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Click, Code, Earn

The Returns to Digital Skills

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Abstract

This paper provides the first comprehensive, cross-country evidence on the wage returns to digital skills, using more than 67 million job postings from 29 countries between 2021 and 2024. The paper develops a harmonized digital skills taxonomy and examines returns across extensive (any digital skill required), intensive (number of digital skills), and qualitative (type of digital skill) margins. Digital skills command substantial wage premiums globally, with particularly pronounced returns in low- and middle-income countries where such competencies remain scarce. Requiring at least one digital skill raises advertised wages by 1.6 percent on average, with returns of 1.3 percent in high-income countries and 7.5 percent in low- and middle-income countries. Each additional digital skill increases wages by 0.5 percent in high-income countries and 2.6 percent in low- and middle-income countries. Intermediate and advanced skills yield even higher premiums of 0.8 percent in high-income countries and 3 percent in low- and middle-income countries. Each traditional artificial intelligence skill offers returns of 2.9 percent across all countries. Most remarkably, generative artificial intelligence skills demonstrate the highest premiums: wage increases of 7 to 9 percent in technical occupations, and sizable premiums of 25 to 36 percent for generative artificial intelligence literacy skills in nontechnical roles, reflecting both their productivity potential and current scarcity. Returns are consistently higher in digitally-intensive industries and occupations and are amplified by workers' education and experience, suggesting strong complementarities between digital competencies and traditional human capital. These findings highlight the critical importance of digital skills for individual earnings and economic development, particularly in low- and middle-income countries.

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Produced by the Research Support Team

Click, Code, Earn: The Returns to Digital Skills

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1 Introduction

Digital technologies are fundamentally reshaping labor markets and transforming how firms operate and how workers produce. While much attention has focused on the job displacement and distributional effects of digitalization (Acemoglu and Restrepo, 2018, 2019, 2022; Autor et al., 2020), a growing body of work has highlighted the increasing demand for digital skills and their role in shaping wage outcomes (Deming and Noray, 2020; Falck et al., 2021; Langer and Wiederhold, 2023). Historically, digital literacy has been associated with positive wage returns (Krueger, 1993; DiNardo and Pischke, 1997; Dolton and Pelkonen, 2008; Fairlie and Bahr, 2018). However, as digital tools have become more prevalent and accessible, basic digital skills may no longer suffice to command wage premiums, necessitating a reexamination of which digital competencies remain economically valuable.

The rapid diffusion of artificial intelligence (AI), including generative AI (GenAI) tools, is accelerating changes in skill demand (Webb, 2019; Eloundou et al., 2024; Alekseeva et al., 2021). This technological transformation is generating a dual effect: while AI automates certain tasks such as basic coding, routine data entry, or information retrieval, it simultaneously creates demand for higher-order digital competencies that enable workers to complement and effectively interact with AI systems. Traditional AI skills—like machine learning, data science, and statistical modeling—represent established competencies that have been valued in labor markets for over a decade. In contrast, GenAI skills constitute an emerging and rapidly evolving domain that includes both technical capabilities (such as developing and customizing large language models (LLMs)) and applied competencies (such as prompt design, AI-assisted content creation, and human-AI collaboration). The novelty of GenAI technologies, combined with their rapid adoption across industries, suggests that these skills may command particularly high wage premiums due to supply constraints and the strategic value they provide to employers.

As a result, workers face growing uncertainty about which skills will remain or become valuable and lead to better labor market outcomes. These trends raise important questions: What are the returns to digital skills, particularly advanced digital skills such as Python, SQL, or cloud computing? Do emerging GenAI skills command distinct wage premiums? How do these returns differ across industries, occupations, and countries at different levels of development? And to what extent are the rewards for digital skills mediated by the levels of education and experience of the workers?

While interest in the economic value of digital skills is rising, systematic evidence remains scarce, especially at the level of individual skills and in a globally comparative setting. Existing studies often rely on survey or occupational data, which lack granularity and may fail to reflect the full range of digital competencies that employers seek. Moreover, little is known about how returns vary across high-income countries (HICs) and low- and middle-income countries (LMICs), where structural differences in labor markets and the digital divide may influence both demand and supply.

This paper addresses these gaps using a large dataset of over 67 million online job postings from 29 countries between 2021 and 2024, sourced from Lightcast.[1] The data contain rich vacancy-level information–posting and closing dates, employer name, industry, job title, occupation, location, employment type (full-time, part-time, in-person, remote, hybrid), job description, required skills, and advertised wages–allowing for fine-grained analysis of the wage returns to digital skills across extensive (any digital skill required), intensive (number of digital skills), and qualitative (type of digital skill) margins.

We find robust evidence that jobs requiring digital skills are associated with significantly higher advertised wages. This digital skill wage premium remains positive and statistically significant across different specifications designed to control for unobservable heterogeneity, including occupational, sectoral, country, city, and firm fixed-effects. In our preferred specification, which includes controls for occupation, sector, city-year, and other covariates, we estimate that jobs requiring at least one digital skill offer a wage premium of 1.6%, with returns exceeding 6% in LMICs. Each additional digital skill is associated with a 0.5% increase in posted wages globally, and a substantially larger 2.6% increase in LMICs, where such skills are scarcer.

Returns also vary considerably by skill type. Additional basic digital skills, such as typing or operating social media, are negatively associated with offered wages within an occupation, suggesting they may be perceived as minimum requirements for lower-complexity roles advertised on online job portals, a pattern consistent with findings in the existing literature (Garcia-Lazaro et al., 2025). In contrast, intermediate and advanced digital skills (e.g., SAP, programming, data analytics, cloud computing) are positively and significantly rewarded, with each additional intermediate or advanced skill raising wages by 0.8% in HICs countries and nearly 3% in LMICs.[2]

Our analysis reveals particularly striking patterns for AI-related skills. Traditional AI skills are highly rewarded, with each listed AI skill associated with a 3% wage increase. GenAI skills demonstrate the most substantial and occupation-dependent returns. In digital core occupations[3]—primarily roles focused on developing digital solutions—job postings

[1]https://lightcast.io

[2]Kuhn and Shen (2012) find that in higher-skill jobs, firms reduce gender targeting because thinner labor markets force them to broaden search—an effect that parallels how digital skills scarcity shapes recruitment.

[3]Digital core occupations include ISCO-08 codes 1330, 2152, 2153, 2356, 2434, 2511, 2512, 2513, 2514, 2519, 2521, 2522, 2523, 2529, 3114, 3511, 3512, 3513, 3514, 3521, 3522, 7421, and 7422, with detailed

requiring GenAI development and advanced use skills offer wage premiums of 7%–9% in addition to traditional AI skills, reflecting employers' valuation of workers capable of building and adapting GenAI models. Even more notable are the returns observed in digitally enhanced occupations[4]—including marketing, finance, and other professional roles that extensively utilize digital technologies. In these positions, GenAI literacy skills generate estimated wage premiums of 25%–36%, exceeding returns in digital core occupations. These pronounced wage differentials reflect intensifying demand for workers who can either develop or effectively use GenAI technologies.

Returns are also higher in IT intensive industries and ICT occupations, indicating that digital skills are more valuable in environments where digital technologies are more deeply embedded in production processes. In addition, returns to digital skills are amplified by education and work experience, suggesting that digital skills are more valuable when combined with cognitive and domain-specific skills acquired through education and the tacit knowledge gained from practical work experience.

This paper contributes to three strands of literature. First, several studies estimate wage returns to ICT skills using survey-based or test-based proficiency measures. Falck et al. (2021) use PIAAC data to demonstrate that higher ICT proficiency is associated with significantly higher wages, especially in digitally intensive occupations. Similarly, Grundke et al. (2018) report that ICT-related skills carry wage premiums approximately twice as large as numeracy skills, with returns magnified when combined with non-cognitive traits like self-organization and communication. Langer and Wiederhold (2023) find that each additional month of digital skills training in German apprenticeships increases wages by 2.1%, with rising returns over time. While these studies provide important cross-country evidence, they rely on stylized skill definitions and self-reported income data.

Second, a complementary literature uses job posting data to examine how firms value different skill bundles. Deming and Kahn (2018) document that U.S. firms demanding both cognitive and social skills offer higher wages and exhibit superior performance, even within narrowly defined occupations. These employer-side differences in skill demand account for a sizable share of wage variation. Ziegler (2024) uses Austria's legally mandated vacancy-level wage disclosures to estimate that each additional listed skill raises posted wages by 0.6% on average. Their findings suggest that wage premiums are larger for analytical and managerial skills, and that skill-intensive vacancies take longer to fill, consistent with supply-side frictions.

occupation names provided in the appendix (see Table A8).

[4]ISCO groups 1–4 excluding digital core occupations. These encompass managers (ISCO 1), professionals (ISCO 2), technicians and associate professionals (ISCO 3), and clerical support workers (ISCO 4) excluding digital core occupations.

Third, very few studies quantify the returns to digital skills using job vacancy data. Garcia-Lazaro et al. (2025) examine the UK energy sector using Lightcast job posting data and show that each additional digital skill raises posted wages by 1% on average, with particularly large premiums for advanced skills. These frontier skills yield wage increases of 4.8%–5.4% per skill. Another study by Lightcast (2025) provide early evidence on the wage premium for AI skills in the United States, estimating that jobs requiring at least one AI skill pay 28% more than non-AI roles, and those with two or more skills about 43% more.

This paper advances our understanding of digital skill premiums through four distinct contributions that address critical gaps in the existing literature.

First, to the best of our knowledge, this is the first comprehensive, cross-country analysis of returns to digital skills along the extensive, intensive, and qualitative margins. While previous studies have been constrained by limited geographical or sectoral scope, our analysis represents the first large-scale quantification of wage returns across 29 countries spanning both HICs and LMICs. This global perspective reveals systematic differences in skill valuations that single-country studies cannot capture. Although Lightcast (2025) employs similar underlying data, their analysis relies exclusively on descriptive comparisons without formal econometric estimation. Garcia-Lazaro et al. (2025), while employing comparable methodology, restrict analysis to the UK energy sector alone. Our study significantly expands this foundation by examining returns across all economic sectors and diverse country contexts. Crucially, we advance beyond binary skill indicators by capturing three dimensions of digital skill requirements: whether skills are required (extensive margin), how many skills are demanded (intensive margin), and which specific skill types are valued (qualitative margin). This multidimensional approach enables fine-grained assessment of evolving digital skill demands, particularly emerging AI competencies.

Second, this paper advances the methodological framework employed in prior studies by incorporating a comprehensive set of fixed effects, thereby addressing key endogeneity and simultaneity concerns. The paper demonstrates that these results are robust to the inclusion of firm fixed effects and controls for other non-digital skills.

Third, we document substantial heterogeneity in returns across countries, sectors, occupations, and worker profiles. In particular, we show that wage premiums associated with digital skills are significantly larger in LMICs and in digitally intensive sectors and occupations, among college graduates, and more experienced workers.

Finally, we offer novel estimates on AI and GenAI skill premiums. Unlike Lightcast (2025), who aggregate all AI-related competencies into a single category, we distinguish between traditional AI skills—reflecting established demand patterns—and GenAI skills, which we further subdivide into two categories. GenAI literacy skills represent accessible competencies available to any worker with basic digital proficiency, while GenAI development and advanced use skills (GenAI development skills) encompass the specialized capabilities required for building and adapting GenAI models. Our analysis reveals that these skill categories exhibit distinct occupation-specific demand and command different premiums.

The remainder of this paper is organized as follows. Section 2 introduces the dataset and the digital skills framework employed in this analysis, along with descriptive statistics. Section 3 outlines the empirical strategy and regression specifications. Section 4 presents the main findings across the extensive, intensive, and qualitative margins. Section 5 examines the robustness of our results by incorporating additional fixed effects, including firm fixed effects, and controlling for other skills mentioned in job postings. Section 6 investigates how returns to digital skills vary across sectors, occupations, experience levels, and educational requirements. Section 7 concludes with implications and directions for future research.

2 Data

2.1 Lightcast data

Our primary data source is the online job posting data compiled by Lightcast (previously Burning Glass). Lightcast aggregates information from tens of thousands of online job boards, company websites, and other digital recruitment platforms around the world, employing deduplication algorithms to ensure that each job posting is unique. The data set comprises 2.5 billion individual job postings during 2010-2024 across over 150 economies. For each job posting, the data set includes detailed information on posting and closing dates, company name, job title, hiring company's industry affiliation (at the NAICS 2-digit level), detailed occupation (at the ISCO-08 4-digit level), job description, qualifications (including detailed skills requirements, education, experience, etc.), job location, salary information (annualized and in USD[5]), job type (full-time vs. part-time, in-person, hybrid or remote), etc.

However, the data has some limitations. Biases arise due to the nature of online job postings, as many roles are not advertised online. For example, nearly half of mining, shipping, and machinery manufacturing candidates in the U.S still rely on local newspapers, making such roles underrepresented. Consequently, the coverage of online job postings tends to be skewed toward big cities, high-skill industries, and white-collar occupations, reducing representativeness, especially in LMICs and for non-white-collar roles. The reliance on English and European language scraping results in an incomplete picture of the job market

[5] Lightcast converts salary figures from local currencies to USD using prevailing exchange rates.

in non-Western language countries such as China, Japan, the Republic of Korea, and Viet Nam. For example, Revelio Labs reports 200,000 active vacancies in China in the last week of December 2024, while Lightcast records only 20,000 job postings during the same period.[6] Additionally, the data reflects only active job openings, excluding the broader employment stock, informal sector, and freelance or gig work.

Despite these limitations, Lightcast data provides timely and nuanced insights into global digital skills demand unavailable in traditional labor market surveys or household surveys. The data encompasses the near universe of job postings in advanced economies such as the U.S., Canada, Australia, New Zealand, Singapore, and major European countries. Past studies, such as Acemoglu et al. (2022) and Hershbein and Kahn (2018), show that Lightcast captures the majority of jobs recorded by Job Openings and Labor Turnover Survey (JOLTS) and closely tracks the evolution of overall vacancies in the U.S. Moreover, the occupational (and industry) composition of Lightcast data is closely aligned with those found in Occupational Employment Statistics (OES) and JOLTS. Cammeraat and Squicciarini (2021) found that Lightcast data exhibit good statistical properties and are a useful source of timely information about labor market demand, especially for high-skill occupations and recruitment processes that are more likely to happen online.

2.2 Sample selection

Our main variable of interest, advertised salary information extracted from job postings, captures compensation levels listed in publicly accessible job advertisements. Unlike conventional salary surveys that aggregate employer/employee-reported data retrospectively, this source reflects the salaries that firms are currently offering for specific roles. From a labor market perspective, this data provides real-time signals about employer demand, particularly in sectors that rely more heavily on online recruitment. In the context of digital skills, fluctuations in advertised salaries can indicate shifting valuation of specific skills. For policy makers and firms, this information helps assess emerging skill gaps and adapt hiring strategies accordingly. It also supports more responsive workforce planning by aligning training programs with observable market demand.

An important limitation of using online job posting data is the high incidence of missing salary, industry and occupational information.[7] Thus, we restrict the final data based on

[6] Table A1 compares the total number of online job postings from Lightcast with labor force size across countries.

[7] Few employers, particularly in LMICs, publicly disclose wage details in their advertisements. Without regulatory mandates, the absence of wage information obscures the mapping between skills and pay, making it difficult to observe the true returns to skills in the labor market. Colorado's Equal Pay for Equal Work Act shows that mandating salary transparency leads firms to raise wages, especially in occupations with

several criteria. First, we exclude job postings that lack information on key variables: advertised salary, occupational title (coded using ISCO-08 at 4-digit level), employer's industry (coded using NAICS at 2-digit level), and skills required for the role. Second, we exclude economies where either the number of valid observations falls below 30,000 per year or where the final sample constitutes less than 1% of the original postings. Third, the analysis is limited to the 2021–2024 period, as reliable data coverage for most LMICs becomes available only from 2021 onward (see Figure A1). Thus, the final dataset used in this paper comprises 29 economies – 8 of which are classified as LMICs – and includes over 67 million unique job postings during 2021–2024. Table A2 reports the distribution of original and final vacancy counts by country, along with the share of postings retained in the final sample relative to the original data. We retain 13.1% of the postings from the original data. This retention rate varies widely between countries. For example, in the United States, around 30% of the postings remain in the final sample, while in China, only 0.8% are retained.

A second limitation of advertised salary data is that some employers post broad compensation ranges, which may not reflect the actual offer extended to candidates. This practice introduces selection bias. Employers may list wide ranges to allow room for negotiation, align with internal pay bands, or comply with transparency regulations, rather than to signal true willingness to pay. As shown by Batra et al. (2023), in the U.S., wage information in job postings is sparse and systematically biased: higher-paying firms are more likely to omit salary data or use broader ranges. To mitigate this bias, we use the average advertised salary as a benchmark. This choice standardizes comparison across postings and yields a conservative estimate of the wage floor that employers publicly commit to. This choice smooths reporting variation and facilitates comparability across postings with heterogeneous range widths. While it may not capture the actual wage, it provides a consistent estimate of the employer's stated willingness to pay, conditional on disclosure. We winsorize the salary data by excluding values in the top and bottom 2% within each country, year, and 4-digit occupation group.

The distribution of job postings by country and year are presented in Table A3 and Table A4, and the distribution of job postings across all occupational categories and sectors are presented in Table A5 and Table A6. Most postings are concentrated in professional, technician, and sales roles, followed by managers. The overall occupational composition is broadly similar in both HICs and LMICs. Table A7 presents the share of job postings that include both skill and wage information across sector-occupation combinations for all countries in our final sample. The shares are relatively consistent, mostly ranging between 30%

prior wage suppression, suggesting that hidden frictions had dampened the observed returns to skills before disclosure (Arnold et al., 2025).

and 40%, which suggests limited sample selection bias. The main exception is Public Administration (NAICS 92), where coverage exceeds 60%, likely reflecting regulatory transparency requirements in public sector recruitment.

2.3 Digital skills framework

Of the 67 million job postings, approximately 47% require at least one digital skill, ranging from basic tasks such as managing social media or listing products online to more advanced competencies like SQL, Python, and data analysis. Across the full corpus of Lightcast job postings, nearly 14,000 unique digital skills are referenced. To analyze this diversity, we employ a three-tier classification framework: basic, intermediate, and advanced digital skills, as summarized in Table 1. Basic skills refer to fundamental digital literacy, such as operating devices, navigating the internet, and using simple mobile applications. Intermediate skills involve the use of office and industry-specific software for productivity, content creation, and digital communication. Advanced skills encompass the development and maintenance of digital technologies, including coding, data science, cybersecurity, and AI development. Given that these jobs are advertised online, it is a reasonable assumption that even when basic digital skills are not explicitly mentioned, candidates are expected to possess some level of basic digital skills, like competency to navigate online job portals and perform related tasks. Accordingly, our analysis places greater emphasis on intermediate and advanced digital skills.

Table 1: Classification of Digital Skills

Skill	Description	Examples of Tasks & Roles
Basic	Basic digital device operation and internet navigation, use mobile apps and simple software	Turn on/off device, navigate settings, set up password, use basic apps/software like social media apps, taxi hailing apps, entertainment apps, make and receive payments
Intermediate	Use office software and industry-specific software for business and productivity purposes, digital content creation and marketing	Use Microsoft Office suite; use industry-specific software like Photoshop, Salesforce, SAP, Oracle, electronic health record software, accounting software etc.
Advanced	Develop or maintain digital tools and technologies	Coding, programming, cybersecurity, data science, AI development and customization, electronics engineering, telecommunication

Source: Authors' calculation

Out of approximately 14,000 unique digital skills in our dataset, 256 were identified as AI skills, defined as capabilities related to the development or application of systems that perform tasks typically associated with human intelligence—such as machine learning, computer vision, and neural networks. Within this set, 15 skills were identified as GenAI skills, which refer to skills relevant to the use, integration, or development of GenAI models that produce text, code, images, or other forms of content. These include, for example, ChatGPT, vector embeddings (VEC), prompt engineering, and LLMs.[8] For analytical clarity, we distinguish traditional AI skills—encompassing all AI competencies except GenAI—from GenAI skills, which we subdivide into two distinct categories. GenAI literacy skills require only basic digital competence and involve user-level interaction with GenAI tools (e.g., using ChatGPT or DALL·E through standard interfaces). GenAI development skills, conversely, encompass the technical capabilities needed to design, develop, or adapt advanced GenAI applications (e.g., developing LLMs, prompt engineering, or utilizing GitHub Copilot or Cursor AI for

[8]The initial list of candidate GenAI skills was provided by Lightcast, drawing on their classification of skills potentially relevant to GenAI. However, not all skills in the broader list clearly indicate involvement with GenAI models. For example, terms like "autoencoders" or "deep learning frameworks" may support various machine learning tasks but are not uniquely or necessarily tied to GenAI. To isolate skills directly associated with GenAI usage or development, we evaluated the candidate list using multiple GenAI models, each prompted to rate the importance of a given skill on a 0–1 scale, along with textual justifications. Skills consistently rated above 0.8 were classified as "necessary", and we restrict our analysis to this subset to ensure precision in identifying GenAI-specific labor demand.

code generation).[9]

2.4 Descriptive statistics

Table 2 shows the average number of skills listed per job posting across three categories: the full sample (column 1), LMICs (column 2), and HICs (column 3). On average, employers list 12 skills per posting, of which 2 relate to digital skills. Most digital skills fall into the advanced category, such that on average, postings include 1 advanced digital skill, 0.8 intermediate, and 0.3 basic.[10] In LMICs, job postings list about half as many total and digital skills as those in HICs. Figure A3 shows that the types of digital skills required are largely similar across HICs and LMICs. Employers in both LMICs and HICs consistently list SQL, data analysis, automation, and Microsoft Office tools. Basic digital skills such as computer literacy, Microsoft Outlook, and word processing also appear frequently in both contexts. HICs feature a greater presence of advanced tools like Amazon Web Services and DevOps, but the core set of digital skills remains similar.

Table 3 shows that, in addition to lower skill intensity, job postings in LMICs also offer substantially lower salaries. The average advertised annual salary in HICs is $58,811, while in LMICs it is $7,590—an 8-fold difference. This wage gap persists across digital skill categories. For example, postings requiring at least one digital skill pay $65,736 on average in HICs and $9,389 in LMICs, a difference of nearly 7 times. At the high end, jobs requiring advanced digital skills pay $76,838 in HICs and $12,232 in LMICs. Jobs that require at least one AI skill pay $112,976 in HICs and $19,735 in LMICs. The same skill bundle is therefore far more expensive to employ in high-income countries. Jobs requiring GenAI skills command the highest average salaries, and the wage gap between HICs and LMICs narrows. Jobs that require GenAI skills pay $137,720 in HICs and approximately half, at $70,769, in LMICs. This points to a strong demand for workers with the specialized skills needed to develop

[9]GenAI literacy includes skills such as Generative Artificial Intelligence (for non-ICT occupations), ChatGPT, Stable Diffusion, AI copywriting, Google Bard (Gemini), and DALL·E image generation; GenAI development includes Generative Artificial Intelligence (for ICT occupations), Generative Adversarial Networks, Transformers, LLMs, Natural Language Generation, Prompt Engineering, Variational Autoencoders, AWS Bedrock, Azure OpenAI, Azure AI Studio, and GitHub Copilot.

[10]The distribution of total, digital, and specific types of skills per job posting is highly right-skewed, as shown in Figure A2. Many postings list zero skills, while a small number include more than 100, creating a long right tail. We use the raw number of digital skills as our main independent variable, winsorized at the top 0.05% of the distribution for each skill type. Log transformations are not defined at zero, and using a common workaround such as log(1+x) would implicitly treat job postings with zero digital skills as having some digital content. This redefinition alters the interpretation of the variable and weakens the distinction between jobs with and without digital requirements. Full winsorization or compression through logs would also remove meaningful variation among high-skill postings that explicitly list many digital tools. By only trimming the most extreme upper tail, we retain both the extensive and intensive margins of digital skill intensity while ensuring the variable remains interpretable and comparable across postings.

and deploy GenAI technologies in both HICs and LMICs. These lower wages, coupled with fewer digital skills listed in job postings, reflect earlier stages of economic development, lower per-capita income, limited digital maturity, simpler job tasks, and a lower market valuation of skills. For global firms, such cost differentials create strong incentives to offshore digital tasks when comparable quality can be maintained.

Table 2: Average number of skills in a job posting by country group, 2021-2024

	(1) All	(2) LMICs	(3) HICs
Total Skills	11.498	6.060	11.689
	(10.31)	(5.895)	(10.38)
Number of Digital Skills	2.101	1.253	2.131
	(4.886)	(3.077)	(4.935)
Number of Basic Digital Skills	0.279	0.122	0.285
	(0.672)	(0.411)	(0.678)
Number of Intermediate Digital Skills	0.837	0.559	0.846
	(1.737)	(1.127)	(1.754)
Number of Advanced Digital Skills	0.985	0.572	1.000
	(3.799)	(2.470)	(3.837)
Number of AI Skills	0.022	0.011	0.022
	(0.282)	(0.167)	(0.285)
Number of GenAI Skills	0.001	0.001	0.001
	(0.0469)	(0.0311)	(0.0474)
Observations	67,428,707	2,290,470	65,138,237

Notes: The table reports the average number of digital skills per job posting, with standard deviations shown in parentheses.
Source: Authors' calculation using Lightcast data.

Table 3: Average Salary offered in online advertised jobs by type of skills and country group, 2021-24

	(1) All	(2) LMICs	(3) HICs
All skills	57,071	7,590	58,811
	(40819.9)	(13346.8)	(40366.7)
≥1 digital skill	63,972	9,389	65,736
	(42152.3)	(17189.6)	(41536.6)
≥1 basic skill	56,502	8,556	57,349
	(35153.7)	(14574.4)	(34821.5)
≥1 intermediate skill	67,860	9,360	69,806
	(42873.8)	(16432.0)	(42103.7)
≥1 advanced skill	75,043	12,232	76,838
	(47264.9)	(22838.6)	(46550.4)
≥1 AI skill	110,745	19,735	112,976
	(57431.6)	(39025.9)	(55981.1)
≥1 GenAI skill	136,766	70,769	137,720
	(61260.3)	(85773.9)	(60307.8)
Observations	67,428,707	2,290,470	65,138,237

Notes: The table reports the average salary offered, with standard deviations shown in parentheses.
Source: Authors' calculation using Lightcast data.

3 Empirical strategy

To examine the wage premium associated with digital skills, we distinguish between the extensive, intensive, and qualitative margins of digital skill demand. We begin by estimating a Mincer-type wage equation on the full sample to assess the extensive margin, i.e., whether jobs that require any digital skills are associated with higher advertised wages. In the second step, we estimate an alternative specification to examine how the number of digital skills is associated with advertised wages. Finally, we categorize digital skills into basic, intermediate, and advanced skills and estimate the associated premium with each type of skill. The first-stage specification is as follows:

$$log(w_{icsot}) = \alpha_0 + \alpha_1 \text{AnyDigital}_{icsot} + X'_{icsot}\beta + \theta_c + \sigma_o + \gamma_s + \lambda_t + \epsilon_{icsot} \quad (1)$$

where $log(w_{icsot})$ denotes the logarithm of the wage posted in vacancy i, located in country c, sector s, occupation o at time t, and AnyDigital_{it} is a binary indicator equal to one if the job requires any digital skills, and zero otherwise. The vector X_{icsot} includes control variables such as education and experience, as well as indicators for whether the job is full-time or remote. We include fixed effects at the country level (θ_c), 4-digit occupation level (σ_o), 2-digit sector level (γ_s), and year level (λ_t) to absorb unobserved heterogeneity. Standard errors are clustered at the occupational level. We then shift our focus to the intensive margin by replacing the independent variable with the number of digital skills listed in each job posting. This yields the following specification:

$$log(w_{icsot}) = \alpha_0 + \alpha_1 \text{NumDigital}_{icsot} + X'_{icsot}\beta + \theta_c + \sigma_o + \gamma_s + \lambda_t + \epsilon_{icsot} \quad (2)$$

where NumDigital_{it} denotes the number of digital skills required in vacancy i, located in country c, sector s, occupation o, and posted at time t. Finally, we examine the relationship between advertised wages and the number of digital skills classified as basic, intermediate, or advanced, resulting in the following specification:

$$log(w_{icsot}) = \alpha_0 + \alpha_1 \text{Bas}_{icsot} + \alpha_2 \text{Int}_{icsot} + \alpha_3 \text{Adv}_{icsot} + X'_{icsot}\beta + \theta_c + \sigma_o + \gamma_s + \lambda_t + \epsilon_{icsot} \quad (3)$$

where (Bas_{icsot}) captures the number of basic skills mentioned in a given job ad, while (Int_{icsot}) and (Adv_{icsot}) measure the number of intermediate and advanced digital skills.

A central identification concern in estimating the above equations is that job vacancies requiring digital skills may differ systematically from other postings in ways that also affect wages. High-paying roles are more likely to occur in sectors or occupations that adopt digital technologies, offer more autonomy, or demand greater cognitive complexity. If these underlying features, rather than the requirements for digital skills, drive higher wages, the coefficient of digital skills will overstate the true return. To address this, we control for experience and minimum education required as well as fixed effects for occupation, sector, year, and country. These absorb persistent cross-sectional differences in pay across job types, time periods, and national labor markets. In this setup, identification comes from within-industry, within-occupation, within-country, same-year variation in whether a given job posting includes digital skill requirements.

A second source of potential bias is firm-level heterogeneity. High-paying firms may be both more likely to adopt digital tools and more likely to list detailed skill requirements in postings. If this is the case, the observed wage premium may reflect firm characteristics rather than the value of digital skills. This would imply that digital skills act as a proxy for unobserved firm performance. To test this, we conduct robustness checks controlling for firm/employer fixed effects. If firm-level sorting were the primary driver of the correlation, the wage premium should disappear once we condition on employer identity. Persistence of the association within firms would instead suggest a real link between posted skill content and wage offers.

4 Results

4.1 Extensive margin: Returns to any digital skills

Table 4 presents OLS estimates of the wage returns to digital skills across various model specifications based on Equation 1. In column (1), we control for fixed effects for country, year, sector, and occupation. This specification yields a large 3.9% wage premium for jobs requiring digital skills. Column (2) adds controls for education, experience, employment type, and work arrangement, reducing the premium to 2.1% as part of the raw differential reflects correlation with other valuable job characteristics. Our preferred specification in column (3) incorporates city-year fixed effects to control for location-specific and time-varying factors such as cost of living, local labor market conditions, and regional salary structures, yielding a more conservative but robust estimate of 1.6%. This estimate, while lower than the 5.8% reported by Garcia-Lazaro et al. (2025) for the UK energy sector, represents a credible average return across diverse industries and countries.

Column (4) reveals striking heterogeneity across country development levels by interacting digital skills with an LMIC indicator. The premium for HICs stands at 1.3%, and the premium in LMICs is about 6 percentage points higher, totaling 7.5%. This substantial differential reflects the relative scarcity of digitally skilled workers in LMICs. Two potential mechanisms may explain this scarcity. First, the supply of workers with adequate digital competencies may be limited, as education systems often fall short in providing effective training in digital skills in the LMICs (Winthrop et al., 2016; James, 2021). Second, even when such workers are available, firms in LMICs face intense competition from foreign companies that offer remote jobs with wages lower than in HICs rates but still higher than in LMICs (Drenik et al., 2022).

Table 4: Returns to Digital Skills, 2021-24

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Digital Skills	0.0387***	0.0206***	0.0155**	0.0131*
	(0.00798)	(0.00695)	(0.00683)	(0.00696)
LMICs × Digital Skills				0.0615***
				(0.0141)
Constant	10.72***	10.63***	10.63***	10.63***
	(0.00379)	(0.0117)	(0.0114)	(0.0114)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	67,428,704	67,428,704	67,423,920	67,423,920

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

4.2 Intensive margin: Returns to the number of digital skills

We next examine the intensive margin by analyzing how the number of digital skills required affects wage outcomes. Table 5 presents results from regressing log posted wages on the count of digital skills listed in job advertisements, with coefficients capturing the marginal return to each additional digital skill while controlling for cross-country differences, temporal trends, occupational wage structures, and sector-specific compensation norms. Our preferred specification in column (3) reveals that each additional digital skill requirement is associated with a 0.5% wage increase globally. Column (4) again demonstrates substantial heterogeneity across development levels: while each additional digital skill commands a 0.5% premium in HICs, the marginal return in LMICs reaches 2.6%—more than five times higher.

To test whether the wage returns to digital skills decline as more digital skills are added, we extend the baseline specification in Table 5 by including a quadratic term in the number of digital skills, as shown in Table B1. The results confirm a concave relationship: the marginal return to each additional skill falls, as indicated by the negative and statistically significant coefficient on the squared term. However, the rate of decline is relatively small. The marginal return remains positive across nearly the entire distribution and only converges to zero at around 37 digital skills, a point far above the average of 2 digital skills per posting. Although firms continue to value additional digital skills, each successive skill adds less to expected productivity and thus commands a smaller wage premium.

Table 5: Returns to and Additional Digital Skill, 2021-24

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Number of Digital Skills	0.0105***	0.00564***	0.00517***	0.00494***
	(0.00173)	(0.00124)	(0.00111)	(0.00111)
LMICs × Number of Digital Skills				0.0213***
				(0.00171)
Constant	10.72***	10.63***	10.63***	10.63***
	(0.00363)	(0.0105)	(0.0104)	(0.0104)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	67,428,704	67,428,704	67,423,920	67,423,920

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

We further restrict the sample to digitally-enhanced occupations to better understand the wage returns to digital skills. This approach is useful for two reasons: First, it mitigates sample selection bias. Online job postings under-represent low-skill, less digitalized jobs. By focusing on digitally-enhanced roles that are well-represented in the data, we can avoid a biased sample and generate more reliable estimates. Second, it isolates the effect of digital skills where they are most relevant. Low-skill occupations typically require few, if any, digital skills, while digital-core occupations are centered entirely on them. Digitally-enhanced occupations, which require a mix of intermediate and advanced digital skills, provide a more suitable setting to measure the wage premium for acquiring these skills. This targeted analysis offers a clearer picture of how digital proficiency translates into higher wages for the majority of jobs being transformed by technology.

Analysis of the digitally enhanced occupations subsample confirms the robustness of our main findings. The digital skill premium remains positive and consistently larger in

LMICs across both extensive and intensive margins (see Table B2 and Table B3). Notably, however, the extensive margin premium—the wage benefit from requiring at least one digital skill—is statistically significant only in LMICs (7.8%, column 4 in Table B2), while becoming insignificant in HICs. This may reflect the scarcity of digital skills in LMICs. In contrast, in advanced economies, the presence of digital skills alone may not be sufficient to justify higher wage offers, particularly in occupations where basic digital proficiency is already expected. The intensive margin results reinforce this interpretation (Table B3), showing that while both HICs and LMICs reward the accumulation of multiple digital skills, the marginal returns in LMICs (2.9% per additional skill) substantially exceed those in HICs (0.5% per additional skill), consistent with steeper skill supply curves in developing economies.

4.3 Returns by types of digital skills

4.3.1 Basic, intermediate, and advanced digital skills

The returns to digital skills are likely to vary depending on the type of digital skill demanded in the job posting. For instance, incorporating an additional basic digital skill may yield a different and possibly lower wage impact compared to adding an intermediate or advanced skill. Thus, we now examine whether the wage premium varies by the level of digital skill, classified as basic, intermediate, or advanced, as defined in Table 1. Table 6 presents the main results, with columns following the same structure as in the previous tables. A number of interesting findings emerge. First, we find a negative correlation between the number of basic digital skills listed in a job posting and advertised wages. For example, in column (3), an additional basic skill listed reduces the posted wages by almost 4%. This negative association may reflect the ubiquity of basic digital skills. In addition, listing multiple basic digital skills can signal more routine and lower-paid functions. These results are consistent with Garcia-Lazaro et al. (2025), who also find a negative premium for basic digital skills.

Second, intermediate and advanced digital skills are consistently associated with positive wage returns across all specifications in Table 6. In column (3), each additional intermediate or advanced digital skill is associated with a 0.8% increase in posted wages. These estimates remain robust and statistically significant across all specifications, indicating that more complex digital skills are highly valued in the labor market. Notably, the coefficients on advanced skills are slightly smaller than those for intermediate skills. Two additional results help explain this result. First, when we restrict the analysis to digitally enhanced occupations, which are more likely to require complex technological capabilities, the premium to advanced skills becomes larger than for intermediate ones (see Table B4). Each advanced digital skill corresponds to a 1.7% increase in posted wages, compared to 0.6% for intermediate skills. Second, when we take the logarithm of one plus the number of digital skills, the estimated return to advanced skills increases relative to intermediate. This change reflects the fact that the distribution of digital skills is highly right-skewed, with most job postings listing few skills and only a small number requiring many. In this context, using a log transformation reduces the influence of outliers and better captures marginal returns at the lower end of the distribution, where adding an advanced skill may have a more meaningful wage signal than in postings already listing many skills (see Table B5). For example, in column (3), a 1% increase in the number of advanced skills is associated with a 0.08% increase in advertised wages, compared to 0.02% for intermediate skills. Although the log specification improves the flexibility of the model, it complicates its interpretation. For example, a 10% increase in digital skills from a baseline of two skills corresponds to just 0.2 additional skills, making it less intuitive to express in real-world terms.

Finally, the interaction terms in column (4) of Table 6 provide further insight into how the returns to digital skills vary by countries' development stage. The positive and statistically significant coefficients on the interaction terms for intermediate and advanced digital skills indicate that firms in LMICs are willing to offer higher wage premiums for these types of skills. Notably, the magnitudes of the interaction terms are substantial relative to the baseline coefficients. The return to an additional intermediate or advanced digital skill is 0.8% in HICs, while the interaction term adds another 2.5 and 2.2 percentage points in LMICs, respectively, bringing the total return to over 3%.

When these percentage returns are mapped to the average advertised salaries in Table 3, the gap in salary offered between HICs and LMICs becomes clear. For intermediate skills, a 0.8% premium in HICs amounts to about $573 on the average posting, while the 3% premium in LMICs adds only $260. For advanced skills, the additional pay is about $585 in HICs compared with $332 in LMICs. Firms in LMICs therefore post higher proportional premiums to attract scarce talent, but the absolute wage offers remain higher in HICs because of the much larger base salaries. Workers in LMICs see stronger relative rewards from skill acquisition, while firms in richer economies continue to post higher dollar amounts for the same types of skills. This combination reflects international wage gaps in job advertisements and creates incentives for firms in advanced economies to offshore digital tasks when comparable quality can be secured.

Table 6: Returns to Basic, Intermediate, and Advanced Digital Skills, 2021-24

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Number of Basic Digital Skills	-0.0493***	-0.0393***	-0.0386***	-0.0386***
	(0.00430)	(0.00345)	(0.00342)	(0.00344)
Number of Intermediate Digital Skills	0.0203***	0.0101***	0.00845***	0.00812***
	(0.00238)	(0.00166)	(0.00150)	(0.00148)
Number of Advanced Digital Skills	0.0117***	0.00782***	0.00772***	0.00751***
	(0.00267)	(0.00222)	(0.00215)	(0.00216)
LMICs $\times$ Number of Basic Digital Skills				-0.00742
				(0.00921)
LMICs $\times$ Number of Intermediate Digital Skills				0.0248***
				(0.00462)
LMICs $\times$ Number of Advanced Digital Skills				0.0223***
				(0.00185)
Constant	10.72***	10.64***	10.65***	10.64***
	(0.00394)	(0.00989)	(0.00981)	(0.00981)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	67,428,704	67,428,704	67,423,920	67,423,920

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

4.3.2 AI skills

To better capture the heterogeneity in wage returns across digital competencies, we distinguish AI-related skills from the broader category of advanced digital skills. Demand for AI capabilities has increased in recent years as companies increasingly seek to integrate machine learning, automation, and data-driven decision making into core business operations (Alekseeva et al., 2021). Despite the fact that demand has grown rapidly, only 1.1% of job postings require AI skills in HICs, compared to 0.7% in LMICs. Table 7 reports the results from a regression where the number of traditional AI skills and non-AI advanced digital skills are included as distinct regressors, controlling for basic and intermediate digital skills. Although each advanced non-AI digital skill is associated with a 0.7% increase in offered wages, the return to AI-related skills is substantially higher, and each AI skill corresponds to a 2.9% increase in wages (see column (3)). Column (4) explores whether these effects differ across country income groups. The interaction terms reveal that intermediate and non-AI advanced digital skills yield higher returns in LMICs, consistent with earlier findings of skill scarcity. However, we find no clear evidence of an additional premium for traditional AI skills in developing countries. These results are similar when concentrating in the sub-sample of digitally-enhanced occupations, as presented in Table B6.

Table 7: Returns to AI Skills, 2021-24

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Number of Basic Digital Skills	-0.0490***	-0.0389***	-0.0383***	-0.0383***
	(0.00429)	(0.00343)	(0.00341)	(0.00343)
Number of Intermediate Digital Skills	0.0200***	0.00975***	0.00818***	0.00785***
	(0.00242)	(0.00170)	(0.00152)	(0.00151)
Advanced Skills (excluding AI)	0.0113***	0.00732***	0.00734***	0.00712***
	(0.00263)	(0.00219)	(0.00211)	(0.00212)
Traditional AI Skills	0.0374***	0.0354***	0.0292***	0.0293***
	(0.00592)	(0.00452)	(0.00479)	(0.00490)
LMICs × Number of Basic Digital Skills				-0.00769
				(0.00919)
LMICs × Number of Intermediate Digital Skills				0.0249***
				(0.00462)
LMICs × Advanced Skills (excluding AI)				0.0224***
				(0.00189)
LMICs × Traditional AI Skills				0.0189
				(0.0160)
Constant	10.72***	10.64***	10.65***	10.64***
	(0.00397)	(0.00990)	(0.00982)	(0.00981)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	67,428,704	67,428,704	67,423,920	67,423,920

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

4.3.3 GenAI skills

GenAI skills have rapidly emerged as one of the fastest-growing subsets of the broader AI skill category. Virtually absent from job postings just two years ago, GenAI is now a key driver of hiring patterns and is associated with substantial wage premiums across occupations.

According to Lightcast (2025), demand for GenAI skills has increased by over 800% in non-tech roles in the U.S. since the launch of ChatGPT.

We classify GenAI skills into two distinct categories based on their functional requirements: GenAI development skills and GenAI literacy skills, as outlined in Section 2.3. GenAI development skills encompass the technical capabilities needed to build, customize, or adapt GenAI models that generate text, code, images, and video content. GenAI literacy skills involve the applied competencies required to effectively use GenAI-powered applications—such as conversational AI systems like ChatGPT or image generators like DALL·E—that are increasingly embedded in workplace tools and workflows.

Despite explosive growth, GenAI skills remain nascent in our global sample: only 0.09% of job postings (approximately 60,000) mention GenAI development skills, while 0.07% (roughly 45,000) require GenAI literacy skills. These postings are heavily concentrated in HICs, with LMICs accounting for fewer than 900 postings in each category. Due to limited LMIC observations, we estimate pooled premiums across all countries.

Our empirical strategy distinguishes between traditional AI skills and GenAI competencies within digitally intensive roles. For GenAI development skills, we focus on digital core occupations—the most technical roles where such skills are applicable—and estimate separate premiums for traditional AI and GenAI development requirements. For GenAI literacy skills, we examine digitally enhanced occupations where workers use but do not necessarily develop GenAI tools, estimating premiums relative to other digital skills without separate traditional AI controls. This approach captures the distinct value proposition of each GenAI skill type within its relevant occupational context.

We implement this comparison using the following specifications, which allows us to observe distinct effects of traditional AI and GenAI skills for digitally enhanced (Equation 4) and digital core (Equation 5) occupations:

$$\log(w_{icsot}) = \alpha + \beta_1 \text{Trad AI}_{icsot} + \beta_2 \text{GenAI Dev}_{icsot} + X_{icsot}\gamma + \theta_c + \sigma_o + \gamma_s + \lambda_t + \epsilon_{icsot} \quad (4)$$

$$\log(w_{icsot}) = \alpha + \beta_2 \text{GenAI Lit}_{icsot} + X_{icsot}\gamma + \theta_c + \sigma_o + \gamma_s + \lambda_t + \epsilon_{icsot} \quad (5)$$

where TradAI_{icsot} is a dummy equal to one if posting i in country c, sector s, occupation o, and year t requires at least one traditional AI skill (excluding GenAI skills), and GenAIDev_{icsot} is a dummy equal to one if the posting requires at least one GenAI development skill. The coefficient β_1 captures the wage premium associated with traditional AI skills relative to other digital skills, while β_2 captures the premium associated with GenAI development skills. For the GenAI literacy specification, we instead include only GenAILit_{icsot}, defined as a dummy equal to one if the posting requires at least one GenAI literacy skill. Here, β_2 captures the wage premium associated with GenAI literacy skills relative to other digital skills, without a direct comparison to traditional AI.

Table 8 and Table 9 present the estimated returns to GenAI skills in digital core and digitally enhanced occupations, respectively. The results point to economically and statistically significant wage premiums for GenAI skills. In digital core occupations, traditional AI skills command significant premiums of 11%–14%, while GenAI development skills provide an additional 7%–9% premium beyond traditional AI capabilities. In digitally enhanced occupations, GenAI literacy skills generate wage premiums of 25%–36% relative to comparable postings without GenAI requirements. These pronounced differentials exceed even those observed in technical roles, reflecting both the productivity potential of GenAI in traditionally non-technical domains and the current shortage of professionals who can bridge domain expertise with GenAI capabilities.

These results underscore how GenAI expertise, though still relatively new, has already emerged as one of the most valuable skill sets in the labor market. At the very top end, technology companies engaged in an epic battle for talent have gone so far as to extend offers reportedly worth up to 1 billion USD to a handful of elite GenAI programmers.[11] While such extreme cases capture headlines, the broader evidence suggests that substantial wage premiums for GenAI skills extend well beyond superstar programmers, cutting across a wide spectrum of white-collar occupations.

[11] The Epic Battle for AI Talent—With Exploding Offers, Secret Deals and Tears.

Table 8: Returns to GenAI Skills in digital core occupations

Dependent variable: Log(Wage)	(1)	(2)	(3)
Traditional AI Skills	0.139***	0.127***	0.105***
	(0.0240)	(0.0180)	(0.0204)
GenAI Development Skills	0.0876***	0.0930***	0.0667***
	(0.0137)	(0.0130)	(0.0108)
Constant	11.30***	11.03***	11.04***
	(0.00205)	(0.0246)	(0.0221)
Country	Yes	Yes	
Year	Yes	Yes	
Occupation	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Additional Controls		Yes	Yes
Country X City X Year			Yes
Observations	4,114,923	4,114,923	4,110,336

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

Table 9: Returns to GenAI Skills in digitally enhanced occupations, 2021-24

Dependent variable: Log(Wage)	(1)	(2)	(3)
GenAI Literacy Skills	0.355***	0.289***	0.252***
	(0.0274)	(0.0199)	(0.0152)
Constant	10.89***	10.71***	10.72***
	(0.0000234)	(0.0119)	(0.0114)
Country	Yes	Yes	
Year	Yes	Yes	
Occupation	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Additional Controls		Yes	Yes
Country X City X Year			Yes
Observations	21,377,682	21,377,682	21,373,326

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

5 Robustness

We also perform a number of robustness checks to test the validity of our findings. First, to strengthen our identification strategy, we extend the analysis by controlling for other skill requirements. Including other non-digital skills helps isolate the specific contribution of digital competencies by accounting for the broader skill bundle associated with each job posting. Second, we add firm fixed effects, which allows us to compare wage differences within the same firm, thereby controlling for unobserved firm-level heterogeneity such as productivity, compensation policies, or technology intensity. However, this comes at the cost of reduced identifying variation, as the estimates now rely exclusively on differences in the number of digital skills across postings from the same firm, within the same occupational group. As a result, identification hinges on firms that post multiple vacancies for similar roles but vary in their digital skill requirements—greatly reducing the sample variation but improving the precision by accounting for firm-level confounders.

The results reported in Table 10 and Table 11 are consistent with our main findings. In both tables, column (1) replicates the extensive margin results from Table 4, column (2) corresponds to the intensive margin estimates in Table 5, column (3) reproduces the count-based specification from Table 6, and column (4) presents the differentiated returns to AI and non-AI advanced skills as in Table 7. Controlling for other non-digital skills confirms that the wage premiums associated with digital skills are not merely capturing the effect of broader skill bundles. The coefficients for intermediate and advanced digital skills remain positive and statistically significant, while basic skills continue to be associated with lower advertised wages. Importantly, the estimated returns to digital skills are consistently higher than those for other non-digital skills, suggesting that employers place particular value on digital capabilities, beyond general skill requirements.

In addition, the results remain robust when firm fixed effects are included. Both the extensive and intensive margins remain highly significant and similar to the coefficients reported in our baseline regressions, with larger premiums observed in LMICs. Notably, we now find a statistically significant interaction between AI skills and the LMICs dummy. We also estimate stricter specifications using different combinations of fixed effects—including sector-by-year to capture shocks common to all countries within a sector in a given year, such as a global decline in clerical and support jobs due to advances in GenAI, country-by-year to absorb aggregate shocks to national labor markets, for instance a nationwide minimum wage reform, and country-by-sector to account for persistent differences in industry composition across countries, such as China's manufacturing base relative to services. The findings are presented in Table B7, Table B8, and Table B9, respectively. Importantly, applying these alternative fixed effect structures does not alter the main findings.

Table 10: Returns to Digital Skills Controlling for Non-Digital Skills

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Digital Skills	0.00879			
	(0.00604)			
LMICs × Digital Skills	0.0642***			
	(0.0136)			
Number of Digital Skills		0.00465***		
		(0.00108)		
LMICs × Number of Digital Skills		0.0213***		
		(0.00171)		
Number of Basic Digital Skills			-0.0407***	-0.0404***
			(0.00327)	(0.00326)
LMICs × Number of Basic Digital Skills			-0.00635	-0.00661
			(0.00912)	(0.00910)
Number of Intermediate Digital Skills			0.00657***	0.00627***
			(0.00140)	(0.00142)
LMICs × Number of Intermediate Digital Skills			0.0252***	0.0253***
			(0.00460)	(0.00460)
Number of Advanced Digital Skills			0.00749***	
			(0.00216)	
LMICs × Number of Advanced Digital Skills			0.0220***	
			(0.00186)	
Advanced Skills (excluding AI)				0.00708***
				(0.00212)
LMICs × Advanced Skills (excluding AI)				0.0222***
				(0.00190)
Traditional AI Skills				0.0301***
				(0.00496)
LMICs × Traditional AI Skills				0.0180
				(0.0162)
Other Skills	0.00313**	0.00199	0.00388***	0.00394***
	(0.00135)	(0.00146)	(0.00143)	(0.00143)
Constant	10.63***	10.63***	10.64***	10.63***
	(0.0131)	(0.0122)	(0.0119)	(0.0119)
Country X City X Year	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes
Observations	67,423,920	67,423,920	67,423,920	67,423,920

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

Table 11: Returns to Digital Skills Controlling for Firm Fixed Effects, 2021-24

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Digital Skills	0.0141***			
	(0.00392)			
LMICs × Digital Skills	0.0606***			
	(0.0103)			
Number of Digital Skills		0.00440***		
		(0.000797)		
LMICs × Number of Digital Skills		0.0224***		
		(0.00144)		
Number of Basic Digital Skills			-0.0326***	-0.0325***
			(0.00221)	(0.00220)
LMICs × Number of Basic Digital Skills			-0.00413	-0.00418
			(0.00523)	(0.00521)
Number of Intermediate Digital Skills			0.00718***	0.00704***
			(0.00121)	(0.00122)
LMICs × Number of Intermediate Digital Skills			0.0271***	0.0271***
			(0.00373)	(0.00373)
Number of Advanced Digital Skills			0.00627***	
			(0.00155)	
LMICs × Number of Advanced Digital Skills			0.0227***	
			(0.00148)	
Advanced Skills (excluding AI)				0.00610***
				(0.00153)
LMICs × Advanced Skills (excluding AI)				0.0226***
				(0.00148)
Traditional AI Skills				0.0164***
				(0.00319)
LMICs × Traditional AI Skills				0.0298***
				(0.00905)
Constant	10.64***	10.64***	10.65***	10.65***
	(0.00676)	(0.00658)	(0.00588)	(0.00588)
Country X City X Year	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes
Observations	67,146,387	67,146,387	67,146,387	67,146,387

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

6 Heterogeneity

6.1 Sector

The wage returns to digital skills can vary significantly across industries due to differences in the extent of digital transformation, the demand for digital capabilities, and the degree to which digital skills complement core tasks. In sectors like IT, finance, and professional services, where digital tools are integral to productivity and innovation, digital skills are often essential and command a premium. In contrast, in industries such as agriculture, construction, and food services, the adoption of digital technologies is slower or more limited to specific functions, reducing the marginal value of digital proficiency. These variations reflect both structural industry characteristics and how digitalization reshapes work content and skill demand within each industry.

In this section, we examine whether returns to digital skills are higher in more IT-intensive industries. We measure industry-level digitalization using IT intensity, defined as the ratio of IT inputs to total intermediate inputs. IT intensity is calculated for each country and industry using 2020 data from the Trade in Value-Added (TiVA) dataset. Because IT intensity tends to evolve slowly, reflecting structural characteristics of industries, relying on pre-period data helps address concerns about simultaneity with our 2021–2024 study period. Figure B1 shows the distribution of IT intensity across countries and industries in our sample. The Information sector exhibits the highest IT intensity (24%), far surpassing other services such as finance (2.5%) and professional services (2.4%). In contrast, sectors such as real estate (0.6%), agriculture (0.6%), education (0.7%), mining (0.8%), health care (0.9%), and construction (0.9%) show the lowest levels of IT intensity.

Building on this measure, we empirically test whether returns to digital skills are higher in more IT-intensive industries using the following specification:

$$\begin{aligned} log(w_{icsot}) = \alpha_0 + \alpha_1 \text{DS}_{icsot} + \alpha_2 \text{DS}_{icsot} \times \text{IT intensity}_{cs} + \alpha_3 \text{DS}_{icsot} \times \text{LMICs}_c + \\ \alpha_4 \text{DS}_{icsot} \times \text{IT intensity}_{cs} \times \text{LMICs}_c + X'_{icsot}\beta + \theta_c + \sigma_o + \gamma_s + \lambda_t + \epsilon_{icsot} \end{aligned} \tag{6}$$

where DS_{icsot}, is a dummy indicating if a job posting (indexed by i) in country c, industry s, occupation o, and time t mentions at least one intermediate or advanced digital skill. This dummy variable simplifies the specification while capturing the premium associated with higher-level digital proficiency. IT intensity$_{cs}$ represents the IT intensity of industry s in country c, as defined previously.

Table 12 presents the main results of this analysis. First, across all specifications, jobs that require at least one intermediate or advanced digital skill are associated with significantly higher advertised wages, reinforcing the earlier findings. Second, the results indicate that these returns are higher in more IT-intensive sectors. A one–percentage point increase in the share of IT inputs relative to total intermediate goods by an industry raises the digital skill premium by an additional 0.3-0.4%, and the coefficient is highly significant, supporting the hypothesis that digital skills are more valuable in industries where digital technologies are more deeply embedded in production processes. Column (3) further explores heterogeneity by country income group. The triple interaction term (LMICs × Digital Skills × IT Intensity) is negative and statistically significant, suggesting that the complementarity between digital skills and IT intensity is relatively weaker in LMICs compared to HICs. This may reflect underlying differences in technological adoption, firm capabilities, or institutional environments.

Table 12: Returns to Digital Skills in IT intensive sectors, 2021-24

Dependent variable: Log(Wage)	(1)	(2)	(3)
At least Inter. DS	0.0483***	0.0284***	0.0253***
	(0.00815)	(0.00723)	(0.00735)
At least Inter. DS X IT intens.	0.00431***	0.00295***	0.00322***
	(0.00112)	(0.000938)	(0.000946)
LMICs × At least Inter. DS			0.0719***
			(0.0190)
LMICs × At least Inter. DS X IT intens.			-0.00781***
			(0.00149)
Constant	10.73***	10.64***	10.64***
	(0.00352)	(0.0118)	(0.0117)
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Occupation	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Additional Controls		Yes	Yes
Observations	61530553	61,530,553	61,530,553

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

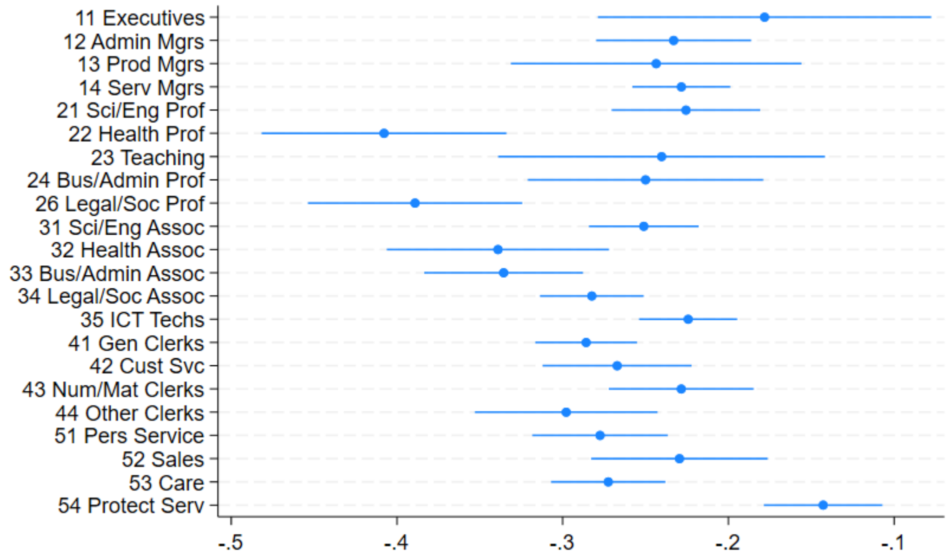
6.2 Occupation

The wage returns to digital skills are also likely to vary across occupations, reflecting differences in task content, skill requirements, and the extent to which digital tools are embedded in day-to-day activities. Digital skills may be more complementary in occupations that involve information processing, problem-solving, and technology-intensive tasks. Conversely, in roles with more routine or manual functions, the marginal value of digital proficiency may be lower. To explore this heterogeneity, we focus on a subset of more skilled occupations, ranging from ISCO major groups 1 to 5,[12] where digital technologies are more likely to be integrated into core job functions and thus more relevant for productivity and wage setting.

Figure 1 presents the heterogeneity in returns to intermediate and advanced digital skills across major occupational groups (ISCO 2-digit level), using ICT professionals (ISCO 25) as the baseline category. All coefficients are negative, indicating that the wage premium for digital skills is highest among ICT professionals. In other words, while digital skills are generally associated with higher wages, their marginal value is significantly lower in all other occupations relative to ICT professionals. However, the size of the differential varies considerably between occupations. The gap is relatively smaller for other high-skilled professional groups such as executives and managers (ISCO 11-14) and science and engineering professionals (ISCO 21), indicating that digital skills are also relatively well rewarded in knowledge-intensive roles. In contrast, the differential is much larger for health professionals (ISCO 22) and legal professionals (ISCO 26). In healthcare and law, critical functions such as clinical decision making or legal judgment rely heavily on domain-specific expertise, human interaction, and regulatory compliance, which digital skills can support but cannot easily substitute or enhance at scale.

[12] ISCO major group 1: Managers; group 2: Professionals; group 3: Technicians and Associate Professionals; group 4: Clerical Support Workers; group 5: Services and Sales Workers.

Figure 1: Returns to Intermediate and Advanced Digital Skills by Occupation (ISCO 1 to 5), 2021-24



Note: The figure displays estimated wage differentials for jobs requiring at least one intermediate or advanced digital skill across ISCO 2-digit occupations, relative to ICT professionals (ISCO 25). Estimates control for city-year and industry fixed effects. Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculation using Lightcast data.

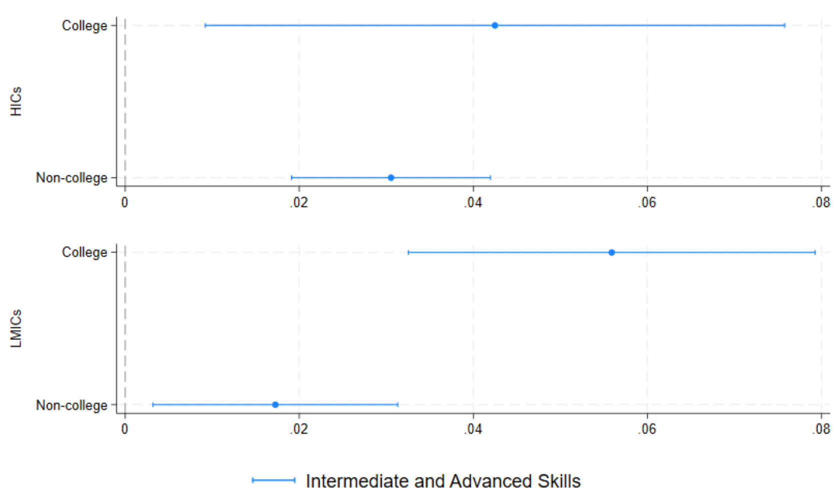
6.3 Experience and education

In the context of job postings, differences in the estimated returns to digital skills by education and experience may reflect how employers value specific skill profiles when setting wages or salary offers. While formal education may signal general cognitive skills or qualification thresholds, many employers prioritize practical, demonstrable skills over formal degrees. As a result, work experience remains a more salient indicator of job readiness and ability to deploy digital tools effectively. Experienced candidates are likely to bring industry-specific knowledge and contextual understanding that make digital skills more productive in practice. This complementarity can result in larger digital skill premiums among more experienced workers, as employers reward combinations of digital fluency and work-based capabilities.

Figure 2 and Figure 3 present the estimated wage returns to intermediate and advanced digital skills, separately by education (Figure 2) and experience (Figure 3). In Figure 2, digital skills are associated with positive and statistically significant wage premiums for both education groups. In HICs, point estimates are slightly higher for college-educated workers, though the difference is not statistically significant given overlapping confidence intervals. In contrast, the difference in estimated returns between college- and non-college-educated workers is statistically significant in LMICs, with college-educated individuals capturing substantially larger premiums.

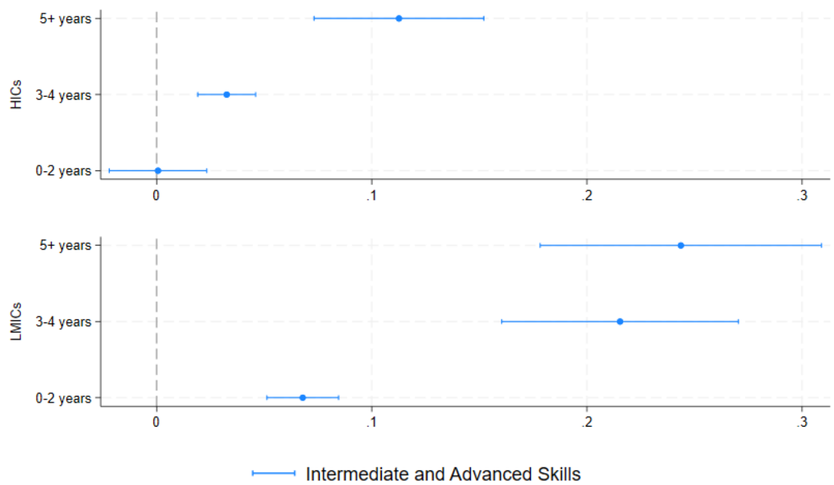
In Figure 3, digital skills yield positive wage premiums across all experience groups in HICs, with the strongest and statistically significant effects observed among workers with five or more years of experience. A similar pattern emerges in LMICs, where returns are also higher for more experienced workers. However, the difference between those with 3–4 years and those with 5+ years of experience is not statistically significant. Overall, these findings suggest that both education and experience amplify the returns to digital skills in LMICs. Employers appear more likely to reward digital proficiency when it is complemented by either higher educational attainment or substantial labor market experience. In contrast to education, the heterogeneity across experience levels is more pronounced, with significantly higher premiums for more experienced individuals.

Figure 2: Returns to Intermediate and Advanced Digital Skills by Educational Groups, 2021-24



Note: The figures display the estimated wage returns to intermediate and advanced digital skills across different education groups, based on interaction terms from a regression model. Horizontal bars represent 95% confidence intervals, with standard errors clustered at the 4-digit occupation level. Returns are measured as marginal effects of skill levels on log wages, conditional on a set of controls and fixed effects (city by year, occupation, and sector). Additional controls include experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified).
Source: Authors' calculation using Lightcast data.

Figure 3: Returns to intermediate and advanced skills by experience groups



Note: The figures display the estimated wage returns to intermediate and advanced digital skills across different experience groups, based on interaction terms from a regression model. Horizontal bars represent 95% confidence intervals, with standard errors clustered at the 4-digit occupation level. Returns are measured as marginal effects of skill levels on log wages, conditional on a set of controls and fixed effects (city by year, occupation, and sector). Additional controls include education requirements (college, non-college, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified).
Source: Authors' calculation using Lightcast data.

7 Conclusion

Technological progress, particularly digital transformation, is continuously reshaping the skills demanded in the labor market. Digital literacy has become a basic requirement, and workers are now expected to navigate an increasingly complex array of digital tools. The rapid proliferation of AI further accelerates these shifts, redefining skill requirements even in highly specialized occupations. In this context, it is essential to understand which skills are likely to remain valuable and lead to better labor market outcomes.

This paper contributes to a growing literature that examines the wage returns to digital skills. Drawing on a rich dataset of over 67 million online job postings from 29 countries during 2021-2024, we estimate that digital skills are consistently associated with higher advertised wages. These wage premiums remain robust after controlling for detailed job characteristics, fixed effects, and firm-level heterogeneity. Importantly, we find that the wage premium for digital skills is considerably larger in LMICs, where digital talent is in shorter supply. This result points to a persistent digital skills gap that may exacerbate labor market inequalities if not addressed.

We also document significant variation in the returns to different types of digital skills. While basic digital skills are associated with lower wages, intermediate and advanced skills yield robust positive premiums. AI-related skills—especially GenAI—offer the highest wage premiums. Finally, we find that returns are higher in IT-intensive sectors and ICT occupations, underscoring the complementarity between digital skills and the intensive use of digital technologies. Furthermore, higher educational attainment and more work experience amplify the returns to digital skills.

The findings carry important policy implications. First, the absence of a wage premium for basic digital skills underscores the growing demand for more advanced competencies. In LMICs, where the supply of intermediate and advanced skills remains limited, this highlights the urgent need to scale up digital skills training through education systems and workforce development programs. Investing in these higher-level digital capabilities is increasingly essential not only for improving job quality but also for enabling broader participation in the digital economy. At the same time, the growing demand for AI capabilities calls for targeted curricula and training programs to ensure that labor markets remain adaptive to emerging technological trends.

Future research could explore how digital skills interact with non-cognitive traits and soft skills, such as problem-solving ability, adaptability, and communication skills, to influence labor market outcomes. Further research could also explore the impact of firm characteristics, such as digital intensity, organizational structure, and innovation capacity, on the returns to digital skills.

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Appendix A Sample and descriptive statistics

Table A1: Lightcast postings versus laborforce, 2024

Economy	Total Postings	Labor Force	Postings per 1,000 laborforce
FRA	15,757,581	31,275,500	503.8
BEL	2,128,283	5,370,800	396.3
NLD	2,973,048	10,235,400	290.5
AUT	1,346,320	4,733,000	284.5
DEU	11,808,215	44,778,100	263.7
GBR	8,946,784	34,910,572	256.3
IRL	679,913	2,880,400	236.0
CZE	1,242,304	5,331,200	233.0
USA	37,396,936	168,106,208	222.5
SGP	1,639,438	9,714,851	168.8
PRT	905,847	5,463,400	165.8
CHL	1,510,266	10,209,066	147.9
CAN	3,167,066	21,924,920	144.5
HKG	511,564	3,807,406	134.4
ITA	3,302,330	25,595,800	129.0
POL	2,107,492	17,742,600	118.8
COL	2,477,201	25,487,716	97.2
MYS*	1,422,041	16,022,100	88.8
MEX	5,287,770	60,966,744	86.7
AUS	1,242,930	15,013,883	82.8
ESP	1,874,943	24,424,600	76.8
PHL*	1,341,586	18,511,044	72.5
PER	1,207,155	18,666,092	64.7
BRA	6,258,922	109,563,152	57.1
JPN	1,455,130	69,570,000	20.9
CHN	875,175	77,328,536	11.3
IND	5,512,737	503,816,992	10.9

Note: This table compares the total number of online job postings from Lightcast with labor force size across countries. While the U.S. has the highest absolute number of postings, several European countries such as France, Belgium, and the Netherlands show higher posting intensity when normalized by labor force size. Lower ratios in emerging economies like India, the Philippines, and China may reflect limited digital job market penetration or undercoverage in Lightcast data.

Table A2: Final job postings versus original postings by economy, 2021–2024

Economy	Lightcast Postings	Final Postings	Postings Share (%)
USA	168,768,897	46,982,868	27.8
GBR	43,695,006	6,536,737	15.0
FRA	50,504,134	2,633,870	5.2
DEU	47,742,998	2,153,714	4.5
CAN	11,070,477	1,964,620	17.7
MEX	18,025,102	1,083,965	6.0
NLD	12,140,124	894,531	7.4
SGP	8,287,766	841,910	10.2
AUT	5,770,347	663,384	11.5
COL	9,662,451	485,308	5.0
ESP	7,797,709	445,290	5.7
JPN	3,999,373	435,224	10.9
AUS	5,480,888	313,001	5.7
IRL	2,756,344	281,061	10.2
IND	24,734,683	276,064	1.1
CZE	5,695,707	246,677	4.3
BRA	16,438,029	178,823	1.1
CHL	6,223,740	160,546	2.6
POL	10,736,173	152,192	1.4
BEL	10,058,998	124,241	1.2
ITA	11,457,653	102,563	0.9
HKG	2,979,482	96,942	3.3
PER	4,943,429	76,312	1.5
PHL	5,391,306	69,827	1.3
CHN	8,675,862	65,051	0.7
MYS	5,800,827	55,120	1.0
PRT	4,386,956	44,460	1.0
HUN	2,398,979	33,313	1.4
NZL	1,229,007	31,093	2.5
Total	516,852,447	67,428,707	13.1

Source: Lightcast Data

Table A3: Final postings share by economy, 2021-24

Economy	2021	2022	2023	2024
HICs				
USA	72.8	69.7	67.5	69.7
GBR	12.8	11.6	9.2	6.5
FRA	1.5	2.7	4.5	5.9
DEU	1.5	2.9	3.8	3.9
CAN	2.6	3.0	2.9	3.1
NLD	1.1	1.2	1.5	1.4
JPN	0.5	0.2	0.6	1.2
AUT	0.7	0.9	1.2	1.0
SGP	1.3	1.6	1.2	0.9
ESP	0.6	0.7	0.7	0.6
AUS	0.6	0.4	0.5	0.4
IRL	0.4	0.6	0.4	0.4
CZE	0.3	0.4	0.4	0.4
BEL	0.1	0.2	0.2	0.2
ITA	0.1	0.1	0.1	0.2
POL	0.2	0.3	0.2	0.2
HKG	0.1	0.2	0.2	0.1
PRT	0.1	0.1	0.1	0.1
HUN	0.0	0.0	0.1	0.0
NZL	0.0	0.1	0.1	0.0
CHL	0.3	0.3	0.2	0.2
LMICs				
MEX	1.4	1.4	1.8	1.7
COL	0.4	0.5	1.1	0.7
BRA	0.1	0.2	0.3	0.3
IND	0.4	0.4	0.5	0.3
PHL	0.0	0.0	0.1	0.2
MYS	0.0	0.0	0.1	0.1
PER	0.1	0.1	0.2	0.1
CHN	0.1	0.1	0.1	0.1

Source: Lightcast Data

Table A4: Number of observations by year

Year	Obs.
2021	12,897,089
2022	15,967,685
2023	18,856,997
2024	19,706,936
Total	67,428,707

Source: Lightcast Data

Table A5: Final job postings versus original postings by occupation, 2021–2024

ISCO–08 (1 digit)	Lightcast Postings	Final Postings	Postings Share (%)
Managers	64,563,394	6,789,427	10.5
Professionals	177,457,878	17,629,008	9.9
Technicians and Associate Professionals	111,757,862	12,813,352	11.5
Clerical Support Workers	42,572,388	5,728,919	13.5
Service and Sales Workers	77,347,418	10,622,284	13.7
Skilled Agricultural, Forestry and Fishery Workers	2,681,718	329,571	12.3
Craft and Related Trades Workers	35,253,949	3,944,973	11.2
Plant and Machine Operators, and Assemblers	29,797,871	4,892,826	16.4
Elementary Occupations	27,940,555	4,678,347	16.7
Total	569,373,033	67,428,707	

Source: Lightcast Data

Table A6: Final job postings versus original postings by sector, 2021–2024

NAICS-2	Lightcast Postings	Final Postings	Postings Share (%)
11	724,720	201,241	27.8
21	733,385	113,841	15.5
22	1,102,551	286,671	26.0
23	6,560,075	2,115,787	32.3
31	22,254,637	3,940,741	17.7
42	8,922,526	2,168,188	24.3
44	23,759,838	5,704,516	24.0
48	6,493,460	2,157,653	33.2
51	7,373,860	1,656,886	22.5
52	12,113,874	2,547,391	21.0
53	5,222,960	1,640,178	31.4
54	29,119,410	6,299,006	21.6
55	994,153	193,634	19.5
56	52,149,535	17,494,217	33.5
61	10,056,487	3,399,144	33.8
62	26,753,600	8,411,867	31.4
71	1,765,422	655,905	37.2
72	15,242,006	4,034,905	26.5
81	7,052,591	2,174,588	30.8
92	3,586,261	2,232,348	62.2
Total	241,981,351	67,428,707	

Source: Lightcast Data

Table A7: Final postings out of total postings by sector and occupation, 2021–2024

NAICS-2/ISCO-1	1	2	3	4	5	6	7	8	9
11	0.26	0.21	0.32	0.30	0.37	0.41	0.40	0.40	0.43
21	0.14	0.11	0.17	0.22	0.26	0.20	0.22	0.28	0.31
22	0.23	0.25	0.31	0.35	0.42	0.50	0.25	0.34	0.31
23	0.28	0.24	0.38	0.38	0.37	0.36	0.43	0.38	0.45
31	0.15	0.13	0.18	0.23	0.30	0.27	0.29	0.36	0.36
42	0.20	0.17	0.24	0.32	0.32	0.40	0.32	0.40	0.43
44	0.22	0.19	0.25	0.25	0.25	0.33	0.28	0.38	0.34
48	0.20	0.15	0.22	0.45	0.33	0.25	0.32	0.50	0.53
51	0.20	0.19	0.27	0.30	0.47	0.21	0.41	0.32	0.36
52	0.18	0.19	0.28	0.24	0.29	0.21	0.30	0.34	0.35
53	0.30	0.24	0.37	0.36	0.37	0.38	0.36	0.46	0.47
54	0.20	0.18	0.28	0.32	0.34	0.40	0.30	0.40	0.40
55	0.16	0.17	0.19	0.23	0.26	0.29	0.30	0.30	0.32
56	0.31	0.32	0.36	0.41	0.40	0.43	0.36	0.42	0.43
61	0.39	0.32	0.35	0.40	0.40	0.44	0.31	0.37	0.37
62	0.31	0.31	0.31	0.35	0.38	0.31	0.26	0.35	0.31
71	0.40	0.33	0.41	0.39	0.43	0.52	0.32	0.37	0.42
72	0.27	0.20	0.26	0.31	0.30	0.27	0.27	0.33	0.32
81	0.30	0.24	0.33	0.39	0.40	0.40	0.38	0.38	0.43
92	0.64	0.61	0.67	0.65	0.58	0.67	0.61	0.63	0.69

Note: This table shows the share of postings with skill and wage information across sector-occupation combinations for all the countries in our final sample. The values are relatively consistent, mostly falling between 30% and 40%, suggesting that sample selection bias is minimal. The only major deviation is in Public Administration (NAICS 92), where coverage exceeds 60%, likely due to regulatory transparency requirements in public hiring.

Table A8: Digital Core Occupations

ISCO-08 Code	Occupation Title
1330	Information and Communications Technology Service Managers
2152	Electronics Engineers
2153	Telecommunications Engineers
2356	Information Technology Trainers
2434	ICT Sales Professionals
2511	Systems Analysts
2512	Software Developers
2513	Web and Multimedia Developers
2514	Applications Programmers
2519	Software and Applications Developers and Analysts n.e.c.
2521	Database Designers and Administrators
2522	Systems Administrators
2523	Computer Network Professionals
2529	Database and Network Professionals n.e.c.
3114	Electronics Engineering Technicians
3511	ICT Operations Technicians
3512	ICT User Support Technicians
3513	Computer Network and Systems Technicians
3514	Web Technicians
3521	Broadcasting and Audiovisual Technicians
3522	Telecommunications Engineering Technicians
7421	Electronics Mechanics and Servicers
7422	ICT Installers and Servicers

Figure A1: Lightcast Postings: HICS vs. LMICs

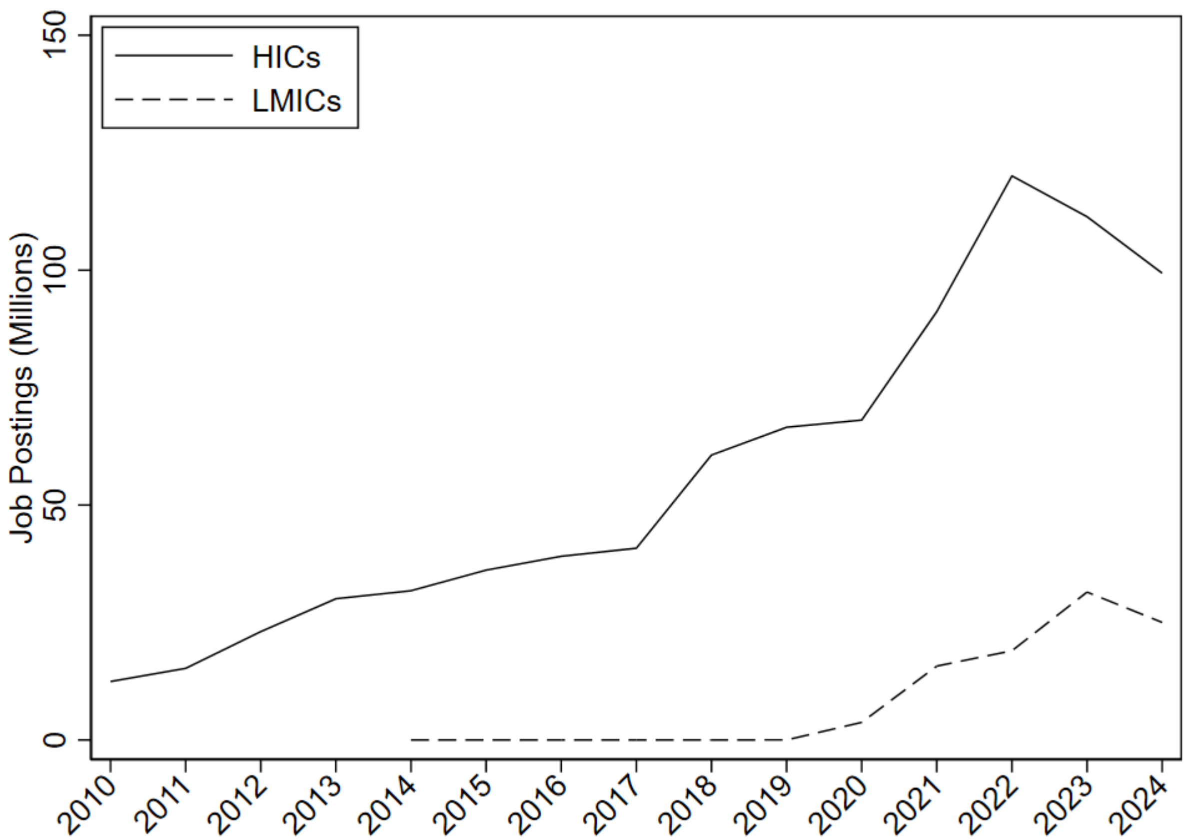


Figure A2: Distribution of skills per Job Posting

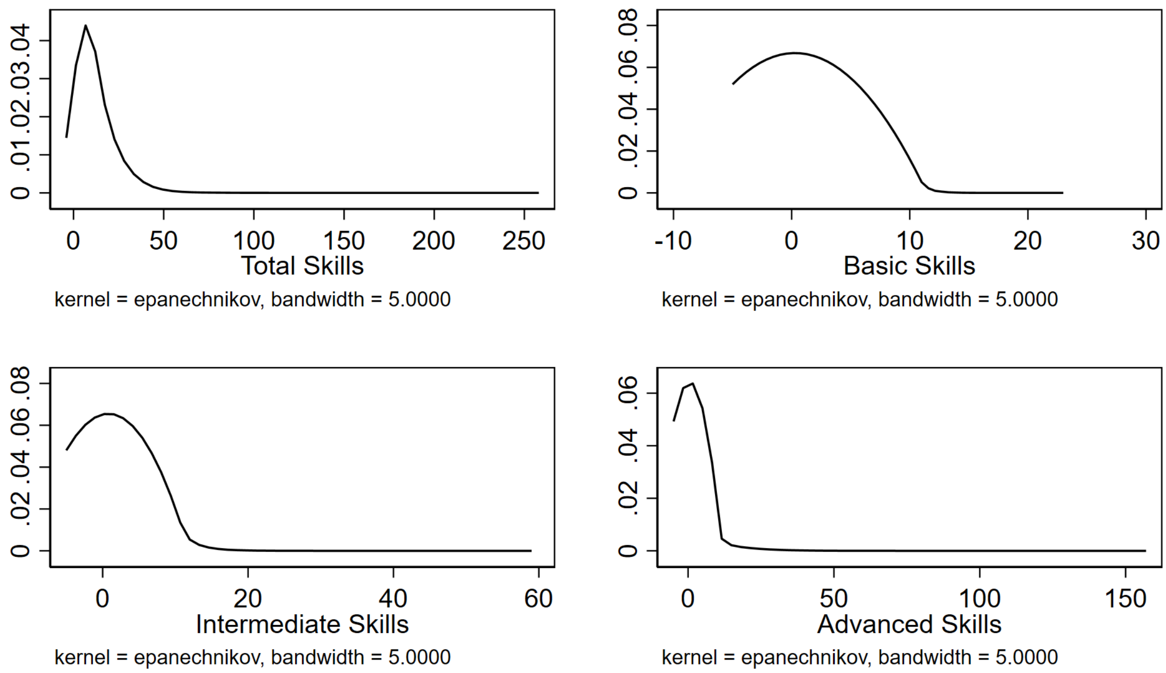


Figure A3: Demand for digital skills by skill level across country income groups

(a) HICs

(b) LMICs

Note: Word clouds represent the frequency of digital skills mentioned in online job postings from 2021-2024. Green labels account for basic digital skills, while blue and dark blue account for intermediate and advanced digital skills. The analysis is based on the sample used in this paper, restricted to postings with available information on salaries, occupations, industries, and skills.

Appendix B Additional Results

Table B1: Non-linear Returns to Additional Digital

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Number of Digital Skills	0.0184***	0.0111***	0.00977***	0.00928***
	(0.00164)	(0.00121)	(0.00115)	(0.00117)
Number of Digital Skills (Squared)	-0.000219***	-0.000151***	-0.000127***	-0.000119***
	(0.0000216)	(0.0000178)	(0.0000175)	(0.0000176)
Constant	10.71***	10.62***	10.62***	10.62***
	(0.00293)	(0.0105)	(0.0104)	(0.0104)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	67,428,704	67,428,704	67,423,920	67,423,920

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2: Returns to Digital Skills in Digitally Enhanced Occupations

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Digital Skills	0.0297***	0.00656	0.000495	-0.00274
	(0.0106)	(0.00849)	(0.00834)	(0.00853)
LMICs × Digital Skills				0.0776***
				(0.0168)
Constant	10.85***	10.71***	10.72***	10.72***
	(0.00586)	(0.0173)	(0.0168)	(0.0168)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	38,711,450	38,711,450	38,706,586	38,706,586

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B3: Returns to Additional Digital Skills in Digitally Enhanced Occupations

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Number of Digital Skills	0.0128***	0.00643***	0.00545***	0.00514***
	(0.00143)	(0.00103)	(0.000976)	(0.000992)
LMICs × Number of Digital Skills				0.0237***
				(0.00435)
Constant	10.84***	10.71***	10.71***	10.71***
	(0.00274)	(0.0155)	(0.0151)	(0.0151)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	38,711,450	38,711,450	38,706,586	38,706,586

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B4: Returns to Digital Skills in Digitally Enhanced Occupations

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Number of Basic Digital Skills	-0.0612***	-0.0467***	-0.0456***	-0.0457***
	(0.00477)	(0.00399)	(0.00409)	(0.00411)
Number of Intermediate Digital Skills	0.0189***	0.00809***	0.00624***	0.00572***
	(0.00266)	(0.00182)	(0.00166)	(0.00165)
Number of Advanced Digital Skills	0.0238***	0.0173***	0.0168***	0.0166***
	(0.00228)	(0.00176)	(0.00155)	(0.00158)
LMICs × Number of Basic Digital Skills				0.00681
				(0.0106)
LMICs × Number of Intermediate Digital Skills				0.0314***
				(0.00596)
LMICs × Number of Advanced Digital Skills				0.0204***
				(0.00556)
Constant	10.86***	10.73***	10.73***	10.73***
	(0.00388)	(0.0148)	(0.0145)	(0.0145)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	38,711,450	38,711,450	38,706,586	38,706,586

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B5: Returns to Digital Skills - Logarithm

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Log(1 + Basic Digital Skills)	-0.102***	-0.0821***	-0.0802***	-0.0799***
	(0.00810)	(0.00633)	(0.00617)	(0.00619)
Log(1 + Intermediate Digital Skills)	0.0528***	0.0259***	0.0207***	0.0197***
	(0.00675)	(0.00521)	(0.00482)	(0.00483)
Log(1 + Advanced Digital Skills)	0.117***	0.0862***	0.0829***	0.0810***
	(0.00626)	(0.00503)	(0.00475)	(0.00498)
LMICs × Log(1 + Basic Digital Skills)				-0.00865
				(0.0176)
LMICs × Log(1 + Intermediate Digital Skills)				0.0435***
				(0.0101)
LMICs × Log(1 + Advanced Digital Skills)				0.0949***
				(0.0193)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	67,428,704	67,428,704	67,423,920	67,423,920

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B6: Returns to AI Skills in Digitally Enhanced Occupations

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Number of Basic Digital Skills	-0.0611***	-0.0465***	-0.0455***	-0.0456***
	(0.00475)	(0.00397)	(0.00408)	(0.00410)
Number of Intermediate Digital Skills	0.0188***	0.00805***	0.00620***	0.00569***
	(0.00267)	(0.00182)	(0.00166)	(0.00166)
Advanced Skills (excluding AI)	0.0231***	0.0166***	0.0162***	0.0160***
	(0.00226)	(0.00173)	(0.00153)	(0.00156)
Traditional AI Skills	0.0489***	0.0430***	0.0375***	0.0378***
	(0.00666)	(0.00526)	(0.00448)	(0.00452)
LMICs × Number of Basic Digital Skills				0.00673
				(0.0106)
LMICs × Number of Intermediate Digital Skills				0.0315***
				(0.00598)
LMICs × Advanced Skills (excluding AI)				0.0212***
				(0.00580)
LMICs × Traditional AI Skills				-0.00606
				(0.0249)
Constant	10.86***	10.73***	10.73***	10.73***
	(0.00387)	(0.0148)	(0.0145)	(0.0145)
Country	Yes	Yes		
Year	Yes	Yes		
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls		Yes	Yes	Yes
Country X City X Year			Yes	Yes
Observations	38,711,450	38,711,450	38,706,586	38,706,586

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B7: Robustness check with sector-by-year fixed effects

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Digital Skills	0.0139**			
	(0.00691)			
LMICs × Digital Skills	0.0582***			
	(0.0143)			
Number of Digital Skills		0.00495***		
		(0.00112)		
LMICs × Number of Digital Skills		0.0209***		
		(0.00177)		
Number of Basic Digital Skills			-0.0386***	-0.0383***
			(0.00344)	(0.00343)
LMICs × Number of Basic Digital Skills			-0.00879	-0.00904
			(0.00997)	(0.00994)
Number of Intermediate Digital Skills			0.00824***	0.00796***
			(0.00149)	(0.00151)
LMICs × Number of Intermediate Digital Skills			0.0244***	0.0244***
			(0.00476)	(0.00475)
Number of Advanced Digital Skills			0.00749***	
			(0.00217)	
LMICs × Number of Advanced Digital Skills			0.0220***	
			(0.00197)	
Advanced Skills (excluding AI)				0.00708***
				(0.00214)
LMICs × Advanced Skills (excluding AI)				0.0220***
				(0.00203)
Traditional AI Skills				0.0298***
				(0.00484)
LMICs × Traditional AI Skills				0.0226
				(0.0174)
Constant	10.63***	10.63***	10.64***	10.64***
	(0.0114)	(0.0104)	(0.00984)	(0.00985)
City	Yes	Yes	Yes	Yes
Occupation	Yes	Yes		
Sector-Year	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes
Observations	67,427,339	67,427,339	67,427,339	67,427,339

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B8: Robustness check with country-by-year fixed effects

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Digital Skills	0.0182***			
	(0.00703)			
LMICs × Digital Skills	0.0597***			
	(0.0150)			
Number of Digital Skills		0.00540***		
		(0.00123)		
LMICs × Number of Digital Skills		0.0220***		
		(0.00196)		
Number of Basic Digital Skills			-0.0390***	-0.0387***
			(0.00346)	(0.00344)
LMICs × Number of Basic Digital Skills			-0.00504	-0.00535
			(0.0110)	(0.0110)
Number of Intermediate Digital Skills			0.00969***	0.00935***
			(0.00164)	(0.00168)
LMICs × Number of Intermediate Digital Skills			0.0255***	0.0255***
			(0.00512)	(0.00511)
Number of Advanced Digital Skills			0.00761***	
			(0.00221)	
LMICs × Number of Advanced Digital Skills			0.0230***	
			(0.00212)	
Advanced Skills (excluding AI)				0.00711***
				(0.00218)
LMICs × Advanced Skills (excluding AI)				0.0230***
				(0.00217)
Traditional AI Skills				0.0352***
				(0.00460)
LMICs × Traditional AI Skills				0.0283
				(0.0189)
Constant	10.63***	10.63***	10.64***	10.64***
	(0.0115)	(0.0105)	(0.00984)	(0.00984)
Country-Year	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes
Observations	67,428,704	67,428,704	67,428,704	67,428,704

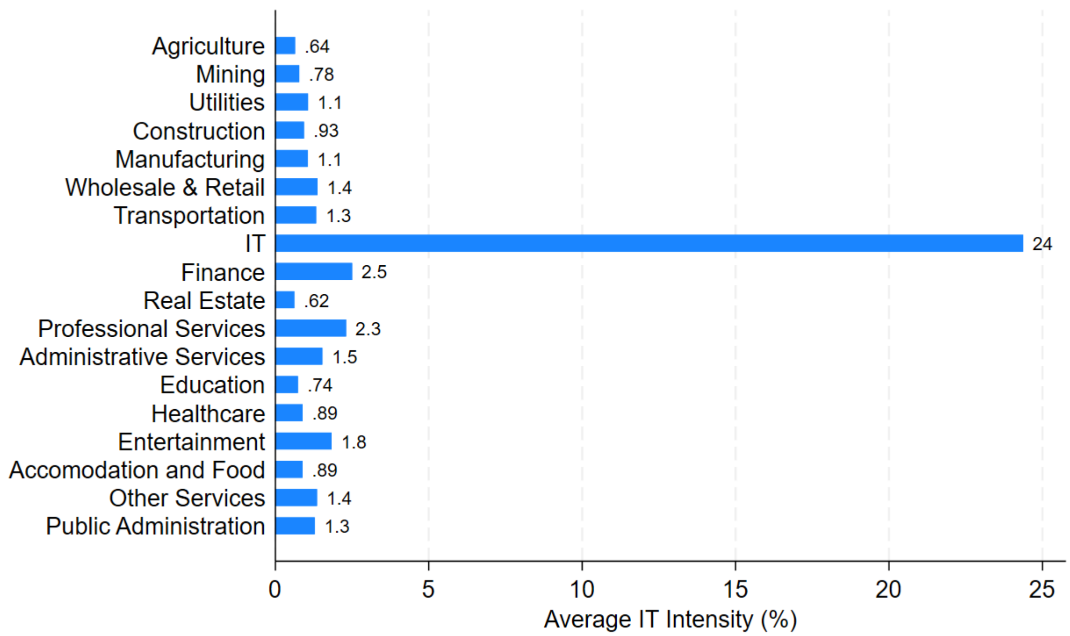
Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B9: Robustness check with sector-by-country fixed effects

Dependent variable: Log(Wage)	(1)	(2)	(3)	(4)
Digital Skills	0.0190***			
	(0.00668)			
LMICs × Digital Skills	0.0587***			
	(0.0145)			
Number of Digital Skills		0.00540***		
		(0.00123)		
LMICs × Number of Digital Skills		0.0213***		
		(0.00209)		
Number of Basic Digital Skills			-0.0389***	-0.0385***
			(0.00341)	(0.00339)
LMICs × Number of Basic Digital Skills			-0.00469	-0.00501
			(0.0100)	(0.0100)
Number of Intermediate Digital Skills			0.00968***	0.00934***
			(0.00160)	(0.00164)
LMICs × Number of Intermediate Digital Skills			0.0246***	0.0247***
			(0.00519)	(0.00516)
Number of Advanced Digital Skills			0.00760***	
			(0.00222)	
LMICs × Number of Advanced Digital Skills			0.0222***	
			(0.00217)	
Advanced Skills (excluding AI)				0.00711***
				(0.00219)
LMICs × Advanced Skills (excluding AI)				0.0223***
				(0.00218)
Traditional AI Skills				0.0347***
				(0.00457)
LMICs × Traditional AI Skills				0.0185
				(0.0237)
Constant	10.63***	10.63***	10.64***	10.64***
	(0.0112)	(0.0103)	(0.00960)	(0.00961)
Year	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes
Country-Sector	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes
Observations	67,428,703	67,428,703	67,428,703	67,428,703

Note: Additional controls include education requirements (college, non-college, or unspecified), experience requirements (less than 3 years, 3–4 years, more than 4 years, or unspecified), employment type (full-time, part-time, or unspecified), and work arrangement (remote, non-remote, hybrid, or unspecified). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure B1: IT Intensity across Sectors



Note: Figure shows the average IT intensity by sector, calculated as the cross-country mean across all countries included in the final sample.