AI-related competencies, such as Digital Twin Technology or other AI-enabled applications, appear only in specific contexts. The lower prominence of AI development-oriented competencies, such as Machine Learning, programming or data science skills, suggests that AI demand in ISCO 33 is primarily associated with the adoption and use of AI-enabled tools within commercial and administrative processes.

Similarly to business and administration and ICT professionals, the GENOE index for these associate professionals shows analogous exposure to AI displacement, as their task content -particularly that related to software management- is quite similar. The C-AIOE index for this subgroup, however, is smaller than that of ISCO 24, which can be attributed to the closer relationship that these occupations must maintain with customers, as seen in the appearance of skills such as Customer Service and Sales Acumen among the top soft skills.

Clerical support workers (ISCO 41–43)

Clerical support occupations display a skill profile centered on administrative processes, information management and customer support activities. Technical non-AI skills show a strong presence of transversal digital productivity tools, particularly Microsoft Excel and Microsoft Office, which appear consistently across countries and occupational groups. In addition, occupation-specific competencies reflect the different functional roles within this category: billing and administrative support are prominent among office and administrative support workers (ISCO 41), phone support and customer-related activities among customer service clerks (ISCO 42), and digital information-management systems among numerical and material recording clerks (ISCO 43).

Soft skills reveal both commonalities and internal differentiation across clerical occupations. As in previous occupational groups, Effective Communication is among the most frequently requested competencies. However, the complementary skills vary according to the nature of the work. Office and administrative support workers (ISCO 41) and numerical and material recording clerks (ISCO 43) are more frequently associated with Organizational Skills, Detail Orientation, Accountability and Teamwork, reflecting the importance of accuracy, reliability and coordination in information-processing activities. By contrast, customer service clerks (ISCO 42) display a more interaction-oriented profile, with Customer Service, Empathy and Hospitality appearing prominently alongside communication skills.

AI-related skills among office and administrative support workers (ISCO 41) show a transversal profile. Across countries, demand is concentrated on broad AI concepts, particularly Artificial Intelligence and Applications of Artificial Intelligence, complemented by user-oriented generative AI tools such as ChatGPT and, in some cases, Google Gemini and chatbots. The limited presence of more specialized AI competencies suggests that AI adoption in these occupations is primarily associated with the use of AI-enabled tools to support administrative workflows rather than with the development of AI systems.

By contrast, customer service clerks (ISCO 42) display greater cross-country variation in AI-related demand. While Brazil shows the most diversified profile, including Chatbots and generative AI assistants such as ChatGPT, Google Gemini and Microsoft Copilot, Colombia and Mexico show a more concentrated demand around the broad category Artificial Intelligence, with Chatbot appearing as a complementary competency in Mexico. Finally, numerical and material recording clerks (ISCO 43) do not show a visible demand for AI-related skills in the analyzed job postings.

Clerical support occupations, given the more routine tasks they perform, exhibit higher exposure to AI replacement than previous subgroups, independently of the index used. Administrative support workers (ISCO 41) rank highest according to GENOE, followed by numerical and material recording clerks (ISCO 43), and lastly customer service clerks (ISCO 42). This ranking reflects the more data-centric nature of this subgroup of workers (Benítez and Parrado (2024)), which can be replaced by the current AI advances, and highlights the importance of the more interaction-focused profile of the customer service clerks.

| Service and sales workers (ISCO 51–53)

Technical non-AI skills among service and sales occupations closely reflect the specific content of each occupational group. Hospitality, food service and related workers (ISCO 51) display a highly consistent profile across countries, with competencies related to food preparation, food safety and quality standards, housekeeping, bartending and mise en place among the most frequently requested skills. Sales workers (ISCO 52) combine commercial competencies, such as Customer Relationship Management, Closing (Sales), Consultative Selling and sales management-related skills, with more general digital tools such as Microsoft Office and Microsoft Excel in some countries. Personal care workers (ISCO 53) show a particularly stable occupational profile centered on care and health-related competencies, including Vital Signs, First Aid, Elderly Care, Personal Care, Drug Administration and Activities of Daily Living. Overall, technical non-AI skills in these occupations strongly reproduce their expected functional content, with limited evidence of convergence across groups beyond general digital tools.

Soft skill profiles also reflect clear differences in the nature of these occupations. Hospitality workers (ISCO 51) are characterized by a combination of teamwork, customer-oriented attitudes and the ability to perform under time constraints, with Teamwork, Hospitality, Customer Service and Working Quickly appearing frequently across countries. Sales workers (ISCO 52) display a stronger commercial and interaction-oriented profile, with Effective Communication, Customer Service, Sales Acumen, Bargaining and Goal Orientation among the most common competencies. In contrast, personal care workers (ISCO 53) emphasize relational and responsibility-based skills, particularly Empathy, Patience, Accountability and Effective Communication. These patterns suggest that, while communication-related competencies are relevant across service occupations, their role differs according to the type of interaction involved: customer experience in hospitality and sales versus interpersonal support and care in personal services.

AI-related skills show substantially greater heterogeneity across these occupations and countries. Sales workers (ISCO 52) display the clearest evidence of AI adoption within this occupational group. Across countries, AI-related demand includes broad AI concepts such as Artificial Intelligence and Applications of Artificial Intelligence, as well as user-oriented tools such as ChatGPT, Google Gemini, Chatbots. This pattern is consistent with the potential use of AI for supporting sales activities, customer relationship management and commercial processes.

In terms of AI exposure, these workers exhibit a higher index than their peers within this subgroup. Even though much of their work requires social interaction, a significant portion of their tasks involves digital tools, as mentioned above, which can be, to some extent, fully replaced with AI. Sales workers' relative potential to be replaced by artificial intelligence ranks similarly to that of business and administration professionals (ISCO 24) according to C-AIOE, but slightly higher according to GENOE.

By contrast, hospitality workers (ISCO 51) and personal care workers (ISCO 53) show no explicit demand for AI-related skills in the analyzed job postings across countries. The absence of AI-related skills in these occupations appears consistent with their task content, which relies heavily on interpersonal interaction and context-specific activities. In personal care occupations, the central role of empathy, communication and direct assistance may partly explain the limited incorporation of AI-related requirements in vacancy descriptions. Similarly, hospitality occupations appear to rely primarily on occupation-specific technical skills and customer-oriented soft skills rather than on AI-enabled tools.

The effect of these occupations' soft skill profiles, discussed above, can be observed in their respective AI exposure indexes: as Pizzinelli et al. (2023) discuss, jobs requiring physical proximity to others remain valuable to society, since not only can most of the manual tasks involved not be performed by AI applications, but the substitution of these occupations by AI would also be socially jarring. Even where technically feasible given the latest technological advances, the replacement of jobs such as hospitality and personal care workers by AI would likely be poorly received, given the interpersonal and physical trust these roles require.

| Craft and related trades workers (ISCO 71, 72 and 74)

Technical non-AI skills among craft and related trades workers (ISCO 71–74) closely reflect the specific technical content of each trade. Building and related trades workers (ISCO 71) display a consistent profile across countries, with skills related to construction and maintenance activities, including Plumbing, Painting, Masonry, Piping-related tasks and Safety Standards. Metal, machinery and related trades workers (ISCO 72) are characterized by competencies associated with machinery operation, repair and fabrication, including Machinery, Blueprint Reading, Soldering, Welding, Electricity and mechanical repair skills. Electrical and electronic trades workers (ISCO 74) show a convergence across countries, with Electricity, Electrical Systems, Electromechanics, Electrical Installation and Machinery among the most frequently requested competencies. Overall, technical non-AI skills in these occupations reproduce the specific knowledge and practical requirements of each trade, with limited overlap across occupational groups.

Soft skill profiles among craft and related trades workers are relatively homogeneous across occupations and countries, although with some differences in emphasis. Teamwork and Accountability emerge consistently across ISCO 71, 72 and 74, reflecting the collaborative and responsibility-based nature of technical work. Attention to detail is particularly relevant among building and machinery-related occupations, while Problem Solving appears more frequently among electrical and mechanical trades. Compared with service occupations, where communication and customer interaction dominate, soft skills in craft occupations are more closely associated with reliability, coordination, precision and compliance with work requirements.

AI-related skills show a different pattern from the previous occupational groups, with demand concentrated mainly on automation-related technologies rather than on generative AI tools. Building and related trades workers (ISCO 71) show no explicit demand for AI-related skills in job postings across countries. Metal, machinery and related trades workers (ISCO 72) display limited and uneven demand, with Automation Systems appearing in some countries and more specialized technologies such as Machine Vision or algorithm-related skills appearing only in isolated cases. In contrast, electrical and electronic trades workers (ISCO 74) show a more consistent association with technology-related skills, particularly Automation Systems, which appears across countries, complemented by Artificial Intelligence in Mexico. These patterns suggest that, within craft occupations, the adoption of AI-related technologies is more closely linked to industrial automation and intelligent equipment than to the use of general-purpose AI tools.

As for their risk of being replaced by AI, these occupations rank among the lowest, independently of the measure used. Two of the main reasons for this are that most of the tasks carried out by these occupations require manual dexterity, which AI cannot yet replace, and the artificial intelligence cannot take responsibility, which is one of the most required skills for these workers.

Plant and machine operators, and assemblers (ISCO 81 and 83)

Technical non-AI skills among plant and machine operators and drivers (ISCO 81 and 83) also closely mirror the operational content of these occupations. Stationary plant and machine operators (ISCO 81) display a highly consistent profile across countries, with Machinery, Machine Operation, Production Lines, Safety Standards and Quality Policy among the most frequently requested competencies, highlighting the importance of equipment operation and production processes. Drivers and mobile plant operators (ISCO 83) are characterized by skills directly associated with professional driving, including Traffic Laws, Safety Standards, Truck Driving, Passenger Transport, Motor Vehicle Operation and vehicle handling. As in the previous occupational groups, technical non-AI skills closely reproduce the specific functional requirements of each occupation.

Soft skill profiles are also relatively homogeneous across countries. Among stationary plant and machine operators (ISCO 81), Teamwork, Accountability, Organizational Skills and Attention to Detail emerge consistently, reflecting the importance of coordination, precision and compliance with production procedures. Drivers and mobile plant operators (ISCO 83) place greater emphasis on Accountability, Punctuality and Effective Communication, together with customer-oriented competencies in some countries, consistent with occupations that frequently combine operational responsibilities with direct interaction with clients or passengers.

AI-related skills remain limited among plant and machine operators and drivers. The only occupation-specific technology identified is Advanced Driver Assistance Systems, which appears only in some cases among drivers. This marks a difference with the greater risk of displacement by AI that machine operators face according to both the C-AIOE and GENOE indexes. Given that both metrics are based on the task content and requirements present in O*NET, they identify that machine-AI integration is more readily applicable to this occupational group's tasks, predisposing them to replacement. This, however, is contingent on the production matrix's access to the resources needed to adopt these frontier technologies, which does not yet seem to be the case for the analyzed countries.

The appearance of Accountability as one of the top skills required also helps explain the relatively lower indexes for both sets of workers within this subgroup. As for drivers, their close relationship with customers can be considered one of the reasons for their smaller AI exposure index.

| Elementary occupations (ISCO 91 and 93)

Technical non-AI skills among elementary occupations (ISCO 91 and 93) are also closely aligned with the operational nature of these jobs. Cleaners and helpers (ISCO 91) are characterized by competencies related to cleaning, sanitation and hygiene procedures, including Cleaning Products, Housekeeping, Disinfecting and hazardous waste management, with some country-specific variation reflecting particular work environments. Laborers in mining, construction, manufacturing and transport (ISCO 93) display a more heterogeneous technical profile, combining logistics- and warehouse-related competencies such as Order Picking, Material Handling and Warehouse Management Systems with occupational safety requirements and basic digital tools.

Soft skill profiles are relatively homogeneous across countries. Accountability, Punctuality, Teamwork and Attention to Detail emerge consistently across both occupational groups, highlighting the importance of reliability, coordination and compliance with operational procedures. Finally, no AI-related skills appear among the most frequently requested competencies in either occupational group in any of the four countries. Given the relatively basic and operational nature of the tasks performed in these occupations, this is not an unexpected finding and is broadly consistent with the slower diffusion of AI-related skill requirements into elementary occupations.

Similarly to previous subgroups, elementary occupations rely heavily on manual dexterity skills, such as cleaning and material handling, which have not been replaced by artificial intelligence. Given that Accountability and Teamwork are the most required abilities for this subgroup of workers, it is also less likely that they will be replaced by AI.

7 | RESULTS III: EDUCATION AND EXPERIENCE DEMAND

Finally, two additional dimensions captured by the traditional job portals (this information is generally unavailable in Workana) are educational requirements and previous work experience. Together, these variables provide a more complete picture of employers' hiring requirements beyond the specific skills requested.

Table 24 reports, for each country, the distribution of educational requirements and the share of job postings requiring previous work experience. A striking finding is that the vast majority of postings require previous work experience, highlighting the importance employers attach to prior labor market experience. This finding has important implications for young workers and first-time job seekers, who often face greater barriers to labor market entry because they lack the experience demanded by employers.

A first point worth noting concerns the availability of information on educational requirements across countries. Information on the required level of education is reported much more frequently in Colombia and Mexico than in Argentina and Brazil. This difference largely reflects the composition of the underlying data sources. In Colombia and Mexico, Computrabajo is the only traditional portal included in the analysis and consistently reports educational requirements, whereas the Argentine and Brazilian datasets combine several job portals with different reporting practices.

Additionally, educational requirements are concentrated at the secondary and post-secondary levels, although their composition varies across countries. Considering only postings that explicitly specify an educational requirement, at least half of all postings require secondary education in each of the four countries. With the exception of Brazil, fewer than 5% require only primary education. This is the same representativeness caveat raised in Section 3: elementary occupations are underrepresented in online postings because employers filling low-skilled roles tend to recruit through informal channels rather than digital platforms. Secondary education is followed by bachelor's degrees, which account for roughly one-quarter to one-third of postings in most countries. Colombia is the main exception, where tertiary education represents the second most frequently requested educational level.

TABLE 24 Educational and experiential requirements by country. 2026

Education level	Argentina	Brazil	Colombia	Mexico
Primary	2.2	11.9	3.2	4.2
Secondary	40.4	39.2	47.1	67.2
Tertiary	11.6	6.9	33.0	0.0
Bachelor	23.5	18.9	15.1	28.0
Postgraduate	0.5	0.8	1.7	0.3
Doesn't require education	21.8	22.4	0.0	0.2
Total	100.0	100.0	100.0	100.0
Doesn't require experience	14.3	47.0	10.2	14.5
Requieres experience	85.7	53.0	89.8	85.5

Source: Authors' calculation based on data from job portals.

An important question is whether educational attainment and previous work experience act as substitutes or complements in employers' hiring decisions. On the one hand, if formal education provides workers with the knowledge and competencies required for the job, employers may rely less on previous work experience, implying a substitution relationship. On the other hand, education and previous work experience may provide complementary forms of human capital. Formal education is primarily associated with the accumulation of general human capital, providing broad knowledge and transferable competencies, whereas previous work experience contributes more occupation- and firm-specific human capital through the acquisition of practical skills, job-specific knowledge, and familiarity with workplace practices. Under this view, employers are expected to value both dimensions jointly rather than treating one as a substitute for the other.

Table 25 reports the share of job postings requiring previous work experience by educational level. A clear positive association emerges between educational requirements and employers' demand for previous work experience. With the exception of Argentina, where the relationship is not strictly monotonic, the incidence of experience requirements increases steadily with the level of education required. In Argentina, Colombia, and Mexico, around 90% or more of postings requiring tertiary education or above also require previous work experience. Experience requirements are systematically less prevalent in Brazil across all educational levels, although the same upward relationship is observed.

TABLE 25 Share of job postings that require previous work experience by education level and country. 2026

Education level	Argentina	Brazil	Colombia	Mexico
Primary	74.5	43.8	81.6	62.5
Secondary	90.0	52.9	86.5	83.4
Tertiary	91.8	67.3	92.9	93.9
Bachelor	85.8	67.0	93.9	93.9
Postgraduate	90.7	76.7	98.1	97.6

Source: Authors' calculation based on data from job portals.

Overall, the evidence points to a strong complementarity between educational attainment and previous work experience. Rather than treating formal education as a substitute for experience, employers appear to value the combination of both credentials, particularly for more highly qualified positions. This mirrors, at the level of credentials, the technical-plus-soft complementarity already documented in Section 5.1: employers here too seem to be stacking requirements rather than trading one off against another. More broadly, these findings reinforce one of the central messages of the paper: employers seem to demand multidimensional worker profiles that combine educational credentials, previous work experience, and a broad set of technical and socio-emotional skills.

8 | CONCLUSIONS

This paper set out to provide a systematic, evidence-based account of how the demand for soft, AI-related and non-AI digital skills is evolving in four of Latin America's largest economies. Building on a novel regional skills taxonomy—combining an international, Lightcast-based framework with a bottom-up lexicon adapted to the linguistic and occupational realities of Argentina, Brazil, Colombia and Mexico—and on more than one million of current and historical online job postings, we document several findings that both confirm and qualify the international literature on technological change and labor demand.

Skill demand is pervasive, multidimensional and highly complementary. Around 90% of job postings in all four countries request at least one identifiable skill, and employers ask for five to seven distinct competencies per posting on average—figures that are high by international standards and point to a labor market that increasingly evaluates workers along multiple, simultaneous dimensions rather than through single, isolated competencies. This multidimensionality is most visible in the strong complementarity between technical and soft skills: the joint requirement of both accounts for the majority of postings in every country (53%–64%), consistent with the growing international evidence on the rising value of combining cognitive and social skills.

AI-related skills remain a small share of explicit hiring requirements, but this should not be read as evidence against AI's broader relevance for the region's labor markets. Between 0.6% and 3.1% of postings request an AI-related skill. Reassuringly, where AI skills are requested, they are demanded overwhelmingly in combination with technical and soft skills rather than in isolation—AI does not appear to be displacing the value of interpersonal and socio-emotional competencies in the region's labor markets, at least as reflected in current hiring practices.

Freelance and traditional job portals reveal systematically different, but not fully disjoint, skill profiles. Across all four countries, Workana postings are more likely to require technical non-AI and AI-related skills, and less likely to require soft skills, than postings on traditional portals—a pattern consistent with Workana's concentration in technical, digital and creative freelance work relative to the broader occupational spectrum, including administrative, operational and customer-facing roles, captured by traditional portals. At the same time, both segments share a common core of office-productivity and commercial competencies, indicating that the distinction between "freelance" and "traditional" labor demand is one of degree and occupational composition rather than a strict separation.

The comparison between current and historical postings (2017–2022) points to a more nuanced pattern than a simple story of ever-increasing skill richness driven by AI diffusion. Coverage of skill requirements rose in Argentina and Brazil, fell in Colombia, and remained essentially unchanged in Mexico, while the average number of skills per posting increased only modestly, and only in Argentina. We interpret this heterogeneity as consistent with several genuine economic mechanisms that can offset an otherwise plausible upward trend: the growing accessibility and user-friendliness of AI tools, which may lower rather than raise the specialized skill threshold needed to use them; the diffusion of AI through the retraining of incumbent workers rather than through new external hiring; and the well-documented lag with which general-purpose technologies typically translate into measurable labor market outcomes.

Skill demand closely tracks occupational content, validating both the extraction methodology and a central substantive finding of the paper. At the two-digit ISCO level, technical non-AI skills reproduce the specific knowledge associated with each occupation—engineering tools for engineers, clinical competencies for health professionals, trade-specific skills for construction and machinery workers—while soft skills follow equally intuitive, occupation-consistent patterns, such as the centrality of Leadership among managers and of Empathy among personal care workers. AI-related skills, in turn, reveal a qualitatively important distinction that, to our knowledge, has not been previously documented for the region: in professional, administrative and clerical occupations, AI demand is concentrated in data- and language-based competencies (Machine Learning, Generative AI, chatbots, AI copilots), whereas in technical trades—particularly metal, machinery and electrical occupations—AI demand is dominated almost entirely by Automation Systems and related industrial technologies. The same pattern shows up in the exposure indexes: occupations that are mostly administrative, characterized by repetitive, routine tasks and requiring basic software management, score higher on both the C-AIOE and GENOE metrics, while occupations built around physical dexterity or closer person-to-person interaction remain comparatively less exposed to displacement by artificial intelligence.

Educational credentials and work experience act as complements, not substitutes, in employers' hiring requirements, with the incidence of experience requirements rising steadily with the level of education requested.

Taken together, these findings offer, to our knowledge, the first systematic, cross-country evidence on the demand for soft, AI-related and non-AI digital skills in Latin America's online labor markets, using a methodology explicitly adapted to the region's structural and linguistic specificities. They suggest that, while artificial intelligence has not yet become a first-order explicit requirement in the region's hiring practices, its diffusion is already visible—in a still-nascent but growing share of postings, in its distinct occupational "signatures," and in its complementarity with the technical and socio-emotional skills that continue to anchor labor demand across the region. From a policy perspective, these results underscore the importance of education and training systems that jointly promote technical, digital and socio-emotional competencies, of monitoring frameworks capable of tracking the ways in which AI is being incorporated into different occupations, and of continued efforts to develop labor market intelligence tools tailored to the specific structural conditions of developing economies, including their higher levels of informality and the corresponding limitations of vacancy-based data. Future research combining this evidence with information from formal employment records and household surveys would help to further validate and extend these findings beyond the segment of the labor market captured by online recruitment platforms.

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A | SKILLS TAXONOMY CONSTRUCTION AND MATCHING PROCEDURE

A.1 | Expansion prompt and output schema

The system instruction and prompt used to generate the multilingual expansion described in Section 4.1 were as follows:

```
SYSTEM_INSTRUCTION = "You are a professional technical recruiter and labor
market taxonomy expert for Latin America."

PROMPT_UNIVERSAL = """Translate the following English professional
skills into the terminology actually used in regional job postings.

You are translating skills for the following domain:
Category: {category}
Subcategory: {subcategory}

For each skill:
1. Briefly state your translation strategy in the ‘strategy_reasoning‘ field.
2. Provide a single list (‘es_terms‘) of all Spanish terms
   (Argentina/Colombia/Mexico) used for this skill. Include the main
   translation, regional variants, and abbreviations.
3. Provide a single list (‘pt_terms‘) of all Brazilian Portuguese terms.
4. Provide a list (‘en_terms‘) of common English acronyms, aliases, or
   short-names used in the industry. If the skill is usually kept in English
   in LATAM job postings (like software brands or international
   certifications), include those base terms here.

If a language does not have any terms for this skill, leave that language’s
array empty.

Skills:
{skills_json}"""
```

The model was required to return a structured JSON output enforcing a fixed schema per skill, guaranteeing no missing fields and forcing explicit reasoning before the term lists were generated. Each output record followed a fixed schema: id, name, strategy_reasoning, es_terms, pt_terms, en_terms, and a boolean flag is_used_as_english flagging whether the skill is conventionally kept in English in regional postings. Enforcing this schema guaranteed no missing fields and required the model to state its reasoning before producing the term lists.

This expansion was run in batches using Google Vertex AI. Because the expansion was performed skill by skill, independently of the rest of the taxonomy, identical terms occasionally surfaced as valid expressions for more than one Lightcast skill. These collisions were identified and resolved through manual review assisted by a language model, which in some cases involved reassigning a term from one skill to a more appropriate, closely related one.

The final output of this stage was a multilingual term bank—Spanish, Portuguese, and English variants for each canonical Lightcast skill name—which, together with the original English skill names, constitutes the vocabulary used for matching against job posting text.

A.2 | Exclusion rules and matching implementation

The exclusion process removed one subcategory entirely ("Physical Abilities"), together with 448 skills and 600 individual terms judged too ambiguous or noisy for reliable matching. No full categories were dropped. Terms of two characters or fewer were also removed automatically, since such short strings tend to generate a disproportionate number of false matches in short texts. Every run of the pipeline logs how many skills and terms were excluded at each of these stages, which keeps the process auditable and reproducible.

All text was normalized to Unicode NFC form before matching began. The matching itself relies on two FlashText automata running side by side: one case-insensitive, used by default, and a second, case-sensitive one reserved for a curated set of acronyms and short proper names that happen to double as ordinary Spanish or Portuguese words in their lowercase form—terms that would otherwise trigger many false positives. Each automaton returns non-overlapping matches on its own, but together they can still overlap; when that happens, the left-most match wins, and if two matches start at the same point, the longer one is kept (so "machine learning," for instance, takes precedence over "learning"). Cases where the same span of text could reasonably belong to more than one skill are set aside and logged for manual review rather than resolved automatically.

A.3 Educational Level and Experience Requirements: Classification Scheme and Extraction Procedure Country-specific degree mapping. Several categories rely on institutional details not covered in Section 4.3. Technical captures short, post-secondary vocational programs: SENA (Servicio Nacional de Aprendizaje) in Colombia, CONALEP, CBTIS, and CECATI in Mexico, SENAI and SENAC in Brazil, and secondary-level technical tracks in Argentina. Tertiary covers university short-cycle programs below a full bachelor's: the TSU (Técnico Superior Universitario) in Mexico, the tecnólogo in Colombia and Brazil, and tecnicaturas or analista universitario titles in Argentina. Bachelor's spans the region's standard full degree titles—licenciatura, ingeniería, bacharelado—and their direct professional equivalents.

Portal-specific vocabulary. InfoJobs (Brazil) offers a small, fixed set of educational categories that map onto the harmonized scheme without much difficulty, running from primary and secondary through technical, bachelor's, master's, and doctorate. Short professional courses with no clearly defined formal level are conservatively coded as technical.

Computrabajo (Argentina, Colombia, Mexico) works differently: it reports education as free text inside a structured field ("Minimum education: [value]"), and since the wording varies by country, each expression has to be mapped individually. Most basic and advanced degrees translate directly, but some expressions need closer attention—country-specific tertiary titles (tecnólogo, técnico superior universitario, analista universitario), signs of an incomplete degree (estudiante universitario, universitario en curso, pasante), and locally specific professional credentials (titulado con cédula profesional, profesional universitario). These get classified by where they actually sit in that country's education system, not by translating the words literally.

Automated classification. When the rule-based steps in Section 4.3 leave a posting unresolved, a supervised classifier takes over: a TF-IDF representation feeding a logistic regression, trained separately for Spanish and Portuguese on postings already labeled by the earlier steps.

Experience requirements. portal detail. InfoJobs (Brazil) reports experience through a structured field distinguishing no experience ("Sem experiência") and internship-only roles ("Só estágios") from explicit ranges spanning under a year to more than ten. All explicit ranges count as requiring experience; internship-only postings are coded as not requiring substantive prior experience, consistent with the binary criterion used throughout.

B | DISTRIBUTION OF JOB POSTINGS

B.1 | Distribution of job postings by employment area

As mentioned, we constructed a set of "employment areas" based on the classifications used by job portals themselves. These areas combine occupations with sectors of economic activity. To ensure comparability of the results, a crosswalk was performed across the different classifications, and a common one was constructed for all countries. Table B.1 presents the distribution of job postings with at least one skill by employment area for each country and by portal.

TABLE B.1 Distribution of job postings by employment area, portal and country. 2026

ARGENTINA		
Employment areas	**Non-Workana**	**Workana**
Sales, Commercial & Marketing	24.6	14.6
Production, Engineering & Manufacturing	13.0	9.0
Administration, Accounting & Finance	12.6	26.8
Logistics, Warehousing & Supply Chain	7.9	0.0
Technology & IT Systems	7.0	15.2
Customer Service & Reception	6.6	0.0
Maintenance & Repairs	4.9	0.0
Healthcare, Medicine & Nursing	4.4	0.0
Hospitality, Gastronomy & Tourism	4.2	0.0
Trades & Miscellaneous	3.2	0.0
Construction & Civil Engineering	2.6	0.0
Human Resources & Training	2.3	0.0
General Services & Cleaning	1.4	0.0
Education, Teaching & Research	1.1	0.0
Purchasing & Foreign Trade	1.0	0.0
Design, Arts & Architecture	0.9	16.4
Executive & General Management	0.8	0.0
Legal, Juridical & Advisory	0.7	2.5
Insurance	0.4	0.0
Technical Support & Deparment	0.2	0.0
Mining, Oil & Gas	0.2	0.0
Maritime, Port & Naval	0.0	0.0
Sciences & Social Services	0.0	0.0
Translation, Languages & Content	0.0	15.6
Total	100.0	100.0

Notes: "Non-Workana" postings correspond to Computrabajo and ZonaJobs for Argentina; Catho and InfoJobs for Brazil; and Computrabajo for Colombia and Mexico. *Source:* Authors' calculation based on data from job portals.

TABLE B.2 Distribution of job postings by employment area, portal and country. 2026 (continued)

BRAZIL		
Employment areas	**Non-Workana**	**Workana**
Sales, Commercial & Marketing	26.3	14.4
Administration, Accounting & Finance	19.1	12.9
Logistics, Warehousing & Supply Chain	8.5	0.0
Production, Engineering & Manufacturing	7.4	6.9
Hospitality, Gastronomy & Tourism	5.8	0.0
Customer Service & Reception	4.5	0.0
Healthcare, Medicine & Nursing	3.9	0.0
Trades & Miscellaneous	3.8	0.0
Construction & Civil Engineering	3.5	0.0
General Services & Cleaning	3.2	0.0
Technology & IT Systems	2.9	24.0
Human Resources & Training	2.5	0.0
Education, Teaching & Research	2.1	0.0
Security & Surveillance	1.3	0.0
Purchasing & Foreign Trade	1.2	0.0
Design, Arts & Architecture	1.0	29.7
Transportation & Driving	0.9	0.0
Legal, Juridical & Advisory	0.9	3.4
Insurance	0.4	0.0
Specialized Technical	0.3	0.0
Agriculture & Veterinary	0.2	0.0
Mining, Oil & Gas	0.1	0.0
Sciences & Social Services	0.1	0.0
Translation, Languages & Content	0.0	8.7
Uncategorized	0.0	0.0
Total	100.0	100.0

Notes: "Non-Workana" postings correspond to Computrabajo and ZonaJobs for Argentina; Catho and InfoJobs for Brazil; and Computrabajo for Colombia and Mexico. *Source:* Authors' calculation based on data from job portals.

TABLE B.3 Distribution of job postings by employment area, portal and country. 2026 (continued)

COLOMBIA		
Employment areas	**Non-Workana**	**Workana**
Sales, Commercial & Marketing	20.3	13.6
Customer Service & Reception	16.9	0.0
Logistics, Warehousing & Supply Chain	11.8	0.0
Administration, Accounting & Finance	11.3	27.3
Production, Engineering & Manufacturing	10.1	10.6
Healthcare, Medicine & Nursing	6.6	0.0
Maintenance & Repairs	5.7	0.0
General Services & Cleaning	3.8	0.0
Construction & Civil Engineering	2.7	0.0
Hospitality, Gastronomy & Tourism	2.6	0.0
Technology & IT Systems	2.5	16.2
Human Resources & Training	1.9	0.0
Education, Teaching & Research	1.6	0.0
Purchasing & Foreign Trade	1.0	0.0
Design, Arts & Architecture	0.7	15.6
Legal, Juridical & Advisory	0.5	1.9
Executive & General Management	0.3	0.0
Translation, Languages & Content	0.0	14.9
Total	100.0	100.0

Notes: "Non-Workana" postings correspond to Computrabajo and ZonaJobs for Argentina; Catho and InfoJobs for Brazil; and Computrabajo for Colombia and Mexico. *Source:* Authors' calculation based on data from job portals.

TABLE B.4 Distribution of job postings by employment area, portal and country. 2026 (continued)

MEXICO		
Employment areas	**Non-Workana**	**Workana**
Sales, Commercial & Marketing	28.7	15.4
Customer Service & Reception	18.1	0.0
Logistics, Warehousing & Supply Chain	11.8	0.0
Administration, Accounting & Finance	12.0	23.6
Healthcare, Medicine & Nursing	4.6	0.0
Production, Engineering & Manufacturing	4.4	6.9
Maintenance & Repairs	4.3	0.0
General Services & Cleaning	3.2	0.0
Hospitality, Gastronomy & Tourism	2.9	0.0
Human Resources & Training	2.7	0.0
Technology & IT Systems	2.3	17.4
Construction & Civil Engineering	1.5	0.0
Education, Teaching & Research	1.3	0.0
Purchasing & Foreign Trade	0.9	0.0
Legal, Juridical & Advisory	0.7	2.3
Executive & General Management	0.5	0.0
Design, Arts & Architecture	0.4	17.5
Translation, Languages & Content	0.0	17.0
Total	100.0	100.0

Notes: "Non-Workana" postings correspond to Computrabajo and ZonaJobs for Argentina; Catho and InfoJobs for Brazil; and Computrabajo for Colombia and Mexico. *Source:* Authors' calculation based on data from job portals.

B.2 | Distribution of job postings by skill type, portal and country

TABLE B.5 Distribution of job postings by skill type, portal and country. 2017–2022 / 2026

	ARGENTINA		BRAZIL	
Skill type	Workana	Non-Workana	Workana	Non-Workana
Technical non AI	99.1	91.2	99.3	85.0
Soft	53.5	76.9	54.7	78.5
AI	7.2	2.6	9.9	0.8
Skill combination	Workana	Non-Workana	Workana	Non-Workana
Technical non-AI + Soft	48.3	66.1	47.9	62.8
Only Technical non-AI	43.8	22.6	41.5	21.4
Only Soft	0.7	8.8	0.6	14.9
Technical non-AI + Soft + AI	4.4	2.0	6.1	0.7
Technical non-AI + AI	2.6	0.5	3.7	0.1
Only AI	0.1	0.0	0.1	0.0
Soft + AI	0.1	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0
	COLOMBIA		MEXICO	
Skill type	Workana	Non-Workana	Workana	Non-Workana
Technical non AI	99.1	85.8	99.4	84.6
Soft	52.7	67.6	53.8	73.0
AI	7.1	0.5	6.4	0.5
Skill combination	Workana	Non-Workana	Workana	Non-Workana
Technical non-AI + Soft	47.5	53.0	49.6	57.2
Only Technical non-AI	44.6	32.2	43.5	26.9
Only Soft	0.8	14.2	0.6	15.4
Technical non-AI + Soft + AI	4.3	0.4	3.6	0.4
Technical non-AI + AI	2.7	0.1	2.7	0.1
Only AI	0.0	0.0	0.0	0.0
Soft + AI	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0

Notes: “Non-Workana” postings correspond to Computrabajo and ZonaJobs for Argentina; Catho and InfoJobs for Brazil; and Computrabajo for Colombia and Mexico. *Source:* Authors’ calculation based on data from job portals.