WOMEN AND FUTURE JOBS

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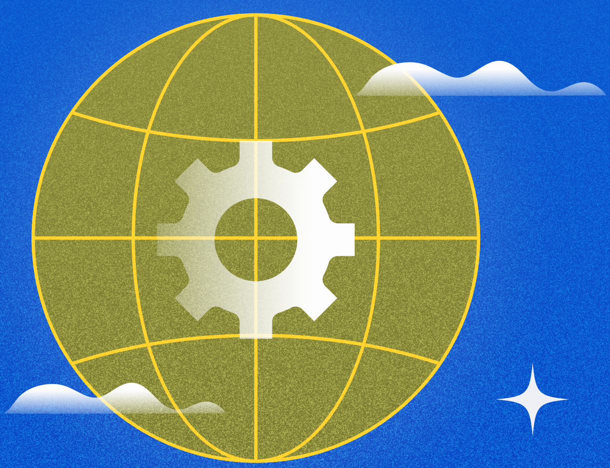

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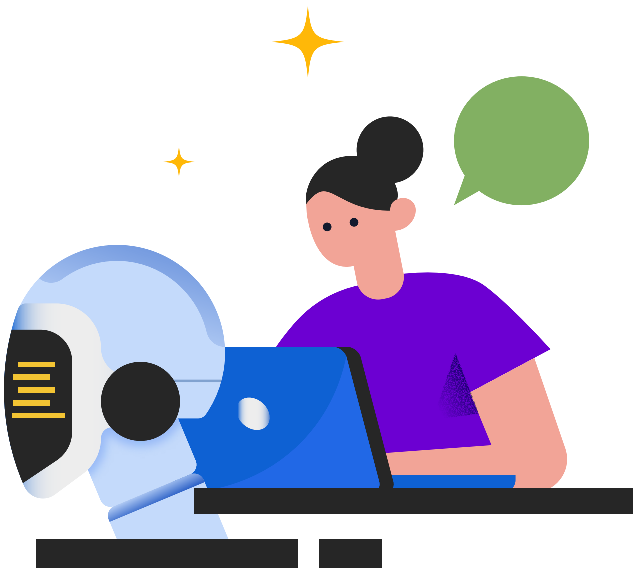
INTRODUCTION

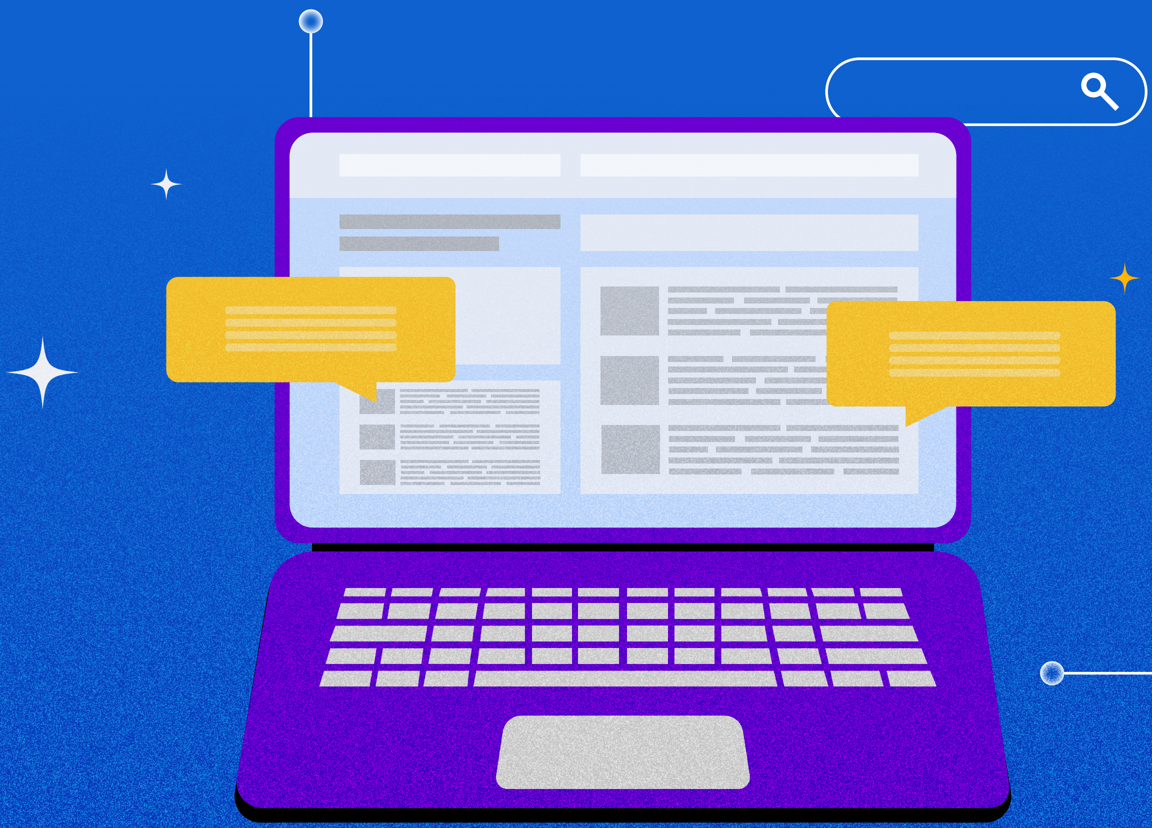


ARTIFICIAL INTELLIGENCE (AI) IS RAPIDLY TRANSFORMING LABOUR MARKETS, PRESENTING BOTH OPPORTUNITIES AND CHALLENGES FOR GENDER EQUALITY. GENERATIVE AI (GAI) HAS THE POTENTIAL TO SIGNIFICANTLY IMPACT THE OCCUPATIONAL LANDSCAPE, WITH ESTIMATES SUGGESTING THAT GAI COULD SUBSTITUTE UP TO ONE-FOURTH OF EXISTING JOBS.[1]

However, these impacts are not uniform and could disproportionately affect women.

Women workers are more likely to be employed in sectors and occupations that could be disrupted by GAI. Yet, these disruptions may also create new opportunities. Based on self-reported skills data on LinkedIn profiles, more women than men tend to list competencies, such as teamwork, which are less likely to be replicated by GAI.

Given GAI's expected impact on labour markets, it is important that policymakers and businesses take concerted action to ensure that AI fosters inclusive growth. This includes enhancing productivity, promoting professional advancement, developing skills and securing economic stability for all workers. As many organizations are still in the experimental phase, and governments are developing frameworks to guide AI's trajectory, this is an opportune moment to examine the potential labour market effects on women and men workers before inequalities are created or entrenched.



METHODOLOGY

This brief is primarily based on anonymized and aggregated data from the LinkedIn Economic Graph. LinkedIn Economic Graph is a digital representation of the global economy based on LinkedIn's member base, which consists of over a billion members worldwide and over 320 million in the Asia and the Pacific (AP) region. LinkedIn Economic Graph data have some limitations. It represents the world as seen through the lens of LinkedIn data. As such, it is influenced by how members choose to use the site, which can vary based on professional, social and regional culture, as well as overall site availability and accessibility.

To complement insights from the LinkedIn Economic Graph, this brief also leverages secondary data sources. A full methodology and reference list is available in the Appendix.

DEFINING AI

AI refers to the intelligence demonstrated by machines, encompassing the abilities to perceive, synthesize and infer information. This distinguishes machine intelligence from human or animal intelligence. The term "intelligence" encompasses learning, reasoning, generalization and inferential abilities.[2]

GAI is a subset of AI capable of generating text, images, video or other forms of output by using probabilistic models trained across domains. These models learn from large amounts of curated training data to identify and replicate complex patterns and structures. The generated output mimics the characteristics of the training data, enabling many novel applications.[3]

KEY FINDINGS

GAI is changing the nature of work

Between 2016 and 2023, the skills needed for any given job changed by almost 40% across the AP region. By 2030, with GAI, skills for jobs would have changed by 71% (compared to 2016).

While most jobs will require skills that can be performed by GAI technologies, not every job will be affected the same way

To understand the potential impact of GAI on the labour market, LinkedIn developed a conceptual framework to explain how skills – and consequently jobs – can be impacted by GAI technologies. The framework categorizes jobs into three groups of occupations: insulated, augmented or disrupted.

Labour market disruptions from GAI could disproportionately impact women

According to the skills-based framework developed by LinkedIn, women tend to be more highly represented in disrupted occupations. These include roles such as administrative assistants, legal assistants and customer service representatives.

Women tend to be underrepresented in AI engineering and AI literacy skills

Women are underrepresented in AI engineering occupations, highlighting the need to close this gap. Globally, 2% of male LinkedIn members list AI engineering skills on their profile, double the proportion that listed the skill two years ago, compared to 1% of women. A similar trend is observed with AI literacy skills.

When switching jobs, women are less likely to transition into GAI-insulated occupations

LinkedIn analysis finds that when workers transition from one job to another, they tend to stay within the same category of occupations. This means that women who were previously working in a GAI-disrupted job are more likely to transition into another GAI-disrupted job. Jobseekers from GAI-disrupted roles face the longest re-employment times, potentially widening the gender gap.

Women and men self-report skills differently on their LinkedIn profiles

There are nuanced differences in how men and women explicitly list skills on their LinkedIn profiles. Even when women work in the same role as men, they are less likely than men to list hard technical skills, and more likely to list soft skills. On average 13.6% of the skills listed by women on LinkedIn are soft skills like strategic leadership and cross-team collaboration, compared to 10.6% of men.

Skills-based hiring can expand opportunities for women, especially in a GAI world of work

Traditionally, employers would hire talent based on typical requirements such as educational qualifications or prior job title requirements. But adopting a skills-based approach, where the focus is on a candidate's skills to do the job, could significantly benefit women. Globally, a skills-based approach could lead to a 13% increase in female representation in industries in which women are currently most severely underrepresented.

1

AI IS CHANGING LABOUR MARKETS

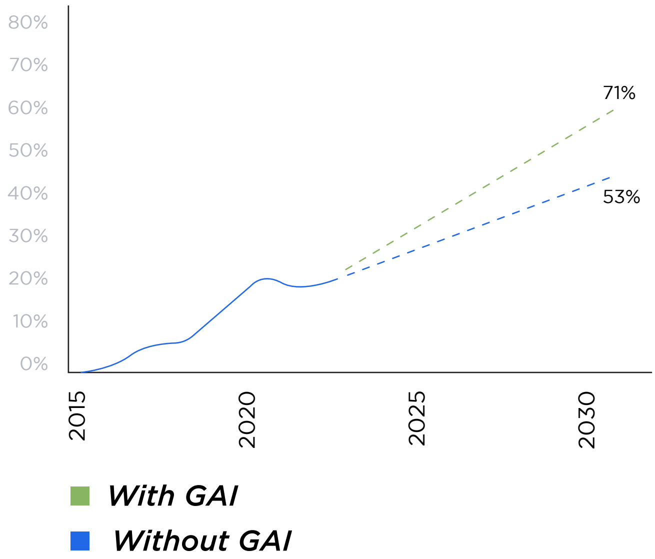
KEY DEFINITIONS

Skills: There are more than 41,000 standardized skills in LinkedIn's skills taxonomy. By matching these to the requirements of specific jobs, it is possible to see how skills requirements of occupations change over time.

Occupational landscapes of labour markets are always in flux. For example, 60% of today's workforce are in jobs that didn't exist in 1940.[4] The advent of AI is expected to further transform jobs. According to the World Economic Forum's Future of Jobs report, there could be 170 million new jobs, equivalent to 14% of today's employment, and the displacement of 92 million jobs (8%) by 2030.[5] The trajectory is likely to hinge on the ways that AI diffuses across the economy and on which tasks and functions it most readily replaces.

Skill requirements are also likely to change. Between 2016 and 2023, the skills needed for any given job across the AP region changed by 40%, even if a worker had not changed jobs. GAI is likely to accelerate this change. Across the AP region, skills for a job could change by as much as 71% in 2030 with the effects of GAI, compared to 53% without the effects of GAI.

Figure 1. *GAI impact: Percentage change in skills, 2016-2030, AP region*



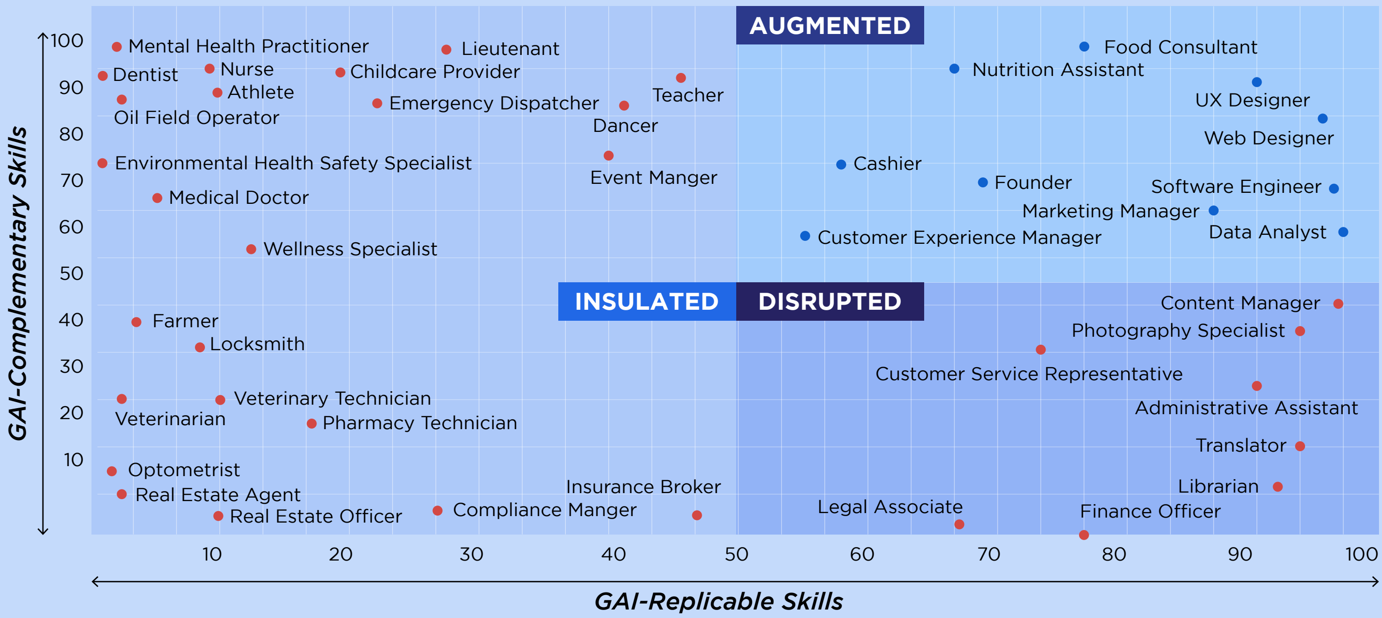
Source: LinkedIn Economic Graph
Asia-Pacific countries and special administrative regions consist of: Australia, Hong Kong, India, Indonesia, Japan, Malaysia, New Zealand, Philippines, Republic of Korea and Singapore

WHILE SOME SKILLS CAN BE REPLICATED BY GAI, OTHER SKILLS WILL BE EXCLUSIVELY PERFORMED BY PEOPLE AND COMPLEMENTED BY GAI

To understand the potential impact of GAI on the labour market, this brief leverages a conceptual framework developed by LinkedIn to explain how skills – and consequently jobs – can be impacted by GAI technologies. The framework first identifies skills that can likely leverage GAI technologies ("GAI-replicable skills") and skills that intrinsically rely on human proficiency and can likely complement these technologies ("GAI-complementary skills").

LinkedIn's skills-based framework allows us to classify each occupation by the percentage of core skills that are potentially replicable by GAI and the share of core skills that are complementary to GAI. This categorization results in three groups of occupations: insulated, augmented and disrupted.

Figure 2. *Occupational composition by GAI-replicable and GAI-complementary skills*



Source: LinkedIn Economic Graph. For more information, see this note

MOST JOBS WILL REQUIRE SKILLS THAT CAN BE PERFORMED BY GAI TECHNOLOGIES, BUT NOT EVERY JOB WILL BE AFFECTED THE SAME WAY

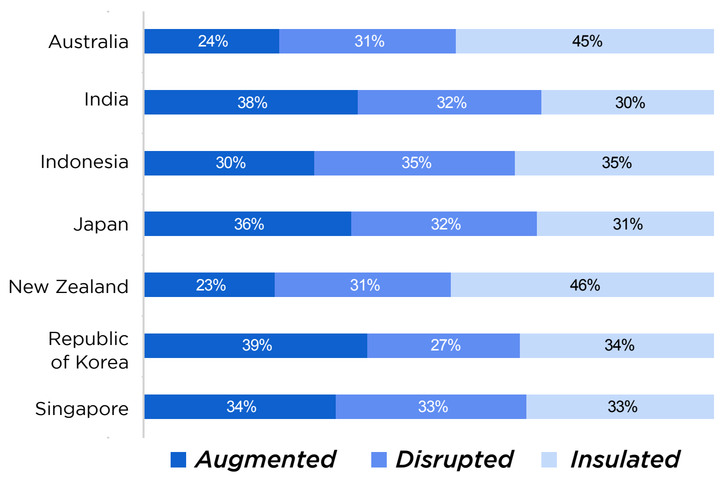
- **Augmented by GAI.** These jobs require a significant share of both GAI-replicable and people skills. Data analysts, for example, can use GAI to automate the computation and interpretation of metrics – leaving more time to focus on complementary skills like cross-functional influencing and stakeholder engagement. **An estimated 23–38% of LinkedIn members in select AP countries are in occupations that could be augmented by GAI.**

- **Disrupted by GAI.** These jobs require a large share of GAI-replicable skills but a relatively low share of people skills – meaning they can potentially be largely automated. For example, language translator jobs may significantly shift from doing translations from scratch to reviewing machine-generated translations. **An estimated 27-32% of LinkedIn members in these AP countries are in jobs that could be disrupted by GAI.**

- **Insulated from GAI.** These jobs require a relatively small share of GAI-replicable skills. Nurses, for example, might use GAI to perform some tasks – but their core skill, patient care, is hard for GAI to replicate. **An estimated 30–46% of LinkedIn members in these AP countries are in jobs that are insulated by GAI,** although these jobs may be susceptible to other forms of automation, like robotics.

see figure 3 on the following page.

Figure 3. *Potential impact of GAI on job roles, 2025*



Source: LinkedIn Economic Graph

WE NEED POLICYMAKERS TO TAKE ACTION, ENSURING THAT AI LITERACY IS AT THE CORE OF PUBLIC EDUCATION FOR EVERY STUDENT IN EVERY CLASSROOM.

AI needs to be integrated into internship programs, apprenticeships, and youth development initiatives. At the end of the day, every action is about serving the greater community so the future isn't just about building with AI. It's about who we build it for, and who we build it with.

Shreya Katuwal, Startup founder, backend developer, software engineer, entrepreneur, inclusive tech access, Nepal

EVERY TECHNOLOGICAL INNOVATION HAS RESULTED IN THE REDUNDANCY OF CERTAIN JOBS.

Our attempts to solve these undesired consequences cannot take the form of post-facto interventions: they will be too little, and too less. We must strive to recognize how emerging technologies reinforce the social and political structures that define the job market and who gets to access it - based on gender, race, caste, class, ability and more.

Kirthi Jayakumar, Feminist researcher (feminist foreign policy and tech geopolitics), India

GIVEN THEIR HIGH REPRESENTATION IN ROLES IMPACTED BY GAI, WOMEN ARE MORE LIKELY TO BE AFFECTED

Women's labour force participation has increased over time. However, women are more likely to be working in occupations that could be disrupted by GAI. According to LinkedIn data, women tend to be more highly represented in roles such administrative assistants, legal assistants and customer service representatives.

In almost all AP countries, insights from the LinkedIn Economic Graph find that men are more likely than women to work in occupations expected to be insulated from AI. For example, in India, 80% of women work in roles that may be augmented or disrupted by GAI, compared with 75% of men.

Research from the International Labour Organization (ILO) similarly found that 3.7% of all female employment worldwide is in jobs that could be automated by GAI, compared to only 1.4% of male employment, with this disparity even more pronounced in high-income countries.[6] Globally, the effects of AI and automation on labour markets are expected to be highly gendered.

Figure 4. *Proportion of job roles potentially impacted by GAI, male, 2023*

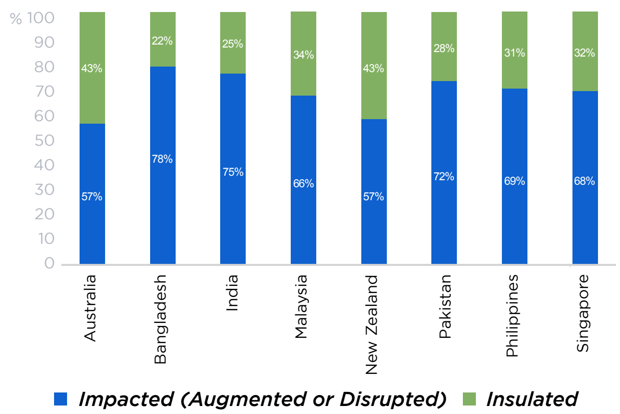
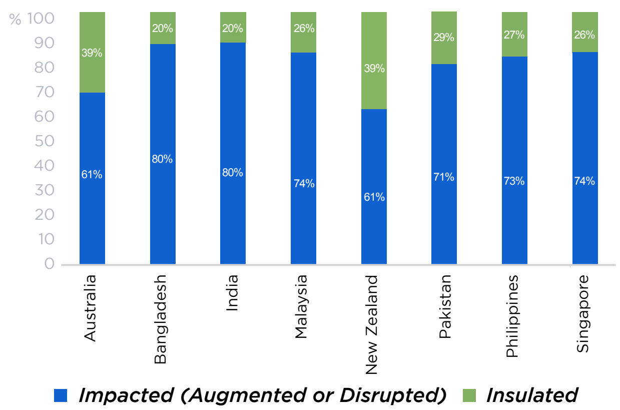


Figure 5. *Proportion of job roles potentially impacted by GAI, female, 2023*



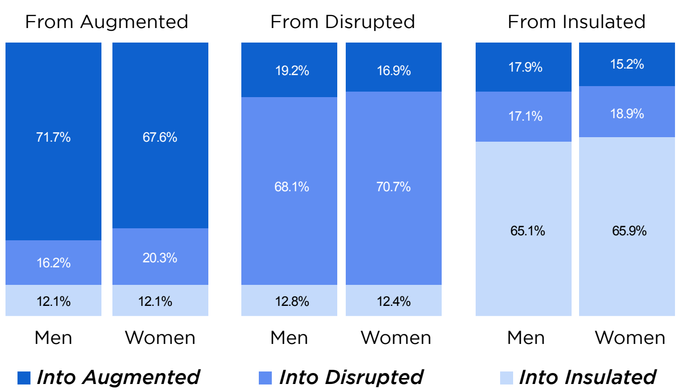
Source: LinkedIn Economic Graph. For more information, see this note

WHEN SWITCHING JOBS, WOMEN ARE LESS LIKELY THAN MEN TO TRANSITION INTO OCCUPATIONS THAT LOWER THEIR EXPOSURE TO JOB DISPLACEMENT

LinkedIn Economic Graph research finds that when workers transition from one job to another, they are likely to stay within the same GAI bucket (often, within the same occupation.) This is particularly true for workers who start in augmented occupations. Globally, 68% of women and 72% of men who leave a job in a GAI-augmented occupation transition into another job that is still in an augmented occupation. Women in the GAI-augmented group are more likely than men to transition into a GAI-disrupted job role, which further exposes them to potential risks of displacement. For example, a female software engineer may stay as a software engineer but for a new firm. This would mean she holds the same job, as well as same occupation and same GAI classification as augmented. Or she could change jobs while changing occupations. For example, she could become a data scientist, which would be a new job and new occupation, but have the same GAI classification of augmented. The worker could also change jobs and occupations in a way that changes GAI classifications. For example, to a new job as mental health practitioner, which would be a new occupation, and new GAI classification, as insulated.

LinkedIn research also finds that when switching jobs from a disrupted or insulated job, men are more likely to move to an augmented occupation job (e.g., 19.2% of men who leave jobs in disrupted occupations transition into a job in an augmented occupation, compared to only 12.8% of those men transitioning into insulated jobs). The reverse is true for women, with augmented jobs being the least-likely destination when they have disrupted or insulated jobs. This may be because augmented jobs are more likely to belong to male-dominated occupations or sectors in which women face barriers to entry.

Figure 6. *Job transitions and changes in GAI categories, global, through 2025*



Source: LinkedIn Economic Graph. For more information, see this note

GAI IS SET TO IMPACT EQUITY IN LABOUR MARKET SEARCHING. THERE IS EVIDENCE THAT EMERGING GENDER DIFFERENCES IN EXPOSURE TO GAI-DISRUPTED OCCUPATIONS COULD INTENSIFY PRE-EXISTING DISADVANTAGES.

When switching jobs, LinkedIn Economic Graph research finds that women take longer to enter a new job than men, regardless of whether they were previously working in an augmented, disrupted or insulated job role. There are various reasons that may explain this phenomenon, such as less flexibility in work circumstances, like commuting or hours for women with caregiving responsibilities. Because women are disproportionately concentrated in jobs most vulnerable to disruption—and take longer, on average, to secure new roles—these dynamics can compound, widening the overall gender gap.

When it comes to job applications, men send a higher share of applications to augmented and insulated occupations, and women a higher share to disrupted occupations. The gender gaps in application rates are shrinking for workers in disrupted or insulated occupations overall, but increasing for workers in augmented occupations. Nonetheless, the gender disparity remains lowest for workers in augmented occupations, at around 12.2% more applications sent for men in augmented occupations compared to women in augmented occupations in January 2025.

This may be due to multiple factors, but when these trends are taken together, gender differences in job search may intensify the overrepresentation of women in occupations disrupted by GAI.

Figure 7. *Average time between jobs, global*

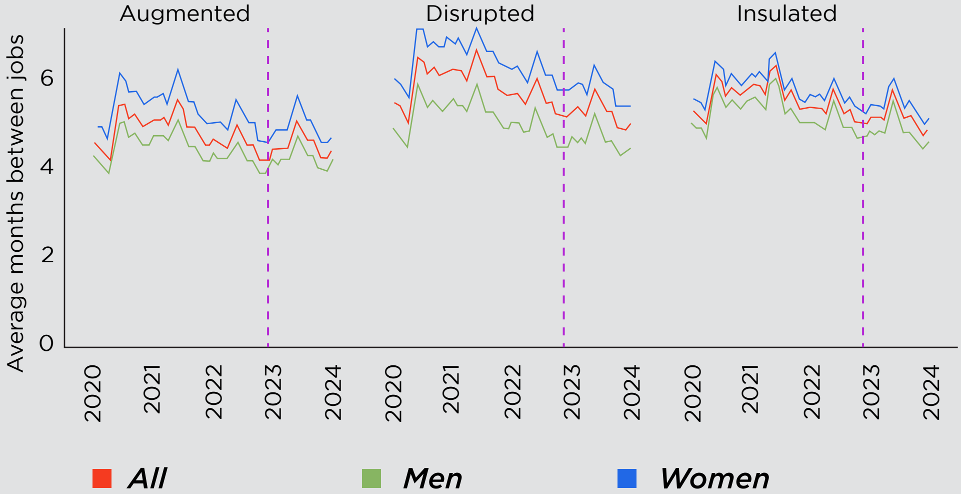
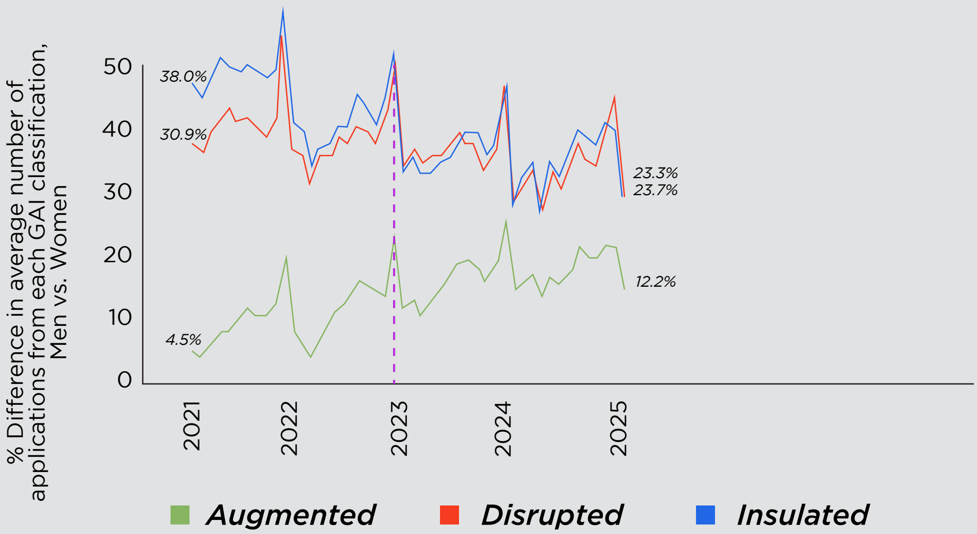


Figure 8. *Gender gaps in average number of job applications sent, global, %*



Source: LinkedIn Economic Graph. For more information, see this note

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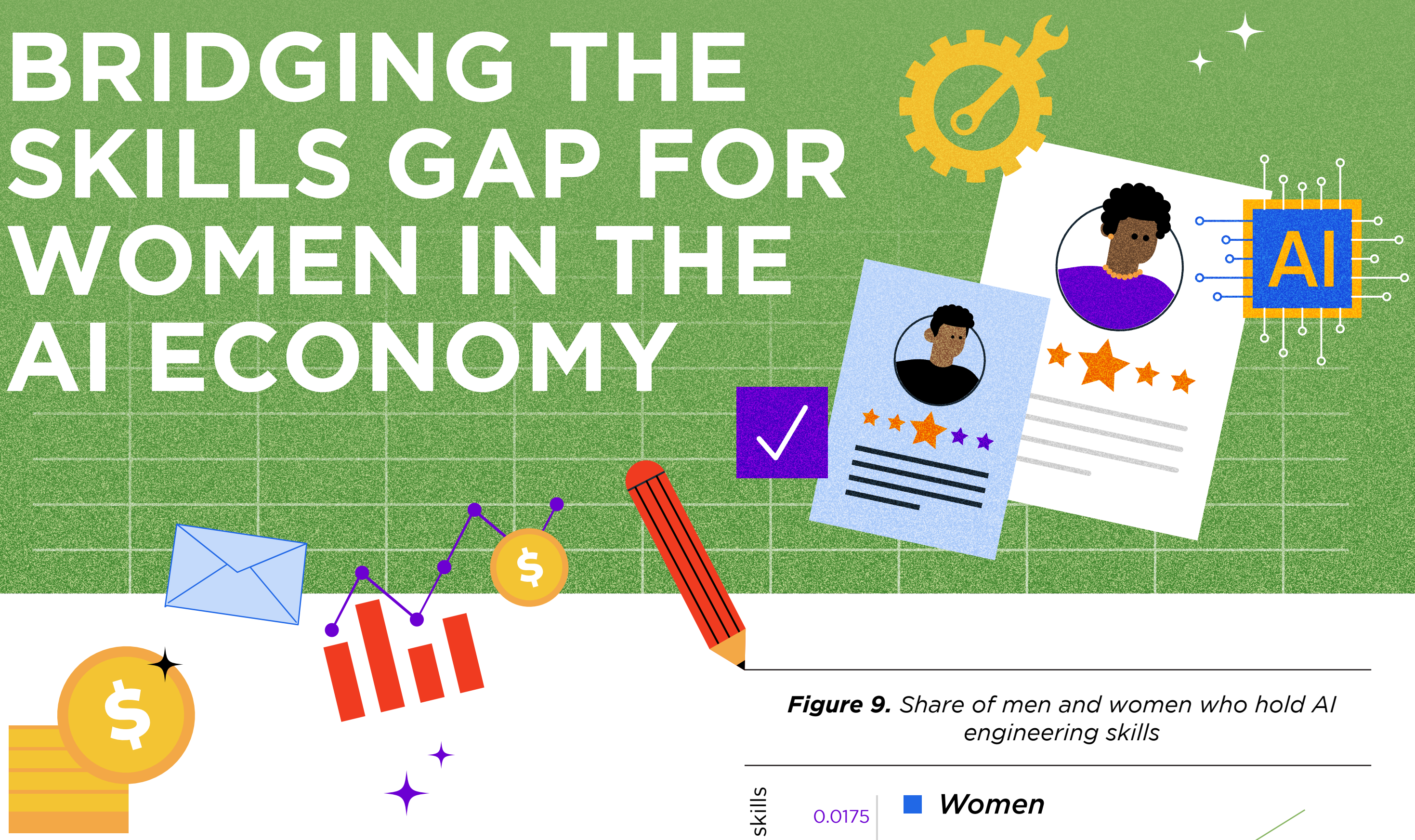
BRIDGING THE SKILLS GAP FOR WOMEN IN THE AI ECONOMY



As AI continues to scale across industries and occupations, there will be a growing demand for related skills. AI engineers and AI consultants were the two fastest-growing jobs in the US last year, for example.[7] However, the skills demand extends beyond just AI engineering to include AI literacy skills, which are essential for effectively leveraging GAI.

Currently, women are underrepresented in AI engineering occupations, highlighting the need to close this gap. This is in line with the global gender divide in digital access, reinforcing existing disparities between men and women's digital literacy and access to technology. Globally, 2% of male LinkedIn members list AI engineering skills on their profile, double the proportion that listed the skill two years ago, compared to 1% of women. This may be affected by self-reporting, with women feeling less confident in listing their AI skills due to awareness of the sector's gender gap.

Men are also more likely than women to list AI literacy as a skill, suggesting their higher confidence in using GAI tools. Although the proportion of women on LinkedIn listing AI literacy more than quadrupled in 2024, men have a large lead that is growing over time. AI literacy is also expected to become crucial in a growing number of occupations as GAI tools are increasingly integrated into more workflows.

Figure 9. *Share of men and women who hold AI engineering skills*

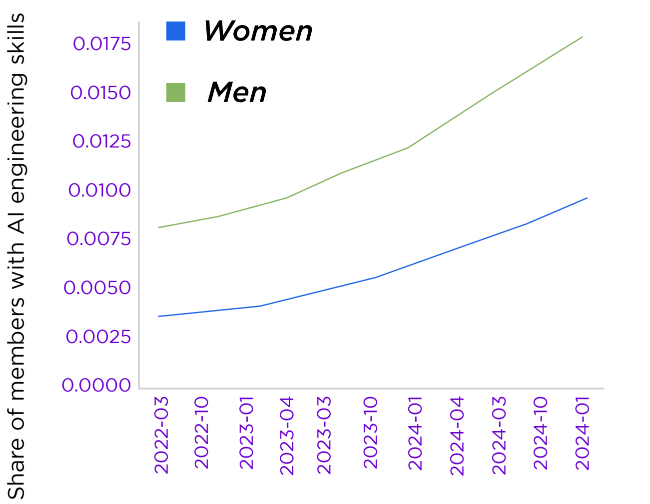
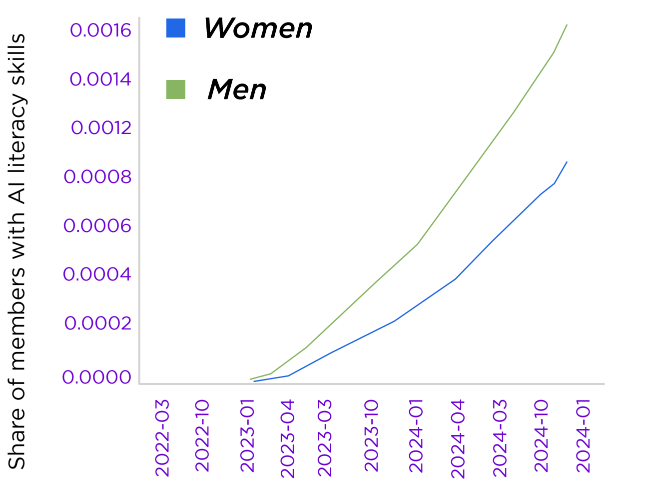
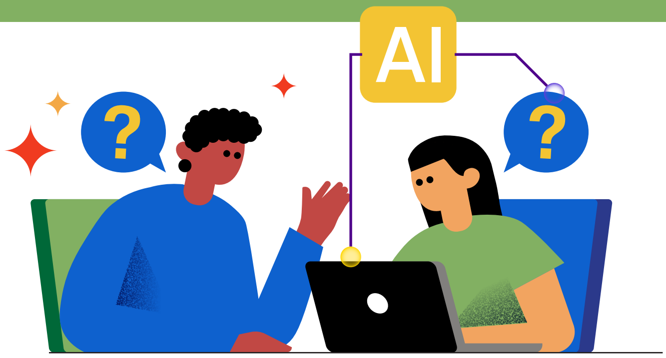


Figure 10. *Share of men and women who hold AI literacy skills*



Source: LinkedIn Economic Graph. For more information, see this note

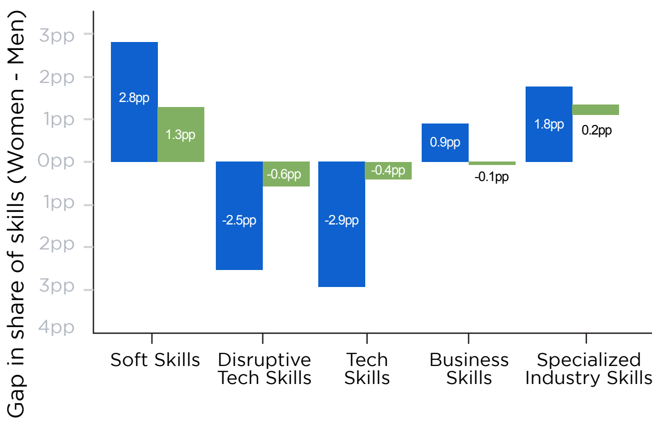


GENDER DIFFERENCES IN AI SKILLS COULD BE DUE TO OCCUPATION DIFFERENCES OR LACK OF EXPLICIT SKILLS LISTED

The gender difference in skills is in part a result of occupation. According to the LinkedIn Economic Graph, women are less likely to have tech skills because they are less likely to work in engineering roles or the tech industry. When comparing men and women who work in similar roles, or the same industry, skills gaps narrow substantially. Social norms may play a role. Stereotypes around women's place in society and role in the workforce can make them less likely to consider roles in this industry, so challenging these norms can help close the gap.

For example, when measuring the difference in the average share of disruptive tech skills held by women and men, there is a gap of 2.5 percentage points in favour of men. However, if the gap within each occupation/industry is measured and then the gaps are averaged, then there is a mean difference of only 0.6 percentage points in favour of men.

Figure 11. *Gap in share of skills (accounting for occupation and industry), global*

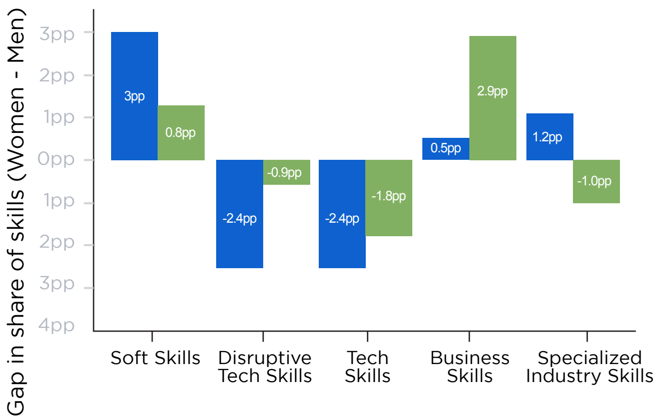


Source: LinkedIn Economic Graph. For more information, see this note

There are also nuanced differences in how men and women explicitly list skills on their LinkedIn profiles. Even when women work in the same role as men, they are less likely to list hard technical skills, and more likely to list soft skills, even if hard skills can be inferred from their job description.

For example, for disruptive tech skills, if considering only member-listed skills, the average share of disruptive tech skills is 2.4 percentage points higher for men, compared to only 0.9 percentage points higher if skills inferred from a job description are included. This indicates less of a skills gap than a communications difference.

Figure 12. *Gap in share of skills (accounting for member added or inferred skills), global*

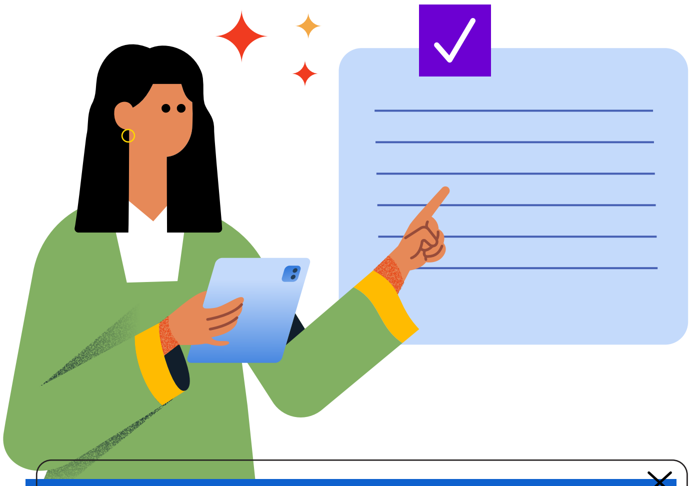


Source: LinkedIn Economic Graph. For more information, see this note

AS SOMEONE PREPARING TO ENTER THE WORKFORCE, I DON'T WANT TO SEE HISTORY REPEAT ITSELF. THE LAST DIGITAL SHIFT LEFT SO MANY WOMEN BEHIND; WE CAN'T LET AI DO THE SAME.

Nala Amirah, Founder of Green Welfare Indonesia, Indonesia

WOMEN, HOWEVER, HAVE A CLEAR ADVANTAGE ON SOFT SKILLS, BASED ON SELF-REPORTING DATA ON LINKEDIN. THESE SKILLS WILL BECOME MORE IN-DEMAND AS GAI CONTINUES TO CHANGE THE NATURE OF JOBS.



Alongside growing demand for AI technical skills and AI literacy, human skills such as communication, relationship-building, creativity and teamwork – which have long been undervalued as "soft skills" – are becoming increasingly important. Women tend to perceive themselves as having an advantage in these skills, while men are less confident.

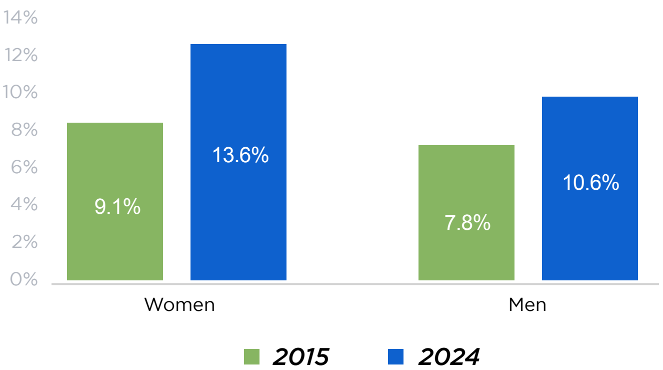
On average, 13.6% of the skills listed by women on LinkedIn are soft skills like strategic leadership and cross-team collaboration, compared to 10.6% for men. This gap has widened over the last nine years: in 2015, 9.1% of skills listed by women were soft, compared to 7.8% of skills listed by men.

Women are also more likely than men to believe that soft skills are becoming more important than ever with the rise of GAI. More than 70% of women in LinkedIn's Fall 2024 Workforce Confidence Index agreed with this statement, compared to less than 65% of men.

WOMEN AND UNDERREPRESENTED COMMUNITIES MUST BE PART OF DESIGNING, GOVERNING, AND SHAPING AI. WE'RE NOT JUST USERS—WE'RE CO-CREATORS, ETHICAL STEWARDS, AND DECISION-MAKERS. AS THE FUTURE OF WORK CONTINUES TO BE REWRITTEN, WE DESERVE A SAY IN HOW THE NEXT CHAPTER UNFOLDS.

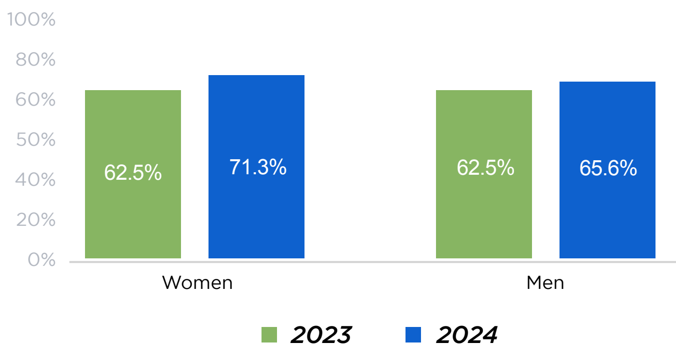
Ayu Pratiwi Muyasyaroh, Energy researcher, SDG storyteller, Mentor, Indonesia

***Figure 13**. Percentage of skills listed on LinkedIn profiles that are soft skills, by gender, global, 2015 vs. 2024*



Source: LinkedIn Economic Graph

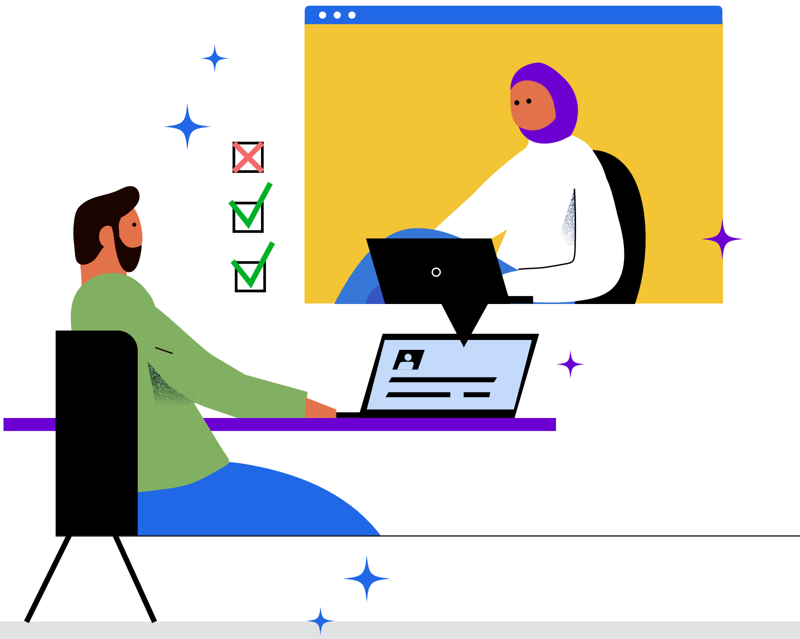
***Figure 14.** Responses to LinkedIn Workforce Confidence Index Survey question: "With the growing popularity of AI, soft skills are more important than ever", global, 2023 vs. 2024*



Source: LinkedIn Economic Graph

SKILLS-BASED HIRING CAN EXPAND OPPORTUNITIES FOR WOMEN, ESPECIALLY IN A GAI WORLD OF WORK.

SKILLS- BASED HIRING COULD LEAD TO A 13% INCREASE IN WOMEN IN UNDERREPRESENTED OCCUPATIONS.

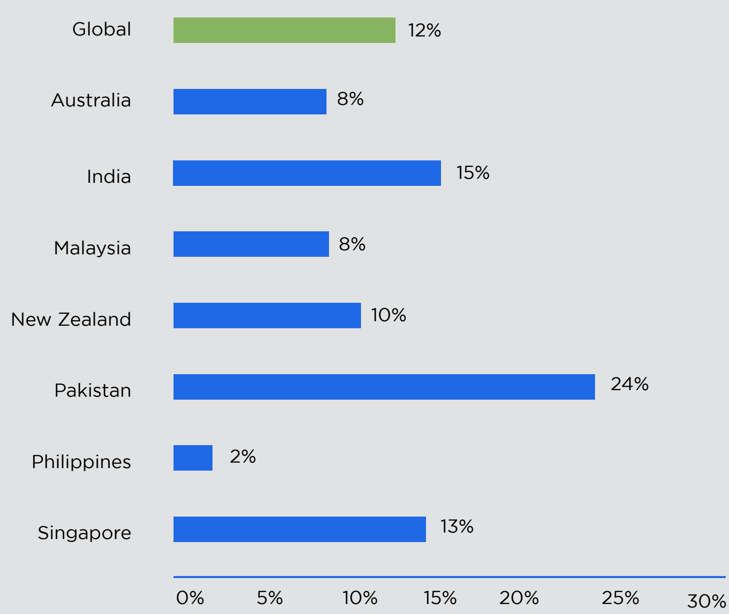


Understanding these nuanced reasons for gender differences in skills is crucial. The significance of a worker's occupation and industry suggests the gender skills gap in AI engineering skills, for example, and could be narrowed by increasing female representation in engineering roles. This is why skills-based hiring is important. Skills-based hiring approaches is especially beneficial in emerging fields such as AI, where the demand for talent outpaces supply of formally qualified candidates. And as GAI potentially disrupts some roles, governments and businesses will have to quickly upskill and transition workers into new roles.

Traditionally, employers would hire for candidates who have had similar job experience or graduated from a four-year degree programme in the field. This approach, based on traditional educational credentials, is insufficient due to male dominance in technology-related university courses. Narrowing the gender gap in engineering and technology may require understanding the factors that lead to differing attitudes, such as why women are less likely than men to claim AI and tech skills even when their jobs suggest they have them. Some research also suggests that women are more concerned about the ethics of using AI and fear being judged in the workplace for relying on it.

This suggests that a different approach is needed. Instead of hiring based on typical requirements such as educational qualifications or prior jobs, adopting a skills-based approach, where the focus is on a candidate's skills to do the job, could significantly benefit women. In India, only 12% of workers with the job title 'equity trader' are currently women, yet women make up 29% of the talent pool when skills are prioritized.

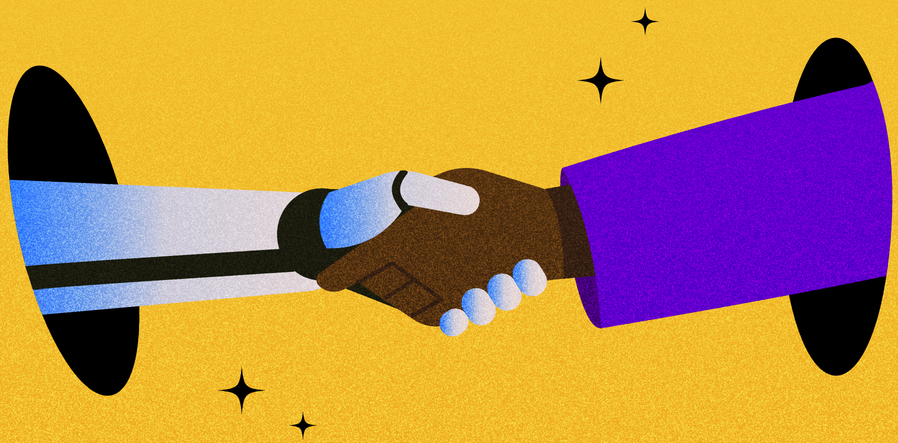
Figure 15. *Percentage increase in the share of women in the talent pool when hiring based on skills, amongst occupations where women are underrepresented, 2025*



Source: LinkedIn Economic Graph. For more information, see this note

GLOBALLY, A SKILLS-BASED APPROACH WOULD LEAD TO A 13% INCREASE IN FEMALE REPRESENTATION IN OCCUPATIONS IN WHICH WOMEN ARE CURRENTLY MOST SEVERELY UNDERREPRESENTED.

3 THE WAY FORWARD



Without intervention, GAI's labour market disruption could exacerbate existing gender inequalities in the world of work. However, the current moment is one of opportunity. Organizations are at an early stage of experimenting and deploying AI and governments are still developing governance frameworks. Timely interventions could ensure that the benefits of AI leave no one behind, reaching both women and men, girls and boys, young people and the elderly, people living with disabilities; now and in the future.

Pathways towards a future of work in the digital area may call for:

PILLAR 1:

Creating an enabling environment for inclusive and responsible AI

1. Embed gender-parity targets into multi-stakeholder bodies that shape AI or digital-public-goods strategies.

2. Embed feminist principles in national digital-policy frameworks, including:
(i) universal, affordable connectivity;
(ii) human-rights-based content moderation;
(iii) gender-responsive AI-risk governance; and
(iv) open, gender-tagged digital public goods.

3. Adopt a "UN Commission on the Status of Women 67 (CSW 67) Alignment Action Plan" to ensure that every national AI-and-jobs strategy formally incorporates the most relevant Agreed Conclusions of CSW 67 — from universal connectivity and gender-transformative STEM education to algorithmic-bias audits, Technology-Facilitated Gender-Based Violence (TFGBV), or TFGBV safeguards, women's tech-leadership targets, and sex-disaggregated labour-market data.

PILLAR 2:

Investing in full AI access, skills development and opportunities for all

Build workforce resilience

4. Address AI's workforce impact through cross-sector collaboration to support workers in disrupted jobs, shifting away from traditional industry-specific approaches. Women, more likely to hold disrupted roles, would benefit significantly from targeted interventions enabling transitions to more less impacted positions.

5. Identify and support workers in high-risk jobs and sectors with preemptive interventions, such as targeted skilling, re-skilling and upskilling and career pathways to leverage the augmented effect of AI, and ensure government workforce development plans are responsive to the effects and opportunities of AI.

6. Launch awareness campaigns to educate the public about AI's impact and encourage hiring practices that recognize the importance of new skills and opportunities.

7. Implement workforce development reforms to ensure existing programmes are data-driven and responsive to AI-driven skill shifts, focusing on at-risk occupations.

8. Support gender-responsive AI impact assessments and recommend all public-funded AI deployments and large private employers to publish a "gender impact forecast" that maps task-level exposure of female versus male workers before rollout and sets mitigation targets.

Skills development

9. Invest in skills training by funding training for individuals in disrupted roles and providing employer incentives for upskilling. Expand tax incentives for both, to offset training costs.

10. Foster international collaboration to establish trusted credentials validating in-demand AI skills. Encourage training providers to create clear pathways towards these credentials, allowing workers to showcase competencies.

11. Provide targeted funding to educational institutions and labour groups to expand access to quality AI training, especially for those less likely to use AI at work.

12. Promote AI integration in education by supporting schools and universities in safely integrating AI tools and developing AI literacy curricula.

13. Set national gender-parity targets for AI technical faculty and trainers: Increase public funding to promote female representation among instructors in government-funded AI bootcamps and university programmes by 2030.

14. Create an 'AI Apprenticeship for Care' track: Pair frontline care-economy workers with AI specialists to co-design assistive tools (e.g., predictive patient-monitoring). This leverages the high female share of care roles while upgrading wages and status.

15. Launch a credential-conversion scholarship for clerical workers: Offer subsidised micro-credentials that translate legacy clerical competencies (accuracy, compliance) into AI-era roles such as data-labelling quality assurance. Women dominate clerical work now at greatest risk.

THE TURNING POINT CAME WHEN I COLLABORATED ON A PROJECT INVOLVING SMART WATER MANAGEMENT SYSTEMS, INTEGRATING AI TO OPTIMIZE RESOURCE DISTRIBUTION.

This experience reinforced my belief that AI can empower women to break through traditional barriers. Now, I am focused on utilizing AI for sustainable development and advocating for women in STEM, creating pathways for others to follow.

Faazla Iqbal, AgriTech Diplomat, Pakistan

AI literacy and inclusive access

16. Boost AI literacy by leveraging online resources and community organizations to reduce skills gaps, addressing the fact that women are less likely to use AI tools at work.

17. Expand funding and fiscal support to enable organizations to invest in upskilling and closing access gaps

18. Support the broader workforce with inclusive policies that ensure widespread AI literacy and access to digital devices, helping all workers adapt to the AI economy, especially women who are less likely to use AI at work.

19. Address the digital divide by providing incentives to improve Internet connectivity and device access, essential for AI education and workforce integration as well as narrowing the access gap for low-income countries.

20. Negotiate zero-rating of AI-learning content for girls: Partner with telecom operators to exempt curated AI-skills platforms from mobile-data charges, mirroring successful zero-rating of educational sites during COVID-19.

IN THE REFUGEE CAMP IN ACEH, I WATCHED A ROHINGYA WOMAN GENTLY PRESS HER FINGERS TO A LAPTOP FOR THE FIRST TIME.

"Will this change my life?" she asked. We had brought laptops, not miracles—but, in that moment, I saw something shift. Today, as generative AI rewrites the future of work, I wonder: will she be written in?

Noor Azizah, Director of Rohingya Maiyafuìnor Collaborative Network. Australia (Rohingya from Myanmar)

PILLAR 3:

Fostering Partnerships for strengthened awareness, advocacy and investment in inclusive and responsible AI

Multi-stakeholder partnerships to strengthen data, investments and capacities for inclusive AI Systems

21. Build AI capacities in government workforces and offer professional development for educators. For example, Singapore's National Institute of Education aims to offer training in AI for education for all trainee teachers by 2026.

22. Improve and enhance data systems to provide workers with accessible, actionable insights on AI's job impact, emerging roles and required skills. Partnerships with third parties can enhance real-time data collection and dissemination for analysis of the gendered impacts of AI. These resources should also include capabilities for understanding gender-based harms facilitated by AI.

23. Partner with private and philanthropic sectors to create national AI skilling banks and reduce AI training costs for underrepresented workers.

24. Establish a "Gender & AI Policy Sandbox" with regulators: Co-design and test regulatory models (algorithmic-bias audits, explainability standards) before nationwide adoption, ensuring gender outcomes are tracked.

25. Create a women-led AI Venture Catalyst Fund: Pool philanthropic, Development Finance Institutions, and sovereign resources to provide first-loss capital plus technical mentorship for female-founded AI start-ups that address the SDGs.

26. Deploy a gender-disaggregated AI labour-market dashboard: Work with international research centers and national statistics offices to publish quarterly data on AI talent flows, wage gaps and attrition rates.

APPENDIX
DATA SOURCES

LINKEDIN ECONOMIC GRAPH IS THE PRIMARY SOURCE OF DATA FOR THIS REPORT

1.1B Global members	**69M** Companies	**41K** Skills	**139K** Schools

The LinkedIn Economic Graph analyses LinkedIn's global membership of over 1.1 billion individuals and 69 million companies. Through a prism of 41,000 standardized skills self-reported by LinkedIn members on their LinkedIn profiles, it is possible to gather real-time and granular insights on the labour market. Analysis using LinkedIn Economic Graph has unique strengths in that it enables new insights into emerging digital sectors and skills, like AI and its impact. Many knowledge-intensive industries have good coverage across income levels and geographic locations, which allows for global benchmarking.

Limitations: LinkedIn Economic Graph data have some limitations. While rendered anonymous before being aggregated, the data are influenced by how individual members use the platform, which varies by professional, social and regional culture, as well as according to site accessibility. The data are neither a random sample of a country's workforce nor fully representative either of industries or professions. This is because people who are familiar with the Internet and possess basic digital literacy are more likely than others to use LinkedIn. Some occupations and industries are better represented on LinkedIn than others. Further, as skill data are self-reported, and members may inflate their skills or present them differently, rendering data not entirely comparable across members and occupations.

FOR MORE INFORMATION, PLEASE VISIT:
HTTPS://ECONOMICGRAPH.LINKEDIN.COM/

LINKEDIN'S MEMBERSHIP ACROSS AP REGION

LINKEDIN HAS OVER 320 MILLION MEMBERS ACROSS AP COUNTRIES. LINKEDIN DATA ARE BEST AT REPRESENTING SKILLED LABOUR IN THE KNOWLEDGE-INTENSIVE AND TRADABLE SECTORS.

Although LinkedIn may have better coverage in developed than developing countries, there are certain knowledge-intensive and tradable sectors – such as information and communication; professional, scientific and technical activities; financial and business services; arts and entertainment; manufacturing; and mining and quarrying – that have good LinkedIn coverage globally.

FOR FURTHER VALIDATION OF LINKEDIN'S DATA, PLEASE SEE THIS VALIDATION REPORT CONDUCTED BY THE WORLD BANK.

TO COMPLEMENT INSIGHTS FROM THE LINKEDIN ECONOMIC GRAPH, THIS REPORT REFERENCED OTHER PUBLICLY AVAILABLE DATA

1. **Goldman Sachs. 2023**. "The Potentially Large Effects of Artificial Intelligence on Economic Growth."

2. **UK Government. 2025.** "AI Insights: Generative AI."

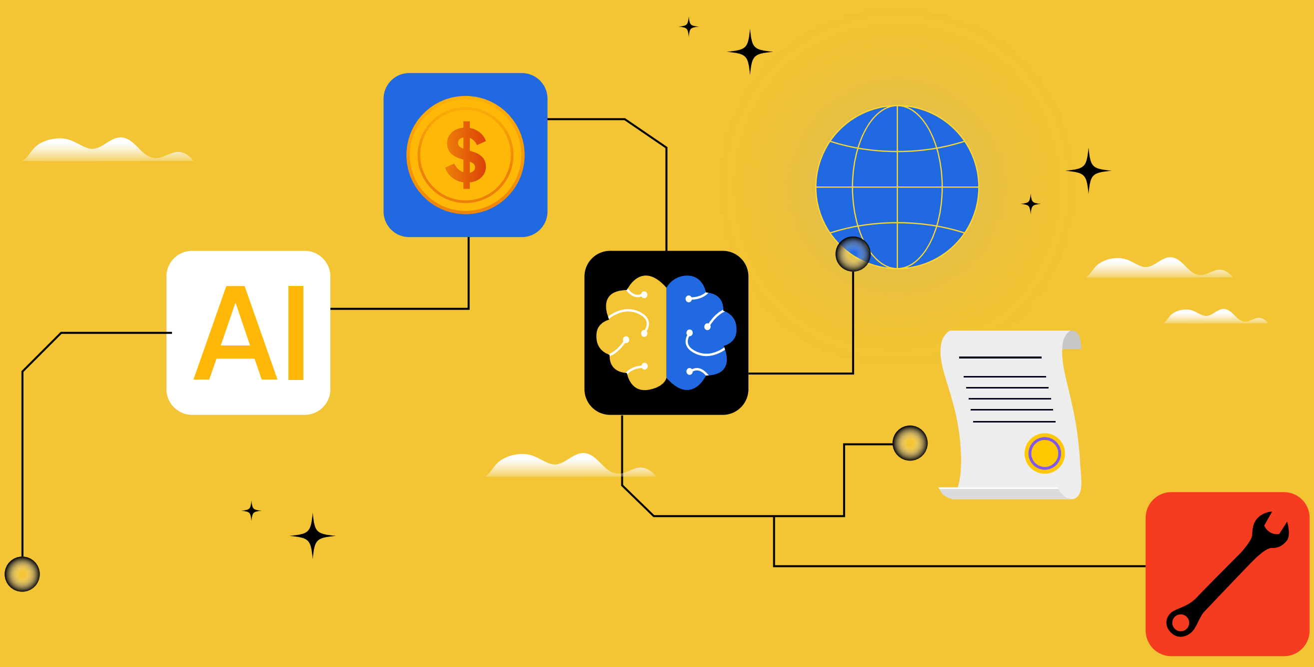
3. **World Economic Forum. 2025.** The Future of Jobs Report 2025.

4. **International Labour Organization. 2023.** Generative AI and jobs: A global analysis of potential effects on job quantity and quality. ILO Working paper 96.

5. **Cazzaniga, M. et al. 2024.** "Gen-AI: Artificial Intelligence and the Future of Work." International Monetary Fund.

6. **AI for Good. 2024.** AI for Good Impact Report.

7. **Harvard Business School. 2025.** Global Evidence on Gender Gaps and Generative AI.



METHODOLOGY

Skills
Refers to the 41,000+ skills that are sourced from LinkedIn members (skills explicitly listed on member profiles, or inferred from other aspects of members' profiles, such as job titles, fields of study, etc.) or from job postings on LinkedIn. Skills are the main building blocks of the insights in this report.

Country coverage
Figures in the report cover AP countries that meet LinkedIn's data thresholds.

Gender classification
We recognize that some LinkedIn members identify beyond the traditional gender constructs of "man" and "woman." If not explicitly self-identified, we have inferred the gender of members included in this analysis either by the pronouns used on their LinkedIn profiles or inferred on the basis of first name. Members whose gender could not be inferred as either man or woman were excluded from any gender analysis. Please note that we filter out countries where our gender attribution algorithm does not have sufficient coverage.

Generation classification
A LinkedIn member's generation (Gen Z, Millennial, Gen X, Baby Boomer) is inferred based on graduation years, listed on their LinkedIn profile. The Pew Research Center's definition for each generation is used, with 'Gen Z' being born between 1997 and 2012, 'Millennials' being born between 1981 and 1996, 'Gen X' being born between 1965 and 1980, and 'Baby Boomers' being born between 1946 and 1964.

Jobs or occupations
A job is a specific instance of employment. An occupation is a category of jobs that are similar with respect to the work performed and the skills possessed by workers. LinkedIn member titles are standardized and grouped into approximately 15,000 occupations. These are not sector- or country-specific. These occupations are further standardized into approximately 3,600 occupation representatives. Occupation representatives group occupations with a common role and specialty, regardless of seniority.

Skills genome
For any entity (occupation, country, industry, etc.), the skills genome is an ordered list of the 50 'most characteristic skills' of that entity. These most characteristic skills are identified using a TF-IDF algorithm to identify the most representative skills of the target entity while down-ranking ubiquitous skills that add little information about that specific entity (e.g., Microsoft Word).

AI skills set and talent
LinkedIn members self-report their skills on their LinkedIn profiles. Currently, more than 41,000 distinct, standardized skills are identified by LinkedIn. These have been coded and classified by taxonomists at LinkedIn into 249 skill groupings, which are the skill groups represented in the data set. The researchers tracked 121 AI skills, finding that the top skills that make up the AI-skill grouping are: machine learning, natural language processing, data structures, AI, computer vision, image processing, deep learning, TensorFlow, Pandas (software) and OpenCV, among others.

AI talent refers to members who are or have been employed in an AI job (like a machine-learning engineer, for example) or list at least two AI skills on their LinkedIn profiles.

METHODOLOGY (CONTINUED)

AI jobs and AI-related jobs
In this report, the term “AI jobs” refers to technical jobs with ‘AI’ or ‘machine learning’ in their job title or as part of their required skills (e.g. machine-learning engineer). AI-related jobs to refer to non-technical jobs (e.g. a salesperson who knows how to use AI products).

Impact of GAI on the workforce
LinkedIn researchers identify GAI-replicable and GAI- complementary skills, combining GAI tools with skill embeddings and matching techniques, and mapping it to occupations using their skills genome. This way, each occupation on LinkedIn is classified as augmented, disrupted or insulated from GAI based on the medians of this metric. These occupations are further mapped to LinkedIn members and their selected characteristics across countries to estimate the share of members in each group that fall within each category.

GAI-replicable and GAI-complementary skills
These skills are identified via the following steps:

1. Researchers asked ChatGPT 3.5 (Feb 2023) the following prompts: a. "What are the 100 top skills that AI technologies (ChatGPT, Dall-E, LaMDA, etc.) can perform very well?" b. "What are the 100 top skills that can currently exclusively be performed by humans?" They then mapped these lists to LinkedIn’s taxonomy with LinkedIn’s taxonomy API, and refined matches manually.

2. The researchers then expanded coverage further by applying skill similarities based on skill embeddings to score skills that are similar to those flagged in each list, and by manually reviewing the skills in the popular skill groups containing the skills from the previous steps.

3. For external validation, the researchers ingested and mapped their taxonomy three exposure scores from academic literature (Webb (2019); Felten, Raj, & Seamans (2023), and Felten, Raj, & Seamans (2021)). They then used these scores to train a model that learns which skills contribute more to these three rankings, and used this model to score all skills in LinkedIn’s taxonomy.

Occupations exposed to GAI and complementary skills
To calculate the percentage of skills that are exposed to GAI by occupation, each occupation’s skills genome is used. An occupation’s skills genome is the ranking of its top 30 most relevant skills based on a TF-IDF model. In this model, skills are relevant when they tend to be disproportionately added by members in this occupation compared to other occupations. The thresholds for classifying occupations into high and low exposure to GAI and to GAI-complementary skills are based on the metrics’ medians.

Segments exposed to GAI and complementary skills
Based on the classification of occupations by GAI-complementary exposure, the share of LinkedIn members in each category is computed as a share of all members in that segment, gender, generation group, etc. The researchers then reported these shares and ran linear regressions to compare GAI exposure against dimensions of interest, such as skill type, industry, education and experience.

Talent pool
The number of potential skilled candidates for a certain job. This research considered all active members with valid skill listings, regardless of their job searching status.

Prior job title talent pool
The number of potential candidates considered when hiring for an open job, looking at workers who have held that target job title in the past five years. Job titles include exact matches (e.g., an employer is searching for a recruiter and the worker has experience as a recruiter) as well as equivalent matches (e.g., the worker has experience as a recruiting specialist).

METHODOLOGY (CONTINUED)

Skills-based talent pool
The number of potential candidates considered when hiring for an open job, looking at workers who have held jobs in the last five years with a large skill overlap (50%+ shared top skills) with the target job and meet a threshold of similar worker transitions. For example: a nurse may have a large skill overlap with a doctor, but that isn't a common transition due to the high level of retraining, so nurses wouldn't be included in the skills-based talent pool if the open role is for a doctor.

Skills-based talent pool increase
The ratio of the number of potential candidates for a given job identified using a skills-based talent pool approach to the number of eligible workers for that job identified using the direct jobs experience talent pool approach. Country and industry-level aggregates are defined by taking the median talent pool increase across occupations in the given segment

2025

WOMEN AND FUTURE JOBS

A UN WOMEN AND LINKEDIN COLLABORATION