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Artificial Intelligence Adoption in Chinese Enterprises

Productivity Effects, Workforce Implications, and Policy Challenges

Ekkehard Ernst (ILO), Zhong Zhao, Huilin Zhu, Yuhui Li, Xin Wei, Hao Zhang, Zeyang Chen (Renmin University China)

Key points

- AI adoption is pervasive across Chinese enterprises of all sizes. Across the 21 firms studied through in-depth interviews spanning manufacturing, finance, business services, construction, education, media, and travel, every company reported either active AI deployment or concrete plans for imminent adoption. A complementary survey of 1,591 professionals found that 56 per cent view AI as an inevitable trend, while 47 per cent believe AI creates more jobs than it displaces.
- Productivity gains are substantial where measured, but measurement itself remains patchy. Reported improvements include a 57 per cent reduction in recruitment cycle time, a 150 per cent increase in daily customer-query throughput, efficiency gains of 30–100 per cent across core workflows, production efficiency improvements of 20–30 per cent in smart manufacturing, and labour-equivalent savings of 5–6 full-time employees from AI data handling. Yet most firms lack systematic evaluation frameworks.
- Enterprises adopt AI through three distinct organisational models: centralised specialist teams (common in technology firms), business-embedded integration (prevalent in customer-facing industries), and organic bottom-up diffusion (typical of smaller firms). Productivity impact deepens as firms progress from tool-assisted efficiency through process-embedded optimisation to business-model innovation.
- Workforce implications are significant: employee resistance, age-related digital divides, and displacement anxiety are widespread, with 39 per cent of surveyed professionals anticipating income declines. Firms report that AI is most effective in automating repetitive, data-intensive tasks, creating hybrid human–AI workflows rather than eliminating human oversight. Output quality limitations, regulatory constraints, and skills gaps remain the dominant barriers to deeper integration.

Introduction

China has emerged as one of the world's most dynamic arenas for enterprise-level artificial intelligence adoption. Driven by national strategic priorities, declining computational costs, and the maturation of foundation models, Chinese firms across a broad range of sectors are actively integrating AI into their operations, products, and service delivery. Understanding the granular realities of this adoption—how firms select and deploy AI tools, what productivity effects they observe, how workers are affected, and what governance challenges arise—is critical for evidence-based labour market policy. This is especially relevant to the International Labour Organization's agenda on decent work, skills development, and just transitions in the context of rapid technological change.

This research brief synthesises evidence from two complementary sources. The first is a set of structured qualitative interviews conducted with 21 Chinese enterprises spanning manufacturing, finance, insurance and real estate, business services, construction, communication, education, and travel. These interviews, conducted by researchers at Renmin University of China, explored AI adoption motivations, current applications, productivity measurement, implementation challenges, and future investment plans. In addition, a quantitative survey of 1,591 Chinese professionals was conducted across different industries, organisational types (state-owned, private, and foreign-invested enterprises), and career levels, which captured workforce perceptions of AI's impact on employment, income, and work organisation. Together, these sources provide a uniquely rich, multi-perspective picture of AI's unfolding impact on the Chinese world of work.

Overview of the Sample

The qualitative interview sample encompasses 21 firms representing considerable diversity in sector, size, ownership structure, and stage of AI maturity. Company sizes range from a media startup with 8 employees and a venture capital firm with 21 staff to an opto-electronics manufacturer with over 20,000 workers and a giant insurance conglomerate with 270,000 employees. Annual revenues span from confidential startup-stage figures to over 1.14 trillion yuan. The sample includes state-owned enterprises (such as a digital services subsidiary of a state-owned manufacturing enterprise), private technology firms, and foreign-invested manufacturers, offering a cross-section of China's diverse enterprise landscape.

The sectoral composition deliberately prioritises variation. Manufacturing is represented by six firms, including an advanced opto-electronics manufacturer ("Digital manufacturer"), a food and consumer goods leader, a high-tech hardware company, a high-tech chip design firm, a digital services firm in industrial services, and an advanced manufacturer. The finance, insurance, and real estate sector is covered by four firms: a giant insurance group, a commercial bank, a venture capital firm, and a separate insurance company. Business services account for four firms: an HR services company, an AI-native talent management firm, a travel services company, and a law firm. Communication, construction, and education technology are each represented by one firm. This distribution reflects the deliberate aim of capturing both early-adopter and later-stage AI users across services and industry.

The quantitative survey complements the interview data by providing breadth across a larger population. The 1,591 respondents span a wide range of industries, include employees from entry-level to senior management, and cover state-owned, private, and foreign-invested enterprises. This dual-method design enables both deep, contextual understanding of firm-level dynamics and broader generalisations about workforce attitudes and expectations.

Motivations for AI Adoption

Across the full sample, the motivations driving AI adoption converge on three core dimensions: efficiency improvement, quality enhancement, and cost control. These are complemented by sector-specific drivers including competitive survival, national policy alignment, and the maturation of underlying technologies.

Efficiency gains are the most universally cited motivation. Firms as diverse as the giant insurance group, the venture capital firm, the HR services company, the advanced manufacturer, and the media startup all described efficiency improvement as a primary or sole driver. For service-sector firms, this typically means automating repetitive administrative tasks—screening resumes, processing documents, answering routine queries—to free employees for higher-value work. The giant insurance group explicitly framed AI adoption as a means of "helping employees shift from simple, low-value tasks to more valuable work." In manufacturing, the digital manufacturer described AI as a necessary breakthrough for overcoming production parameter bottlenecks in the semiconductor panel industry, while the high-tech hardware manufacturer cited supply-chain requirements as the primary impetus.

Cost reduction features prominently among smaller and more resource-constrained firms. The media startup with 8 employees emphasised cost savings alongside efficiency, while the travel services company highlighted AI's role in reducing the need for 5–6 additional staff in a context of high overseas labour costs. The AI-native talent management firm reported that AI enables junior consultants to deliver work previously requiring mid-to-senior expertise, substantially lowering delivery costs and

▶ **Table 1. Sample Distribution by Sector (Interview Sample)**

Sector	Number of Firms	Share of Sample
Manufacturing	6	29%
Finance, Insurance & Real Estate	4	19%
Business Services	4	19%
Communication / Media	1	5%
Construction	1	5%
Personal Services / Education	1	5%
Unclassified	4	19%
Total	21	100%

Source: Author compilation from interview documents.

making previously unviable international projects feasible. This is in notable difference to current discussions in the United States about the risk of entry-level jobs disappearing. [1]

National policy alignment is a distinctive driver in the Chinese context. The digital services firm explicitly linked its AI strategy to China's "two centenary goals" and the 2035 modernisation target, describing AI adoption as part of a broader mandate to advance high-end manufacturing, and the Digital China strategy. This policy-driven motivation is most pronounced among state-owned enterprises, which face both strategic imperatives and demonstration-effect expectations from government stakeholders. Across the sample, leadership commitment and government policy were identified as critical enablers, with the recommendation that state-owned enterprises should "set an example and actively adopt AI technology" to create demonstration effects across the economy.

A notable finding is the role of technology timing. Several firms described deliberate strategies of waiting for the right moment to adopt AI, rather than being early movers. The digital services firm explicitly cited the risk of "sunk cost" from premature investment, choosing to enter when open-source foundation models had matured and computing costs had declined. The digital manufacturer's trajectory illustrates a different pattern: the company began AI training programmes as early as 2016, well ahead of the current generative AI wave, reflecting a long-term commitment to AI capability building in the manufacturing sector.

Patterns of AI Application

Application Domains

The AI applications described across the sample cluster into several functional domains, with considerable cross-sectoral overlap. Customer service and client interaction represent the most widely adopted category, with at least seven firms deploying AI to handle queries, improve response quality, or personalise service delivery. The insurance company reported an increase in daily customer-issue throughput from 6,000 to 15,000 following AI deployment, while the talent management firm described AI-driven automation of client touchpoints as solving the problem of "lost contact" with candidates.

Human resource management and talent matching constitute a second major cluster. The giant insurance

[1] https://digitaleconomy.stanford.edu/publication/canaries-in-the-coal-mine-six-facts-about-the-recent-employment-effects-of-artificial-intelligence/

group uses AI across recruitment and training; the HR services firm deploys AI for automated question answering, request processing, and RPA generation; and the talent management firm has built an AI-native recruitment platform serving over 2,000 clients and connecting 300,000-plus candidates.

Internal operations and process automation form a third broad domain, encompassing code generation and quality inspection (HR services firm, advanced manufacturer), document processing and knowledge management (the digital services firm, insurance company, ed-tech), office automation (construction firm), and collaboration tool enhancement (venture capital firm, advanced manufacturer). Supply-chain optimisation is reported in manufacturing, with the food and consumer goods firm developing proprietary AI models using internal data, and the digital manufacturer offering multi-factor analysis platforms for parameter recommendation and virtual measurement in production lines.

More specialised applications reflect sector-specific needs. In manufacturing, the digital manufacturer deploys embodied AI including walking robots with mechanical arms for factory data collection, and AI sensors for predicting equipment lifecycle. The digital services firm is developing industry-specific AI models for geological survey data processing and a cultivation advisory system for farmers. The law firm uses AI for case retrieval and international legal research, while the media firm collaborates with an AI platform to replicate the company founder's capabilities for content moderation. A particularly striking finding is the prevalence of general-purpose AI tools alongside specialised solutions: multiple firms report using tools such as Doubao, Kimi, Yuanbao, Copilot, and the collaboration platform Feishu, often comparing across platforms before settling on preferred tools.

Organisational Models for AI Integration

Three distinct organisational models through which enterprises integrate AI were identified in the employee survey, a typology corroborated by the broader interview evidence. In the specialised team model, a centralised AI team leads implementation and develops proprietary tools; this approach is common in technology-focused firms such as the digital manufacturer and the talent management firm, both of which maintain dedicated AI product and algorithm teams. In the business-embedded model, AI capabilities are woven into existing business units and workflows rather than concentrated in a separate team; this is prevalent in customer-facing industries such as insurance and banking. In the spontaneous diffusion model, AI adoption spreads organically across teams without top-down coordination, typically in smaller, more flexible organisations; the venture capital firm exemplifies this pattern, where employees-initiated AI tool usage bottom-up before the company formalised support.

The company survey identifies a progression of AI impact depth: from tool-assisted efficiency (using AI to speed up existing tasks), through process-embedded optimisation (restructuring workflows around AI capabilities), to business-model innovation (fundamentally redefining how value is created). Most firms in the sample remain at the first or second stage, with a few—the talent management firm, the digital manufacturer, and the ed-tech company—showing signs of moving towards the third.

Productivity Implications

Quantified Gains

Where firms track productivity effects through quantitative metrics, the reported gains are substantial. The digital manufacturer reported that its "lighthouse factory" achieved a 30 per cent improvement in production efficiency following AI small-model deployment in 2021, with other client factories achieving approximately 20 per cent gains. The company described a case where a client's team of over 10 employees dedicated to reading customer specification documents was reduced to 2–3 employees, and another where parameter adjustment changeover time fell from 120 minutes to 60 minutes. In specific production scenarios, the company's AI products can reduce labour costs by approximately 80 per cent.

In the services sector, the insurance company reported that 300 customer-service employees increased their daily throughput from 6,000 to 15,000 issues, a 150 per cent improvement. The giant insurance group's HR department recorded a reduction in recruitment cycle time from 30 days to 13 days, a 57 per cent improvement. The talent management firm reported that project managers increased their simultaneous project load from 2–3 to 5–6, that client-response speed improved by 30 per cent, and that core efficiency metrics improved by 30–100 per cent. The HR services firm measured a 30 per cent decrease in R&D working hours in the first quarter of the year and a 28 per cent increase in per capita customer-service output in the third quarter. The digital services firm reported

▶ **Table 2. AI Application Domains Across the Sample**

Application Domain	Firms Reporting	Key Sectors
Customer service / client interaction	7+	FIRE, Business services, Ed-tech, Travel
HR / recruitment / talent matching	5	FIRE, Business services
Internal operations / process automation	8+	All sectors
Code generation / software development	3	Business services, Manufacturing
Supply chain / production optimisation	4	Manufacturing
Data analysis / knowledge management	6	Manufacturing, FIRE, Business services
Content creation / moderation	2	Communication, Ed-tech
Embodied AI / robotics / sensors	2	Manufacturing

Source: Author categorisation from interview data. Firms may appear in multiple domains.

preliminary feedback suggesting that repetitive work can be reduced by over 50 per cent. The travel services firm estimated AI data-handling capacity equivalent to 5–6 full-time employees, and the ed-tech company reported cost reductions sufficient to halve its service pricing, with AI study-room operating costs running 80 per cent below traditional tutoring classes.

The Measurement Gap

Across the sample the absence of systematic productivity evaluation frameworks in most firms is noticeable. The giant insurance group reported having no formal metrics on the business side, only ad hoc tracking on the operations side. The venture capital firm described improved quality of research reports and meetings without any quantitative measurement. The advanced manufacturer acknowledged improved code accuracy from AI but lacked formal metrics. The media firm reported no quantitative assessment at all. The digital services firm candidly stated that while AI-assisted project response speed had clearly improved, “full quantification has not yet been achieved.” The digital manufacturer articulated the core challenge: while AI small-model applications in specific production scenarios yield measurable returns, generative AI’s impact on overall employee productivity is “difficult to evaluate and quantify.” The company is developing a factor-decomposition approach, breaking client KPIs into component factors and assessing the AI technology application rate and potential improvement for each.

This measurement gap has direct policy implications. Firms are committing significant resources to AI adoption without robust frameworks for assessing returns—not only in terms of output per worker but also in terms of job quality, task composition, and working conditions. The absence of standardised metrics limits both enterprise decision-making and the evidence base available to policymakers.

▶ **Table 3. Selected Quantified Productivity Gains**

Firm / Sector	Metric	Reported Impact
Digital Mfg.	Lighthouse factory production efficiency	+30% (other clients ~20%)
Digital Mfg.	Spec-reading team size	Reduced from 10+ to 2–3 employees
Digital Mfg.	Parameter changeover time	Reduced from 120 to 60 minutes
Digital Mfg.	Labour cost in specific scenarios	Reduced by ~80%
Insurance company	Daily customer queries (300 staff)	6,000 → 15,000 (+150%)
Giant insurance group	Recruitment cycle time	30 → 13 days (−57%)
Talent mgmt.	Project manager simultaneous projects	2–3 → 5–6 projects
Talent mgmt.	Core efficiency metrics	+30–100%
HR services firm	R&D man-hours	−30% (Q1)
HR services firm	Per capita customer-service output	+28% (Q3)
Digital services	Repetitive work reduction	>50% (preliminary)
Travel services	Data-handling labour equivalent	5–6 FTEs saved
Ed-tech	Service pricing / operating costs	Halved; AI rooms 80% cheaper

Source: Interview data. All figures are self-reported by firm representatives.

Workforce Perceptions and Employment Effects

The quantitative survey of 1,591 professionals provides a broader window into how Chinese workers perceive AI's labour-market implications. A majority (56 per cent) view AI adoption as an inevitable trend, reflecting widespread acceptance of AI's growing role. On net employment effects, 47 per cent believe AI creates more jobs than it displaces—a more optimistic outlook than surveys in many OECD countries have found. However, approximately one-third of respondents expressed concerns about AI's impact on social stability and human uniqueness, indicating significant unease alongside the prevailing optimism.

Income expectations reveal important patterns of divergence. Overall, 39 per cent of respondents anticipate that AI will lead to income declines, a substantial minority. The survey uncovered notable gender differences: male employees show higher levels of both optimism and pessimism regarding AI's income effects, suggesting greater sensitivity to perceived income changes. High-skilled male employees are disproportionately represented among those expecting income growth from AI, hinting at an emerging pattern where AI's benefits accrue unevenly across the occupational hierarchy.

These survey findings resonate with the qualitative evidence from firm interviews. The giant insurance group reported explicit employee resistance, with HR staff perceiving AI as a direct threat to their roles and observed that headquarters employees adapt more readily than branch-level workers. The advanced manufacturer found that some employees resist even basic AI-enabled collaboration tools, preferring familiar applications. The ed-tech company identified an age-based divide, noting that

▶ **Table 4. Workforce Perceptions of AI (n = 1,591)**

Perception	Share of Respondents
View AI adoption as an inevitable trend	56%
Believe AI creates more jobs than it displaces	47%
Express concerns about social stability / human uniqueness	~33%
Anticipate income declines due to AI	39%

Source: Renmin University of China. Survey of 1,591 professionals across industries and career levels.

employees over 40 years old demonstrate markedly weaker AI application capabilities. Multiple firms described a shift in the skill sets they value: the travel services company is revising its recruitment criteria to favour candidates with AI literacy, the talent management firm requires all employees to use AI tools and provides weekly training, and the venture capital firm partner observed that in the future, "people in this industry will become 'cheaper'" as AI democratises capabilities previously dependent on experience and expertise.

Implementation Challenges

The interviews reveal a consistent set of challenges that recur across sectors and firm sizes, clustering into five broad categories: output quality and reliability, workforce skills and resistance, regulatory and data-security constraints, system integration difficulties, and cost-to-value concerns.

Output Quality

Output quality is the most pervasive concern across the sample. The giant insurance group described current AI output as "not yet ideal," the HR services firm reported that AI customer-service accuracy falls below the 95 per cent threshold required for direct client deployment, and code-generation quality faces persistent bottlenecks. The media firm's founder treats AI output as equivalent to that of "an ordinary clerical worker." The ed-tech company abandoned direct AI generation of educational animated videos due to prohibitive correction costs, pivoting instead to developing its own AI School Intelligent Agent. The digital manufacturer drew a fundamental distinction: while AI small models can reliably solve specific production problems, generative AI remains in a phase of "technological disenchantment" where its true capabilities have not yet been fully discovered. The insurance company and the venture capital firm both noted the problem of AI "hallucinations," though the latter observed that these are becoming less frequent. The digital services firm identified a deeper structural challenge: in domains requiring strong chains of reasoning and domain-specific knowledge (such as geological surveying with data stretching back to 1952), AI models struggle to replicate expert experience faithfully, and specialised data annotation is extremely costly and time-consuming.

Workforce Skills and Resistance

The workforce dimension of AI adoption poses challenges that are both practical and deeply human. The giant insurance group reported that many employees lack an "AI mindset" and the ability to use AI tools effectively, with a clear performance gap between headquarters and branch staff. Explicit resistance from HR employees who perceive AI as a threat to their jobs was reported. The advanced manufacturer found passive resistance in the form of employees avoiding AI-enabled systems. The ed-tech company identified an age divide, with workers over 40 showing significantly weaker AI capabilities. The digital services firm framed the talent challenge as the most fundamental barrier encountered with clients: "Although current AI technology is relatively mature and computing costs are not prohibitively high, many clients' internal employees have deficiencies in capability and mindset that impede the enterprise's AI adoption process." The company also highlighted a cross-disciplinary gap: algorithm teams understand the technology but lack industry-application knowledge, necessitating long-term investment in "compound talent" with both AI and domain expertise.

Regulatory and Data-Security Constraints

Regulatory challenges are particularly acute in the financial sector but extend across industries. The giant insurance group emphasised that financial-industry data firewalls prevent direct use of AI with certain data, while privacy and security regulations impose strict limitations. The commercial bank flagged regulatory compliance and data security as primary challenges. The HR services firm added a cross-border dimension: multinational clients impose headquarters-level restrictions on AI deployment in their Chinese operations, with some permitting only private model deployment and prohibiting use of open models. Domestic financial institutions also exhibit significant concerns about data security in AI applications. The travel services firm identified a risk of core-data theft when using external AI tools, treating proprietary business data as a "firewall" that must be protected. The law firm highlighted privacy and client-information security as paramount concerns, particularly given the high costs of local AI deployment. These findings point to a multi-layered regulatory landscape: national regulations, sectoral rules (especially in finance), and multinational corporate policies all shape the boundaries of permissible AI use.

System Integration and Cost

Integration with legacy systems is a recurring challenge. The giant insurance group described scattered data across multiple HR systems, the construction firm noted limited fusion between specialised design software and general AI models, and the commercial bank cited cross-departmental collaboration difficulties. The digital services firm identified a governance-mechanism deficit: technology companies lack understanding of industry applications, while industry companies lack understanding of AI technology, creating a prolonged collaboration adjustment period. On the cost side, the giant insurance group reported a pattern of high current investment with low immediate output, the travel services firm highlighted token consumption from using generative AI tools, and the high-tech chip design company focused on the challenge of balancing cost and efficiency given that it is both a developer and user of AI products. The digital services firm noted that while initial ROI and short-term financial returns are difficult to demonstrate, the strategic case for AI investment remains compelling.

▶ Table 5. Frequency of Reported Implementation Challenges

Challenge Category	Firms Citing	Illustrative Examples
Output quality / reliability	8+	Hallucinations, sub-95% accuracy, correction costs
Workforce skills / resistance	6+	Age divide, mindset gaps, passive resistance
Regulatory / data security	6+	Financial firewalls, MNC restrictions, privacy
System integration / governance	5+	Legacy systems, cross-dept. coordination
Cost / ROI concerns	5+	High investment, low short-term returns
Data quality / annotation	2	Specialist data, historical records

Source: Author categorisation from interview data. Firms may cite multiple categories.

The Human–AI Collaboration Paradigm

A cross-cutting theme across the interviews is the predominance of human–AI collaboration rather than full automation. The digital manufacturer articulated this most explicitly, stating that "current AI is still in the human–machine collaboration stage and cannot fully replace people." The company argued that allowing AI to operate independently in "black box" mode within manufacturing carries significant risk, and that it therefore has not incorporated AI applications into daily production processes as autonomous systems. Instead, the company's AI workflows deliberately combine human experience with AI computational power, creating what the digital manufacturer described as "a friendly link between digital intelligence and biological intelligence." In some processes, AI is required to reference specific documents before generating output; if relevant documents have not been consulted, the system is designed to withhold results.

This pattern of managed human oversight recurs throughout the sample. The HR services firm's AI customer-service accuracy of below 95 per cent means that human review remains essential before any AI output reaches clients. The media firm's AI content moderation requires combined AI detection and manual review. The insurance company uses laboratory proof-of-concept verification to evaluate technical suitability before deploying AI in production environments. The ed-tech company's pivot from direct AI video generation to developing its own intelligent agent reflects a strategy of maintaining human control over quality-critical outputs. These practices suggest that for the foreseeable future, AI in Chinese enterprises will augment rather than replace human work, creating hybrid workflows that require new forms of skill—including the ability to effectively direct, verify, and integrate AI outputs.

Future Investment Plans and Trajectories

The sample reveals a generally forward-leaning but heterogeneous investment posture. The HR services firm disclosed that AI-related R&D currently accounts for 20 per cent of total R&D expenditure and plans to increase this to 30 per cent. The talent management firm is investing in both its AI technology team and hardware infrastructure while building comprehensive data security and compliance systems. The giant insurance group plans to hire employees with AI skills, invest in infrastructure, and focus on improving internal acceptance rates. The ed-tech company expects "explosive revenue growth" from its AI study rooms and projects continued operating-cost reductions. The venture capital firm advocates covering AI tool costs for employees and creating incentive structures for internal knowledge sharing.

The digital services firm articulated a particularly ambitious vision: building an industry expert knowledge base with a "digital expert" certification system, establishing joint laboratories with research institutions and industry associations, and investing in solving the data collection and annotation challenges for specialised professional domains. The digital manufacturer's strategy focuses on abstracting standardised capabilities from diverse enterprise scenarios, combining them with hardware to create "plug-and-play" products, and developing both product lines and platform ecosystems that enable other enterprises to build their own AI applications.

Not all firms share this optimism. The media firm reported no plans for radical AI investment, reflecting a startup-stage caution. The construction firm described future AI potential in construction robotics and design phases in speculative rather than committed terms. The advanced manufacturer called for top-down, systematic application rather than organic adoption, suggesting dissatisfaction with the current pace. These variations indicate that while the overall direction of investment is clear, the pace and depth remain contingent on firm-specific factors including digital maturity, sector dynamics, firm size, resource availability, and the quality of early AI experiences.

Implications for Labour and Employment Policy

The evidence presented in this brief carries several implications directly relevant to the ILO's work on decent work, skills development, and just transitions.

Skills Development and Lifelong Learning

The pervasive skills gap—cited as the single most fundamental barrier by the digital services firm and echoed across the sample—demands urgent policy attention. The challenge is not merely technical training in AI tools, but the cultivation of what firms describe as an "AI mindset": the capacity to identify opportunities for AI application, to formulate effective prompts and queries in the use of GenAI tools, and to critically evaluate AI outputs. The age-related digital divide identified by multiple firms suggests that lifelong learning programmes must be specifically designed to support mid-career and older workers who did not grow up with digital technologies. The cross-disciplinary talent gap—algorithm teams lacking industry knowledge, industry experts lacking AI literacy—calls for training approaches that bridge technical and domain-specific competencies.

Managing Displacement and Transition

The concentration of AI's productivity gains in repetitive, data-intensive tasks—document processing, customer-query handling, resume screening, data collection—indicates that displacement pressures will fall most heavily on workers in routine clerical, administrative, and customer-service roles. The digital manufacturer's case of reducing a specification-reading team from over 10 to 2–3 employees illustrates the scale of potential displacement even when overall firm productivity rises. The survey finding that 39 per cent of professionals anticipate income declines signals widespread anxiety that merits policy response. At the same time, the 47 per cent who believe AI creates net employment suggest that transition support—rather than blanket resistance to AI adoption—is the more appropriate policy frame. Programmes that facilitate redeployment to higher-value tasks, as envisioned by the giant insurance group's strategy, should be developed and supported.

AI Governance and Worker Protections

The multi-layered regulatory challenges described by firms—national regulations, sectoral rules, multinational corporate policies—highlight the need for coherent AI governance frameworks that balance innovation with worker protection. The financial sector's data firewalls and the cross-border restrictions imposed by multinational headquarters demonstrate that AI governance is inherently international. The ILO's role in promoting international labour standards that address AI's workforce implications is thus particularly relevant. Firms' own governance practices—the insurance company's proof-of-concept verification approach, the digital manufacturer's insistence on human–AI collaboration, the ed-tech company's strategy of developing proprietary tools to reduce external dependency—offer examples of enterprise-level governance that could inform broader standard-setting.

Productivity Measurement and Decent Work

The absence of systematic productivity measurement in most firms represents both a knowledge gap and a policy opportunity. Developing standardised frameworks for assessing AI's labour-market impacts—including effects on task composition, working conditions, job quality, and distributional outcomes, not only output per worker—would strengthen the evidence base for both enterprise decision-making and public policy. The ILO could play a valuable role in developing and promoting such frameworks, particularly ones that incorporate decent-work dimensions alongside conventional productivity metrics.

Inclusive Adoption and the SME Challenge

The digital services firm's observation that many small and medium enterprises "don't dare to invest and don't know how to invest" in AI, combined with the venture capital firm partner's assessment that AI represents "technological democratisation" raising lower-skilled firms to average capability levels, points to both the opportunity and the risk of uneven AI diffusion. Policies that support SME access to AI capabilities—through shared platforms, subsidised training, and accessible cloud-based AI services—can help ensure that productivity gains are broadly distributed rather than concentrated among large, digitally mature enterprises.

Methods and Limitations

Methodology

This research brief synthesises evidence from two complementary data sources. The primary source is a set of qualitative, semi-structured interviews conducted with representatives of 21 Chinese enterprises by researchers at Renmin University of China. The interviews followed a structured protocol covering five thematic modules: motivations for AI adoption, current AI applications, productivity measurement and effects, implementation challenges and governance practices, and future investment plans and outlook. Respondents included executives, department heads, and core employees, providing multi-perspective insights within each firm. The interview data were analysed through thematic coding and induction and compiled into structured summary documents which formed the basis for the analysis presented here.

The secondary source is a quantitative survey of 1,591 Chinese professionals conducted as part of the same research programme. The survey covered workforce perceptions of AI's impact on employment, income, and work organisation, spanning a wide range of industries, organisational types (state-owned, private, and foreign-invested enterprises), and career levels from entry-level to senior management. Descriptive statistics from this survey complement the qualitative findings by providing broader attitudinal data.

The interview documents were provided in a mixture of Chinese and English. The analysis draws on all available documentation, cross-referencing individual firm interviews, thematic summaries, and a structured overview spreadsheet to ensure completeness and accuracy. Summary statistics presented in this brief are derived directly from the interview and survey data as reported by the research team.

Limitations

Several limitations should be borne in mind when interpreting these findings. The qualitative interview sample of 21 firms, while diverse in sector, size, and ownership, is small and purposively selected rather than randomly drawn. The findings cannot be statistically generalised to the Chinese enterprise population. The sectoral distribution is weighted towards manufacturing and services, with communication, construction, and education each represented by a single firm. Information completeness varies across the sample: some firms provided extensive, richly detailed accounts while others are represented only by summary bullet points, limiting the depth of cross-firm comparison.

All productivity data are self-reported by firm representatives—typically senior managers or department heads—and have not been independently verified. The figures may reflect optimism bias, measurement inconsistencies, or selective reporting. No firm described a controlled experimental evaluation design, meaning that observed productivity changes cannot be rigorously attributed to AI adoption as opposed to concurrent organisational, market, or technological developments. The productivity metrics reported are heterogeneous in nature (cycle-time reductions, throughput increases, FTE equivalents, cost savings) and cannot be directly aggregated or compared.

The interviews capture firm-level and management perspectives but do not directly include worker voices. Employees' experiences of AI-induced changes in task content, workload intensity, job satisfaction, and employment security are filtered through management's assessment. The survey data partially address this gap but are limited to attitudinal measures rather than objective employment outcomes. The cross-border dimension of AI governance—including the multinational restrictions described by the HR services firm—is reported only from the Chinese subsidiary's perspective and may not capture the full picture.

Finally, the data represent a point-in-time snapshot of a rapidly evolving landscape. The pace of AI technological development and policy change in China is such that some findings may quickly become outdated. The research was conducted prior to certain recent developments in AI regulation and industrial policy that may alter the context described here. Future research incorporating longitudinal tracking, worker-level data collection, and larger representative samples would strengthen the evidence base considerably.

Disclaimer: *This research brief has been prepared for informational purposes. The views expressed herein do not necessarily reflect those of the International Labour Organization. All firm-level data are derived from interviews conducted by researchers at Renmin University of China during the first half of 2026 and have not been independently verified. Survey data are as reported by the research team. The research brief has benefited from comments by the Director of the Research Department, Caroline Fredrickson.*

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Contact details
International Labour Organization
Route des Morillons 4
CH-1211 Geneva 22
Switzerland

T: +41 22 799 7239
E: research@ilo.org

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