Exercise 4: How can AI affect our professional life? – Create multimodal content on the topic

4.1

Using NotebookLM by Google

1. Log in to your Google account
2. Go to: https://notebooklm.google.com/
3. Click on “Create New” and upload documents from the Exercise 4 folder
4. Include https://www.youtube.com/watch?v=EWvNQjAaOHw as an additional source

You can ask different questions about the uploaded content such as:

- What should I do to improve my efficiency in daily professional life?
- What are the professions most threatened by AI?

Lear more about NotebookLM here:

https://blog.google/technology/ai/notebooklm-audio-overviews/

4.2

Using Perplexity Pages by Perplexity AI

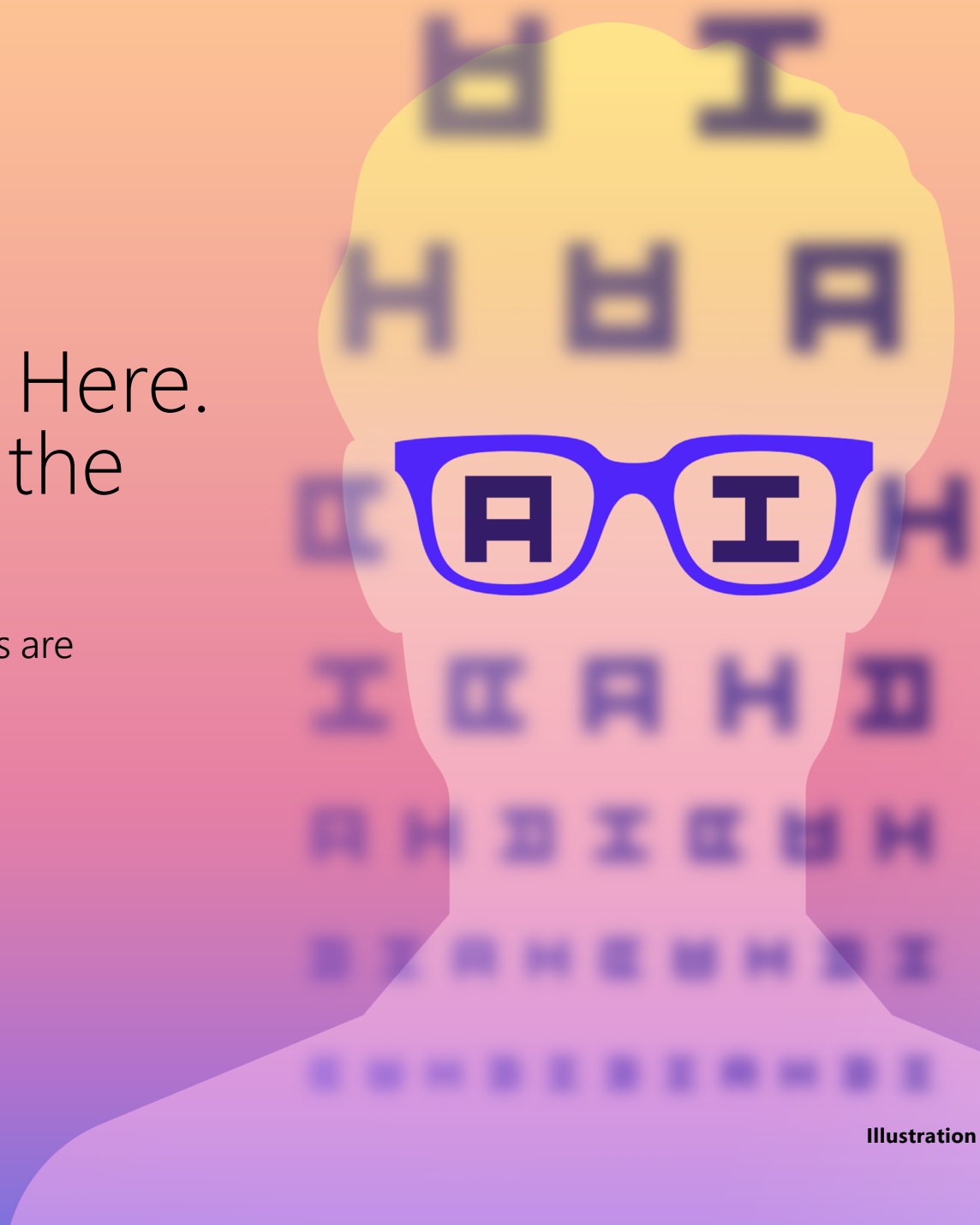
1. Go to: https://www.perplexity.ai/page/new
2. Create a blog post about how AI can affect your envisioned professional life / career using Perplexity Pages

2024 Work Trend Index Annual Report
from Microsoft and LinkedIn

AI at Work Is Here. Now Comes the Hard Part

Employees want AI, leaders are looking for a path forward.

May 8, 2024



Microsoft

Illustration by Ben Wiseman

The data is in: 2024 is the year AI at work gets real. Use of generative AI has nearly doubled in the last six months,[1] with **75%** of global knowledge workers using it. And employees, struggling under the pace and volume of work, are bringing their own AI to work. While leaders agree AI is a business imperative, many believe their organization lacks a plan and vision to go from individual impact to applying AI to drive the bottom line. The pressure to show immediate ROI is making leaders inert, even in the face of AI inevitability.

We've come to the hard part of any tech disruption: moving past experimentation to business transformation. Just as we saw with the advent of the internet or the PC, business transformation comes with broad adoption. Organizations that apply AI to drive growth, manage costs, and deliver greater value to customers will pull ahead.

At the same time, the labor market is set to shift again—with AI playing a major role. Despite fears of job loss, leaders report a talent shortage for key roles. And as more employees eye a career move, managers say AI aptitude could rival experience.

For many employees, AI will raise the bar but break the career ceiling.

To help leaders and organizations overcome AI inertia, Microsoft and LinkedIn looked at how AI will reshape work and the labor market broadly, surveying 31,000 people across 31 countries, identifying labor and hiring trends from LinkedIn, and analyzing trillions of Microsoft 365 productivity signals as well as research with Fortune 500 customers. The data points to insights every leader and professional needs to know—and actions they can take—when it comes to AI's implications for work.

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[1] 46% of survey respondents who use generative AI at work have used it for less than six months.

Findings

1
Employees want AI at work—and they won't wait for companies to catch up.

2
For employees, AI raises the bar and breaks the career ceiling.

3
The rise of the AI power user—and what they reveal about the future.

Finding 1

75%

of knowledge workers use AI at work

Employees want AI at work—and they won't wait for companies to catch up.

Already, AI is being woven into the workplace at an unexpected scale. **75%** of knowledge workers use AI at work today, and **46%** of users started using it less than six months ago. It's paying off:

- Users say AI helps them save time (**90%**), focus on their most important work (**85%**), be more creative (**84%**), and enjoy their work more (**83%**).
- The heaviest Teams users (the top **5%**) summarized 8 hours of meetings using Copilot in the month of March, the equivalent of an entire workday.[2]

While most leaders agree AI is a necessity, the pressure to show immediate ROI is making leaders move slowly.

- **79%** of leaders agree their company needs to adopt AI to stay competitive, but **59%** worry about quantifying the productivity gains of AI.
- This uncertainty is stalling vision: **60%** of leaders worry their organization's leadership lacks a plan and vision to implement AI.

[2] Data represents intentional user Copilot query for meeting summarizations by commercial customers in a rolling 28-day period ending in March 2024. It does not include activity from Teams Intelligent Recap. Heaviest users represent the top 5% of users by number of Copilot queries. Excludes EU usage and education segment.

"We're at the forefront of integrating AI to not just work faster, but to work smarter. It's our responsibility as organizational leaders to ensure that this technology elevates our teams' creativity and aligns with our ethical values."

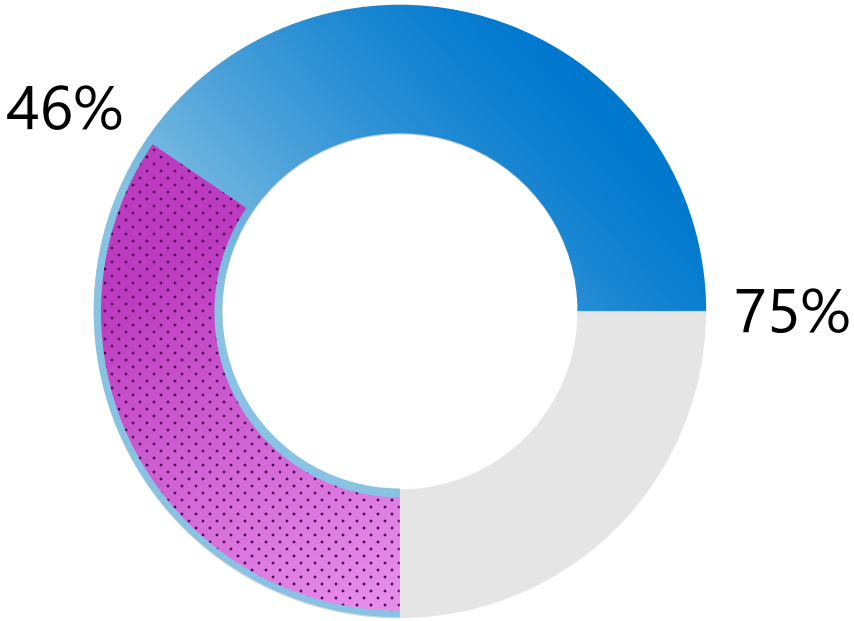
—Karim R. Lakhani, Chair, Digital Data Design Institute at Harvard, and Dorothy & Michael Hintze Professor of Business Administration at Harvard Business School

Three Out of Four People Use AI at Work

Usage nearly doubled in the last six months.

75% of people are already using AI at work

46% of them started using it less than 6 months ago



Survey Questions:
How often do you use generative artificial intelligence (AI) for your work?
How long have you been using generative artificial intelligence (AI) at work?

78%

of AI users are bringing their own AI to work (BYOAI)

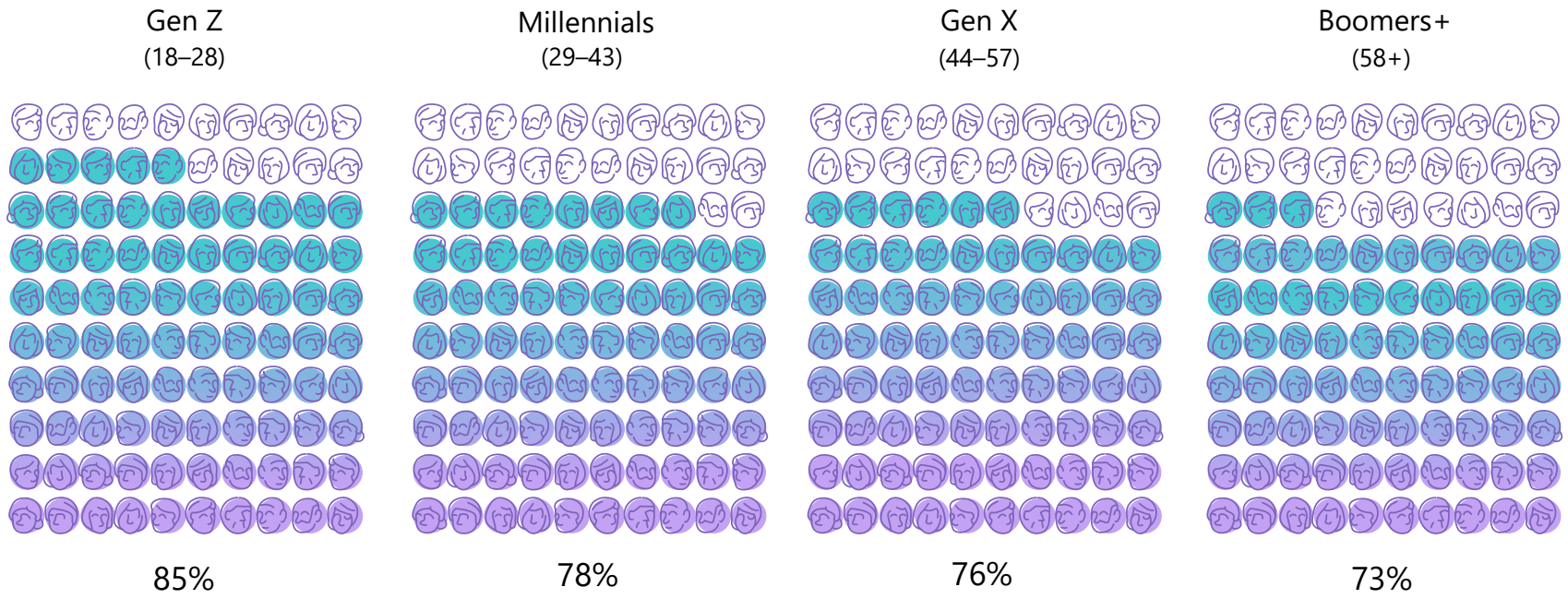
Without guidance or clearance from the top, employees are taking things into their own hands and keeping AI use under wraps:

- **78%** of AI users are bringing their own AI tools to work (BYOAI)—it's even more common at small and medium-sized companies (**80%**).
- And it's not just Gen Z—BYOAI cuts across all generations.
- **52%** of people who use AI at work are reluctant to admit to using it for their most important tasks.
- **53%** of people who use AI at work worry that using it on important work tasks makes them look replaceable.

This approach means missing out on the benefits that come from strategic AI use at scale. It also puts company data at risk in an environment where leaders' **#1** concern for the year ahead is cybersecurity and data privacy.

BYOAI Is Not Just for Gen Z

Employees across every age group are bringing their own AI tools to work.



Share of survey respondents who are using AI tools at work not provided by their organization

Survey Questions:
Are the generative artificial intelligence (AI) tools you use at work provided by your organization?

Another driver of BYOAI: work has accelerated faster than employees' ability to keep up.

- **68%** of people say they struggle with the pace and volume of work, and **46%** feel burned out.
- Email overload persists—**85%** of emails are read in under 15 seconds, and the typical person has to read about **4** emails for every **1** they send.[3]
- Meetings and after-hours work are holding steady at their post-pandemic highs, and the workday still skews toward communication: in the Microsoft 365 apps, users spend **60%** of their time on emails, chats, and meetings, and only **40%** in creation apps like Word and PowerPoint.[4]

As AI use surges ahead, leaders who are "extremely familiar" with AI see its potential to be as transformational as the shift from a typewriter to a computer. Within the next five years, **41%** of these leaders expect to redesign business processes from the ground up with AI. In the same time frame, they anticipate orchestrating (**38%**) and training a team of AI bots (**42%**), and ensuring the ethical use of AI (**47%**) will be a core part of their job.

The data is clear: People are overwhelmed with digital debt and under duress at work—and they are turning to AI for relief. The opportunity for every leader is to channel this momentum into ROI.

[3] Data represents intentional email usage by commercial customers in a rolling 28-day period ending in March 2024. Excludes EU usage and education segment.

[4] Collaboration patterns in Microsoft 365 in a rolling 28-day period ending in March 2024, excluding weekends. Time spent is represented by intentional activity in Microsoft 365 applications including Outlook, Teams, Word, PowerPoint, Excel, and OneNote. Intentional actions include things like attending a meeting, writing an email, analyzing data, and reviewing or editing a document. Includes commercial users and excludes education segment.

"These findings align perfectly with how our brains manage the trade-offs between routine task execution and innovation—different kinds of thinking supported by two distinct but interacting neural networks in the brain. When we're constantly switching, we don't work as well. AI can help liberate workers from menial work and enable innovation and creativity to flourish."

—Michael Platt, neuroscientist and professor at the Wharton School of the University of Pennsylvania

Finding 2

66%

of leaders say they would not hire someone without AI skills

For employees, AI raises the bar and breaks the career ceiling.

We also see AI beginning to impact the job market. While AI and job loss are top of mind for many, the data offers a more nuanced view—one with a hidden talent shortage, employees itching for a career change, and massive opportunity for those willing to skill up on AI.

- Leaders are hiring: The majority (**55%**) of leaders say they're concerned about having enough talent to fill roles in the year ahead. These leaders sit across functions, but the number jumps to **60%** or higher for those in cybersecurity, engineering, and creative design.
- Professionals are looking: While some professionals worry AI will replace their job (**45%**), about the same share (**46%**) say they're considering quitting in the year ahead—higher than the **40%** who said the same ahead of 2021's Great Reshuffle. And in the US, LinkedIn studies show a **14%** increase in job applications per role since last fall, with **85%** of professionals considering a new job this year.[5]

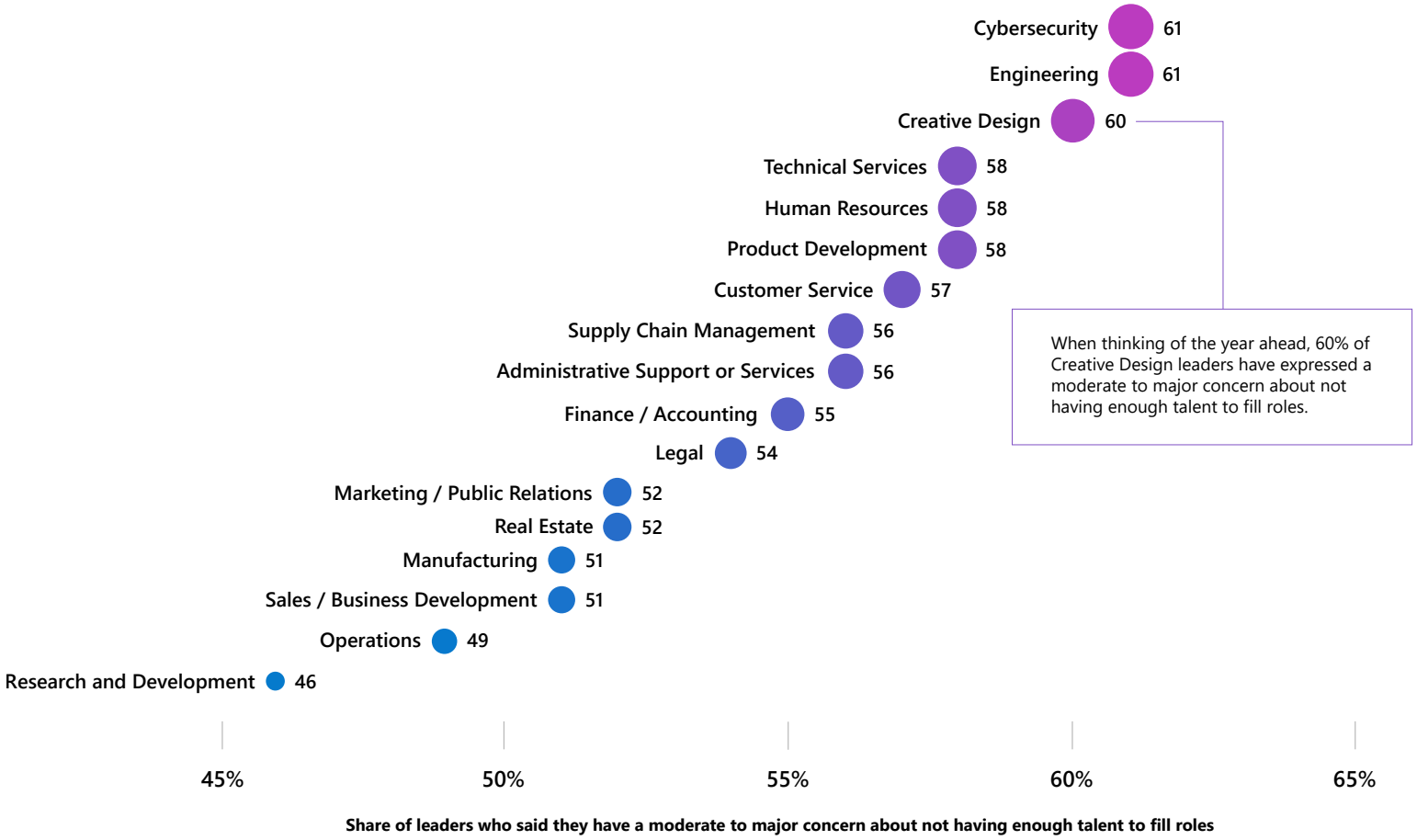
55%

of leaders are concerned about having enough talent to fill roles

[5] Research was conducted by Censuswide on behalf of LinkedIn among 1,013 US working professionals between November 24 and December 12, 2023.

The Hidden Talent Shortage

While employees fear job loss due to AI, most leaders worry they can't fill key roles.



Survey Questions:
When you think about your company in the year ahead, how much of a concern are each of the following?

Leaders have already made their landgrab for technical AI talent, with hiring up **323%** in the past eight years. Now they're turning their sights to non-technical talent with AI aptitude—the skills to use generative AI tools like ChatGPT and Copilot:

- **66%** of leaders say they wouldn't hire someone without AI skills.
- **71%** say they'd rather hire a less experienced candidate with AI skills than a more experienced candidate without them.
- And junior candidates may have a new edge: **77%** of leaders say, with AI, early-in-career talent will be given greater responsibilities.

While leaders recognize the value of bringing on new employees with AI aptitude, they're missing the value of developing their own people:

- **45%** of US executives are not currently investing in AI tools or products for employees.[6]
- Only **39%** of people globally who use AI at work have gotten AI training from their company.
- Only **25%** of companies are planning to offer training on generative AI this year, further cementing this training deficit.[7]

[6] Unpublished data from LinkedIn's Executive Confidence Index

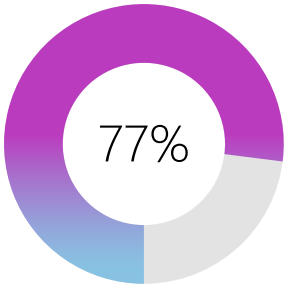
[7] Unpublished data from LinkedIn's 2024 Workplace Learning Report

"Over the past few decades, companies have been renegotiating the psychological contract—the why of work—with their employees, influenced by new generations, labor trends, and the pandemic. Now companies must renegotiate the 'operational contract'—the how of work—with their employees as AI puts more power into the hands of workers in terms of the way the job gets done."

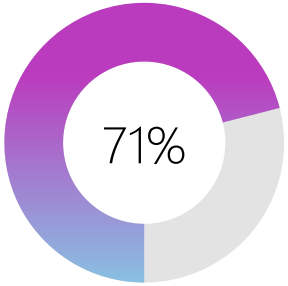
—Constance Noonan Hadley, Organizational Psychologist, Institute for Life at Work and Boston University Questrom School of Business

The New Hiring Imperative

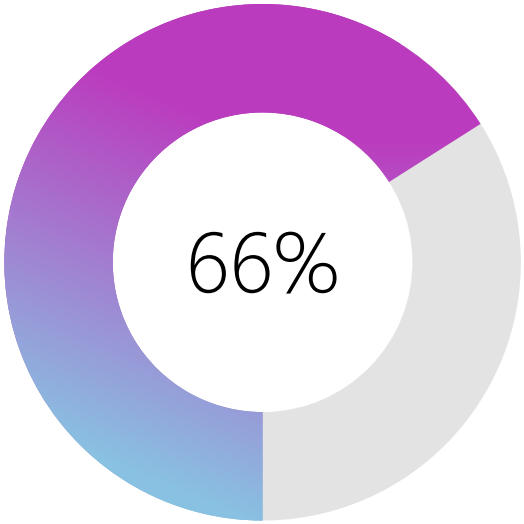
AI aptitude takes center stage.



Leaders say early-in-career talent will get greater responsibilities due to AI



Leaders are more likely to hire a less experienced candidate with AI skills than a more experienced one without them



Leaders would not hire someone without AI skills

Survey Questions:

To what extent do you agree or disagree with the following statements about generative artificial intelligence's (AI's) impact on skills?

- I would be more likely to hire a less experienced candidate with AI skills than a more experienced candidate without AI skills
- In considering job candidates, I would not hire someone without AI skills
- Because they can delegate more work to AI, early-in-career talent will be given greater responsibilities

Professionals aren't waiting for official guidance or training—they're skilling up.

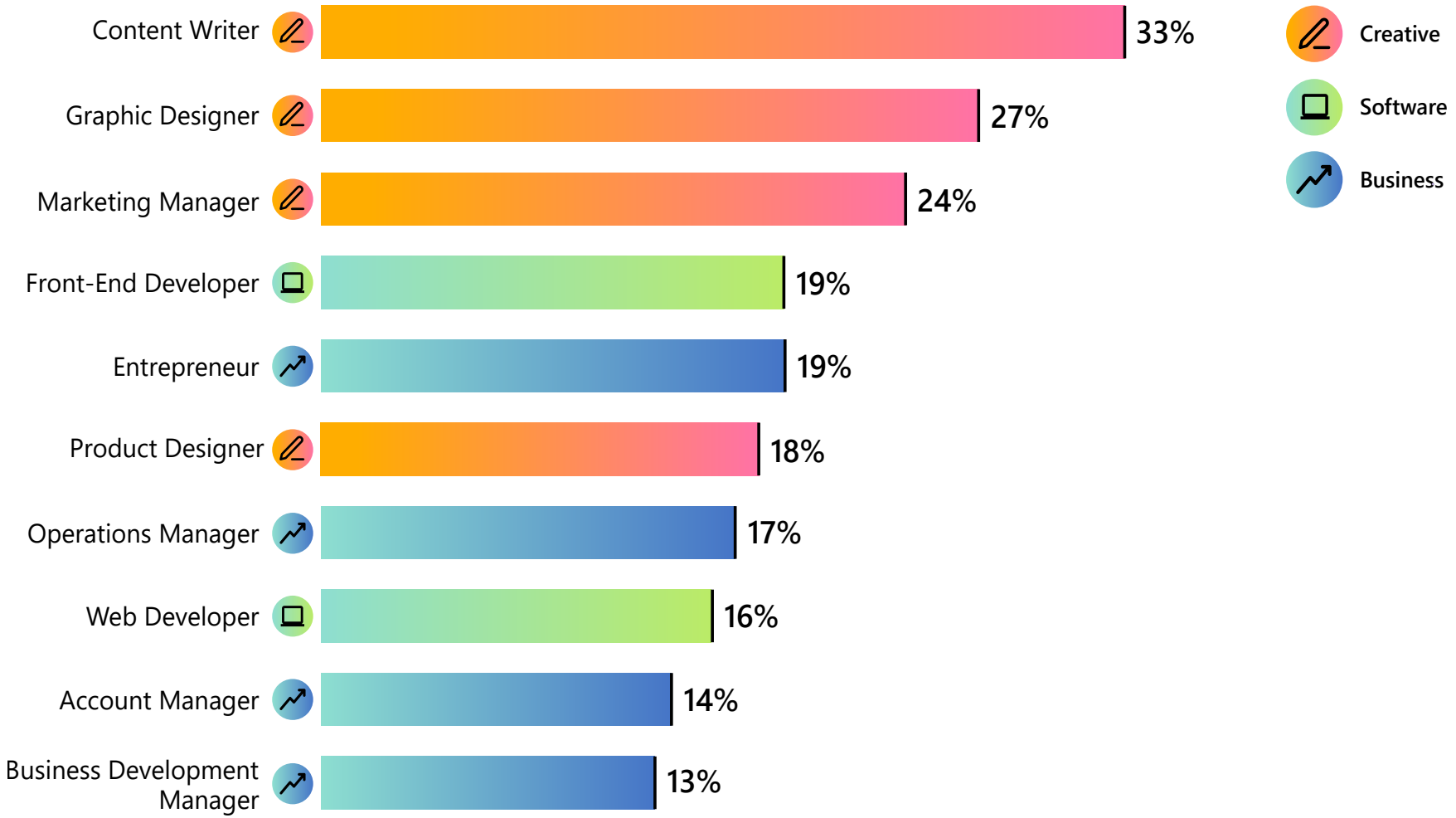
- **76%** of people say they need AI skills to remain competitive in the job market.
- **69%** say AI can help get them promoted faster, and even more (**79%**) say AI skills will broaden their job opportunities.
- In the past six months, the use of LinkedIn Learning courses designed to build AI aptitude has spiked **160%** among non-technical professionals, with roles like project managers, architects, and administrative assistants looking to skill up most.
- We've also seen a **142x** increase in LinkedIn members globally adding AI skills like ChatGPT and Copilot to their profiles—with writers, designers, and marketers topping the list. Marketers are interested for good reason. Two of the top ways B2B marketers say they plan to use generative AI this year include increasing efficiency to focus on higher value work (**55%**) and creating optimized and engaging content that resonates with target audiences (**51%**). When it comes to industries, surprisingly, administrative and support services, real estate, and retail lead the way—ahead of the tech industry.

For the vast majority of people, AI isn't replacing their job but transforming it, and their next job might be a role that doesn't exist yet:

- Globally, skills are projected to change by **50%** by 2030 (from 2016)—and generative AI is expected to accelerate this change to **68%**.
- More than two-thirds (**68%**) of this year's LinkedIn's Jobs on the Rise (fastest-growing roles in the US) didn't exist 20 years ago.
- **12%** of recruiters say they are already creating new roles tied specifically to the use of generative AI.
- Head of AI is emerging as a new must-have leadership role—a job that tripled over the past five years and grew by more than **28%** in 2023.

AI Aptitude Heats Up Across Roles and Industries

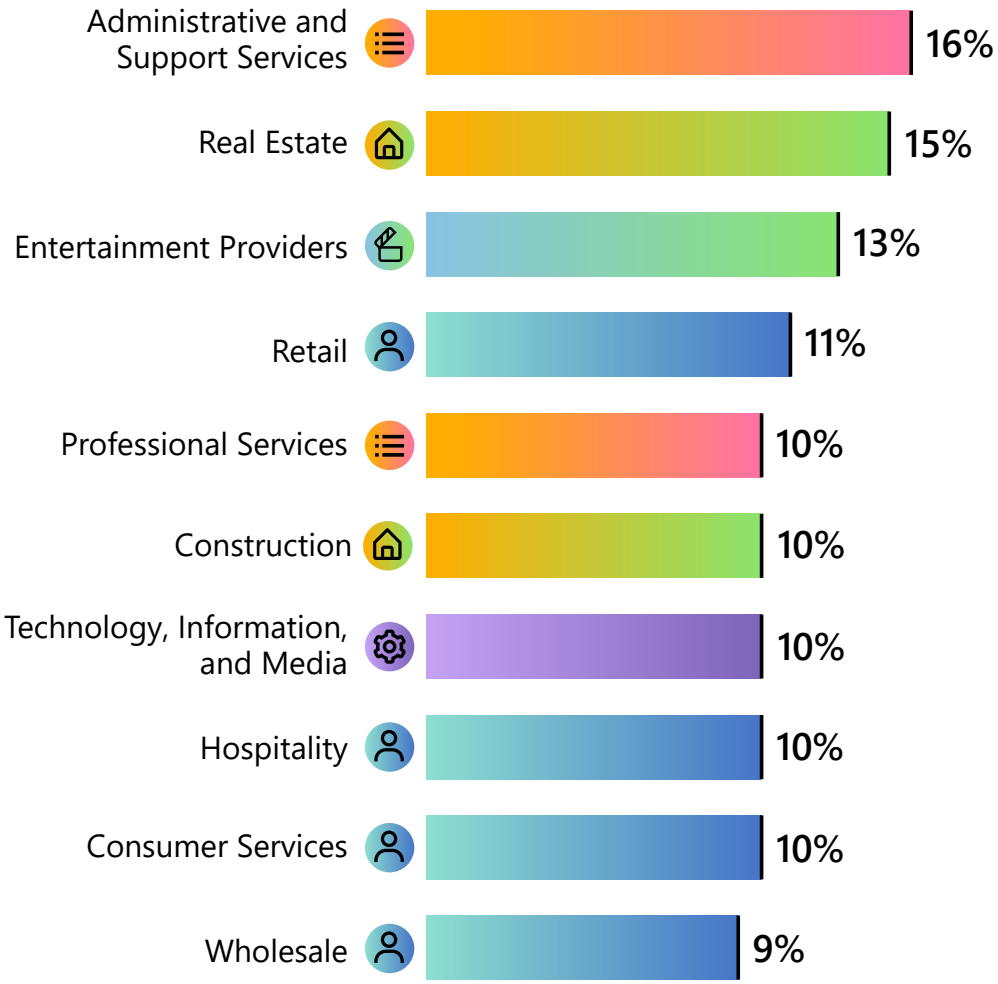
AI is going mainstream, and creative professionals are skilling up fast.



Occupations with the greatest percentage of members on LinkedIn adding AI Aptitude skills to their profiles in 2023

AI Aptitude Heats Up Across Roles and Industries

AI is going mainstream, and creative professionals are skilling up fast.



Industries with the greatest percentage of members on LinkedIn adding AI Aptitude skills in 2023



AI Aptitude Heats Up Across Roles and Industries

AI is going mainstream, and creative professionals are skilling up fast.

1	Project Manager	11	Sales Manager
2	Product Manager	12	Writer
3	Program Manager	13	Administrative Assistant
4	General Manager	14	Human Resources Manager
5	Architect	15	Marketing Specialist
6	Graphic Designer	16	Financial Analyst
7	Account Manager	17	Account Executive
8	Operations Manager	18	User Experience Designer
9	Marketing Manager	19	Business Consultant
10	Accountant	20	Operational Specialist

- Management and Consulting
- Creative, Design, and Marketing
- Business Development, Product Development, and Sales
- Human Resources, Administration, and Operations
- Finance

Top non-technical occupations using LinkedIn Learning to build AI aptitude

And just as we saw with flexible work options, offering AI access could help companies attract top talent:

- LinkedIn job posts that mention artificial intelligence or generative AI have seen **17%** greater application growth over the past two years compared to job posts that don't mention them.

- In another study, **54%** of early-in-career and individual contributor employees—the future of the workforce—said that access to AI would influence their choice of employer.

- In fact, **22%** of recruiters already say they're updating job descriptions to reflect the usage of generative AI in the role.

- And future-looking organizations are already taking action. Many of LinkedIn's Top Companies this year—including JPMorgan Chase, Procter & Gamble, and AT&T—are offering their teams AI learning opportunities to drive transformation at scale.

These are signs that AI could be a rising tide that elevates skills across roles and industries. Entry-level workers will take on more strategic projects, while uniquely human skills like management, relationship building, negotiation, and critical thinking will come to the fore for employees at all levels. Organizations that understand this will retain and attract the best talent, and professionals who skill up will have the edge.

Finding 3

The rise of the AI power user—and what they reveal about the future.

#1

Frequently experimenting with AI is the #1 predictor of an AI power user.

In our research, four types of AI users emerged on a spectrum—from skeptics who rarely use AI to power users who use it extensively, with novices and explorers in between. When we studied the difference between skeptics and power users we saw notable gaps, not only between how they work but how they feel about work.

Power users are familiar to extremely familiar with AI, using it at work at least several times a week and saving more than 30 minutes a day. And it's paying off: power users say AI makes their overwhelming workload more manageable (**92%**), boosts their creativity (**92%**), and helps them focus on the most important work (**93%**)—and it helps them feel more motivated (**91%**) and enjoy work more (**91%**).

The path to becoming a power user starts with developing new habits. Power users are **68%** more likely to frequently experiment with different ways of using AI—in fact, it's the **#1** predictor of whether someone will be a power user or not. When compared to other survey respondents, they're also more likely to frequently pause before a task and ask themselves if AI can help (**+49%**), to keep trying if they don't get the perfect response the first time (**+30%**), and to research and try new prompts (**+56%**).

Power users also bookend their day with AI—using it to start the day (**85%**) and get ready for the following workday (**85%**).

Power users have also reoriented their work patterns in fundamental ways. They are **56%** more likely to use AI to catch up on missed meetings, to analyze information (**+51%**), to design visual content (**+49%**), to interact with customers (**+49%**), and to brainstorm or problem-solve (**+37%**). And they're already moving past individual tasks: they're **66%** more likely to redesign their business processes and workflows with AI.

The Power User Payoff of AI at Work

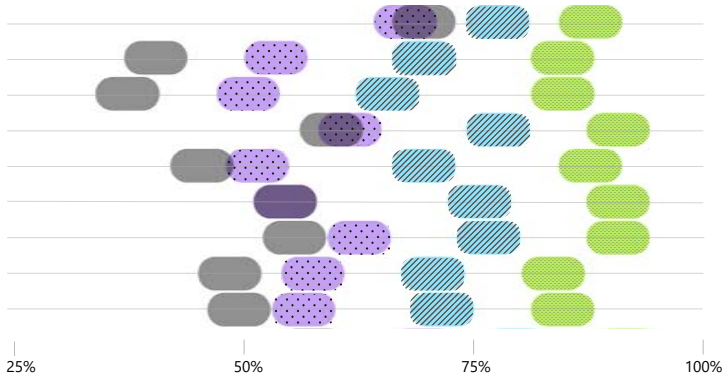
Power users are reshaping the workday and reaping the benefits.

Skeptics
are at least familiar with AI, but they only use it a few times a month (if ever). They say AI saves them 10 minutes or less per day.

Novices
are only somewhat familiar with AI (if at all) and use it only a few times a month (if ever). They say AI saves them 30 minutes or less per day.

Explorers
are only somewhat familiar with AI (if at all) and use it a few times a month or once a week. They say AI saves them between 5 and 30 minutes per day.

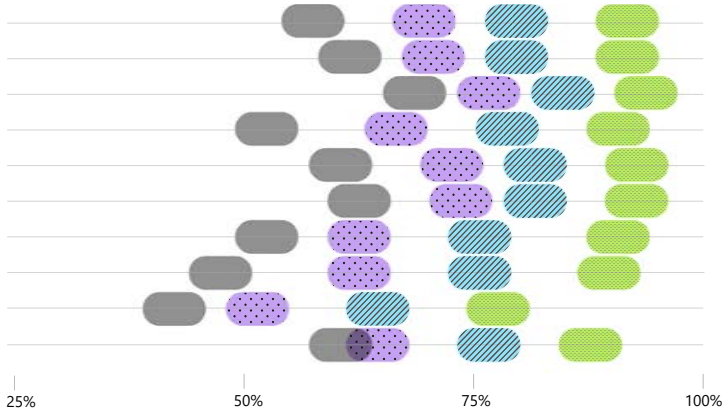
Power users
are at least familiar with AI and use it at least several times per week. They say it saves them more than 30 minutes per day.



Percent of each group selecting at least occasionally

How I use AI

When I don't get the response I want from the first prompt, I try again
I use AI to get ready for the following workday
I start my day using AI
I research and try new prompts
I regularly share my prompts / top tips on AI usage with my co-workers
I regularly experiment with different ways of using AI
I make it a priority to learn how to use AI effectively
I ask co-workers what prompts they find most useful
Before starting a task, I ask myself, "could AI help me with this?"



Percent of each group who agree

How AI impacts my experience at work

It makes my overwhelming workload more manageable
It helps me be more creative
It helps me be more productive
It helps me enjoy my work more
It helps me focus on more fulfilling work
It helps me focus on the most important work
It makes me feel more motivated
It has improved my work-life balance
I wish AI could do even more on my behalf
I don't want to go back to working without AI

Survey Questions:
When using artificial intelligence (AI) at work, how frequently do you do each of the following?
We'd now like you to reflect on how you feel about using artificial intelligence (AI) in your work. To what extent do you agree or disagree with the following statements?

The research also shows that power users are empowered by a different kind of organization. At their companies:

- **Senior leaders lean in:** AI power users are **61%** more likely to hear from their CEO about the importance of using generative AI at work, **40%** more likely to hear from the leader of their department, and **42%** more likely to hear from their manager's manager.

- **Company culture is change-ready:** AI power users are **53%** more likely to receive encouragement from leadership to consider how AI can transform their function, and **18%** more likely to say their company encourages innovation.

- **They get tailored training:** AI power users are **37%** more likely to say their company has a virtual learning program. They're also more likely to have received training on prompt writing (**+37%**), how to use AI for their role or function (**+35%**), or specific use cases such as writing or analyzing data (**+32%**).

AI power users provide a window into the future—revealing what's possible when employees embrace new ways of working and leaders lean in.

"To stay ahead of the curve, we've made AI training a priority to ensure everyone can leverage the power of Copilot for Microsoft 365 and other AI solutions. We also launched the GenAI Academy, supporting employee growth and development with the aim of increasing ambassadors and GenAI power users across the globe. We are already seeing benefits that are transforming the way we work and innovate."

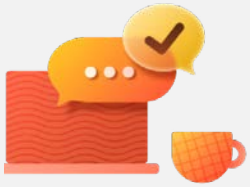
—Sheila Jordan, SVP, Chief Digital Technology Officer, Honeywell

Copilot Study: How AI Could Reshape the Workday

Microsoft researchers designed a six-month randomized control trial of 60 Copilot customers across industries. The study is the first mass-scale observation of 3,000 individuals using AI in their natural work environment with no interventions from the researchers to encourage use. Preliminary results show how AI could reshape the anatomy of the workday in fundamental ways—reducing time spent in inboxes, making meetings more valuable, and increasing time spent on high-value focus work.



Emails: Overall, Copilot users read **11%** fewer individual emails and spent **4%** less time interacting with them. The customers who saw the most impact spent **25%–45%** less time reading emails.



Meetings: In some companies time spent in meetings increased, in others it decreased. One hypothesis is that AI makes meetings more valuable—as stores of information and a shortcut to creation, like a brainstorming meeting, easily turned into a first draft. For some companies, the increased efficiency leads to fewer meetings, and at others the increased value leads to more. As AI capabilities progress, researchers expect this effect to continue—allowing us to reduce time in some meetings while making the meetings we do have more valuable.



Documents: Overall, Copilot users edited **10%** more documents in Word, Excel, and PowerPoint—the companies that saw the largest impact noticed a **20%** increase. This may suggest that people are repurposing the time they save for high-value focus work like creating and consuming information.

Key Takeaways

The opportunity ahead for leaders is to channel employee enthusiasm for AI into business transformation. This will look different for every organization, but here's how to get started.

Identify a business problem, then apply AI: There are efficiency gains to be had across every function—the key is to pick a process and apply AI. For example, start with customer service and focus on improving call-handling time. Global advertising network dentsu applied AI to its creative development process. Estée Lauder is using it to reimagine product development and customer experience.

Take a top-down, bottom-up approach: Going from experimentation to transformation requires engagement at every level of the organization, from the CEO to the entry-level employee. Business gains will come when you enlist your business line leaders to activate teams around AI. As we've rolled out Copilot at Microsoft, we've relied on internal champions at all levels to model and spread AI enthusiasm and aptitude.

Prioritize training: AI power users aren't doing it on their own—they receive ongoing training, both on universal tasks and uses more tailored to their role and function. LinkedIn Learning is a great place to start to skill up, and the Copilot Scenario Library provides use cases for specific roles and functions.

The Path Forward

We've arrived at a pivotal moment for AI at work. Just as we look back at the pre-PC era, we'll one day wonder how work got done without AI. Already, AI is helping people be more creative and productive, and giving job seekers an edge. Over time, it will change every aspect of work. As we reach the hard part of this tech disruption—turning experimentation into tangible business impact—companies that face the challenge head-on will surge ahead. In this moment, fortune favors the bold.

See how the data compares for small and medium-sized businesses and in US metropolitan areas. Learn how Microsoft and LinkedIn are innovating to help organizations and professionals thrive in the era of AI.

Sign up for the WorkLab newsletter for the latest research, insights, and trends on generative AI at work.

Methodology

Work Trend Index Survey

The Work Trend Index survey was conducted by an independent research firm, Edelman Data & Intelligence, among 31,000 full-time employed or self-employed knowledge workers across 31 markets between February 15, 2024 and March 28, 2024. This survey was 20 minutes in length and conducted online, in either the English language or translated into a local language across markets. One thousand full-time workers were surveyed in each market, and global results have been aggregated across all responses to provide an average. In the US, an additional sample of 2,800 full-time employed or self-employed knowledge workers was collected across nine sub-regions/metros.

Global markets surveyed include:
Argentina, Australia, Brazil, Canada, China, Colombia, Czech Republic, Finland, France, Germany, Hong Kong, India, Indonesia, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Philippines, Poland, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, United Kingdom, United States, and Vietnam.

Sub-regions/Metros in the United States surveyed include:
Atlanta, Austin, Boston, DC Metro, Houston, New York City, North Carolina, Pittsburgh, and the San Francisco Bay Area.

Audiences mentioned in the report are defined as follows:

Knowledge Workers: those who typically work at a desk (whether in an office or at home). This group includes those who are in person or working remotely in some capacity.

AI Power Users: knowledge workers who are at least familiar with generative AI, use it at work at least several times a week, and save more than 30 minutes a day by using it.

Business Leaders/Business Decision Makers: knowledge workers in mid to upper job levels (i.e., SVP, VP, Sr. Director, General Manager, EVP, C-Suite, President, etc.) and have at least some decision-making influence related to hiring, budgeting, employee benefits, internal communications, operations, etc.

Employees/Non-Business Decision Makers: knowledge workers who are not in mid to upper job levels or have no influence on decision making related to hiring, budgeting, employee benefits, internal communications, operations, etc.

LinkedIn Economic Graph Research Institute

LinkedIn's Economic Graph is a digital representation of the global workforce, covering over 1 billion members, 67 million companies, and 134,000 schools. LinkedIn's Economic Graph Research Institute (EGRI) drives research focused on answering members' and leaders' top questions about the economy and the labor market, based on the Economic Graph data. EGRI's metrics in this report include*:

- AI Aptitude Skills: These are standardized skills referring to the ability to use generative AI tools such as ChatGPT, Copilot, GitHub Copilot, etc.

- Professionals adding AI Aptitude Skills: We compute the growth in the share of members adding AI Aptitude skills to their profiles, relative to the number of members adding any skill.

- Top Occupations adding AI Aptitude Skills: For every occupation in the LinkedIn taxonomy, we compute the growth in the share of members adding AI Aptitude skills to their profiles, relative to the number of members adding any skill.

- Head of AI Roles: We identify members whose job titles include the keywords "AI," "Artificial Intelligence," or "Machine Learning" coupled with the keyword "Head," or LinkedIn's standardized seniority levels "Director," "VP," and "CXO." We then build a time series of the number of companies with at least one member in Head of AI roles.

- LinkedIn's Jobs on the Rise (JOTR) that didn't exist 20 years ago (US only): Every year, we publish LinkedIn's JOTR, a ranked list of the fastest growing jobs (in terms of number of members holding that title) over the previous three years. Internships, volunteer positions, interim roles, or student roles are excluded. To compute the share of JOTR that did not exist 20 years ago, we compared the list to O*NET's 2000 taxonomy by name or job description. O*NET is the US primary source for occupational information, consisting of a database developed under the sponsorship of the US Department of Labor. It contains hundreds of job definitions and is used extensively in academic research.

- Projected Skills Change: We predict how skills will change over time by looking at how they changed in the past and estimating how they will change in the future via linear extrapolation. We also consider the impact of generative artificial intelligence (GAI) technology by imagining a scenario where skills that can be easily replicated by GAI become less important compared to other important skills.

*Unless otherwise specified, results reported are global, including the UK, Germany, France, India, Singapore, Australia, and Brazil.

LinkedIn Executive Confidence Index

LinkedIn's Executive Confidence Index (ECI) is an online survey taken every quarter by ~5,000 LinkedIn members (at the VP level or above). The most recent wave ran from March 4–19, 2024. Members are randomly sampled and must be opted into research to participate. We analyze data in aggregate and will always respect member privacy. Data is weighted by Seniority and Industry to ensure fair representation of executives on the platform. The results represent the world as seen through the lens of LinkedIn's membership; variances between LinkedIn's membership and the overall market population are not accounted for.

LinkedIn Workplace Learning Report

The LinkedIn Learning 2024 Workplace Learning Report surveyed 1,636 L&D and HR professionals with L&D responsibilities who have some influence on budget decisions, and 1,063 learners. Surveyed geographies include: North America (United States, Canada); South America (Brazil); Asia-Pacific (Australia, New Zealand, India, Japan, Cambodia, Indonesia, Singapore, Malaysia, Myanmar, Philippines, Thailand, Hong Kong); and Europe (United Kingdom, Ireland, Belgium, Netherlands, Luxembourg, Norway, Finland, Sweden, Iceland, Denmark, France, Germany, Austria).

2024 Global Marketing Jobs Outlook Report

Insights were leveraged from Ipsos & LinkedIn research conducted in 2023 using a sample of 1,577 senior-level B2B marketing leaders, including 377 CFOs, from various industries in NAMER (US), EMEA (UK, DE, FR) , APAC (IN, AU, SG), and LATAM (Brazil).

Appendix: Key Global Trends

1. Employees want AI at work—and they won't wait for companies to catch up.

Aggregated Totals

75% of knowledge workers around the world use generative AI at work.

By Region

North America: 66%
Latin America: 82%
Asia-Pacific: 83%
Europe: 65%

By Market

North America
Canada: 62%
US: 71%

Latin America
Argentina: 80%
Brazil: 83%
Colombia: 81%
Mexico: 82%

Asia-Pacific
Australia: 84%
China: 91%
Hong Kong: 88%
India: 92%
Indonesia: 92%
Japan: 32%
Malaysia: 84%
New Zealand: 84%
Philippines: 86%
Singapore: 88%
South Korea: 73%
Taiwan: 84%
Thailand: 92%
Vietnam: 88%

Europe
Czech Republic: 68%
Finland: 57%
France: 56%
Germany: 69%
Italy: 60%
Netherlands: 67%
Poland: 61%
Spain: 68%
Sweden: 63%
Switzerland: 82%
UK: 69%

* Data point unavailable due to low sample size.

1. Employees want AI at work—and they won't wait for companies to catch up.

Aggregated Totals

While 79% of leaders believe their company needs to adopt AI to stay competitive, 60% of leaders worry their organization's leadership lacks a plan and vision to implement it.

By Region

North America: 76%, 59%
Latin America: 80%, 57%
Asia-Pacific: 84%, 61%
Europe: 74%, 59%

By Market

North America
Canada: 74%, 59%
US: 77%, 60%

Latin America
Argentina: 77%, 60%
Brazil: 87%, 51%
Colombia: 78%, 60%
Mexico: 80%, 57%

Asia-Pacific
Australia: 80%, 70%
China: 78%, 54%
Hong Kong: 85%, 66%
India: 91%, 54%
Indonesia: 92%, 48%
Japan: 67%, 49%
Malaysia: 88%, 66%
New Zealand: 77%, 74%
Philippines: 89%, 55%
Singapore: 83%, 68%
South Korea: 80%, 68%
Taiwan: 78%, 73%
Thailand: 91%, 64%
Vietnam: 89%, 48%

Europe
Czech Republic: 78%, 77%
Finland: 74%, 71%
France: 74%, 57%
Germany: 77%, 55%
Italy: 76%, 50%
Netherlands: 74%, 68%
Poland: 69%, 49%
Spain: 77%, 59%
Sweden: 69%, 61%
Switzerland: 70%, 51%
UK: 81%, 52%

* Data point unavailable due to low sample size.

1. Employees want AI at work—and they won't wait for companies to catch up.

Aggregated Totals	By Region	By Market	
78% of AI users are bringing their own AI to work (BYOAI).	**North America:** 70% **Latin America:** 77% **Asia-Pacific:** 79% **Europe:** 80%	**North America** Canada: 79% US: 63% **Latin America** Argentina: 75% Brazil: 74% Colombia: 83% Mexico: 76% **Asia-Pacific** Australia: 78% China: 66% Hong Kong: 86% India: 72% Indonesia: 76% Japan: 78% Malaysia: 83% New Zealand: 81% Philippines: 83% Singapore: 84% South Korea: 85% Taiwan: 79% Thailand: 81% Vietnam: 70%	**Europe** Czech Republic: 86% Finland: 83% France: 78% Germany: 71% Italy: 73% Netherlands: 88% Poland: 79% Spain: 77% Sweden: 86% Switzerland: 83% UK: 75%

* Data point unavailable due to low sample size.

2. For employees, AI raises the bar and breaks the career ceiling.

Aggregated Totals	By Region	By Market
66% of leaders say they would not hire someone without AI skills.	**North America:** 57% **Latin America:** 60% **Asia-Pacific:** 70% **Europe:** 65%	**North America** Canada: 50% US: 65% **Latin America** Argentina: 62% Brazil: 58% Colombia: 57% Mexico: 63% **Asia-Pacific** Australia: 74% China: 79% Hong Kong: 65% India: 75% Indonesia: 69% Japan: 35% Malaysia: 62% New Zealand: 73% Philippines: 70% Singapore: 71% South Korea: 70% Taiwan: 81% Thailand: 74% Vietnam: 76% **Europe** Czech Republic: 79% Finland: 68% France: 58% Germany: 69% Italy: 62% Netherlands: 64% Poland: 53% Spain: 64% Sweden: 65% Switzerland: 70% UK: 57%

* Data point unavailable due to low sample size.

2. For employees, AI raises the bar and breaks the career ceiling.

Aggregated Totals

71% of leaders say they'd rather hire a less experienced candidate with AI skills than a more experienced candidate without them.

By Region

North America: 67%
Latin America: 66%
Asia-Pacific: 76%
Europe: 67%

By Market

North America
Canada: 63%
US: 71%

Latin America
Argentina: 67%
Brazil: 65%
Colombia: 65%
Mexico: 68%

Asia-Pacific
Australia: 79%
China: 82%
Hong Kong: 77%
India: 80%
Indonesia: 76%
Japan: 51%
Malaysia: 65%
New Zealand: 77%
Philippines: 68%
Singapore: 77%
South Korea: 77%
Taiwan: 84%
Thailand: 90%
Vietnam: 78%

Europe
Czech Republic: 82%
Finland: 69%
France: 67%
Germany: 69%
Italy: 61%
Netherlands: 67%
Poland: 55%
Spain: 64%
Sweden: 62%
Switzerland: 74%
UK: 64%

* Data point unavailable due to low sample size.

3. The rise of the AI power user—and what they reveal about the future.

Aggregated Totals

AI power users are 40% more likely to frequently ask co-workers what prompts they find most useful and 68% more likely to experiment with different ways of using AI.

By Region

North America: +40%, +75%
Latin America: +24%, +76%
Asia-Pacific: +31%, +51%
Europe: +61%, +86%

By Market

North America
Canada: +33%, +124%
US: +40%, +45%

Latin America
Argentina: +1%, +59%
Brazil: +17%, +71%
Colombia: +23%, +93%
Mexico: +51%, +64%

Asia-Pacific
Australia: +45%, +19%
China: +19%, +29%
Hong Kong: -5%, +15%
India: +37%, +47%
Indonesia: +24%, +73%
Japan: *, *
Malaysia: +26%, +48%
New Zealand: +24%, +33%
Philippines: +52%, +65%
Singapore: +26%, +38%
South Korea: +23%, +68%
Taiwan: +35%, +27%
Thailand: +25%, +45%
Vietnam: +14%, +51%

Europe
Czech Republic: +54%, +54%
Finland: *, *
France: +45%, +68%
Germany: +68%, +69%
Italy: +93%, +84%
Netherlands: +31%, +53%
Poland: +13%, +149%
Spain: +40%, +81%
Sweden: *, *
Switzerland: +84%, +103%
UK: +67%, +91%

* Data point unavailable due to low sample size.

3. The rise of the AI power user—and what they reveal about the future.

Aggregated Totals

AI power users are more likely to hear from their leadership about the importance of generative AI—CEO (61% more likely), function/department lead (40% more likely), and manager's manager (42% more likely).

By Region

North America: +45%, +50%, +51%

Latin America: +83%, +54%, +64%

Asia-Pacific: +44%, +29%, +27%

Europe: +80%, +41%, +53%

By Market

North America

Canada: +65%, +75%, +62%

US: +30%, +32%, +40%

Latin America

Argentina: +107%, +125%, +109%

Brazil: +75%, +38%, +20%

Colombia: +55%, +4%, +50%

Mexico: +70%, +53%, +85%

Asia-Pacific

Australia: +21%, +33%, +39%

China: +25%, +10%, -7%

Hong Kong: +23%, +41%, +35%

India: +65%, +34%, +44%

Indonesia: +34%, +27%, +35%

Japan: *, *, *

Malaysia: +50%, +24%, +9%

New Zealand: +36%, +33%, -19%

Philippines: +57%, +41%, +107%

Singapore: +44%, +5%, +43%

South Korea: +42%, +29%, +20%

Taiwan: +31%, -6%, +12%

Thailand: +32%, +28%, +20%

Vietnam: +45%, +11%, +10%

Europe

Czech Republic: +26%, +33%, +62%

Finland: *, *, *

France: +86%, +52%, +14%

Germany: +110%, +42%, +70%

Italy: +87%, +45%, +77%

* Data point unavailable due to low sample size.

3. The rise of the AI power user—and what they reveal about the future.

Aggregated Totals

AI power users are more likely to hear from their leadership about the importance of generative AI—CEO (61% more likely), function/department lead (40% more likely), and manager's manager (42% more likely).

By Region

North America: +45%, +50%, +51%

Latin America: +83%, +54%, +64%

Asia-Pacific: +44%, +29%, +27%

Europe: +80%, +41%, +53%

By Market (continued)

Netherlands: +91%, +26%, +42%

Poland: +38%, +21%, -11%

Spain: +79%, +9%, +11%

Sweden: *, *, *

Switzerland: +78%, +67%, +89%

UK: +79%, +16%, +48%

* Data point unavailable due to low sample size.

3. The rise of the AI power user—and what they reveal about the future.

Aggregated Totals

AI power users are more likely to get training (42% more likely), especially on prompts (37% more likely) and how to use AI for their specific role or function (35% more likely).

By Region

North America: +33%, +57%, +35%

Latin America: +51%, +42%, +39%

Asia-Pacific: +36%, +28%, +28%

Europe: +39%, +43%, +41%

By Market

North America

Canada: +57%, *, *

US: +18%, *, *

Latin America

Argentina: +69%, +40%, +47%

Brazil: +48%, +30%, +25%

Colombia: +44%, +62%, +30%

Mexico: +35%, +21%, +45%

Asia-Pacific

Australia: +41%, *, *

China: +17%, +19%, +24%

Hong Kong: +14%, +26%, +23%

India: +19%, +32%, +23%

Indonesia: +27%, +13%, +20%

Japan: *, *, *

Malaysia: +41%, +42%, +22%

New Zealand: +34%, *, *

Philippines: +30%, +23%, +37%

Singapore: +12%, +33%, -10%

South Korea: +63%, *, *

Taiwan: +17%, *, *

Thailand: +22%, +25%, +35%

Vietnam: +57%, +20%, +30%

Europe

Czech Republic: +6%, *, *

Finland: *, *, *

France: +41%, *, *

Germany: +53%, +44%, +46%

Italy: +69%, *, *

Netherlands: +11%, *, *

Poland: +20%, *, *

Spain: +24%, *, *

Sweden: *, *, *

Switzerland: +41%, +61%, +51%

UK: +63%, *, *

* Data point unavailable due to low sample size.

3. The rise of the AI power user—and what they reveal about the future.

Aggregated Totals

85% of AI power users start their day with AI and 85% use it to get ready for the following day.

By Region

North America: 79%, 83%
Latin America: 85%, 87%
Asia-Pacific: 88%, 87%
Europe: 80%, 81%

By Market

North America
Canada: 77%, 86%
US: 80%, 82%

Latin America
Argentina: 85%, 88%
Brazil: 88%, 91%
Colombia: 80%, 79%
Mexico: 85%, 90%

Asia-Pacific
Australia: 89%, 88%
China: 91%, 93%
Hong Kong: 85%, 83%
India: 90%, 91%
Indonesia: 93%, 94%
Japan: *, *
Malaysia: 85%, 82%
New Zealand: 80%, 75%
Philippines: 86%, 86%
Singapore: 87%, 82%
South Korea: 83%, 81%
Taiwan: 85%, 83%
Thailand: 86%, 84%
Vietnam: 93%, 94%

Europe
Czech Republic: 73%, 77%
Finland: *, *
France: 84%, 85%
Germany: 80%, 83%
Italy: 91%, 91%
Netherlands: 68%, 69%
Poland: 75%, 80%
Spain: 82%, 83%
Sweden: *, *
Switzerland: 80%, 81%
UK: 82%, 78%

* Data point unavailable due to low sample size.

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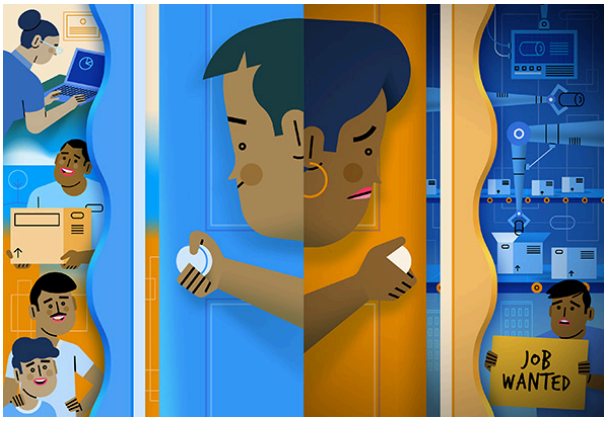
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Technology

Choosing AI's Impact on the Future of Work

Rapid advances in AI threaten to eliminate many jobs, but there are still two distinct paths this AI revolution could take.

By Daron Acemoglu & Simon Johnson | Oct. 25, 2023

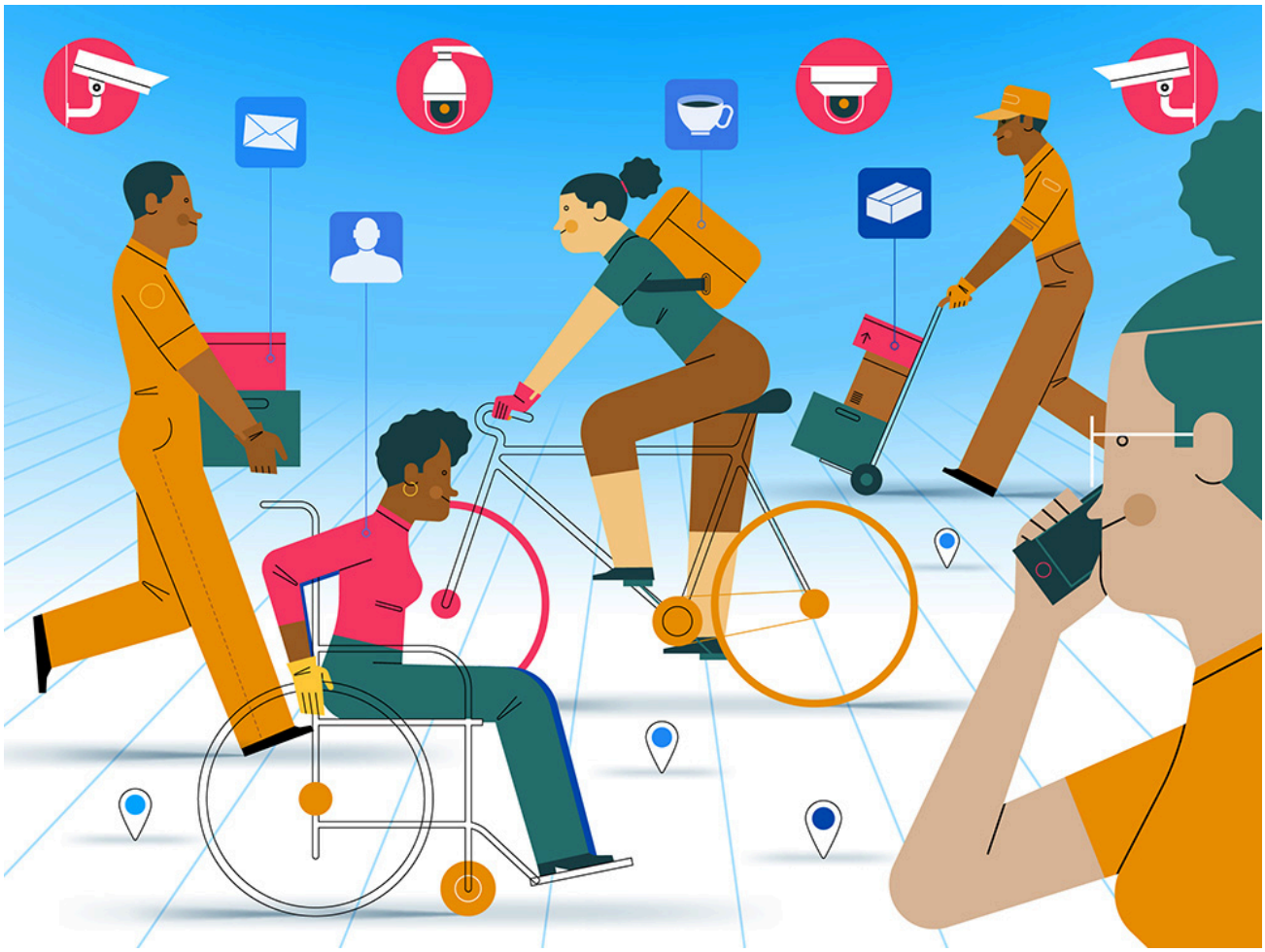


(Illustration by Hugo Herrera)

In November 2022, OpenAI grabbed headlines by releasing ChatGPT, and "generative AI" became a term used in households around the world. According to Open AI CEO Sam Altman, "A lot of people working on AI pretend that it's only going to be good; it's only going to be a supplement; no one is ever going to be replaced." But, he adds, "jobs are definitely going to go away, full stop." Two major labor strikes this year, by the Writers Guild of America and the actors union (SAG-AFTRA), have helped focus attention on the threat AI poses to well-paid jobs.

Artificial Intelligence is poised to upend work around the world over the coming decades. Whether this lessens or increases inequality remains to be seen. AI technology is relatively new, but the impacts of previous high-impact innovations like the power loom, steam engines, electricity, and digital computers shed ample light on what could happen next. The consequences of any technology depend on who gets to make pivotal decisions about how the technology develops. This is doubly true for AI, because these new tools can be developed for many different types of activities, with the potential to spread rapidly in every sector of the economy and in every aspect of our lives.

Too many commentators see the path of technology as inevitable. But the historical record is clear: technologies develop according to the vision and choices of those in positions of power. As we document in *Power and Progress: Our 1,000-Year Struggle over Technology and Prosperity*, when



Making Tech Work for Workers

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these choices are left entirely in the hands of a small elite, you should expect that group to receive most of the benefits, while everyone else bears the costs—potentially for a long time.

Rapid advances in AI threaten to eliminate many jobs, and not just those of writers and actors. Jobs with routine elements, such as in regulatory compliance or clerical work, and those that involve simple data collection, data summary, and writing tasks are likely to disappear.

But there are still two distinct paths that this AI revolution could take. One is the path of automation, based on the idea that AI's role is to perform tasks as well as or better than people. Currently, this vision dominates in the US tech sector, where Microsoft and Google (and their ecosystems) are cranking hard to create new AI applications that can take over as many human tasks as possible.

The negative impact on people along the "just automate" path is easy to predict from prior waves of digital technologies and robotics. It was these earlier forms of automation that contributed to the decline of American manufacturing employment and the huge increase in inequality over the last four decades. If AI intensifies automation, we are very likely to get more of the same—a gap between capital and labor, more inequality between the professional class and the rest of the workers, and fewer good jobs in the economy.

There is a second, very different path available to us, however. This path would focus on creating new tasks and capabilities for humans, rather than sidelining them. This too is not new in history. The augmentation of human capabilities, by creating new tasks and providing better tools and information for workers, was the bedrock of wage growth and shared prosperity during the decades that followed World War II.

In principle, AI could magnify the possibilities for human-complementary technological change. It could enable the development of a wide array of tools that provide better information to human decision-makers. Critically, this need not be limited to office workers and professionals. Much of the workforce today, from blue-collar workers in factories to electricians, plumbers, educators, and health care providers, depends on problem-solving and real-time decision-making. With better context-specific information, these workers could become more productive in the tasks they are performing and venture into new, more complex tasks.

Alas, this more hopeful path is not where we are heading. Three big social changes would be necessary for such a path, and each one of them is a tall order.

First, management needs to see and understand workers as a key resource whose productivity should be augmented, whose information should be improved, and whose training should be a priority. But the dominant perspective in most C-suites views labor as a cost to be cut, either to withstand competition or to better remunerate shareholders. What gets lost in the rush to reengineer the corporation with fewer workers is the long-term health of the companies, which never achieve the promised productivity gains from so-so automation and offshoring. Companies must recognize that, in reality, labor is a critical resource for productivity growth.

Second, the tech sector needs to prioritize helping workers, rather than focusing on tools of automation and surveillance. The industry's vision has too long been shaped by an ill-advised quest for artificial general intelligence and autonomous machine intelligence, and many technologists are still preoccupied by showing how their algorithms can reach "human parity." In practice, that means automating as many tasks as possible.

Third, labor needs to have a voice in how technologies are used. This voice is critical not only for resisting excessive emphasis on labor cost-cutting and automation. It is also essential because workers typically know which parts of their jobs would benefit from automation and which would not. They recognize which tasks could be made more efficient, freeing them to spend time on more productive activities, or even creating new opportunities for increased productivity. Increased worker buy-in reduces businesses' incentives for further intensification of worker monitoring and surveillance. It also ensures that any productivity gains are shared more fairly between capital and labor.

These three social changes are possible, even if very unlikely to happen without a coordinated effort.

There is much greater pushback against the "shareholder values revolution"—which elevated cost-cutting and the interests of shareholders at the expense of workers—than at any other time over the last four decades. A new philosophy prioritizing long-term productivity growth may yet emerge, which management and workers can work together to achieve.

The tech sector can change, too. It was always an aberration that arguably the most powerful industry in the US (and the world) would ignore all social responsibility and elevate the virtues of "disruption" with an almost religious zeal. In its next, more mature phase, the industry could focus on providing better tools for workers and augmenting human capabilities, rather than replacing them wholesale.

And labor can become better organized and better focused on charting a new course for involvement in the production process during the age of AI, which will also enhance productivity. In fact, pro-union sentiment is higher than we've seen in decades, and the WGA strike has set an example of how focusing on technology—who controls it and how it will be used—could become central to contract negotiations in other industries.

It is crucial, however, that the renewed energy of organized labor is channeled in the right way. Labor cannot hope to ask for and obtain high wages unless technology moves in a more pro-worker direction. Nor can one reasonably expect that opposing new technologies, including AI, will be a viable option for the union movement. Rather, leaders and rank-and-file workers alike must understand the potential of new tools, including artificial intelligence, and articulate a vision for how these technologies can be used in a way that helps both labor and corporations. Making workers more productive in their decision-making and problem-solving tasks is the bedrock of such an approach.

None of this will happen automatically. Any meaningful change must start with a recognition of the problem—technology is heading in an anti-labor direction. People promoting change must also recognize the feasibility and desirability of a pro-worker direction for technological change.

Neither the tech industry nor other large corporations will undertake a huge course correction without strong pressure from others in society. In addition to robust labor voices, government regulation and civil society organizations have previously played a critical role in pushing companies in the right direction. This role is even more important today when we need a fundamental redirection of AI technology.

The government should adopt a set of complementary policies encouraging a better path for technology use and development, as we detail in a recent policy memo (jointly written with our MIT colleague David Autor, through the new MIT Shaping the Future of Work Initiative that we collectively co-direct) entitled "Can We Have Pro-Worker AI?"

Lawmakers should revise the federal tax code to equalize the tax burden across labor and machines, so companies are encouraged to hire, train, and retain human workers. Regulatory agencies should also find ways to include and amplify worker voice on how AI and other technology is used in the workplace—including regulating AI-assisted personnel management and placing safeguards around workplace surveillance.

The public sector should invest in research that prioritizes human-complementary AI technology and create a federal government consultative AI center of expertise to support lawmakers and officials who need to understand this technology. We should use this federal expertise to assess whether specific AI technologies live up to their promise to augment human work before they are rolled out in any publicly funded programs such as education or health care.

There is much to be alarmed about when it comes to AI. But if AI brings a dystopian future, it will not be because this was the only path available to us. It will be because we failed to grasp how this technology could be developed and used, and how it could help workers, rather than just replacing them. Understanding this is a first step toward the right type of AI revolution.

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Impact of artificial intelligence on employment and workforce development: Risks, opportunities, and socioeconomic implications

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Impact of artificial intelligence on employment and workforce development: Risks, opportunities, and socioeconomic implications

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[1] *Hurix Digital, Andheri, India*

Abstract:

Artificial intelligence (AI) is changing employment and workforce dynamics worldwide, creating opportunities and challenges with far-reaching socioeconomic effects. This paper analyzes AI's dual impact on employment, including job displacement, new roles, and job redefinition. As automation and machine learning become more common, AI is taking over routine tasks in manufacturing, retail, and customer service, threatening job losses. AI also opens up new fields like data science, cybersecurity, and AI ethics, requiring new skills and requiring advanced workforce training and development. Reskilling and upskilling the workforce to close the skills gap and improve adaptability is essential for AI-driven job transformation. To adapt to the changing AI landscape, governments, educational institutions, and private companies must invest in workforce development. This paper also examines AI adoption's socioeconomic effects on income inequality, employment polarization, and work-life balance. AI can boost economic growth and productivity, but its equitable integration requires ethical, regulatory, and social policies to protect vulnerable populations. This paper seeks to help policymakers, business leaders, and educators navigate the complex intersection of AI, employment, and workforce development through nuanced analysis.

Keywords: Artificial Intelligence (AI), Workforce Development, Employment Impact, Job Automation, Job Displacement, Reskilling and Upskilling

Introduction

AI has revolutionized the workforce and employment landscape in economies, industries, and societies worldwide [1-4]. AI systems can now perform complex tasks previously reserved for humans thanks to advances in machine learning, robotics, natural language processing, and data analytics [2,5-7]. AI has changed almost every industry, from administrative tasks to financial services predictive analytics and manufacturing [8-12]. This technological advancement excites and worries policymakers, business leaders, workers, and researchers [3,13-17]. As AI advances, its effects on employment and workforce development, including risks to certain job categories, opportunities for new roles, and socioeconomic effects on societies worldwide, are still being studied [3,18-23]. Automation and AI can eliminate 85 million jobs by 2025, especially in repetitive industries like manufacturing, retail, and data processing, according to the World Economic Forum. “Intelligent automation,” which uses AI and robotics to improve efficiency, worsens this. Lower-skilled and routine jobs are disproportionately affected by automation, widening income gaps and economic inequality [3,24-28]. With strong digital infrastructure, the US, China, and Germany can adapt to these changes more easily than emerging economies, which may struggle to reskill their workforce for AI-driven industries.

AI can boost economic growth and create jobs, but the displacement narrative ignores this [1,29-32]. AI could create data science, AI ethics, cybersecurity, and machine learning engineering jobs for every job it eliminates [15,33-35]. McKinsey Global Institute estimates AI could create 97 million jobs worldwide, offsetting traditional sector losses. New jobs require more education and specialized skills, driving workforce development and training. Singapore and Sweden have developed AI upskilling strategies to mitigate AI-induced disruptions. Reskilling and upskilling programs are helping companies retain and prepare workers for automated jobs in the AI era, which could boost competitiveness [2-3,36-40]. AI changes work and job creation and elimination. Complex decisions made by AI systems blur the line between humans and machines [15,41-43]. AI helps doctors diagnose and customize treatments, and AI-driven analytics improve financial investment decisions and risk assessments [3,44-49]. Many professions value digital literacy, critical thinking, and adaptability over traditional

skills due to AI integration. Workers need “human-AI collaboration skills” to use AI [50-53]. Soft skills like emotional intelligence, communication, and teamwork are valued more because humans outperform AI.

AI has significant socioeconomic effects on employment beyond jobs and skills [6,54-58]. AI adoption can increase national and international inequality. AI benefits high-skill, high-income workers, but it is more likely to displace low-skill workers [15,59-63]. A polarized workforce where only a few skilled workers can get high-tech jobs threatens social stability and inclusivity. The uneven pace of AI adoption creates a "digital divide," which may widen the economic gap between nations with strong technological infrastructures and those without [2-3,64-67]. Automation could reduce demand for low-cost, labor-intensive work, a growth driver, in developing economies. AI can boost inclusive economic growth if managed well [68-72]. AI-powered tools can improve agriculture, energy, and healthcare productivity in emerging economies, improving living standards and economic resilience. AI can improve crop management, forecast weather, and automate labor-intensive agricultural tasks, increasing yield and reducing resource waste. AI-driven healthcare solutions can also improve remote and underserved medical access. AI can help achieve sustainable development goals (SDGs) and reduce inequality by addressing critical socioeconomic issues if governments, businesses, and international organizations work together to ensure equitable access to AI technologies. AI's impact on employment ethics and regulation matters too. Privacy, data security, algorithmic bias, and accountability are ethical concerns when AI systems are used in the workplace. Biased algorithms may discriminate in hiring and evaluation. AI systems should be fair, transparent, and accountable, say policymakers. The GDPR requires organizations to disclose automated decision-making processes, allowing individuals to challenge algorithmic biases. To embed ethical principles in AI systems and ensure fair and equitable deployment, several organizations and institutions are investigating responsible AI frameworks.

AI’s impact on employment and workforce dynamics

AI is changing employment and workforce dynamics, creating opportunities and challenges [6,73-77]. Machine learning, natural language processing, and robotics are changing industries, creating jobs, and eliminating others [9,78-81]. AI's changing relationship with the workforce raises questions about job displacement, skill requirements, and the future of work. The potential for AI to automate tasks has raised concerns about sector-wide job displacement. Assembly line work, customer service, and data entry are more automated. AI can manage inventory, customer service, and logistics. Business efficiency and cost reduction are achieved with this level of automation, but some jobs are eliminated. Recent studies estimate that millions of jobs could be automated in a decade, requiring job changes in many fields [9,82-86]. AI affects employment beyond job loss. It generates tech and data science jobs [10-11,87-91]. Companies integrating AI systems need data analysts, AI model developers, and technology ethics experts. Many industries need technical and soft skills because AI requires human oversight, contextual understanding, and ethics. Medical, educational, and strategic jobs require creativity, problem-solving, strategic decision-making, and interpersonal skills, making them less susceptible to automation and more likely to benefit from AI [28,92-95]. Thus, AI displaces some jobs but creates others and changes roles, requiring workforce adaptability and skill changes.

AI changed modern workplace skills [9,96-101]. Critical thinking, tech skills, and emotional intelligence are replacing manual labor and admin [102-105]. AI literacy—interacting with AI systems—is needed [23-24,106-109]. Digital literacy, data competency, and AI ethics are crucial in a fast-changing job market. This environment encourages lifelong learning and reskilling as AI technologies evolve to advance careers. AI changes workflows and organizational structures beyond skills. Many companies use AI-driven productivity tools for flexibility in hybrid work models [110-112]. AI-powered project management systems simplify collaboration and tracking for distributed teams. AI-enhanced remote work has boosted the gig economy, where professionals work on projects without full-time jobs. Because of this, freelance platforms that match clients and freelancers using AI algorithms are growing, showing the gig economy's dependence on AI. The gig economy illustrates AI-driven work shifts' pros and cons. AI increases worker autonomy but also job insecurity and lower benefits. Gig workers lack certain protections, making income consistency, healthcare, and retirement difficult. AI-based gig economy job-matching algorithms can also bias and unfairly affect workers' access to jobs and pay. An AI-enabled economy requires fair treatment and protections for gig workers.

AI has transformed hiring [113-115]. Companies are using AI to screen resumes, evaluate candidates, and predict job performance. Automatic AI assessments can assess candidates' strengths, weaknesses, and role fit. AI in recruitment raises ethical and fairness concerns. Historical data-trained algorithms may unintentionally reinforce race, gender, and socioeconomic hiring biases, affecting diversity and inclusivity. Thus, AI-driven recruitment must be fair and transparent to avoid biases and ensure equitable hiring. AI is vital to employee development and hiring. AI-powered platforms can customize training to help employees adapt to changing demands. AI can recommend personalized learning paths based on worker performance and skill gaps, improving training. These applications show how AI can help retain and develop employees. These personalized programs raise privacy concerns as employees worry about performance data use. AI's decision-making power affects workplace diversity and inclusion. AI can show institutional biases like pay, representation, and promotion. Unmanaged AI systems trained on biased data may perpetuate inequality. AI can make workplaces fairer, but it must be carefully designed and implemented to avoid side effects.

AI has vast and complex economic effects on employment [9-11,116-118]. AI could boost macroeconomic productivity and growth. AI may boost global GDP by trillions by the end of the decade. Technology, data, and AI oversight jobs may rise with economic growth. Growth benefits may not be distributed evenly. Some sectors and regions may gain, but others—especially those doing manual or repetitive work—may lose, worsening income inequality and socioeconomic issues. AI sectors need coordinated reskilling, transition, and safety net programs to close gaps. Public policy will determine AI's workforce impact. As AI grows, policymakers must balance innovation and worker protection. Global regulatory frameworks for ethical AI use, especially in socially impactful areas like recruitment, are being considered. To reduce AI-related job loss, UBI and other social safety nets have been proposed. Government intervention is needed to manage AI's disruptive effects, so policymakers are considering tax incentives and initiatives that encourage businesses to invest in workforce reskilling and fair AI practices. To overcome challenges and maximize opportunities, governments, industries, and educational institutions will likely need to collaborate on AI in the workplace. Schools must teach digital and AI literacy to prepare students for AI-driven jobs. Industry partnerships can reskill workers for growth sectors. Ethics like data privacy, algorithmic fairness, and job security must be discussed to make AI's implementation fair and beneficial to society.

AI policy implications and future directions for workforce sustainability

AI's workforce transformation requires sustainable policies [25-26,119-121]. AI can automate, boost productivity, and inspire innovation, changing jobs and industries. Job displacement, changing skill requirements, and economic inequality result from this shift [26-28,122-123]. As AI becomes more embedded in business practices, sustainable workforce development policies must address these challenges. AI integration's policy implications and workforce sustainability strategies are discussed here.

Required Skills for Transition

AI automates many industrial tasks, changing workforce skill needs [9, 123]. Automation threatens repetitive jobs, but technical skills, creativity, and adaptability are needed. This change requires reevaluating educational and vocational programs. To prepare workers for an AI-driven economy, policies must emphasize lifelong learning, reskilling, and upskilling. Schools can develop future-ready skills by teaching digital literacy, programming, and data analysis. This transformation can be driven by government initiatives, industry collaboration, and private company training incentives. Policymakers can fund machine learning, data analytics, and robotics training to help workers transition to less automated jobs. Like technical skills, soft skills like communication, creativity, and empathy can improve AI systems and workplace human-AI synergy. Such comprehensive policies ensure employees adapt to AI's technical demands and bring unique, human-centered contributions to work.

Economic Safety Nets and Inclusive Policies Reduce Job Loss

AI automation raises concerns about manufacturing, retail, and transportation job losses. AI may create some roles but eliminate others. Job displacement policies are crucial for worker morale and social stability. Unemployment benefits, retraining subsidies, and transition programs can reduce job losses. Identification of at-risk jobs and

growth sectors early in displacement management will help workers transition. Inclusive AI policies should consider marginalized groups' job market barriers. Job displacement disproportionately affects women, seniors, and low-income workers. Policymakers can give these groups equal AI training and jobs. By offering reskilling and career support to all demographic groups, governments and organizations can create a more inclusive workforce. To integrate AI without displacement, encourage businesses to use “job-sharing” models where AI helps workers rather than replaces them.

Integrating Ethics and Social Responsibility with Innovation

AI raises ethical concerns about workforce sustainability. Automation can entrench biases, threaten jobs, and alter workplace dynamics. Policymakers must establish ethical AI guidelines with human oversight. AI-driven hiring tools can reinforce biases if not monitored. AI decision-making transparency and organization accountability can reduce such risks and promote AI-augmented hiring and evaluation fairness. Along with ethical hiring, data security and employee privacy are essential. Data overreach and misuse are concerns as AI systems monitor employee performance and productivity. By restricting surveillance and protecting privacy, policies can optimize performance and employee privacy. These policies will increase employer-employee trust, making AI integration easier without compromising ethics

Collaboration for Public-Private Workforce Adaptation

AI-driven workforce transformation requires public-private collaboration. Because governments cannot handle all the complexities, industry leaders must work with them to implement AI integration policies. Manufacturing automation and healthcare AI-driven diagnostics guidelines can be developed through public-private collaboration. Industry alliances for AI workforce sustainability are promising. Alliances can share resources, knowledge, and frameworks to fairly distribute AI benefits. Tech companies and schools can create AI-ready training programs for the next generation. Companies can invest in workforce adaptation through collaborations with tax incentives or innovation funding.

Less inequality and economic inclusion

AI could boost economic growth but increase inequality. As regions without AI infrastructure fall behind, tech-focused urban areas may attract high-skill jobs. Regional and economic inclusion policies can bridge this gap. Governments can support diverse AI economy participants by investing in digital infrastructure and AI training in underserved areas. Also, supporting SMEs in AI adoption can ensure that all businesses benefit from AI advances. SME budgets rarely allow complex AI systems, but improved processes and customer insights can help. Policymakers can boost economic participation by giving smaller businesses AI adoption incentives, grants, and technical support. These initiatives will reduce AI-related wealth concentration in a few large corporations, promoting economic balance.

Accepting Future Workforce Models and Flexibility

AI may increase hybrid, freelance, and remote work. AI can help remote workers balance work and life. Flexible work arrangements, fair freelance and gig economy compensation, and equal remote work tool access can create an AI-ready workforce. As more companies use AI to optimize workflows and tasks, flexible policies can boost worker well-being and productivity. Remote work and task automation let workers focus on creative or strategic tasks without commuting. Policymakers can work with industry leaders to create flexible work model best practices for employers and employees. This will help an AI-enabled workforce adapt and thrive.

Extended workforce development and sustainability

Policymakers must consider AI and workforce sustainability. AI technology requires policy adjustments. Reviewing policies and consulting AI experts can address new issues. Also important is fostering workforce adaptability and resilience. This includes teaching employees new skills and encouraging mental agility, adaptability, and change. Motivating workers to learn and be curious will help them adapt to AI.

Conclusions

Using AI in employment and workforce development presents economic opportunities and challenges. Industry roles, skills, and employment models are changing due to AI. AI can boost productivity and create jobs, but manual laborers are at risk. Due to the rapid adoption of AI, policymakers, industry leaders, and workers are discussing how to balance economic benefits with fair opportunities and protections for those whose jobs may be automated. This paper examined AI's complex effects on employment and workforce dynamics, revealing global labor market implications. AI's biggest impact on the workforce is automating tasks across sectors, which increases efficiency but may displace workers. Automation is most likely to affect repetitive, data-driven, or physically demanding manufacturing, logistics, retail, and customer service jobs. However, many experts believe AI will shift demand toward creative, critical, and complex problem-solving roles, which are harder to automate. Machine learning, data science, ethics, and cybersecurity experts will be needed to develop and manage AI, which could create new tech jobs. Retraining and high-tech career transitions can help companies and governments reduce job losses and adapt their workforce.

AI can boost productivity and foster workforce development beyond automating tasks. AI can streamline administrative tasks so workers can focus on more valuable tasks. AI in healthcare, education, and finance improves customer service and personalization. AI improves job functions and trains a more competent and agile workforce. Companies prioritize “upskilling” activities that teach digital and critical thinking skills to maximize these benefits. Continuous learning programs improve competitiveness and prepare employees for a tech-driven economy. Despite its benefits, workplace AI has major socioeconomic impacts that must be addressed. AI advances may benefit high-skilled workers while leaving low-skilled workers unemployed, increasing economic inequality. Retraining programs and social safety nets may reduce these disparities in high-income countries but worsen them in low-income countries. AI could create monopolistic markets and reduce wage growth in certain sectors by concentrating wealth among tech companies and stakeholders that control proprietary technologies and data. Public investments in digital infrastructure, vocational training, and fair working conditions regulations will be needed to promote equitable AI adoption. As AI advances, workforce planning must consider ethics. Workplaces that use AI for monitoring or decision-making face data privacy, surveillance, and bias issues. Unregulated AI could invade or mistreat marginalized communities. Industry and policymakers must work together to establish ethical standards that protect workers' rights and promote AI transparency. Some countries have laws regulating AI's use in hiring and workplace surveillance, but global standards are needed for digital workforce fairness. These ethical issues must be addressed to build trust and benefit society from AI.

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Exposition à l'intelligence artificielle générative et emploi : une application à la classification socio-professionnelle française

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L'ouverture progressive au public du générateur d'image *DallE-2* au cours de l'année 2022 suivi de près par le lancement de *ChatGPT* en novembre de la même année ont considérablement relancé et amplifié les débats, pourtant déjà anciens, sur les effets potentiellement massifs que pourraient avoir l'intelligence artificielle (IA) sur l'emploi. Bien que des progrès remarquables aient été observés auparavant avec l'émergence de modèles d'IA capables de réalisations de plus en plus sophistiquées,[1] leur utilisation était limitée à un cercle relativement restreint de spécialiste. Ce qui distingue ChatGPT, c'est sa facilité d'utilisation, son coût d'accès quasiment nul et sa diffusion fulgurante[2]. En outre, *ChatGPT*, ainsi que ses concurrents tels que *Midjourney*, *Bard*, *Claude* ou *Perplexity*, ont mis en lumière les capacités génératives impressionnantes de ces IA, tant dans le domaine du texte que dans celui des illustrations. Cette mise en évidence s'accompagne d'une amélioration fulgurante en termes de qualité et de performances, soulignant le potentiel considérable de ces technologies, y compris dans divers secteurs créatifs et à des niveaux professionnels. Dès lors il est apparu que de nombreuses tâches, y compris celles complexes et non répétitives jusqu'alors à l'abri de l'automatisation (Autor, 2015), pourraient être rapidement et avantageusement prises en charge par l'IA. Cela inclut également des tâches traditionnellement réservées à des travailleurs hautement qualifiés, démontrant ainsi l'étendue et la profondeur de l'impact potentiel de ces technologies sur le marché du travail.

[1] L'apparition des *transformers*, une architecture de *deep learning* en 2017 a permis aux langages de modèle de réaliser d'importants progrès

[2] OpenAI, l'entreprise développant ChatGPT a rapporté un record de diffusion avec un million d'utilisateurs enregistrés seulement cinq jours après le lancement public de ChatGPT, en outre depuis mars 2023, ChatGPT continue de connaître un succès massif, attirant environ 1.5 milliards de visites mensuelles

Ce que dit la littérature économique

La littérature économique s'est longuement penchée sur l'évaluation et la prévision de l'impact des technologies à haut potentiel d'automatisation, comme la robotique, le numérique et, plus récemment, l'intelligence artificielle, sur l'économie dans son ensemble et, en particulier, sur le marché du travail. En 2013, une étude marquante de Carl Benedikt Frey et Michael Osborne (publiée en 2017 : Frey et Osborne, 2017) a estimé que près de la moitié des emplois aux États-Unis étaient menacés à moyen terme par les technologies numériques. Cette analyse détaillée confrontait les capacités de l'informatique aux caractéristiques et compétences requises dans divers métiers. Néanmoins, cette perspective quelque peu alarmiste a été tempérée par des études ultérieures. Arntz et al. (2016), par exemple, ont souligné que se concentrer uniquement sur les professions néglige la diversité des tâches effectuées quotidiennement par un individu. Les recherches de David Autor, notamment dans Autor et al. (2003) et Acemoglu et Autor (2011), ont révélé une hétérogénéité significative dans la vulnérabilité à l'automatisation des tâches au sein d'une même profession. Certaines activités routinières peuvent effectivement être automatisées, tandis que d'autres, nécessitant des compétences sociales ou plus complexes, pourraient gagner en importance. Ainsi, l'automatisation pourrait transformer la manière dont une profession évolue, valorisant potentiellement certaines compétences dites « *soft* », comme le montrent Aghion et al. (2023). Toutefois, la disparition complète d'une profession n'est pas inéluctable, sauf si toutes ses tâches sont aisément automatisables. Arntz et al. (2016) estiment que seulement 9% des métiers sont menacés de disparition dans les pays de l'OCDE, et non 47%.

La question devient encore plus complexe lorsqu'on considère les effets d'équilibre général (voir Aghion et al., 2022a pour une discussion). L'impact de ces technologies sur les travailleurs variera selon que la technologie agit comme un complément ou un substitut à certaines tâches. Par exemple, un journaliste pourrait déléguer certaines de ses tâches à un modèle de langage tel que ChatGPT, mais utiliser cet outil pour accroître sa productivité dans d'autres domaines, comme la rédaction d'articles de fond. Une productivité accrue peut avoir des effets positifs à l'échelle globale et, in fine, augmenter l'emploi. Cette approche, connue sous le nom de « *task-based model* », a été notamment adoptée par Acemoglu et Restrepo (2018, 2020) pour évaluer l'effet des robots sur l'emploi, en prenant en compte ces effets d'équilibre général. Cependant, cette question compliquée

peut conduire à des conclusions très variées concernant les effets agrégés, comme l'illustrent les résultats d'Aghion et al. (2022b).

En définitive, bien que ces études se concentrent sur des technologies existantes telles que les robots industriels ou les ordinateurs, dont les potentiels de substitution se limitent principalement aux tâches répétitives et peu créatives, elles procèdent généralement de la manière suivante : elles classent les différentes tâches selon le risque de substitution ou de complémentarité avec la technologie envisagée, en se basant sur une description détaillée de celles-ci. Cependant, cette méthode s'avère complexe à appliquer dans le cas de l'IA générative, tant ses potentialités sont difficiles à cerner et ses développements futurs à anticiper à court ou moyen terme.

Plusieurs études ont proposé des méthodes pour évaluer l'exposition des différents métiers à l'intelligence artificielle comme par exemple, Felten et al. (2021, 2023), Gmyrek et al. (2023), Webb (2020), Eloundou et al. (2023) et Pizzinelli et al. (2023). Webb (2020) a comparé les descriptions de métiers aux textes de brevets dans le domaine de l'IA, suggérant qu'une similarité dans le contenu pourrait indiquer un risque d'automatisation. Eloundou et al. (2023) se sont concentrés sur l'impact du modèle de langage GPT, estimant qu'un métier est exposé si la technologie peut réduire significativement le temps nécessaire pour certaines tâches. Felten et al. (2021) ont créé un indicateur, l'AI Occupational Exposure (AIOE), utilisé également par Pizzinelli et al. (2023), qui évalue l'exposition à l'IA en se basant sur les capacités de cette dernière. Gmyrek et al. (2023) ont employé GPT-4 pour prédire les tâches typiques de divers métiers et évaluer leur degré d'automatisation. Pizzinelli et al. (2023) ont combiné différentes mesures pour proposer une évaluation à deux dimensions : l'exposition AIOE et une mesure de complémentarité avec l'IA.

Il est important de noter que ces travaux partagent une limite importante mais difficile à contourner : la faisabilité de l'implémentation de la technologie. Même si l'IA peut techniquement remplacer de nombreuses tâches avec une plus grande précision et efficacité qu'un humain, cela ne garantit pas que les entreprises décident de l'adopter, en raison des coûts d'installation, de maintenance et d'utilisation qui peuvent être supérieurs au salaire d'un travailleur. Estimer ces coûts nécessite une analyse détaillée de la technologie et du secteur concerné. Svanberg et al. (2024) ont adopté cette approche pour les technologies de vision par ordinateur, concluant que leur implémentation n'est vraiment avantageuse que pour les très grandes entreprises, représentant une faible part de l'emploi

total. Selon eux, même avec une baisse significative des coûts, cette situation persistera probablement à l'avenir.[3] Une autre limite de ces modèles est qu'il est difficile d'anticiper la manière dont les différents travailleurs vont évoluer avec l'IA et développer de nouvelles formes de complémentarité comme cela a pu être le cas avec les technologies passées comme l'ordinateur.

Approche retenue

Dans cette courte note, nous adoptons une démarche similaire à celle de Gmyrek et al. (2023) en nous basant sur les données de la base O*NET pour identifier les diverses tâches liées à 222 professions selon la nomenclature FAP (FAmilles Professionnelles) de la DARES[4]. Ces tâches sont ensuite évaluées selon deux indices d'exposition à l'intelligence artificielle générative : le premier indice mesure la substituabilité (score1), tandis que le second évalue la complémentarité et le potentiel d'amélioration (score2).

Plus précisément, notre analyse part de la table « *Task Rating* » de la version 28.1 de la base de données O*NET, qui recense 16 937 tâches associées à 873 métiers[5], avec une moyenne de 21 tâches par métier et leur degré d'importance pour chaque profession. Ces tâches ont été recensées grâce à des entretiens avec des professionnels du secteur ou des experts du marché du travail. Par exemple, la tâche suivante :

"Consult with product development personnel on product specifications, such as design, color, or packaging"

Est est notée avec une importance de 3.65 sur 5 pour un directeur marketing. Pour chaque tâche, nous avons appliqué le modèle GPT-4 en utilisant une instruction spécifique (ou prompt) présentée dans le Tableau 1. L'objectif de cette démarche est de fournir au modèle de langage une compréhension des limites de l'IA générative et de ses capacités, et d'attribuer à chaque tâche un

[3] L'étude ne prend toutefois pas en compte les gains de productivité qu'une telle technologie pourrait permettre d'obtenir et qui pourraient compenser son coût important.
[4] Notre approche peut être étendue aux quelques 470 professions de la classification PCS (Professions et Catégories Socioprofessionnelles) de l'INSEE qui est donc plus fine. Toutefois la FAP possède l'avantage de proposer une catégorisation plus homogène avec des métiers plus distinguables
[5] Comme expliqué ci-après, la classification utilisée par O*NET diffère de la classification française PCS et contient un niveau de détail un peu plus fin.

score, allant de 0 à 1, pour mesurer le potentiel de substituabilité, c'est-à-dire d'évaluer la probabilité que la tâche puisse être réalisée par l'IA dans un futur proche.

TABLE 1 : PROMPT UTILISE POUR NOTER LES TACHES AVEC LE MODELE GPT-4

AI Capabilities Overview: *Consider the full range of what Generative AI can currently achieve and what it is projected to do efficiently over a reasonable time horizon. This includes advancements in automation, data analysis, natural language processing, creative generation, and other emerging technologies. Take also into consideration what AI cannot do efficiently and the limitation of other related technologies such as robotics.* *Task Assessment:* *Based on AI Capabilities described above, analyze the task '{description}' in the following dimension:* *Substitution Potential (score1): Assess the extent to which AI and generative AI could potentially replace human labor in this task.* *Consider factors like technological feasibility, complexity, ethical considerations, and practical limitations.* *Instructions:* *Provide a score ranging from 0 to 1 with 2 decimals. No explanations are required. Only the scores should be given, representing the substitution potential of AI for the task respectively.* *Score:*

A noter que ce prompt considère non seulement les capacités génératives de l'IA mais également les potentiels liés à l'automatisation en général. Une tâche physique et relativement répétitive se verra donc attribuer un score élevé au même titre qu'une tâche nécessitant la génération de contenu relativement standardisé.

Avant d'aborder les résultats, il est important de souligner trois points clés. Premièrement, les données issues d'ONET reposent sur une classification professionnelle spécifique aux États-Unis, ainsi que sur des caractéristiques élaborées à partir de la réalité professionnelle américaine. Pour extrapoler ces résultats au contexte français, nous partons du principe que ces tâches sont transposables, c'est-à-dire qu'un même métier présentera une composition similaire de tâches en France et aux États-Unis, ou du moins que leur importance relative sera comparable. En outre, nous avons élaboré une table de correspondance pour convertir la classification d'ONET (SOC) en classification professionnelle et sociale (PCS) française, puis en classification FAP. Pour ce faire, nous utilisons la table de conversion du Bureau of Labor Statistics (BLS) permettant de passer de SOC à ISCO, la classification internationale de l'emploi établie par le Bureau International du Travail, puis nous appliquons les données de Hensvik et al. (2020) pour transposer ISCO en PCS. Chacune de ces étapes comporte malheureusement une part d'arbitraire inévitable, tant que des données comparables à celles d'O*NET ne seront pas disponibles en France. Deuxièmement, il est important de noter qu'aussi précise soit la description des tâches inclues dans la base O*NET, celle-ci ne peut pas rendre compte de l'importante diversité des réalités pour deux individus effectuant le même métier dans deux contextes différents. Il faut ainsi interpréter le résultat obtenu comme une mesure de l'exposition à l'IA générative pour un travailleur représentatif de la profession considérée. Enfin, l'exercice ne rend pas compte des éventuelles transformations endogènes des différentes tâches à la suite de l'arrivée d'une technologie comme l'IA ni plus globalement de l'apparition de nouvelles tâches, voire de nouveaux métiers.

Résultats

La procédure précédente permet d'attribuer à chaque tache $t \in T$ une valeur $s_1(t, P)$ comprise entre 0 et 1 et qui dépend a priori du *prompt* P. Nous connaissant en outre grâce à la base O*NET l'importance relative, notée $p(t)$ de la tâche t pour un métier donné p. Nous pouvons ainsi agréger nos deux mesures au niveau de chacune des 222 familles d'emploi de la manière suivante :

$$s_1(p, P) = \sum_{t \in T} \frac{s_1(t, P)p(t)}{\sum p(t')}$$

En d'autres termes, nous évaluons la moyenne des scores individuels de chaque tâche, ajustée selon l'importance de ces tâches. Ce score est normalisé pour s'étendre entre 0 et 1, où la valeur 1 est attribuée à la profession la plus exposée à l'intelligence artificielle, et la valeur 0 à celle la moins exposée. Cet indicateur résume donc la vulnérabilité d'un emploi face à l'IA. Cependant, cette exposition peut être modulée, soit atténuée soit exacerbée, par deux mécanismes. D'une part, comme mentionné précédemment, une forte exposition à l'IA peut aussi indiquer un potentiel élevé de complémentarité, résultant en une collaboration entre l'humain et la nouvelle technologie, ce qui peut significativement améliorer les performances et la qualité du travail accompli. D'autre part, certaines professions peuvent être intrinsèquement plus exposé à l'IA que ce que les analyses basées sur les tâches suggèrent. Par exemple, un photographe pourrait voir plusieurs de ses tâches affectées par l'IA générative, mais des aspects tels que la mise en place du décor ou l'ajustement de l'éclairage, qui sont essentiels mais moins susceptibles d'être influencés par l'IA, ne sont pas au cœur de son activité. Or l'indicateur s_1 pourrait attribuer une valeur moyenne relativement faible en raison de l'importance que prenne ses tâches en termes de temps. Pour intégrer ces deux aspects, nous enrichissons notre indicateur avec l'indice agrégé C-AIOE, issu de Pizzinelli et al. (2023), calculé au niveau ISCO, qui associe un indice de complémentarité et un indice de substituabilité, tous deux basés sur les caractéristiques de la profession plutôt que sur les tâches spécifiques. Pour obtenir un indicateur global sans présupposer une forme fonctionnelle spécifique, nous multiplions simplement ces deux valeurs. Ainsi, une profession est considérée comme hautement exposée si elle a à la fois un score s_1 et un niveau C-AIOE élevé.

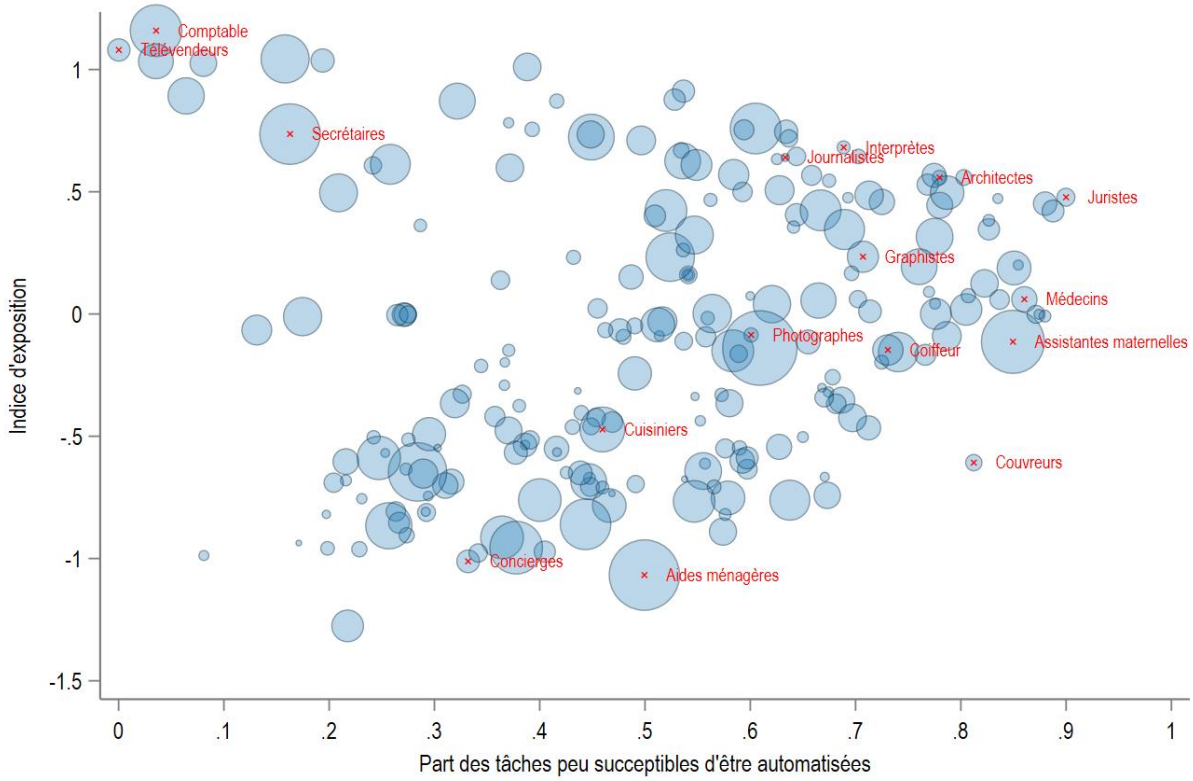
Cette première dimension reflète donc l'exposition théorique d'un métier à l'IA. Toutefois il est possible que cette exposition soit fortement freinée par un coût trop élevé à adopter l'IA. Collecter ou estimer des informations sur les prix est une opération particulièrement difficile comme discuté par Svanberg et al. (2024). Pour approcher cette idée, nous calculons pour chaque emploi une approximation de la part des tâches jugée difficile à automatiser que nous définissons comme les tâches ayant une valeur de $s_1(t, P)$ inférieure à 0.75 (correspondant à la médiane). Ainsi si un métier est par nature exposée à l'IA mais qu'il demeure une part importante de ces tâches qui ne sont pas facilement automatisable, il est probable que cette profession ne soit pas menacée par l'arrivée de ces nouvelles technologies, même si une partie de ces activités va vraisemblablement être bouleversée.

La Figure 1 dispose chaque FAP dans un graphique qui combine nos deux indicateurs. En ordonnées la mesure synthétique d'exposition obtenue en multipliant s_1 à C-AIOE et en abscisse

la part des tâches difficile à automatiser. Chaque cercle symbolise une profession, avec sa taille reflétant l'effectif total dans cette profession. Certaines professions illustratives ont été représentées en rouge.

Les métiers localisés dans le quadrant supérieur droit sont ceux qui font face à une forte exposition à l'IA, mais pour lesquelles il existe encore d'importants freins à l'automatisation et dont on peut donc attendre qu'ils subissent de fortes transformations qui pourraient conduire à un effet "superstar". Cela pourrait bénéficier à certains travailleurs mieux formés et préparés, capables d'exploiter les nouvelles technologies génératives, tandis que d'autres pourraient être confrontés à une concurrence accrue. Les professions situées dans le quadrant supérieur gauche sont particulièrement vulnérables face à l'IA. Elles se caractérisent par une exposition supérieure à la moyenne et à une part importante de leurs tâches qui pourraient se voir remplacer.

FIGURE 1 : POSITIONNEMENT DE CHAQUE FAP DANS UN REPERE EXPOSITION (AXE DES ORDONNEES) ET PART DES TÂCHES DIFFICILE A AUTOMATISER (AXE DES ABSCISSES). LA TAILLE DE CHAQUE CERCLE EST PROPROTIONNELLE A L'EMPLOI TOTAL DANS LA FAP EN FRANCE EN 2017

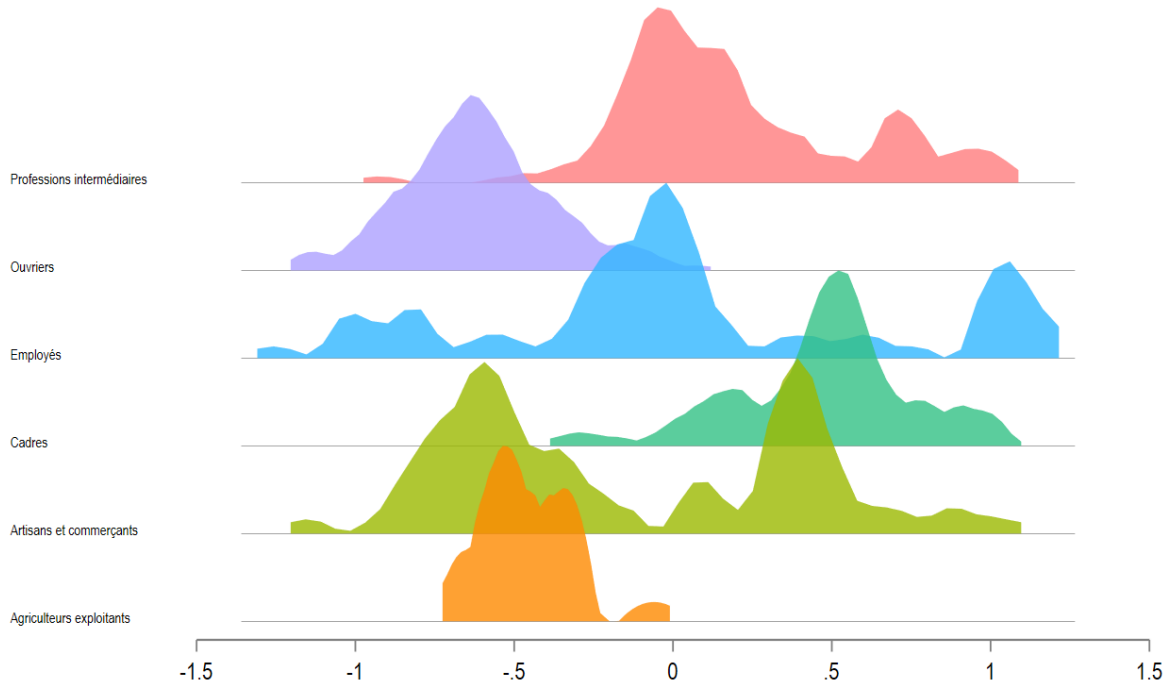


Les professions situées dans la moitié basse, et en particulier dans le cadran inférieur droit sont à ce jour encore préservées par l'arrivée de l'IA.

Pour interpréter la magnitude de l'indicateur d'exposition présenté en ordonnées de la Figure 1, il faut lire qu'une valeur négative correspond à un métier dont le niveau d'exposition CAIOE est inférieur à la moyenne. La valeur de CAIOE a été calculé de sorte qu'une valeur de 1 soit considérée comme particulièrement grande. Notre indicateur multiplie CAIOE par le score s_1 qui est lui-même compris entre 0 et 1. Aussi, même s'il n'existe pas de valeur seuil claire, nous pouvons considérer qu'une valeur supérieure à 0.5 correspond à une exposition forte.

La Figure 2 présente la distribution de l'indicateur d'exposition (l'ordonnée du graphique de la Figure 1) en fonction du niveau 1 de la PCS, c'est-à-dire des grandes catégories d'emploi. On peut y constater qu'il existe une hétérogénéité importante entre les différents métiers et que contrairement aux révolutions technologiques précédentes, ce sont les cadres c'est-à-dire les professions les plus qualifiées qui sont le plus exposées.

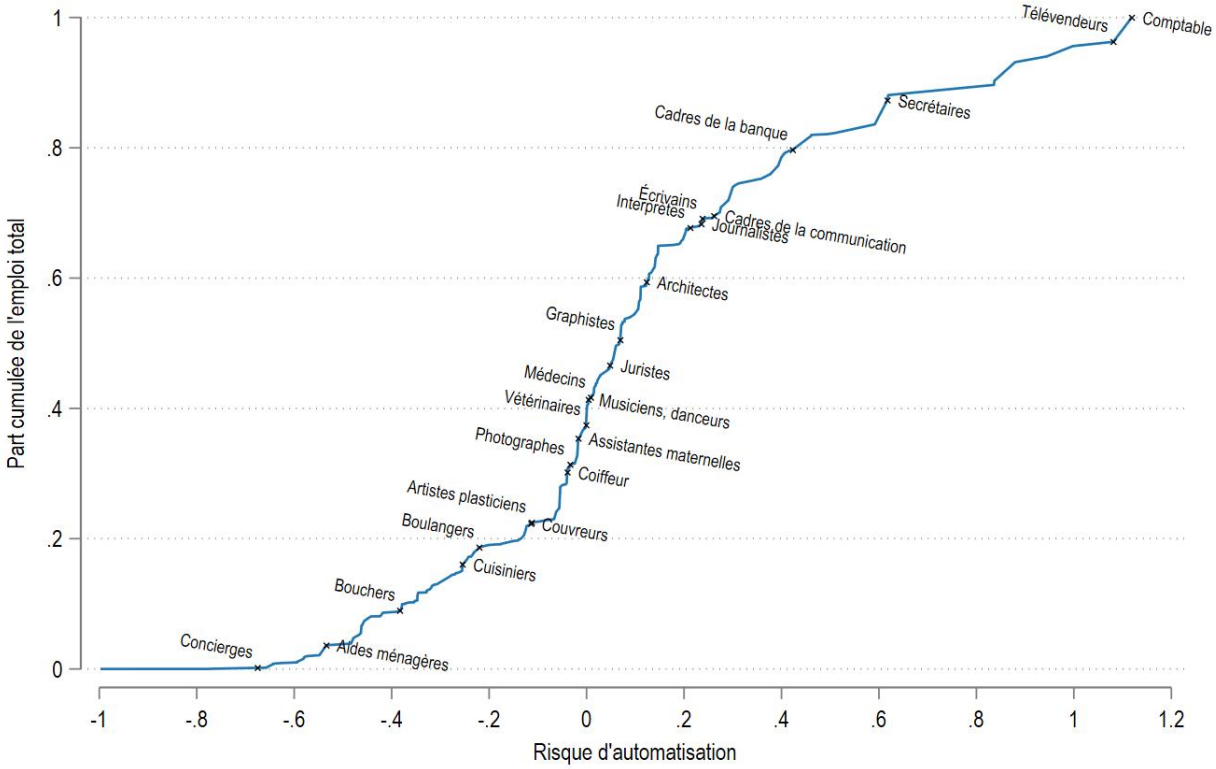
FIGURE 2: DISTRIBUTION DE L'INDICATEUR POUR DES GRANDES CATEGORIES DE TRAVAILLEURS



Enfin la Figure 3 présente la distribution cumulative de l'emploi en fonction d'un indicateur synthétique de risque d'automatisation définie comme le produit de l'indicateur d'exposition en

ordonnée de la Figure 1 et de la part des tâches qui ne sont pas difficile à automatiser. On peut notamment y constater que 20% de l'emploi environ possède un indicateur agrégé supérieur à 0.5 ce qui signifie qu'elles ont à la fois une exposition forte, voir très forte et sont en même temps peu protégé de l'automatisation par la prévalence de certaines tâches difficile à effectuer par une machine, même intelligente.

FIGURE 3: DISTRIBUTION CUMULATIVE DE L'EMPLOI EN FONCTION DU RISQUE D'AUTOMATISATION PAR L'IA



Conclusion

Cette courte note n'a pas pour prétention de donner une idée précise du nombre de métiers qui sont à risque d'être automatisé avec l'arrivée de l'IA, mais de permettre de mesurer l'importante hétérogénéité des niveaux possible d'exposition et l'impact important que cette technologie a et va continuer d'avoir sur certaines professions y compris les plus qualifiées. Une approche plus complète nécessiterait toutefois de prendre en compte l'intégralité de la chaine de valeur associée à un secteur et un métier et d'estimer les effets de réallocation potentiellement importants pouvant conduire à une forte augmentation de l'emploi dans certains métiers. Enfin une extension utile à

cette note pourrait être d'évaluer la robustesse de l'indicateur $s_1(P)$ en fonction du *prompt* P en modifiant la définition de ce qu'est et de ce que peut et ne peut pas faire une IA.

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