Skills that Pay: Digital Skills Demand and Wage Premia in Asia and the Pacific

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Outline

Introduction

Motivation

- Digital and AI technologies are reshaping which skills firms demand—and how much they pay.
- Yet we know little about how digital-skill demand varies *within* occupations, evolves in real time (post-ChatGPT), and is *priced*.
- Particularly salient for Asia and the Pacific: advanced and rapidly digitalizing economies side by side.

What we do

- Using ∼**6 million Indeed job postings** (2019–2024, six APAC economies), our analysis is organized around three research questions:
  1. **How widespread is digital-skill demand?** — across jobs, countries, and time.
  2. **How is it priced?** — wage premia within job title and firm, net of non-digital tasks.
  3. **How is AI-skill demand evolving?** — post-ChatGPT dynamics; AI use vs. development.
- Measurement: **GPT-4.1 mini** classifies each posting (digital skill: None/Basic/Int./Adv.; AI: No/Use/Develop).
- Identification: **within-job-title** variation; ESCO non-digital tasks as controls; posted wages from the same text.

Preview of findings

- Digital skills are **widespread**: $>85\%$ of postings require at least basic digital literacy.
- Growth is concentrated in traditionally low- and mid-digital jobs $\Rightarrow$ **diffusion, not polarization**.
- Large wage premia, within job title and firm, conditional on 24 non-digital tasks:
  - Basic: $\approx 4\%$ Intermediate: $\approx 11\%$ Advanced: $\approx 26\%$
- **AI skill demand has taken off** post-ChatGPT; AI use/development carry an additional premium on top of digital skills.

Contribution to the literature

- **Job polarization vs. diffusion.** Autor and Dorn (2013) document polarization; we find broad digital **diffusion**, closer to Acemoglu and Restrepo (2019).
- **Returns to digital/ICT skills.** Extends Krueger (1993) and Falck et al. (2021): **within-job-title, within-firm digital premia** after controlling for non-digital tasks.
- **AI skill demand.** Complements Acemoglu et al. (2022), Copestake et al. (2023), Jaumotte et al. (2026); separates **AI use** from **AI development** and from general digital proficiency.
- **Methodology.** Validated **LLM** classification at scale: human-level agreement; $\approx 97\%$ replicability.

Data and Measurement

Indeed job postings/descriptions data

- Six APAC economies (AU, PH, IN, MY, SG, KR), Jan 2019–Dec 2024, $\sim$6M postings (stratified by country$\times$year$\times$month$\times$job title).
- Key attributes per posting:
  - Free-text job description
  - Standardized **occupation** ($\sim$53 groups) and **job title** ($\sim$5,000 per country)
  - Firm ID, location, time stamp
  - Posted wage when available
- Advantage over survey data: **direct, high-frequency** measure of employer demand; each posting links job title, skills, and wage.

Measuring digital skills with an LLM

- OpenAI **GPT-4.1 mini** (`gpt-4.1-mini-2025-04-14`); temperature $= 0$, fixed seed $\Rightarrow$ minimal randomness, reproducibility.

Digital-skills prompt (abridged)

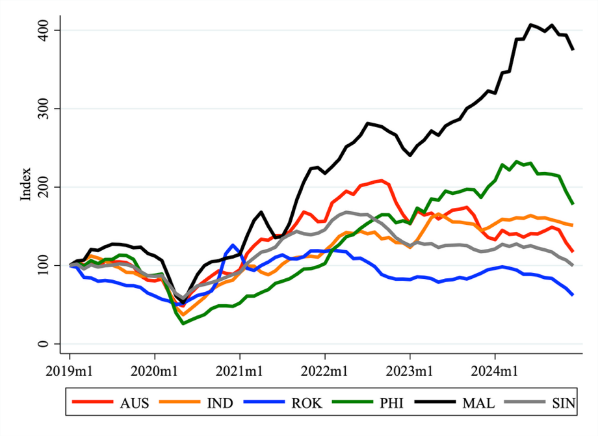
- One job ad at a time $\rightarrow$ classify into **A / B / C / D**.
  - **A** *None*—no digital tools beyond phone/messaging
  - **B** *Basic*—email, Word, simple Excel, data entry, social posting
  - **C** *Intermediate*—CRM, dashboards, advanced Excel, web maintenance, simple code
  - **D** *Advanced*—programming, AI/ML, IT systems management

- **Addressing known LLM issues** (Ludwig et al., 2025):
  - Manual validation—2 human annotators + own review on 200-posting subsample
  - Careful prompt engineering—iterated over many variants, manual scoring
  - Assess measurement error; limit brittleness via fixed seed, $T = 0$

Validation: GPT vs. humans, and replicability

- **Human benchmark.** Two annotators coded the same **200 postings** with the identical rubric.
  Matrices & example
  - GPT vs. Human 1 / 2: **80.2% / 80.8%**; Human 1 vs. Human 2: **79.9%**.
  - $\Rightarrow$ GPT–human disagreement $\approx$ human–human; disagreements mostly one category apart.
- **Replicability.** Same prompt re-run **100 times** on 1,000 postings.
  - Mean agreement with modal class: **97.2%**; Fleiss' $\kappa = 0.94$ (Landis and Koch, 1977) — almost perfect.
  - Classification noise well below what human coders would produce.

Addressing compositional changes in online postings



Trends in Online Job Postings, Jan 2019 = 100.

- Posting growth partly reflects the **expanding reach** of online recruitment—not only labor demand.
- Representativeness varies across countries and over time.
- **Solution:**
  - **Within-job-title** analysis: identify skill changes *within* the same title, not from the shifting mix of titles posted online.
  - When aggregating to the country level, hold occupational structure constant via **fixed job-title weights**.
- Trade-off: abstract from cyclical fluctuations.

Digital Skills Demand

Defining the digital skill score

- To compare digital-skill intensity across jobs, countries, and time, we define a 0–1 score:

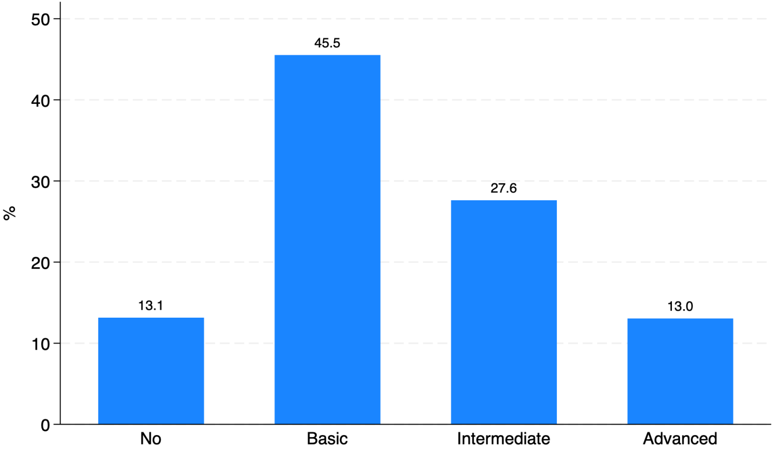
$$\text{Score}_{c,j,t} = \frac{0 \cdot Sh^{\text{no}}_{c,j,t} + 1 \cdot Sh^{\text{basic}}_{c,j,t} + 2 \cdot Sh^{\text{int}}_{c,j,t} + 3 \cdot Sh^{\text{adv}}_{c,j,t}}{3}$$

where $Sh^{i}_{c,j,t}$ is the share of postings in country c, job title j, and period t classified in digital-skill level i.

- Interpretation: Score $= 1$ means *all* postings require advanced skills.
- Aggregate using fixed job-title weights (country-specific for within-country trends; common weights for cross-country comparisons).

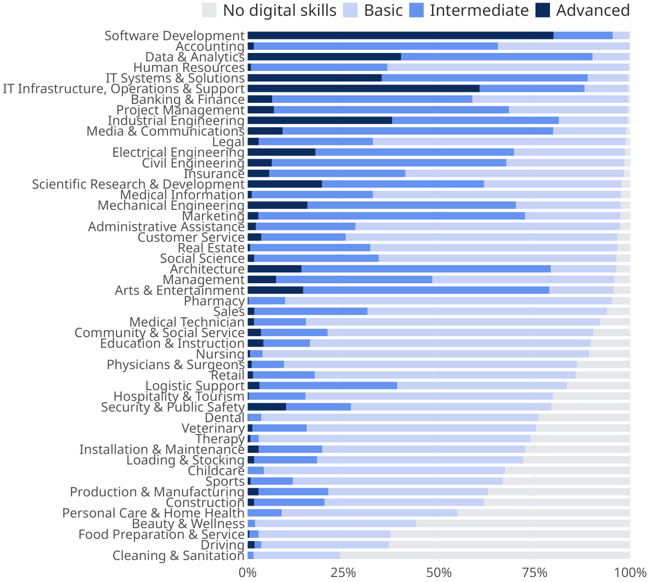
Country breakdown Score by country

Most postings require some digital skills



Share of postings by digital skill level, cross-country average, 2019–2024.

Demand varies widely across occupations

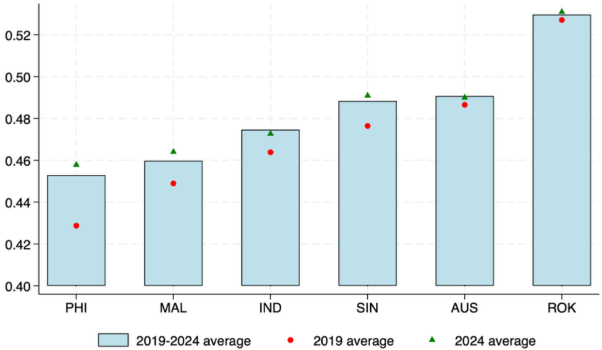


Top end
software dev., IT, data & analytics.

Broad middle
basic digital literacy is widespread outside ICT.

Bottom end
cleaning, food prep, driving.

Cross-country heterogeneity, with the gap narrowing



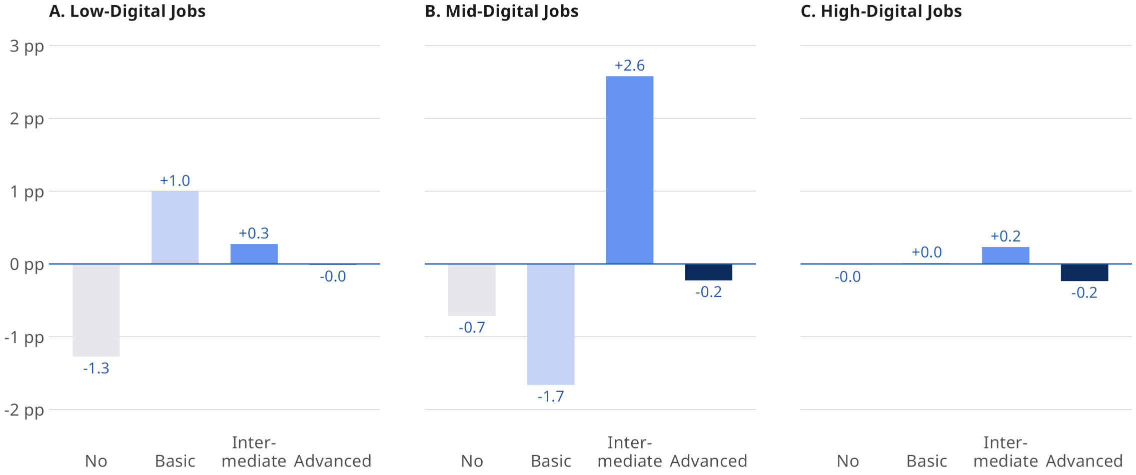
Digital Skill Score, equal job-title weights across countries.

- ROK highest (≈ 0.53); Philippines lowest (≈ 0.45).
- For the *same job*, Korean employers demand $\approx$ 17% **more** digital skills than Filipino employers.
- Demand rose in all six economies; largest gains where the initial level was lowest.

By country

Within-job-title upgrading: diffusion, not polarization

Change in share of job postings by digital skill level demanded, 2019 to 2024, by initial digital intensity



Specific skills demanded: word clouds

(a) No digital skills

(b) Basic

(c) Intermediate

(d) Advanced

Most frequent terms in CBT's motivations, by digital skill category

The Digital Skill Wage Premium

Empirical framework

Identify the **wage premium for digital skills** within job title and firm:

$$\ln(w)_{i,c,o,p,f,t} = \beta^b \,\mathrm{Basic}_{i,c,o,p,f,t} + \beta^i \,\mathrm{Int}_{i,c,o,p,f,t} + \beta^a \,\mathrm{Adv}_{i,c,o,p,f,t} + \delta' S_{i,c,o,p,f,t} + \gamma_{c,o,\mathrm{pf}} + \partial_{c,p} + \theta_{c,o,t} + \varphi_{c,p,t} + \vartheta_{c,f} + \varepsilon_{i,c,o,p,f,t}$$

Indices: i posting, c country, j job title, o occupation, p province, f firm, t time; pf = pay frequency.

- $S_{i,c,o,p,f,t}$: 24 non-digital task requirements (ESCO-based). Non-digital tasks list
- FE: country×job-title×pay-freq, country×firm, country×province, country×occ×t, country×province×t.
- SEs clustered at country–province–t, country–occ–t, country–firm.
- Identified **within job title and firm**, controlling for non-digital task content.

Digital skills carry large, distinct wage premia

	(1) No FE	(2) + FE	(3) + Tasks *preferred*
Basic	20.483***	5.569***	**3.563*****
	(1.161)	(0.490)	(0.423)
Intermediate	35.040***	14.362***	**10.994*****
	(1.337)	(0.560)	(0.513)
Advanced	66.905***	28.819***	**25.863*****
	(1.884)	(0.866)	(0.835)
Cluster (1) (2) (3)	✓	✓	✓
Job title × pay-freq FE	–	✓	✓
Firm, province, occ×t, prov×t FE	–	✓	✓
Non-digital task controls	–	–	✓
R^2	0.93	0.98	0.98
Observations	1,656,609	1,438,265	1,438,248

Dep. var.: ln(hourly wage), coefficients ×100. Standard errors in parentheses, clustered at (1) country–province–time, (2) country–occupation–time, (3) country–firm. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Full table

Putting the premia in context

- **Intermediate digital skills** ($\approx 11\%$) reward jobs more than *non-digital tasks* such as:
  - Negotiating (6.3%), Analyzing/evaluating information (4.6%), Supervising (5.7%), Making decisions (4.3%).
- **Advanced digital skills** ($\approx 26\%$) reward jobs **well above** leadership and strategic-management skills:
  - Leading & motivating (10.8%), Developing objectives & strategies (10.1%).
- Introducing non-digital task controls shrinks the *basic* premium proportionally more than the intermediate or advanced one—intermediate/advanced digital skills are **less substitutable** with non-digital tasks.
- Digital capabilities are a **distinct, complementary input**—not a proxy for general job complexity.

Country heterogeneity in the digital wage premium

	(1) AUS	(2) IND	(3) ROK	(4) MAL	(5) PHI	(6) SIN
Basic	3.316***	5.483***	3.492	3.871***	4.676***	4.604***
	(1.043)	(0.725)	(3.966)	(0.807)	(0.676)	(1.204)
Intermediate	9.750***	11.929***	5.337	11.404***	13.377***	12.142***
	(1.176)	(0.842)	(8.096)	(1.075)	(1.178)	(1.507)
Advanced	17.272***	30.678***	25.755	28.186***	31.969***	30.114***
	(1.615)	(1.489)	(16.804)	(1.842)	(1.728)	(3.179)
R^2	0.72	0.63	0.66	0.68	0.70	0.81
Observations	253,389	415,671	26,414	489,431	210,396	42,947

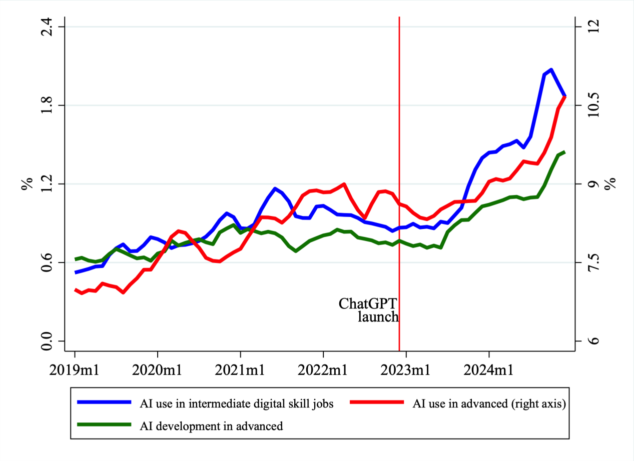
Dep. var.: ln(hourly wage), coefficients $\times 100$; same FE and controls as Column (3) of the pooled specification. SE in parentheses, clustered as in Table 2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. ROK estimates imprecise due to a smaller wage-reporting sample.

AI Skills

Measuring AI skills

- Second-stage classification on the subset of **intermediate and advanced digital** postings.
- Three categories:
  - **No AI**
  - **AI use**—calling APIs, applying pre-built ML libraries, complex prompt engineering, integrating generative AI in workflows.
  - **AI development**—training/fine-tuning models, building custom pipelines, designing AI systems.
- Same LLM, same style of structured prompt (full text: appendix).

AI skill demand has taken off post-ChatGPT

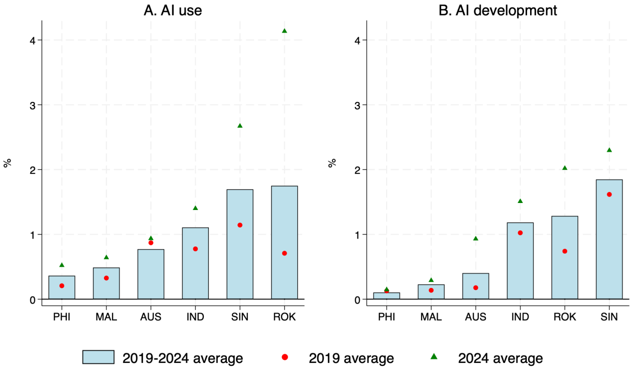


Vertical line: public release of ChatGPT, Nov 2022.

- AI use, intermediate-digital jobs: **∼1%** → **∼2%** (2022→2024).
- AI use, advanced-digital jobs: **∼7%** → **∼11%**.
- AI development, advanced-digital: **∼0.7% nearly doubles**.

AI capabilities are spreading *beyond* high-tech roles.

Cross-country AI skill demand



- **ROK and Singapore** lead in AI skill demand; Philippines lowest.
- In ROK, AI-use demand **grew four-fold** 2019–2024.
- AI *use* diffuses broadly; AI *development* remains concentrated.

AI carries an extra wage premium on top of digital skills

Augment the baseline with AI-use and AI-development dummies:

$$\ln(w)_i = \underbrace{\beta^b \text{Basic} + \beta^i \text{Int} + \beta^a \text{Adv}}_{\text{Digital skills}} + \underbrace{\delta^u \text{AI\_use} + \delta^d \text{AI\_dev}}_{\text{AI skills}} + \text{FE} + \varepsilon_i$$

- Pooled: AI use ≈ **4%**; AI dev ≈ 6% (not significant).
- Consistent with Stephany and Teutloff (2024) and Jaumotte et al. (2026).

	(1) AUS	(2) IND	(3) ROK	(4) MAL	(5) PHI	(6) SIN	(7) All
AI use (δ^u)	−1.978	6.558*	47.381**	3.156	13.939***	−5.767	**3.616****
	(1.538)	(3.592)	(21.285)	(5.326)	(2.969)	(10.603)	(1.743)
AI dev (δ^d)	−3.551	10.881	33.008	−2.638	24.649***	5.116	5.950
	(3.496)	(7.534)	(38.982)	(19.713)	(8.630)	(8.017)	(4.257)
R^2	0.721	0.626	0.663	0.676	0.696	0.807	0.979
Observations	253,389	415,671	26,414	489,431	210,396	42,947	1,438,248

Coefficients ×100. SE in parentheses, clustered at country–province–t, country–occ–t, country–firm. All specifications include the same FE and 24 non-digital task controls as Column (3) of Table 2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Conclusion

Takeaways

- Digital skills are **diffusing** broadly across the occupational distribution—not polarizing.
- Digital wage premia are **large and steep**: $\approx 4\%$ / 11% / 26% for basic / intermediate / advanced.
- Premia are identified **within job title and firm**, conditional on 24 non-digital tasks.
- AI skills carry an **additional** premium on top of digital skills.
- Validated LLM classification is a **scalable** alternative to keyword or expert methods.

Policy implications

- Because digital demand is rising fastest in jobs that used to need little of it, the findings point to a few priorities:
  - **Foundational digital literacy** — treated alongside reading and numeracy (schools, teacher training, ed-tech), not only specialist ICT skills.
  - **Mid-skill and mid-career upskilling**, where demand is growing most.
  - **Online job postings** as a real-time complement to traditional labor-market surveys.
- Encouragingly, several economies in the region are already moving this way — e.g., digital-education strategies in Japan, Korea, and Singapore, and recent digital-workforce and AI reforms in the Philippines.

Appendix

A1. Digital-skills prompt (abridged)

Below is a job posting. Please assess to what extent the job requires digital skills. Use the following classification:

- *A: No digital skills.* No computer/digital tool usage beyond basic communication.
- *B: Basic.* Email, basic Word/Excel/PowerPoint, data entry, social posting.
- *C: Intermediate.* CRM, data analysis and reporting, simple scripts/website edits, advanced Excel, social-media campaign management.
- *D: Advanced.* Programming, AI, machine learning, IT infrastructure management.

Internal reasoning guidance: prioritize explicit mentions; use general knowledge when the description is sparse; consider job title and country context.
Output: JSON with `jobid`, `classification`, `motivation`.

← back

A2. Validation: agreement matrices and a disagreement example

Agreement matrices (200-posting subsample)

GPT vs. H1 (corr. 80.2%)

	A	B	C	D
A	45	0	0	0
B	46	45	0	0
C	3	32	11	1
D	0	1	4	12

H1 vs. H2 (corr. 79.9%)

	A	B	C	D
A	58	1	0	0
B	36	61	2	1
C	0	11	10	0
D	0	5	3	12

Example disagreement (GPT: C; H1: D; H2: B)

"XXX is a major ICT Services supplier to State & Federal Government Departments... ongoing contracts require experienced desktop engineers for PC rollouts, installations, SOE imaging, data transfer, fault diagnosis, and post-installation support. Windows 10 and Office 365 knowledge will also be highly regarded. $35–$40 per hour. In person, Canberra, ACT."

⇒ Ambiguous between B, C, and D—routine tasks but technical context; human–human disagreement of similar magnitude as GPT–human.

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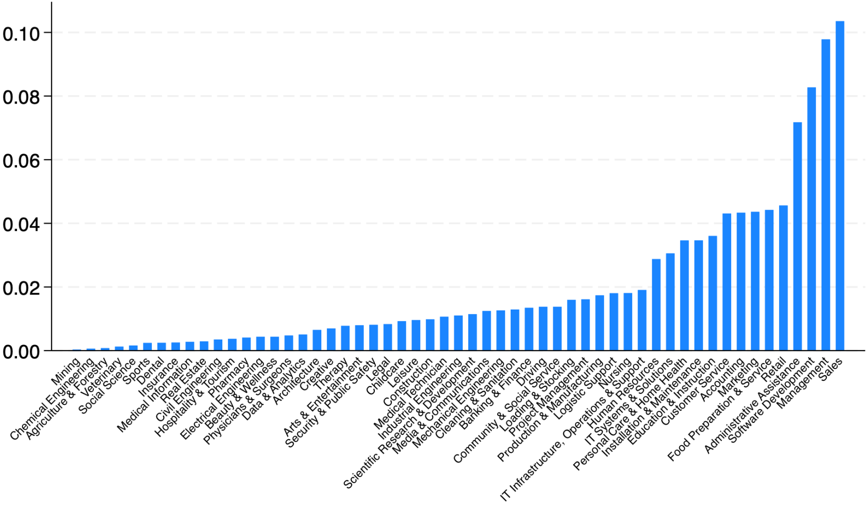
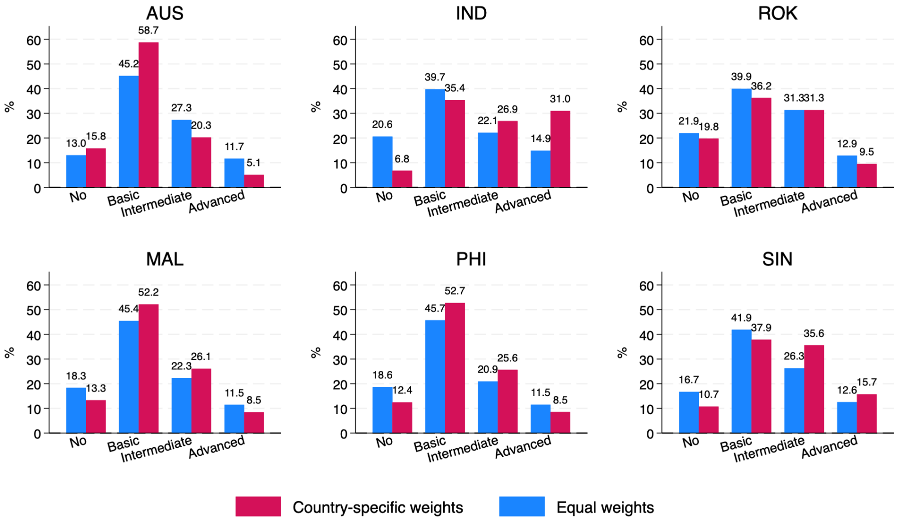
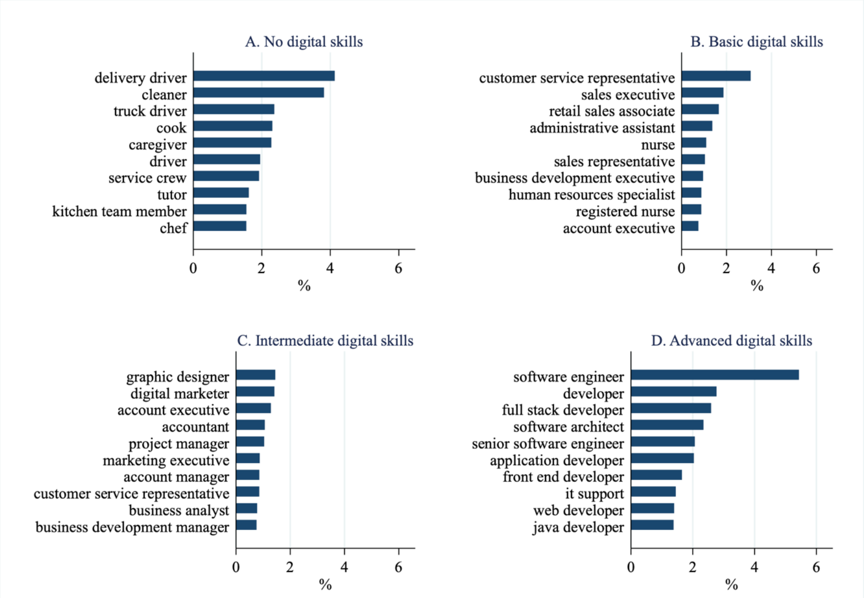
A3. Occupation weights (average country)



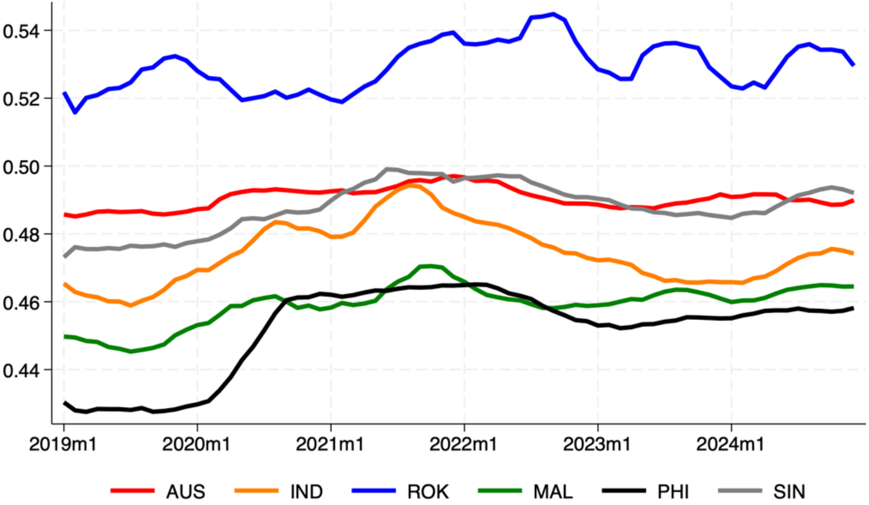
A4. Share of postings by digital skill level, by country



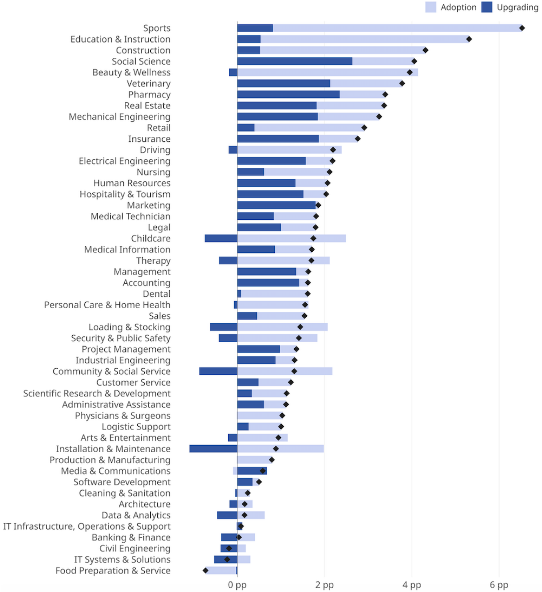
A5. Top 10 job titles by digital skill category



A6. Digital skill score by country over time



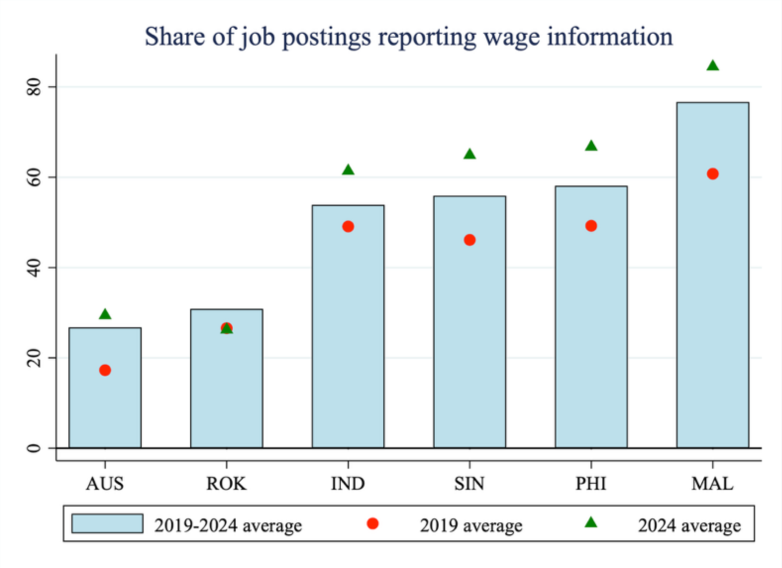
A7. Decomposition: adoption vs. upgrading



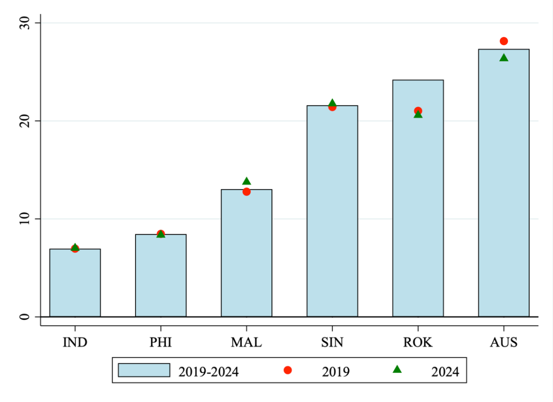
Adoption = postings moving from *None* in 2019 to $\geq$ *Basic* in 2024.

Upgrading = postings already digital moving to a higher category.

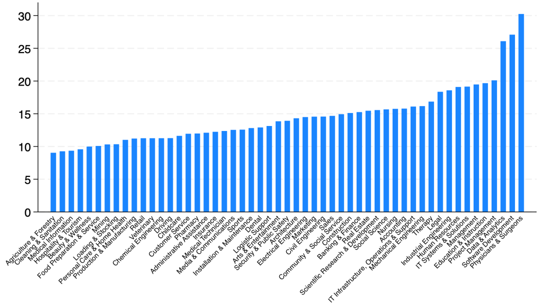
A8. Wage descriptives: share reporting wages, by country



A9. Wage descriptives: by country and occupation



Posted wages by country (2024 USD PPP).



Posted wages across occupational categories, country avg.

A10. AI-skills prompt (abridged)

Provide an assessment whether the job requires specific artificial intelligence (AI) skills:

- *no-ai:* no AI-related skills required (except simple ChatGPT/Copilot use to draft text, code, or summaries).
- *ai-use:* requires using, implementing, or applying existing AI tools—pre-built ML libraries, API calls, complex prompt engineering, generative-AI integration.
- *ai-develop:* requires creating AI tools—training or fine-tuning LLMs, deep learning, custom AI pipelines.

Run only on postings classified as intermediate (C) or advanced (D) digital skills.

A11. Non-digital task requirements (ESCO-based, 24 items)

Communication, collaboration & creativity

1. Negotiating (S1.1)
2. Liaising and networking (S1.2)
3. Presenting information (S1.4)
4. Working with others (S1.8)
5. Solving problems (S1.9)
6. Designing systems and products (S1.11)
7. Writing and composing (S1.13)
8. Using more than one language (S1.15)

Information processing

9. Conducting studies/investigations (S2.1)
10. Documenting and recording information (S2.2)
11. Managing information (S2.3)
12. Processing information (S2.4)
13. Analyzing/evaluating information (S2.7)
14. Monitoring, inspecting and testing (S2.8)

Management

15. Developing objectives & strategies (S4.1)
16. Organising, planning & scheduling (S4.2)
17. Allocating and controlling resources (S4.3)
18. Performing administrative activities (S4.4)
19. Leading and motivating (S4.5)
20. Building and developing teams (S4.6)
21. Supervising people (S4.8)
22. Making decisions (S4.9)

Technical

23. Using precision instrumentation & equipment (S8.6)
24. Installing, maintaining, repairing electrical, electronic & precision equipment (S8.8)

Source: ESCO task taxonomy; see paper Appendix C.

← back

A12. Full pooled wage-premium table (with non-digital controls)

	(1) No FE	(2) + FE	(3) + Tasks
Digital skills			
Basic	20.483*** (1.161)	5.569*** (0.490)	3.563*** (0.423)
Intermediate	35.040*** (1.337)	14.362*** (0.560)	10.994*** (0.513)
Advanced	66.905*** (1.884)	28.819*** (0.866)	25.863*** (0.835)
Selected non-digital controls			
Negotiating	–	–	6.292*** (0.313)
Liaising and networking	–	–	3.886*** (0.250)
Analyzing/evaluating info. & data	–	–	4.577*** (0.283)
Developing objectives & strategies	–	–	10.056*** (0.330)
Allocating and controlling resources	–	–	4.927*** (0.683)
Leading and motivating	–	–	10.814*** (0.319)
Building and developing teams	–	–	6.613*** (0.534)
Supervising people	–	–	5.729*** (0.268)
Making decisions	–	–	4.342*** (0.204)
R^2	0.93	0.98	0.98
Observations	1,656,609	1,438,265	1,438,248
Cluster (1)(2)(3)	YES	YES	YES
Fixed effects	NO	YES	YES
Non-digital task controls	NO	NO	YES

Coefficients ×100. SE in parentheses, clustered at country–province–time, country–occupation–time, country–firm. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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