The Impact of New-Generation Artificial Intelligence on the Gender Employment Gap

Qinqin Zhuang and Yitong Liu

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Qinqin Zhuang: Institute of Quantitative and Technological Economics, Chinese Academy of Social Sciences; Business School, University of Chinese Academy of Social Sciences. Email: zhuangqinqincass@163.com.
Yitong Liu: Business School, University of Chinese Academy of Social Sciences. Email: liuyitong1@ucass.edu.cn. Phone:

Abstract

Revolutionary technological breakthroughs are a central driver of labor-market restructuring and productivity growth. As a rapidly evolving general-purpose technology, new-generation artificial intelligence, represented by large language models (LLMs), may create important opportunities to narrow gender employment gaps and increase women's labor-force participation. Combining the China Family Panel Studies, the Chinese Social Survey, the Seventh National Population Census, and an occupation-level LLM exposure index, this paper evaluates the micro-level impact of new-generation AI on the gender employment gap in China. The evidence suggests that new-generation AI has affected women's employment, but it has not significantly widened the overall gender employment gap, partly because it has promoted women's flexible employment. Mechanism analysis indicates that new-generation AI reshapes the gender structure of employment through four channels: task reallocation, occupational differentiation, time reallocation, and human-capital accumulation. Further analysis shows that the employment effects are more pronounced for older workers and less-educated women, while new-generation AI promotes female employment in education. The paper provides evidence for understanding how AI affects the gender structure of employment and offers policy implications for inclusive AI development.

Keywords: New-generation artificial intelligence; Large language models; Gender employment gap
JEL Classification: J16, J21, J24, O33

I. Introduction

New-generation artificial intelligence, represented by large language models, is developing rapidly (Tables 1 and 2). The technology plays an important role in the new round of scientific and industrial transformation and is also generating unprecedented shocks to the labor market. Women's employment faces both challenges and opportunities. On the one hand, women may use these tools to improve productivity and innovation capacity. On the other hand, unlike earlier technological changes that mainly substituted for human physical labor, AI substitutes more directly for mental and cognitive work (Cai and Chen, 2019). It is especially strong in replacing traditional white-collar and highly procedural jobs, which may expose high-skilled workers, including women, to greater employment shocks.

The practical background is equally important. China is undergoing deep structural adjustment, and employment pressures have become more visible. Compared with men, women face more acute employment constraints (Li et al., 2025). According to the National Bureau of Statistics, China had 320 million employed women in 2024, accounting for 43.4 percent of total employment. Although this share has remained above 40 percent, it is still clearly lower than men's share. Women's human-capital attainment has continued to rise, but the scale and quality of women's employment have not fully matched their educational progress. In 2024, women accounted for 26.614 million students in higher education, or 50.8 percent of all enrolled students. At the same time, China's female labor-force participation rate has long exceeded the world average, but it has declined over the past three decades, from 73 percent in 1990 to 62 percent in 2021 according to World Bank data. Hidden barriers in women's employment remain, and despite substantial improvements in women's education, both employment scale and job quality still lag behind (Liu, 2020).

Female labor-force participation is not only a matter of employment equality; it also affects long-run growth potential. In October 2025, the keynote speech at the Global Leaders' Meeting on Women emphasized the use of technological innovation to empower high-quality development for women. The report to the 20th National Congress of the Communist Party of China also called for removing unreasonable restrictions and discrimination that affect equal employment. Existing research shows that the reduction of occupational entry barriers for women and other disadvantaged groups in the United States since the 1960s improved talent allocation and explains about 20-40 percent of U.S. per capita output growth (Hsieh et al., 2019). Against the background of accelerating AI iteration, it is therefore especially important to achieve both healthy technological development and inclusive growth. Because occupational gender segregation and hidden employment barriers persist, even a technologically neutral AI shock may be transmitted to the gender structure of the labor market through gender differences in occupational distribution. This study asks how new-generation AI affects the gender employment gap and through which channels such effects operate.

Does new-generation AI widen the gender employment gap? Does it bring new opportunities or new challenges for women's employment? These are open questions that require both theoretical and empirical investigation. This paper analyzes the gendered employment effects of new-generation AI at the micro-individual level. It combines 2018-2022 CFPS panel data, 2023 Chinese Social Survey data, occupational-structure information from the Seventh National Population Census, and an occupation-level LLM exposure index. By matching occupational exposure differences to individuals, the paper examines changes in the gender employment gap and the mechanisms through which new-generation AI diffusion affects it.

The paper makes three main contributions. First, it extends research on the economic impact of new-generation AI from the perspective of the gender employment gap. Existing studies focus largely on productivity growth, aggregate employment, and other macro-level outcomes (Ma et al., 2024; Zheng et

al., 2023; Brynjolfsson et al., 2025; Chen et al., 2025; Humlum and Vestergaard, 2025), while paying less attention to the gender structure of employment. Second, it extends research on women's employment by bringing technological factors, especially LLM systems with strong cognitive and reasoning abilities, into the analytical framework. Compared with studies that explain women's employment disadvantages mainly through labor-market institutions and household division of labor, this paper examines how new-generation AI reshapes women's employment scale, job quality, employment structure, and skill requirements. Third, the paper explores mechanisms affecting women's employment in China across task reallocation, time reallocation, occupational redifferentiation, and human-capital reacquisition, helping clarify the dynamic relationship between technological change and gendered division of labor.

Table 1. Development of Large Language Models Outside China

Date	Event / model release	Main contribution and technical significance
June 2017	Transformer architecture proposed	It replaced RNNs entirely with self-attention for the first time and provided a unified architectural foundation for later LLMs.
June 2018	GPT (OpenAI)	The first Transformer-based LLM. It introduced the pretraining-finetuning paradigm using language modeling for pretraining.
October 2018	BERT (Google)	A bidirectional Transformer trained with masked language modeling; it substantially improved natural-language understanding tasks.
February 2019	GPT-2 (OpenAI)	With 1.5 billion parameters, GPT-2 greatly improved text generation and sparked broad discussion of both capabilities and risks.
January 2020	T5 (Google)	It proposed a unified text-to-text framework and improved multitask generalization.
May 2020	GPT-3 (OpenAI)	With 175 billion parameters, GPT-3 displayed strong few-shot generalization and marked a turning point for generative-AI applications.
March 2021	Codex (OpenAI)	Fine-tuned from GPT-3 for code generation and used in GitHub Copilot; it opened the application market for program-language generation.
April 2022	PaLM (Google)	A 540-billion-parameter model that introduced path activation mechanisms to improve computational efficiency.
November 2022	ChatGPT (GPT-3.5) released	OpenAI fine-tuned GPT-3.5 with RLHF, delivering a highly natural conversational experience and marking a turning point in public access to generative AI.
March 2023	GPT-4 released	It strengthened reasoning, supported multimodal input, and became a foundation for general-purpose AI agent systems.
July 2023	LLaMA 2 (Meta)	Meta released an open-source LLM, accelerating open-source development and academic and commercial deployment.
December 2023	Gemini (Google)	Google rebranded Bard as Gemini, supporting native multimodal interaction and competing with GPT-4.
February 2024	Sora (OpenAI)	A Transformer-based video-generation model with complex spatiotemporal understanding, extending generative AI to dynamic multimodal imagery.

Source: Compiled by the authors from public information.

Table 2. Development of Large Language Models in China

Date	Organization	Event / model	Description
March 2019	Baidu	Released ERNIE 1.0	ERNIE 1.0 outperformed BERT on Chinese NLP tasks. From 2019 to 2022, Baidu successively released ERNIE 2.0, ERNIE 3.0, ERNIE-M, ERNIE-Code, and related large models.
Early 2020	Alibaba	Launched the multimodal M6 project	After several iterations, M6 expanded from the trillion-parameter scale to the ten-trillion scale by November 2021. It was among the earlier domestically developed large models used commercially and supported the Double 11 shopping festival in 2021.
April 2021	Huawei	Released the Pangu-Alpha model	A Chinese pretrained model with hundreds of billions of parameters, designed for industrial applications such as meteorology and health care.
June 2021	Beijing Academy of Artificial Intelligence	Released WuDao 2.0	With 1.75 trillion parameters, it was once the world's largest model and covered language, vision, and multimodal modeling.
November 2022	Alibaba	Launched the ModelScope community	Opened more than 300 deployable AI models, including large pretrained models, lowering adoption costs for developers and firms.

November 2022	Baidu	Upgraded ERNIE large models	Added 11 large models and further improved ERNIE APIs, development kits, and enterprise platforms.
March 2023	Baidu	Released ERNIE Bot	A conversational LLM based on the ERNIE architecture, quickly integrated into search, image generation, office tools, and other product lines.
April 2023	Alibaba	Released Qwen	Designed for general generation tasks across scenarios; later opened multilingual and plugin ecosystems and integrated with DingTalk and Alibaba Cloud.
June 2023	Tencent	Tested Hunyuan internally	Focused on multimodal capabilities; formally released in September 2023 and deployed in Tencent Cloud and WeChat systems.
July 2023	ByteDance	Released Doubao	A conversational LLM for lightweight user scenarios, emphasizing usability and ecosystem integration.
November 2023	High-Flyer Quant	Released DeepSeek Coder	On January 20, 2025, DeepSeek released the reasoning model DeepSeek-R1, reporting performance comparable to OpenAI o1 and releasing it as open source.
Since 2024	Multiple firms	Released open-source multimodal models	Examples include continuous upgrades to ChatGLM-4 and the Qwen family, with stronger open-source support.

Source: Compiled by the authors from public information.

II. Literature Review

Traditional AI generally refers to AI achievements before the deep-learning wave, including expert systems based on rule reasoning and knowledge bases, early machine-learning algorithms, and industrial robots. Most AI during this period was specialized AI, focused on specific domains or tasks. Technically, it relied on human-designed rules or training on structured data; in practice, it was concentrated in industrial automation, assembly-line production, and simple decision support. Traditional AI excels at routine and structured tasks, such as robotic arms in manufacturing assembly, algorithm-based process control, or ATMs replacing bank tellers. Its labor substitution mainly takes the form of mechanized and procedural replacement, affecting manufacturing workers, assembly-line operators, and some repetitive white-collar positions.

New-generation AI is a new paradigm that emerged with big data and deep learning. China's 2017 New Generation Artificial Intelligence Development Plan described new-generation AI as having features such as deep learning, cross-domain integration, human-machine collaboration, open collective intelligence, and autonomous intelligence, and as being built mainly on big data. Technically, it uses large-scale neural networks to learn from massive unstructured data, giving it stronger generalization and intelligence than traditional AI that relies on manually extracted features. In applications, it has penetrated natural-language processing and computer vision, producing advances in speech recognition, machine translation, image recognition, chatbots, and content-generation systems (Guan and Xu, 2024). Large language models such as ChatGPT can understand and generate human-like language; generative models such as Midjourney can create visual artworks; and code tools such as Copilot can generate executable code from natural-language instructions. AI is no longer limited to robotic arms in factories or software for fixed workflows; it has entered offices, creative design, marketing, human resources, and many other fields. Traditional AI mainly substitutes for physical labor and rule-based cognitive labor, whereas new-generation AI can perform many unstructured cognitive tasks and even display some creative capacity, directly affecting high-skilled knowledge workers.

In short, if traditional AI played the role of tools and machines, new-generation AI is closer to an agent with learning and reasoning capabilities. It can perform in areas where humans are not yet fully specialized, making its employment effects deeper and more complex (Benmelech and Zator, 2025).

A. Traditional AI and Employment

From the perspective of aggregate employment, traditional AI has both substitution and creation effects. Automation can directly replace workers in many procedural tasks and reduce labor demand (Berg et al., 2018; Acemoglu et al., 2022; Wang et al., 2024). Manufacturing has been the first sector affected. Evidence from Chinese listed manufacturing firms shows that a 1 percent increase in robot penetration reduces firms' labor demand by about 0.18 percent (Wang and Dong, 2020). Evidence from the United States also shows that higher robot density is associated with lower employment and downward wage pressure. At the same time, traditional AI creates demand for new occupations and tasks, generating employment through new tasks and industries (Chen et al., 2024). Historical experience suggests that technological revolutions create new jobs that partly offset the disappearance of old ones (Autor, 2015).

From the perspective of employment structure, traditional automation strongly affects routine occupations, while some nonroutine workers gain opportunities through complementarity. The overall employment structure is therefore adjusted (Long et al., 2020; Song et al., 2025). Automation mainly replaces programmable and repetitive tasks, and its effects differ by skill level and job type, leading to employment polarization. Autor and Dorn (2013) show that middle-skill routine occupations shrank in the United States, while high-skill nonroutine cognitive jobs and low-skill nonroutine service jobs expanded. Similar polarization appears in China. Wang and Dong (2020) find that industrial robots mainly substitute for middle-skill jobs held by workers with junior-college and undergraduate education, while producing a significant crowding-in effect for workers with high-school education or below and little effect on workers with graduate education. Overall, traditional AI has produced an employment adjustment pattern of expansion at the high end and contraction in the middle, challenging the existing human-capital structure.

From the perspective of income and skills, traditional AI also reshapes income distribution and the return to skills. Automation is a form of capital-biased technological change: machines replace labor, increasing capital's income share and reducing labor's share. At the macro level, this is reflected in a falling labor share of GDP; at the firm level, it appears as a lower labor-income share. Yu et al. (2019) find that robot adoption significantly reduces firms' labor-income share, implying that profits and capital returns rise while labor compensation falls. At the same time, traditional AI often raises relative demand for high-skilled labor, widening skill premia and income gaps. Skill-biased technological change theory explains this pattern: new technologies complement high skills and substitute for low skills, raising high-skilled workers' relative wages. In the automation wave, highly educated workers with complex cognitive skills benefit more, while low- and middle-skilled workers in highly automatable jobs face stagnant or falling wage growth.

Task-biased technological change can also cross formal education boundaries. Workers performing nonroutine analytical tasks may benefit regardless of educational level, while workers performing routine operational tasks may be disadvantaged even if they are highly educated. Income distribution therefore depends more on the automatable content of work than on education alone. Acemoglu and Restrepo (2022) show from a task perspective that more than half of the rise in U.S. wage inequality in recent decades can be attributed to automation replacing middle-skill routine tasks. In general, traditional AI tends to raise returns to capital and high-skilled labor while weakening low-skilled workers' bargaining power, contributing to a lower labor share and wider skill wage gaps. The key issue is how to enjoy efficiency gains from technological progress while mitigating the resulting distributional inequality.

Traditional AI also has heterogeneous effects across workers, regions, and industries. Women, less-educated workers, and older workers are often more vulnerable to technological shocks (Zhou et al., 2021; Sun and Zong, 2025; Albanesi et al., 2025). Other studies show that industrial robots change

women's education decisions, fertility decisions, and the gender wage gap. These groups often work in jobs with higher automability or slower skill upgrading and are more easily replaced or displaced. Regionally, eastern coastal provinces with more developed manufacturing and higher automation face stronger employment substitution shocks, whereas central and western regions face weaker direct substitution in the short run but may miss some new jobs created by technology. By industry, manufacturing and assembly-line sectors with high automability are affected first, while education, health care, nursing, and art, which rely more on creativity, interpersonal interaction, and flexible skills, face smaller direct substitution effects. As AI algorithms advance, however, even some service positions such as translation, customer service, and diagnostic assistance have begun to show signs of automation. The general trend is declining manufacturing employment and rising service employment, especially in high-end services, with occupational composition changing within industries.

B. New-Generation AI and Employment

New-generation AI centers on deep learning, natural-language processing, computer vision, and speech recognition. Representative applications include large language models, autonomous-driving perception systems, and intelligent manufacturing scheduling algorithms. Compared with traditional AI, it has achieved qualitative leaps in pattern recognition, knowledge generation, and cross-modal reasoning. It is widely viewed as having the characteristics of a general-purpose technology and as bringing profound, multidimensional shocks to economic structure and labor markets. Compared with traditional AI, new-generation AI is stronger in task substitution, simulation of cognitive ability, and restructuring of production organization. It may reconstruct employment structure and accelerate skill-demand transformation.

First, labor substitution by new-generation AI is no longer limited to low-skill or assembly-line jobs. It reaches high-skill professional positions and creative work (Zhang et al., 2025; Chen et al., 2025; Ma et al., 2024; Agarwal et al., 2023). Earlier technological substitution focused mainly on physical labor and simple cognitive labor, leaving high-skilled groups relatively less exposed. New-generation AI can perform or assist tasks traditionally undertaken by highly educated professionals, such as drafting legal contracts, preparing financial-analysis drafts, and reviewing scientific literature. This weakens the safe boundary of high-skilled labor. Experimental evidence shows that less-experienced workers assisted by AI can produce outputs close to those of more experienced workers (Brynjolfsson et al., 2025; Acemoglu, 2025), potentially narrowing productivity gaps across skill groups and reducing demand for senior high-wage workers. In creative and decision-oriented fields where human judgment remains important, AI has not fully replaced workers but has become a powerful collaboration tool, expanding human-machine work patterns.

Second, new-generation AI also creates new occupations and tasks (Sarala et al., 2025). Just as traditional AI created jobs such as programmers and CNC machine operators, new-generation AI has generated roles such as prompt engineers, AI model trainers, and AI safety evaluators. It also expands the task scope of many existing jobs. Marketing workers now need to use AI to generate text and images; programmers increasingly debug code with AI assistance. This raises skill requirements in some jobs and makes work more diverse and technology-intensive (Tambe, 2026; Fügener et al., 2026).

Overall, new-generation AI shifts labor demand away from automatable cognitive jobs toward jobs that cannot be automated or require human-machine collaboration. It thereby reorganizes occupational structure and job content. This reshaping includes both the decline of some occupations and the creation of new occupations, as well as changes in task composition within existing occupations.

C. Digital Technology and the Gender Employment Gap

Technological change reshapes labor markets and has heterogeneous effects across groups. Earlier changes such as the IT revolution mainly affected low-skilled male workers. Digital technologies including AI, big data, and the internet of things have more directly affected high-skilled workers, including women (Aum and Shin, 2025; Wang et al., 2023). Beyond substitution, digital technology creates new jobs. Yet creation effects vary by industry. While digital technologies create opportunities for technical workers, they may intensify challenges for women in low-skill occupations, especially routine and highly procedural jobs. The extent to which digital technology affects women's labor participation also depends on the availability of digital infrastructure. Tian (2024) finds that expanded digital infrastructure can reduce gender gaps and improve access to education and employment, particularly for rural women. However, women's job quality does not necessarily improve; more opportunities may be created in low-wage sectors rather than high-paid skilled positions.

Although digital technology provides women with more job opportunities and more flexible employment forms, women's employment remains constrained by family responsibilities, traditional gender roles, and occupational gender segregation (Li and Mo, 2025; Qi et al., 2022; Qiu and Yin, 2023; Wu and Zhou, 2025; Song et al., 2025). Occupational gender segregation tends to concentrate women in low-paid and low-prestige jobs while men dominate higher-paid and more powerful occupations (Liu, 2022). This pattern is rooted in social norms and cultural biases that define certain occupations as women's natural work, while assigning them lower social status and economic return (Jayachandran, 2020). Women also face a dual burden of family responsibilities and workplace challenges (Goldin, 2021; Becker, 1993; Niu et al., 2024; Zhang et al., 2023). They sometimes make seemingly voluntary choices to reduce working time in order to balance childcare and family care. Fang et al. (2010) show that women's employment decisions are strongly affected by family responsibilities and that women's employment reduces preferences for the number of children and actual fertility to some extent.

D. New-Generation AI and Women's Employment

The effects of new-generation AI on women's employment operate through both labor demand and labor supply. On the demand side, some studies suggest that AI may support gender equality in the labor market. AI used in recruitment changes the gender distribution of potential employees (Avery et al., 2024). Women are currently concentrated in information-intensive positions such as services, administrative support, and education and training, and these are precisely areas where new-generation AI has strong potential for augmentation. AI may increase productivity in women's jobs and strengthen their labor-market competitiveness (Brynjolfsson et al., 2025; Abis and Veldkamp, 2024). However, if firms use AI to lower professional skill thresholds, compress wage structures, and increase replaceability, women's concentration in middle-skill positions may make them more exposed. AI algorithms themselves may also embed historical data biases (Kanazawa et al., 2026). Algorithms in education and recruitment systems trained on historical gender distributions may reproduce or even strengthen occupational gender segregation (Capraro et al., 2024; Collett et al., 2022).

On the supply side, new-generation AI affects women's labor supply mainly through education and employment decisions. AI can collect and integrate career, training, and education information, helping women make more effective educational investments and occupational choices (Bao et al., 2024; Cortes et al., 2024; Huang et al., 2025). Non-discriminatory AI tutors, for example, may reduce gender bias in traditional education and career counseling and promote women's equal entry into training and occupations. The realization of these positive effects, however, depends on women's own technology adoption. Early adopters of new technologies often gain more economic returns and skill-upgrading opportunities, but Bick et al. (2024) find that women may lag behind men in adopting generative AI. Male workers are 9 percentage points more likely than women to use AI at work and 7 percentage points more

likely to use it at home. This gender gap may come from differences in training opportunities, information channels, household division of labor, and family responsibilities.

E. Discussion of the Literature

Existing research has extensively discussed AI, digital technology, and labor-market change and provides an important foundation for understanding the employment effects of technological progress. Yet it has paid relatively little attention to how new-generation AI affects the gender employment gap. New-generation AI is still in a rapid diffusion stage, and most studies focus on productivity, industrial restructuring, and aggregate employment. They discuss less how the technological shock affects employment opportunities, occupational distributions, and job quality by gender. Studies of traditional AI and industrial robots usually focus on automation substitution, task-biased technological change, and skill premia, examining aggregate employment, job polarization, wage distribution, and labor-income shares. These studies show that technological shocks are heterogeneous across tasks and skills, but their empirical contexts center on manufacturing, routine tasks, and traditional automation. LLMs and related new-generation AI now affect cognitive, unstructured, and service jobs, so conclusions based on robots or traditional automation cannot fully explain the new employment environment. Research on digital technology and women's employment has noted that the internet, platform economy, and digital infrastructure can raise women's labor participation, but there is no consensus on whether technology diffusion simultaneously improves job quality or reinforces occupational segregation.

As LLM-centered new-generation AI diffuses rapidly, technology may compress some jobs by replacing codifiable cognitive tasks, but it may also create adaptation space for women by lowering information-search costs, improving work flexibility, and facilitating skill reacquisition. This paper therefore matches occupation-level LLM exposure to CFPS microdata and examines employment scale, job quality, task allocation, occupational differentiation, time allocation, and human-capital accumulation in order to identify the direction, mechanisms, and boundaries of the effect of new-generation AI on the gender employment gap.

III. Theoretical Analysis and Hypotheses

A. New-Generation AI and the Gender Employment Gap

The impact of new-generation AI on labor markets is complex. It includes substitution for labor and the creation of new jobs and skill demand. Existing studies show that different forms of technological progress affect different workers in significantly different ways. Unlike traditional AI, LLM-centered new-generation AI can process unstructured information and complex cognitive tasks, affecting white-collar high-skilled occupations that were previously considered safe (Zhang, 2024; Zheng et al., 2023; Ma et al., 2024; Brynjolfsson et al., 2025; Bao et al., 2024). The focus of technological shock is therefore expanding from physical and routine cognitive labor to advanced cognitive labor. In theory, this expansion is not clearly biased toward one gender. From the substitution perspective, men account for a relatively high share of many high-skilled jobs, so AI substitution in such jobs could narrow occupational gender gaps. From the augmentation perspective, women also hold positions in high-cognitive and interactive jobs, and AI tools may raise productivity in such work and benefit women.

Existing evidence does not show that generative AI such as LLMs generally widens the gender employment gap. In some respects, it appears neutral or even potentially improving. First, the digital economy and AI provide women with new employment opportunities and more flexible forms of work. New industries and occupations increase labor-market mobility and flexibility, helping women balance work and family and potentially raising labor-force participation (Chen and Xie, 2023). Digital

technology also reduces geographic and physical constraints, allowing women to access opportunities through remote work and online training. Second, AI augmentation may prevent women from being disadvantaged in high-tech jobs. Some evidence suggests that in occupations with higher AI penetration, women's employment shares are relatively higher and gender gaps in wages and working hours narrow or even reverse (Li and Mo, 2025). Third, AI's creation effect expands new occupational space for women. Acemoglu and Restrepo (2018) argue that technological progress creates new occupations and tasks while replacing some existing work. In the rise of generative AI, jobs such as data annotator, AI model trainer, content reviewer, and prompt engineer create new opportunity windows. If women can upgrade digital skills and enter these emerging fields in time, they can share the employment dividends of technological innovation.

Overall, LLM-led new-generation AI has not compressed women's employment in the same way that traditional industrial machines affected some workers, and the gender employment structure has not significantly deteriorated. Some studies and statistics even suggest that active adoption of AI by women may help narrow certain gaps and support more equal employment participation. Because large-scale LLM applications remain at an early stage, their long-run effects are uncertain. Based on current trends and mainstream evidence, however, LLMs and related new-generation AI do not appear to widen the gender employment gap overall and may create opportunities to improve it.

Hypothesis 1: New-generation AI does not significantly widen the gender employment gap overall.

Although new-generation AI has not clearly intensified the gender employment gap overall, both researchers and practitioners warn that LLMs may have negative effects on women's employment, mainly through higher unemployment risk and constrained job opportunities. First, women's jobs may face higher automation risk. Unlike traditional AI, LLMs have stronger effects on nonroutine cognitive work and weaker effects on routine manual work, while women are concentrated in cognitive and nonroutine jobs. According to the 2020 Seventh National Population Census, women accounted for 40.8 percent of all workers, but 49.9 percent of workers in nonroutine manual jobs, 46.5 percent in nonroutine cognitive jobs, 36.8 percent in routine cognitive jobs, and only 32.6 percent in routine manual jobs. This occupational structure increases women's exposure to AI-substitutable tasks and raises the probability that women will be affected by technological shocks. AI may write women out of some work settings and solidify or deepen gender inequality. The negative effect may involve not only current job loss but also long-run career consequences, because women who passively exit some occupational tracks during a technological wave may find it harder to re-enter more competitive emerging jobs.

Second, structural barriers faced by women may be amplified in the AI era. Women's representation in STEM fields and AI-related occupations has long been low, placing them at a disadvantage in competition for new technology jobs and creating entry barriers (Li et al., 2025). If new AI-related occupations are concentrated in algorithm development and data analysis, women who cannot upgrade relevant human capital in time may face constrained choices. Women also continue to bear more family and childcare responsibilities. Although remote work provides some flexibility in AI-driven workplaces, technological upgrading often brings greater job instability and work intensity. For women whose employment stability is already relatively low, AI-induced industrial change may more easily push them out of the labor market (Song, 2021; Huang, 2021). In sum, differences in technology adoption and structural constraints mean that LLMs may negatively affect women's employment participation and employment decisions: some women may be forced to leave existing jobs or face greater barriers in job search.

At the same time, AI development has produced new work forms and employment arrangements, breaking the fixed constraints of workplace and working time. Flexible employment includes remote

work, flexible hours, freelancing, part-time work, and gig work based on platform economies. These forms share greater flexibility in time and location. Because of family responsibilities, women have long had stronger demand for work flexibility, while many high-paying jobs are what Goldin calls greedy work, requiring long hours and on-call responsibilities that disadvantage workers unable to devote all their time, often women with more household and childcare responsibilities. New-generation AI may change this situation. The broad use of LLMs and digital technologies allows information and tasks to be processed and shared automatically, reducing the need for employees to be constantly present and on call (Liu et al., 2025).

As Niu et al. (2024) argue, AI development may suppress the negative externalities of greedy work, increase the supply of flexible work, and lower the opportunity cost women face when choosing between career and family. Women can use AI tools and platforms to work while caring for family members, increasing the possibility of continuous employment and re-entry.

Hypothesis 2: New-generation AI has some negative effect on whether women are employed, but it promotes women's flexible employment.

B. Mechanisms Linking New-Generation AI to the Gender Employment Gap

1. Task Allocation

Modern labor economics views each job as a bundle of different tasks. Technological progress changes which tasks are performed by humans and which by machines, thereby changing the relative demand structure for labor (Zeng et al., 2025). Unlike traditional AI, LLM-centered new-generation AI can perform many cognitive tasks previously done only by humans, such as writing, information summarization, and code generation. This implies that the task structure of some jobs will be reorganized: AI replaces part of routine cognitive work, while human labor is shifted toward higher-order tasks or tasks requiring interpersonal interaction.

The effect on men and women depends on gender differences in comparative advantage and task distribution. On one hand, LLMs may replace many low- and middle-skill cognitive tasks related to content production, copywriting, and data organization, which account for a meaningful share of women's employment, such as editing, junior accounting, and customer-service replies. If such positions decline, women may need to upgrade to higher-skill tasks or change jobs. On the other hand, AI substitution is not linear. Some high-skill tasks are not replaced but augmented by embedded AI tools, forming a human-machine collaboration structure (Fügener et al., 2026). Existing research suggests that compared with men, Chinese female users display stronger long-term orientation and willingness to learn when using AI. Women using generative AI are more likely to focus on improving workflows and workplace capabilities rather than simply replacing manual operations or obtaining immediate returns. This suggests that women's response to AI is not merely passive adaptation but active integration: under LLM-driven task restructuring, women may use AI to enhance professional value rather than remain fixed in traditional roles.

2. Occupational Differentiation

Occupational gender segregation reflects systematic differences in the division of labor between men and women. This pattern partly reflects physical and skill endowments: men tend to have comparative advantages in physically intensive and repetitive mechanical tasks, while women are often stronger in cognitive, communication, and emotional-interaction work. Occupational preferences and path dependence also matter. In traditional society, women facing pressure to balance work and family often choose stable, flexible, or care-related jobs such as education, nursing, and counseling. This historical inertia makes industrial division of labor persistent. Gender norms also shape occupational division.

Jayachandran (2020) emphasizes that social gender norms significantly affect the relationship between development and women's employment and society's institutional expectations for women's work. Together, these factors produce a labor-market division in which physical and technical-operational jobs tend to be male-oriented, whereas medium- and high-cognitive or interpersonal jobs tend to be female-oriented.

Table 3. Current Occupational Gender Division

Occupation code	Occupation	Share of female workers
Selected male-dominated occupations	Selected male-dominated occupations	Selected male-dominated occupations
20400	Aircraft and ship technical personnel	0.07
63000	Transport equipment and general engineering machinery operators and related workers	0.08
61600	Mining workers	0.10
30200	Security, fire-protection, and auxiliary workers	0.11
41200	Repair and fabrication service workers	0.12
40200	Transportation, warehousing, logistics, and postal service workers	0.14
62900	Construction workers	0.14
61800	Basic machining workers in machinery manufacturing	0.16
61700	Metal smelting and rolling workers	0.17
62800	Electricity, heat, gas, and water production and supply workers	0.17
Selected gender-neutral occupations	Selected gender-neutral occupations	Selected gender-neutral occupations
62100	Specialized equipment manufacturing workers	0.40
60300	Tobacco and tobacco-products processing workers	0.40
62400	Electrical machinery and equipment manufacturing workers	0.40
50500	Auxiliary workers in agriculture, forestry, animal husbandry, and fishery	0.40
40600	Real-estate service workers	0.41
62600	Instrument and meter manufacturing workers	0.42
62500	Computer, communication, and other electronic-equipment manufacturing workers	0.42
61400	Rubber and plastic-products manufacturing workers	0.42
60700	Paper and paper-products production workers	0.42
30300	Legal affairs and auxiliary workers	0.42
Selected female-dominated occupations	Selected female-dominated occupations	Selected female-dominated occupations
40900	Water, environmental, and public-facility management service workers	0.61
21000	News, publishing, and cultural professionals	0.61
60500	Textile, garment, leather, and fur-products processing workers	0.64
41400	Health, sports, and leisure service workers	0.66
20800	Teaching personnel	0.67
20500	Health professionals and technicians	0.69
41000	Residential service workers	0.69
20600	Economics and finance professionals	0.71

Note: Data are from the Seventh National Population Census (2020). Because of space limits, the table reports selected occupations with the lowest female shares and occupations closest to gender neutrality, defined as those whose female worker share is closest to the overall female worker share.

In male-dominated occupations, LLMs may reinforce men's comparative advantage. Men often have a stronger physical comparative advantage in these occupations, such as mining, construction, and machinery operation. Because LLMs cannot currently replace physical labor, men's advantages in these fields may be enlarged. Many women in these industries perform auxiliary cognitive or administrative

work, such as clerical work, customer service, and data entry, which are precisely areas where LLMs are effective. Diffusion of LLMs therefore makes women's employment in male-dominated industries more vulnerable. In gender-neutral occupations, gender ratios may be similar, but gender differences remain in job hierarchy, income, and leadership. Men still occupy more favorable positions in promotion, technical mastery, and leadership, while women often work downstream in technical operation and decision-support roles. Because these roles are more substitutable by AI, women face both reduced employment opportunities and pressure to transform as work content is upgraded and redistributed. In female-dominated occupations, LLMs may strengthen women's comparative advantage. Although LLMs can perform many complex tasks, they are weaker in areas requiring human emotion, creativity, and social skills. Women have comparative advantages in these areas and can use AI to raise productivity and service quality, strengthening female-advantaged occupations.

3. Time Allocation

Women have long borne more unpaid housework and childcare responsibilities, which is a major reason for constraints on women's labor-force participation and career development (Becker, 1993; Goldin, 2021). Becker's theory of household division of labor argues that spousal specialization often comes from comparative advantage and gains from specialization. Because women are biologically central to childbirth and early childcare, or because women's market returns are lower, households may allocate women to household production and men to market work to maximize total returns. Even small initial differences can, together with increasing returns to human-capital investment, produce the traditional division of men outside and women inside the home. Under this structure, women spend substantial time on housework and care, reducing the time and energy available for formal employment and generating a gender employment gap.

New-generation AI may affect household time allocation in several ways. First, LLMs may improve the efficiency of household production. They cannot directly perform physical housework, but they can reduce household burdens in information management and decision support, for example by planning meals and purchases, helping with children's homework, and providing parenting knowledge and psychological support. These functions reduce to some extent the skill and time demands of household production. When some housework and childcare tasks become less time-consuming because of technological support, women can devote more time to career development or human-capital investment. This is analogous to the rise in married women's labor-force participation after household appliances such as washing machines and vacuum cleaners reduced housework time in the mid-twentieth century (Greenwood, 2019). Similarly, digital assistants such as LLMs may ease women's dual burden in work and family and weaken constraints from traditional division of labor.

4. Human-Capital Accumulation

Workers' active adaptation to new-generation AI also affects the gender employment gap. Technological progress is often skill-biased, meaning that higher-skilled workers benefit relatively more. Computer technology, for example, raised productivity and wages for highly educated workers while reducing opportunities for low-skilled workers, encouraging movement toward higher education (Acemoglu and Autor, 2011). Although new-generation AI may be more friendly to low-skilled workers than earlier technologies, it may still favor workers with digital skills and adaptability (Tambe, 2026; Kanazawa et al., 2026). Men and women may adopt different human-capital responses, affecting their employment gap.

Women's educational attainment in China has risen substantially over the past half century, and young women's participation in higher education now exceeds men's. In 2024, women accounted for 50.76 percent of students in higher education, 14.15 percentage points higher than in 1995. Female

graduate students accounted for 50.01 percent, 22.43 percentage points higher than in 1995. This means that women as a group have a strong human-capital foundation for adapting to new technology. If women can reacquire human capital in time, for example through programming training, data-analysis learning, AI application skills, and interdisciplinary capabilities, they can seize new job opportunities and avoid displacement (Deng et al., 2025). The abundance of online education and vocational training resources also provides flexible learning channels for women, especially employed women who need to balance family responsibilities. This lowers the threshold for human-capital upgrading and may help women narrow gender gaps in new technology skills (Caplin et al., 2025; Braxton and Taska, 2023).

The above discussion leads to the following hypothesis.

Hypothesis 3: New-generation AI reshapes the gender structure of employment through task reallocation, occupational redifferentiation, time reallocation, and human-capital reacquisition.

IV. Research Design

A. Data Sources

The microdata used in this paper come from the China Family Panel Studies (CFPS). CFPS is a national and comprehensive longitudinal survey covering most provinces, municipalities, and autonomous regions in China, with strong representativeness and temporal continuity. It includes rich information on personal income, employment status, family structure, and time allocation, allowing measurement of residents' labor-supply behavior and socioeconomic characteristics. The paper uses data from 2018 to 2022 for three reasons. First, earlier data have more missing values and different statistical definitions from recent waves, which may affect regression results. Second, the 2017 release of the New Generation Artificial Intelligence Development Plan marked the entry of new-generation AI into a rapid development stage. Third, Vaswani et al. (2017) proposed the Transformer model in 2017, replacing recurrent structures with attention mechanisms and laying a foundation for the development of new-generation AI. As Tables 1 and 2 show, LLMs developed rapidly after 2017. The period after 2018 can therefore be viewed as one of broad penetration by new-generation AI, making it appropriate for examining labor-market impacts.

The paper uses the occupation-level LLM exposure index constructed by Chen et al. (2025) as the proxy for occupational exposure to new-generation AI. The index is based on occupational descriptions in the Occupational Classification Code of the People's Republic of China (2022 edition). It is scored repeatedly by GPT-4, GLM, and InternLM and then averaged. The exposure scores are highly positively correlated with human expert scores and can capture heterogeneous LLM impacts across occupations. At the macro level, traditional AI development is measured by the number of AI patent applications from CNRDS. Provincial GDP per capita and female employment shares come from provincial statistical yearbooks and the national census. The paper also uses 2023 Chinese Social Survey cross-sectional data for robustness checks.

B. Model Specification

To analyze the impact of new-generation AI on the gender employment gap, the paper estimates the following models.

1. Baseline Model

$$Employment_{ioft} = \alpha_1 + \beta_1 exposure_o + \gamma X_{icft} + \mu + \theta_f + \varepsilon_{ioft} \quad (1)$$

The dependent variable is the employment status of working-age woman or man i in household f and occupation o in year t. exposure_o denotes occupation-level LLM exposure, used as exposure to new-

generation AI. X_icft is a vector of individual, household, and city-level controls; mu and theta_f denote fixed effects; and epsilon_ioft is the disturbance term. The coefficient beta_1 captures the effect of new-generation AI development on workers' employment.

2. Gender Interaction Model

To further examine differences by gender, the paper adds the interaction between the new-generation AI exposure index and gender in equation (2):

$$Employment_{ioft} = \alpha_1 + \beta_1 exposure_o + \beta_2 exposure_{ot} \times gender$$

$$+\beta_3 gender + \gamma X_{icft} + \mu + \varepsilon_{ioft} \qquad (2)$$

gender is a gender dummy equal to one for women and zero for men. beta_2 measures the relative effect of AI exposure on women's employment, that is, the gender effect of the new-generation AI shock.

3. Model Choice and Estimation

The dependent variables include binary employment-participation variables and continuous employment-quality variables, requiring different modeling strategies. Employment-participation models are estimated using Probit models to avoid the linear-probability bias and heteroskedasticity that may arise from applying OLS to binary outcomes. These models control for year fixed effects and use robust standard errors. Employment-quality models are estimated with OLS, controlling for individual and year fixed effects to absorb unobserved individual heterogeneity. Standard errors are clustered at the individual level to correct for serial correlation across observations of the same respondent.

C. Main Variables and Descriptive Statistics

To measure the effect of AI development on female workers comprehensively, the paper constructs dependent variables from two dimensions. The first is women's employment status, including whether the respondent has a formal job and whether the respondent is flexibly employed. The second is employment quality, including labor income and working time.

Employment status is identified from self-reported items on current work status and coded as EMPLOY, where EMPLOY=1 indicates being employed and EMPLOY=0 indicates unemployment. The paper focuses on the impact of new-generation AI on employment behavior and job quality among active labor-force participants. Individuals who have exited the labor market do not currently supply labor, and their employment decisions are not directly affected by ongoing labor-market technological change. Including them may introduce systematic bias and dilute the true mechanisms of employment participation and job-quality change. Following Peng et al. (2023), this paper excludes such individuals and focuses on the working-age population with employment potential or willingness. It further excludes individuals younger than 16 and older than 65, considering legal working age and life-cycle features of labor supply.

Individual-level controls include age, education, and personal characteristics such as political status, marital status, and hukou type. Household-level controls include the household dependency ratio and per capita household income. City-level controls include economic development, measured by GDP per capita.

Table 4. Main Variable Definitions

Variable type	Variable	Definition
Employment scale	Labor-force participation	Whether employed (yes=1, no=0)
Employment scale	Flexible employment	Whether in flexible employment (yes=1, no=0). Flexible

		employment includes freelancers, own-account workers, casual workers, temporary workers, part-time workers, labor-dispatch workers, and new forms of employment. Following Yin and Ye (2010) and Qi et al. (2021), the sample excludes family agricultural production, workers with labor contracts, and jobs with formal establishment status.
Employment quality	Labor income	Log of work income
Employment quality	Working time	Daily working hours = weekly working hours / 7
New-generation AI exposure	LLM exposure	Occupation-level exposure to LLMs
Controls	Individual level	Age: survey year minus birth year
Controls	Individual level	Education: primary school or below=6; junior secondary=9; senior secondary=12; junior college or undergraduate=16; graduate education=19
Controls	Individual level	Household-registration type: agricultural hukou=1; non-agricultural hukou=0
Controls	Individual level	Marital status: married=1; not married=0
Controls	Individual level	Political status: Communist Party member=1; non-member=0
Controls	Household level	Household dependency ratio
Controls	Household level	Per capita household income
Controls	Regional level	Regional economic development: log provincial GDP per capita

Table 5 reports descriptive statistics for the main variables. All continuous variables are winsorized at the top and bottom 1 percent.

Table 5. Descriptive Statistics

Variable	VarName	Obs	Mean	SD	Min	Median	Max
Employment	job	53410	0.985	0.123	0.000	1.000	1.000
Flexible employment	flexible_job	36095	0.019	0.138	0.000	0.000	1.000
Second job	second_job	53410	0.216	0.411	0.000	0.000	1.000
Working hours	workhour	46921	6.879	3.021	0.286	7.000	14.286
Work income	lnwage	24457	8.219	0.579	6.397	8.294	9.741
Age	age	53410	42.167	12.246	16.000	42.000	65.000
Education	edu	43208	3.617	1.786	0.000	3.000	10.000
Hukou type	res	49633	1.217	1.584	0.000	1.000	7.000
Marital status	mar	49557	0.831	0.375	0.000	1.000	1.000
Political status	communist	48140	0.017	0.131	0.000	0.000	1.000
Elderly dependency ratio	elder_p	53147	0.149	0.335	0.000	0.000	3.000
Child dependency ratio	child_p	53147	0.326	0.439	0.000	0.200	6.000
GDP per capita (10,000 yuan)	GDP	53140	6.702	2.986	3.134	5.801	17.991
Per capita household income (10,000 yuan)	income_p	51764	2.982	3.243	0.150	2.000	20.100
Occupation-level new-generation AI exposure	exposure	42801	0.257	0.101	0.089	0.203	0.484

V. Baseline Results and Robustness Checks

A. Baseline Regression

Table 6 reports the regression results for the effect of new-generation AI, proxied by LLM exposure, on the gender employment gap. Columns (1)-(4) introduce the gender interaction term. Columns (1) and (2) examine the effects of the interaction term on employment and flexible employment, while columns (3) and (4) use working hours and wage income as dependent variables. The interaction coefficient is insignificant in all models. In column (1), the coefficient on gender x exposure is -0.303 and statistically insignificant, suggesting that LLMs do not significantly widen the employment gap between men and women.

Columns (5) and (6) report regressions for the female sample, with employment and flexible employment as dependent variables; columns (7) and (8) report corresponding regressions for the male

sample. The results show that new-generation AI has a significant negative effect on women's employment but no significant effect on men's employment. Specifically, in column (5), the coefficient on LLM exposure is -0.952 and significant at the 1 percent level, indicating a clear employment substitution effect. By contrast, the coefficient for men's employment is -0.454 and not statistically significant, implying that the effect on men's employment is negative but insignificant. LLMs therefore have a larger employment shock for women than for men. LLMs also significantly affect employment form. The coefficient for women's flexible employment is 1.356 and significant at the 1 percent level; the coefficient for men's flexible employment is 1.257 and also significant at the 1 percent level. This suggests that LLMs promote flexible employment and that women may exit traditional jobs and move into flexible forms of work under the LLM shock.

The baseline results indicate that new-generation AI has a more pronounced effect on female workers and significantly reduces women's employment. This is consistent with the substitution-effect theory of AI: because women's jobs are more concentrated in tasks that AI can replace, AI progress is more likely to displace some women's jobs. By contrast, many male jobs involve physical or highly structured tasks that are less easily replaced by AI in the short run, so men's employment does not change significantly. AI also significantly raises flexible employment among both women and men, suggesting that when traditional employment opportunities are constrained, workers may re-enter the labor market through part-time work, self-employment, platform work, and other flexible forms. Under the AI shock, some women leave previous full-time jobs but do not fully exit the labor market; instead, they move into more flexible employment to compensate for income loss. The interaction results further indicate that although AI has a larger negative effect on women's employment, the overall gender employment gap is not significantly widened, partly because women adjust their employment form.

Table 6. Baseline Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Gender employment gap	Gender employment gap	Gender employment gap	Gender employment gap	Women	Women	Men	Men
	Employment	Flexible employment	Working hours	Wage income	Employment	Flexible employment	Employment	Flexible employment
gender x exp.	-0.303	0.031	1.065	-0.004				
	(0.361)	(0.433)	(0.888)	(0.142)				
exposure	-0.583*	1.263***	1.652***	-0.094	-0.952***	1.356***	-0.454	1.257***
	(0.308)	(0.357)	(0.603)	(0.094)	(0.303)	(0.342)	(0.326)	(0.378)
gender	-0.049	-0.087	-0.514	-0.126				
	(0.108)	(0.117)	(0.703)	(0.081)				
age	0.014***	-0.009***	0.011	-0.084**	0.017***	-0.012***	0.011***	-0.006**
	(0.002)	(0.002)	(0.050)	(0.036)	(0.003)	(0.003)	(0.003)	(0.003)
edu	0.039***	0.027**	0.048*	0.027***	0.056***	0.018	0.019	0.041**
	(0.014)	(0.012)	(0.028)	(0.010)	(0.019)	(0.016)	(0.022)	(0.021)
res	-0.023**	-0.002	-0.004	-0.002	-0.022	0.035*	-0.022	-0.051*
	(0.011)	(0.016)	(0.012)	(0.002)	(0.016)	(0.021)	(0.016)	(0.028)
mar	0.289***	0.258***	-0.002	-0.005	0.291***	0.420***	0.280***	0.195**
	(0.052)	(0.070)	(0.118)	(0.025)	(0.076)	(0.127)	(0.073)	(0.088)
communist	0.445**	-0.360	-0.072	0.025	0.374	-0.283	0.534	-0.433
	(0.212)	(0.280)	(0.195)	(0.035)	(0.272)	(0.413)	(0.345)	(0.386)
elder_p	0.126*	-0.038	-0.158*	-0.003	0.178*	-0.183*	0.083	0.055
	(0.068)	(0.064)	(0.093)	(0.019)	(0.095)	(0.108)	(0.095)	(0.079)
child_p	0.053	0.093**	-0.181**	0.016	0.002	0.122**	0.157*	0.052
	(0.054)	(0.041)	(0.074)	(0.014)	(0.066)	(0.057)	(0.091)	(0.060)
GDP	-0.008	-0.001	0.056***	0.006*	-0.001	0.008	-0.015	-0.008
	(0.007)	(0.009)	(0.018)	(0.003)	(0.010)	(0.013)	(0.010)	(0.012)
income_p	0.032***	0.020***	0.016	0.021***	0.037***	-0.000	0.028**	0.032***
	(0.009)	(0.007)	(0.010)	(0.002)	(0.013)	(0.010)	(0.013)	(0.009)

_cons	1.562***	-2.213***	5.715***	11.089***	1.324***	-2.362***	1.744***	-2.258***
	(0.133)	(0.144)	(2.040)	(1.292)	(0.173)	(0.220)	(0.174)	(0.175)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE			Yes	Yes				
Adj. R2			0.452	0.721				
Pseudo R2	0.047	0.036			0.052	0.049	0.039	0.033
N	31276	19874	20964	10345	14769	9577	16507	10297

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) are estimated using fixed-effects OLS, with standard errors clustered at the individual level in parentheses. In columns (3)-(8), the dependent variable employment is binary and is estimated using a Probit panel model with cluster-robust standard errors.*

B. Robustness Checks

1. Excluding Confounding Factors

To further exclude potential confounding factors, the paper adds year-by-province interaction fixed effects to the baseline specification. These fixed effects absorb unobserved shocks that may vary across provinces and years, such as local industrial policy, economic cycles, and sociocultural changes, so that the estimates more closely reflect the effect of new-generation AI. Table 7 shows that after controlling for these interaction fixed effects, new-generation AI exposure remains significantly negative for women's employment, with a coefficient of -0.890 significant at the 1 percent level. The effect on men's employment remains insignificant, with a coefficient of -0.485. AI exposure remains significantly positive for women's and men's flexible employment, with coefficients of 1.131 and 1.205, respectively, both significant at the 1 percent level. The effect on the gender employment gap remains insignificant. These results support the robustness of the baseline conclusions.

Table 7. High-Dimensional Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment	Flexible employment	Employment	Flexible employment	Employment	Flexible employment
exposure	-0.890***	1.131***	-0.485	1.205***	-0.560*	1.143***
	(0.311)	(0.347)	(0.339)	(0.385)	(0.313)	(0.361)
gender x exp.					-0.292	-0.024
					(0.367)	(0.436)
gender					-0.059	-0.069
					(0.110)	(0.117)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x province FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.082	0.079	0.070	0.068	0.069	0.063
N	13464	8778	14133	9800	29555	19511

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Employment and flexible employment are binary variables and are estimated using Probit panel models with cluster-robust standard errors.*

2. New-Generation AI Pilot Zones

The paper next uses the establishment of new-generation AI pilot zones as an exogenous shock. It constructs a triple interaction among treatment group (treat), time dummy (post), and gender dummy (gender), namely treat x post x gender, to examine the effect of AI policy pilots on the gender employment gap. The econometric specification is:

$$Employment_{ioft} = \alpha_1 + \beta_1 treat \times post + \beta_2 treat \times post \times gender + \beta_3 treat + \beta_4 post + \beta_5 gender + \gamma X_{icft} + \mu + \theta_f + \varepsilon_{ioft} \quad (3)$$

The coefficient beta_2 captures the effect of new-generation AI on the gender employment gap. As Table 8 shows, the coefficient on treat x post x gender in column (1) is -0.131 and significant at the 5 percent level, but the interaction is insignificant in columns (2)-(4). This suggests that the establishment of new-generation AI pilot zones has limited effects on the gender employment gap. The baseline results remain robust: although women are more exposed to the new-generation AI shock, the gender employment gap does not expand widely.

Table 8. New-Generation AI Pilot Zones

	(1)	(2)	(3)	(4)
	Employment	Flexible employment	Working hours	Wage income
treat x post	0.083	-0.078	-0.102	0.005
	(0.061)	(0.071)	(0.069)	(0.012)
treat x post x gender	-0.131**	-0.002	0.113	-0.002
	(0.055)	(0.071)	(0.085)	(0.015)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Pseudo R2	0.048	0.027		
Adj. R2			0.460	0.750
N	35914	23075	34311	18728

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. In columns (1) and (2), the dependent variable employment is binary and is estimated using a Probit panel model with cluster-robust standard errors. Columns (3) and (4) use fixed-effects OLS, with standard errors clustered at the individual level in parentheses.*

3. Excluding the Effect of Traditional AI

Traditional AI has also had important labor-market effects. It is therefore necessary to exclude the influence of traditional AI when analyzing the baseline results, so that the observed effects can be attributed to LLM-centered new-generation AI rather than traditional AI. The paper replaces the explanatory variable with a traditional AI exposure measure, namely the log number of provincial AI patent applications, and examines its effect on the gender employment gap. Table 9 shows that traditional AI has a positive but insignificant effect on women's employment. Its effect on men's employment is negative but also insignificant. Traditional AI has negative but insignificant effects on both men's and women's flexible employment. These results suggest that new-generation AI has labor-market effects that differ significantly from those of traditional AI, and that the baseline results are driven by LLM-centered new-generation AI rather than traditional AI.

Table 9. Traditional AI Technology

	(1)	(2)	(3)	(4)
	Employment	Flexible employment	Employment	Flexible employment
Traditional AI exposure	0.022	-0.013	-0.033	-0.021
	(0.028)	(0.036)	(0.029)	(0.032)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Pseudo R2	0.051	0.032	0.054	0.026
N	16636	10913	19278	12162

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Employment and flexible employment are binary variables and are estimated using Probit panel models with cluster-robust standard errors.*

4. Excluding the Effect of Internet Technology

Although the paper excludes traditional AI, the baseline results may still be affected by other contemporaneous information and digital technologies. To test the exclusiveness of the baseline results, the paper adds an indicator for internet use to the controls, excluding interference from internet diffusion. Table 10 shows that after controlling for internet use, new-generation AI exposure remains significantly

negative for women's employment, with a coefficient of -0.877 significant at the 1 percent level. The effect on men's employment remains insignificant, with a coefficient of -0.441. The magnitude is close to the baseline estimates, indicating that the employment shock is not due to internet diffusion but to LLM exposure.

Table 10. Internet Technology

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment	Flexible employment	Employment	Flexible employment	Employment	Flexible employment
exposure	-0.877***	1.220***	-0.441	1.229***	-0.564*	1.202***
	(0.307)	(0.348)	(0.327)	(0.379)	(0.309)	(0.358)
internet	-0.272***	0.253***	-0.103	0.072	-0.187***	0.157***
	(0.086)	(0.083)	(0.086)	(0.074)	(0.061)	(0.055)
gender x exp.					-0.262	0.001
					(0.363)	(0.435)
gender					-0.067	-0.072
					(0.109)	(0.117)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.057	0.054	0.040	0.034	0.049	0.038
N	14769	9577	16507	10297	31276	19874

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Employment and flexible employment are binary variables and are estimated using Probit panel models with cluster-robust standard errors.*

5. Changing the Regression Sample

In recent years, new-generation AI has entered a period of rapid application. Does it affect the gender employment gap differently during this period? To test robustness, the paper uses 2023 Chinese Social Survey data to analyze the effects of new-generation AI on men's and women's wage income and working time. Table 11 reports the results. Columns (1) and (2) test the gender employment gap; columns (3) and (4) use the female sample; columns (5) and (6) use the male sample. The results show that new-generation AI does not significantly widen the gender employment gap: the interaction coefficients in columns (1) and (2) are insignificant. However, the shock to women is larger, and women's wage income declines significantly. The baseline results therefore remain robust.

Table 11. Alternative Regression Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Gender employment gap	**Gender employment gap**	**Women**	**Women**	**Men**	**Men**
	Wage income	**Working hours**	**Wage income**	**Working hours**	**Wage income**	**Working hours**
exposure	0.196	2.314**	-1.992*	2.077	0.197	1.633
	(0.933)	(0.917)	(1.051)	(1.502)	(1.018)	(1.070)
gender x exp.	-2.096	-1.411				
	(1.476)	(1.435)				
gender	0.740	0.365				
	(0.507)	(0.468)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.038	0.117	0.050	0.133	0.107	0.157
N	2789	2399	903	847	889	746

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The regressions are Probit regressions controlling for province fixed effects and using cluster-robust standard errors.*

C. Mechanism Analysis

To reveal the internal mechanisms through which new-generation AI affects gendered employment, the paper conducts regressions from the perspectives of task characteristics, occupational structure, industrial structure, and individual time reallocation.

1. Task Allocation

The theoretical analysis suggests that the effect of new-generation AI on female workers has a dynamic substitution-reconstruction-augmentation character. On the one hand, AI has significant advantages in structured and routine tasks, creating substitution pressure for some low- and middle-skill jobs. On the other hand, breakthroughs in complex cognition, knowledge processing, and cross-task collaboration allow high-skilled women to gain new comparative advantages through technology adoption, task reshaping, and role repositioning. To test the task-reallocation mechanism, the paper divides jobs into two groups based on task characteristics and gender distribution. The first group consists of nonroutine and cognitive jobs, where women's share is relatively high and dependence on nonroutine tasks and cognitive skills is strong. The second consists of routine manual jobs, where women's share is lower and physical labor dominates. Women are also divided by education: workers with junior-college education or above are defined as highly educated, and workers with high-school education or below are defined as less educated.

As Table 12 shows, in routine manual jobs the coefficient on LLM exposure is -0.132 and insignificant. These jobs rely heavily on physical labor and production processes whose automation path depends mainly on traditional robot technology rather than LLMs, so new-generation AI has limited employment effects in this group. In nonroutine and cognitive jobs, the coefficient on LLM exposure is -1.374 and significant at the 1 percent level, indicating that LLMs significantly reduce women's employment in these jobs. This substitution effect is especially pronounced for less-educated women: the coefficient is -2.374 and significant at the 1 percent level. By contrast, for highly educated women, the coefficient is 1.271 and significant at the 5 percent level. This suggests that new-generation AI substitutes more strongly for less-educated women who lack advanced technical capabilities, while highly skilled women are not clearly displaced and instead show employment advantages. These results support the task-reallocation mechanism.

Table 12. Task Allocation

	(1)	(2)	(3)	(4)
	Routine manual jobs	**Nonroutine and cognitive jobs**	**Nonroutine and cognitive jobs**	**Nonroutine and cognitive jobs**
	Full sample	**Full sample**	**High education**	**Low education**
exposure	-0.132	-1.374***	1.271**	-2.374***
	(1.018)	(0.347)	(0.594)	(0.392)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Pseudo R2	0.096	0.061	0.114	0.084
N	1542	13222	3852	9370

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Employment and flexible employment are binary variables and are estimated using Probit panel models with cluster-robust standard errors.*

2. Social Division of Labor

The theoretical analysis indicates that LLMs may affect the gender employment gap by changing the social division of labor. To test this mechanism, the paper uses data from the 2020 Seventh National Population Census and classifies occupations into male-dominated, gender-neutral, and female-dominated groups according to the share of female workers. It then estimates regressions for the female sample.

Table 13 reports the results. Panel A uses employment scale as the dependent variable, and Panel B uses employment quality.

In male-dominated occupations, columns (1)-(2) show that LLM exposure significantly reduces women's overall employment but has a positive effect on flexible employment. This suggests that in male-dominated industries, women are more likely to hold jobs that can be substituted by AI and therefore may exit formal positions or shift to flexible employment. Although women's working time rises insignificantly, wage income among women who remain employed rises significantly. This may indicate that during job restructuring, only women with higher productivity and stronger skill adaptability remain, raising the average wage. In gender-neutral occupations, columns (3)-(4) show a significant negative employment effect of LLM exposure for women. Women's employment falls significantly, flexible employment rises, working time increases significantly, and wage income falls significantly. This suggests that although these occupations are relatively balanced in gender shares, women are more concentrated in positions vulnerable to LLM substitution and face greater employment pressure.

In female-dominated occupations, columns (5)-(6) show that LLM exposure has no significant effect on women's overall employment, indicating that AI has not generated a substantive employment shock in these occupations. Flexible employment declines slightly, women's working time falls significantly, and income remains relatively stable. These results suggest that in female-dominated occupations LLMs do not have a significant substitution effect on women and may instead have some augmentation effect. Overall, the effect of LLM exposure differs significantly across occupational gender structures, supporting the occupational redifferentiation mechanism. New-generation AI has not yet broken the existing pattern of occupational gender segregation; instead, it may reinforce men's and women's comparative advantages in their respective dominant occupations.

Table 13. Social Division of Labor

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment scale	**Panel A. Employment scale**	**Panel A. Employment scale**	**Panel A. Employment scale**	**Panel A. Employment scale**	**Panel A. Employment scale**	**Panel A. Employment scale**
	Male-dominated	**Male-dominated**	**Gender-neutral**	**Gender-neutral**	**Female-dominated**	**Female-dominated**
	Employment	Flexible employment	Employment	Flexible employment	Employment	Flexible employment
exposure	-2.290**	2.283*	-3.233***	2.975***	0.338	-1.138**
	(1.153)	(1.195)	(0.517)	(0.486)	(0.492)	(0.568)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	976	397	10437	7902	3339	1264
Pseudo R2	0.080	0.065	0.099	0.078	0.047	0.069
Panel B. Employment quality	Panel B. Employment quality	Panel B. Employment quality	Panel B. Employment quality	Panel B. Employment quality	Panel B. Employment quality	Panel B. Employment quality
	Male-dominated	Male-dominated	Gender-neutral	Gender-neutral	Female-dominated	Female-dominated
	Working hours	Wage income	Working hours	Wage income	Working hours	Wage income
exposure	4.174	1.095**	9.755***	-0.620*	-2.914**	-0.217
	(2.524)	(0.505)	(1.555)	(0.344)	(1.201)	(0.260)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.493	0.815	0.463	0.677	0.519	0.759
N	314	242	6215	1872	1782	1463

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. In Panel A, the dependent variables are binary and are estimated using Probit panel models with cluster-robust standard errors. In Panel B, the dependent variables are continuous and are estimated using fixed-effects OLS, with standard errors clustered at the individual level in parentheses.*

3. Individual Time Allocation

The broad application of new-generation AI reshapes not only labor-market occupational structure but also individual time allocation. Compared with men, women usually bear more housework and childcare tasks. As Table 14 shows, in the data women spend an average of 2.45 hours per day on

housework and 6.37 hours on market work, while men spend 1.48 hours on housework and 7.29 hours on market work. With LLM applications, especially in information management and decision support, women may free more time for market work. To test the time-reallocation mechanism, the paper examines the effects of LLM exposure on men's and women's working time, housework time, and leisure time. Table 15 reports the results.

Columns (1)-(3) report results for the female sample. LLM exposure has a significantly positive effect on women's working time, with a coefficient of 2.761 significant at the 1 percent level. This indicates that under the new-generation AI shock, women's working time increases significantly. At the same time, LLM exposure significantly reduces women's housework time, with a coefficient of -1.015 significant at the 1 percent level, suggesting that AI helps perform or support some household tasks and further releases women from housework. The effect on women's leisure time is insignificant, possibly because the time released from housework is used more for additional work than for leisure, reflecting an intensification trend in women's labor participation.

Columns (4)-(6) report results for the male sample. AI exposure also significantly increases men's working time, with a coefficient of 1.594 significant at the 1 percent level, but the coefficient is smaller than the estimate for women. It reduces men's housework time by -0.586, significant at the 5 percent level, again with a smaller absolute value than for women. The effect on men's leisure time is positive, though insignificant, and has the opposite direction from the estimate for women. This may mean that men enjoy more discretionary time for leisure under the technological shock.

The results show that LLM exposure significantly changes the structure of time allocation across market work, housework, and leisure. Compared with men, women increase working time more, reduce housework time more, and do not increase leisure time. This supports the individual time-reallocation mechanism.

Table 14. Descriptive Statistics for Individual Time Allocation

Variable	Obs	Mean	SD	Min	Max
Women: working hours	21081	6.370	3.060	0.286	14.286
Men: working hours	25840	7.293	2.924	0.286	14.286
Women: housework hours	21890	2.452	1.841	0	9.571
Men: housework hours	26613	1.485	1.727	0	9.571

Table 15. Individual Time Allocation

	(1)	(2)	(3)	(4)	(5)	(6)
	Women	Women	Women	Men	Men	Men
	Working hours	Housework time	Leisure time	Working hours	Housework time	Leisure time
exposure	2.761***	-1.015***	-4.158	1.594***	-0.586**	2.676
	(0.657)	(0.314)	(9.929)	(0.605)	(0.280)	(8.976)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.450	0.391	0.457	0.421	0.325	0.507
N	9693	9911	1651	11246	11391	2260

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered at the individual level are reported in parentheses.*

4. Human-Capital Accumulation

New-generation AI affects not only gender and occupational division of labor in the labor market but also the channels and methods of human-capital accumulation, thereby further affecting the gender employment gap. To test this mechanism, the paper examines the effect of LLM exposure on women's

and men's educational expectations and human capital. Following Tian (2024), it uses CFPS interviewer observation scores as a proxy for individual human capital, combining interviewer assessments of respondents' health, tidiness of dress, appearance, intelligence, and eagerness to end the interview.

Table 16 reports the results. Columns (1) and (2) use the female sample. LLM exposure has a significantly positive effect on women's educational expectations, suggesting that as new-generation AI diffuses, women's educational expectations for career development rise, which may encourage them to value skill and degree upgrading more. Column (2) shows that the effect on women's human capital is not yet significant, possibly because women face time and resource constraints that prevent human-capital upgrading from fully appearing. Columns (3) and (4) report results for the male sample. LLM exposure has a negative but insignificant effect on educational expectations and a significantly negative effect on men's human capital. Combined with the time-allocation results, men may be more inclined than women to enjoy the utility gains brought by AI and allocate more time to leisure rather than further skill or educational upgrading. Women, by contrast, are more likely to adopt active skill-upgrading strategies to adapt to the high technical requirements of emerging industries. These findings support the human-capital reacquisition mechanism.

Table 16. Human-Capital Accumulation

	(1)	(2)	(3)	(4)
	Women	Women	Men	Men
	Educational expectations	Human capital	Educational expectations	Human capital
exposure	0.574*	7.445	0.129	-15.312*
	(0.329)	(5.617)	(0.312)	(8.995)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Adj. R2	0.532	0.162	0.557	0.126
N	363	455	549	384

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered at the individual level are reported in parentheses.*

VI. Further Analysis

To examine the boundaries of the LLM shock to the gender employment structure, the paper studies heterogeneity by industry, education, and age.

A. Industry Heterogeneity

Existing research suggests that the effect of new-generation AI on the gender employment gap may differ across industries (Zheng et al., 2023; Deng et al., 2025). Theoretically, the employment effect of AI depends on industry task structures and the degree to which tasks are exposed to technological shock. The paper therefore examines four industry dimensions: manufacturing, producer services, consumer services, and education. Table 17 reports the results.

In education, the coefficient of LLM exposure for women's employment is 3.168 and significant at the 10 percent level, suggesting that new-generation AI significantly promotes women's employment in education. This may be because education has strong interpersonal-interaction characteristics and high demand for communication and emotional labor, tasks in which women have some comparative advantage. Current AI still has limits in complex interpersonal communication and contextual understanding, which may strengthen women's relative advantage. In producer services and consumer services, the coefficients on LLM exposure are positive but insignificant, suggesting that AI's employment-promoting effect for women in these sectors is not yet clear. These service sectors contain

both automatable procedural tasks and nonprocedural tasks that are harder to replace, so the net effect is statistically insignificant. In manufacturing, the coefficient is negative but insignificant.

The results further support the view that under the new-generation AI shock, AI reshapes employment structure at the industry level by changing relative demand for different types of tasks. Its effect on women's employment is therefore clearly industry-dependent.

Table 17. Industry Heterogeneity

	(1)	(2)	(3)	(4)
	Education	Producer services	Consumer services	Manufacturing
exposure	3.168*	1.175	0.797	-0.669
	(1.627)	(1.163)	(0.540)	(0.691)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Pseudo R2	496	534	2951	1683
N	0.236	0.110	0.133	0.122

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Employment is a binary variable and is estimated using a Probit panel model with cluster-robust standard errors.*

B. Education Heterogeneity

The analysis of task reallocation suggests that the employment effect of new-generation AI may differ by workers' education. Less-educated workers are constrained by limited advanced technical capabilities and are more likely to be replaced, while high-skilled workers show stronger employment resilience and may even gain new opportunities. The paper divides workers into two groups, high school or below and above high school, and examines the effect of LLMs on employment forms by education. Table 18 reports the results.

Among workers with high-school education or below, the coefficients on LLM exposure for women's overall employment and flexible employment are -1.729 and 1.738, respectively, both significant at the 1 percent level. New-generation AI therefore reconstructs the employment form of less-educated workers: overall employment opportunities are affected, but flexible employment opportunities increase, reflecting efforts by this group to achieve reemployment by adjusting employment form under technological shock. By contrast, among workers with education above high school, the employment coefficient is 1.144 and significant at the 5 percent level, while the flexible-employment coefficient is -1.130 and insignificant. Highly educated workers are not negatively affected by AI and may obtain more opportunities because of stronger technology-complementarity capabilities, further strengthening employment stability. This is consistent with the earlier discussion of human-capital reacquisition: new-generation AI may be biased toward workers with digital skills and adaptability. Less-educated workers often face passive transformation of employment form, while highly educated workers can use cognitive flexibility and skill adaptability to consolidate or improve employment status through human-machine collaboration.

Table 18. Education Heterogeneity

	(1)	(2)	(3)	(4)
	High school or below	**High school or below**	**Above high school**	**Above high school**
	Employment	**Flexible employment**	**Employment**	**Flexible employment**
exposure	-1.729***	1.738***	1.144**	-1.130
	(0.350)	(0.391)	(0.535)	(0.802)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Pseudo R2	0.072	0.062	0.111	0.075
N	10702	8346	4067	1205

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Employment and flexible employment are binary variables and are estimated using Probit panel models with cluster-robust standard errors.*

C. Age Heterogeneity

Because of differences in digital-skill accumulation and learning adaptability, workers of different ages may respond differently to technological shocks. Older workers are often more vulnerable (Chen et al., 2025). The paper divides women into three age groups: young women below age 35, middle-aged women aged 35 to 45, and older women above age 45. It then estimates the effect of new-generation AI on women's employment in each group. Table 19 reports the results.

The coefficient on LLM exposure is -1.722 for older women and significant at the 5 percent level; it is -1.668 for middle-aged women and also significant at the 5 percent level; and it is -0.590 for young women and insignificant. These results show a clear age gradient: the older the women, the stronger the employment shock from LLMs. This supports the theory of age vulnerability under technological shock. Older workers have weaker digital skills and more limited occupational transformation capacity, placing them at a disadvantage in technological change (Liu et al., 2024). Middle-aged women have work experience but face higher replacement risk and transformation barriers. Young women show stronger employment resilience because of better digital skills and adaptability.

Table 19. Age Heterogeneity

	(1)	(2)	(3)
	Older women	**Middle-aged women**	**Young women**
exposure	**-1.722****	**-1.668****	**-0.590**
	(0.715)	(0.658)	(0.377)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
Pseudo R2	0.077	0.071	0.050
N	4720	3406	5833

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Employment is a binary variable and is estimated using a Probit panel model with cluster-robust standard errors.*

VII. Conclusions and Policy Implications

A. Conclusions

New-generation AI, especially general-purpose intelligent tools represented by LLMs, is reshaping labor-market structure at unprecedented speed and depth. From the perspective of the gender employment gap, this paper systematically evaluates the early-stage impact of new-generation AI on women's employment and documents dynamic changes in gendered employment under technological change. The results show that although new-generation AI has had some impact on women's employment, it has not significantly widened the gender employment gap overall. Instead, technology diffusion has promoted growth in women's flexible employment to some extent, providing women with more diverse and flexible employment paths.

Mechanism analysis indicates that new-generation AI reshapes the gender employment structure through task reallocation, occupational redifferentiation, time reallocation, and human-capital reacquisition. First, new-generation AI, especially LLM applications, replaces many highly repetitive and structured procedural tasks and promotes within-job task restructuring. Second, LLMs further reinforce men's and women's comparative advantages in physical and communication tasks. In gender-neutral occupations, men still hold more high-paid and managerial jobs, while women are concentrated in more replaceable auxiliary roles, making women's employment more affected by LLM penetration. Third, new-generation AI partly eases women's time constraints arising from family-care responsibilities and

increases the possibility and continuity of labor participation. Fourth, under the influence of new-generation AI, women recognize the importance of education and actively improve their human capital. This active adaptation may help women achieve skill upgrading and narrow the gender employment gap during technological change. Further analysis shows that LLM-centered new-generation AI has especially pronounced employment shocks for older workers and less-educated women, while promoting women's employment in education. This highlights the importance of improving women's human capital and strengthening their ability to adapt to technological change.

The empirical analysis is based mainly on 2018-2022 data and therefore examines the relatively early stage of new-generation AI development and application diffusion. Since 2022, generative AI, AI agents, and embodied AI have evolved rapidly, and AI's effects on task structure, labor demand, and employment differentiation may have changed. The conclusions of this paper are therefore more suitable for explaining the early-stage effect of new-generation AI on the gender employment gap and should not be mechanically extrapolated to later stages in which generative AI is deeply embedded in production and organizational management. Future research can combine newer data with emerging AI trends to further examine how different technological forms affect women's employment opportunities, job structure, and career development, providing stronger evidence for using technological innovation to promote higher-quality women's employment.

B. Policy Implications

The findings have the following policy implications.

First, policy should make full use of the potential of new-generation AI to empower disadvantaged groups and use technological innovation to support women's employment. The evidence shows that new-generation AI is reshaping the gender employment structure. New technologies not only restructure job tasks but also provide disadvantaged groups with new opportunity windows beyond time and space constraints. Introducing intelligent tools such as LLMs into grassroots public services, rural education, and social governance can expand participation channels for women, especially less-educated women, and help them move toward higher-value segments of the production chain.

Second, more inclusive and adaptive skill-upgrading and retraining systems should be built to improve women's human capital. New-generation AI has stronger employment shocks for less-educated and older women, indicating that replacement risk depends heavily on technology-adaptation capacity grounded in individual human capital. Based on existing vocational training, policymakers should accelerate digital-skill education for women, expand online resources in programming, data processing, and AI applications, and build flexible curricula suited to women's learning pace and needs.

Third, household labor should be further socialized to systematically ease women's structural family and childcare burdens. The evidence shows that women bear more housework than men: women spend 2.45 hours per day on housework on average, far above men's 1.48 hours. Although LLM tools can support household decision making and childcare tutoring and thus initially reduce time pressure, fundamentally releasing women's labor potential requires improved childcare services, parental-leave arrangements, flexible-work institutions, greater male participation in housework and childcare, and comprehensive improvements in women's employment scale and quality.

Fourth, flexible employment should be actively cultivated and regulated to expand women's employment space. New-generation AI pushes women's employment forms toward flexibility. LLM diffusion broadens the boundaries of remote work, self-employment, platform labor, and other new employment forms. Policy can encourage employers to provide more flexible positions and support women's diverse career paths through the platform economy. At the same time, labor-rights protection

should be improved so that flexible employment does not become a cover for informal employment, and women's income stability and social security under new employment forms should be protected.

Fifth, policy should pay closer attention to women workers' welfare protection and labor rights. Compared with men, women tend to allocate time saved by AI to additional work rather than leisure, which may increase work pressure and health risks. Policy should therefore emphasize women's workplace welfare, including health protection, working-time management, rest and leisure rights, and equal labor conditions and social security as women face new opportunities from technological progress. Psychological-health support and career-development pathways for women should also be strengthened so that women do not bear excessive burdens during technological adaptation and can receive adequate social protection and welfare support in new employment forms.

Endnotes

1. 2024 China New Flexible Employment Report.

2. Source: The Practice and Achievements of China in Promoting Women's All-Round Development in the New Era, a white paper released by the State Council Information Office on September 19, 2025.

3. Exiting the labor market refers to not engaging in any form of work, not actively looking for work in the past month, and being unable or unwilling to start work within the near term, usually two weeks, even if a job opportunity exists. This status usually corresponds to retirement, inactivity, voluntary withdrawal, or other non-labor-supply states.

4. An individual is coded as employed if any of the following applies: (1) the person worked at least one hour in the past week; (2) the person did not actually work but was on leave, sick leave, temporary leave, or temporarily away because of schooling or training and could return to the original position within a definite time or within six months; or (3) the person did not actually work because of seasonal suspension, such as the slack season for self-employment or agricultural work. An individual who does not satisfy the employed definition is coded as unemployed if the person looked for work in the past month and could start work within two weeks if a job opportunity became available.

5. The first batch of new-generation AI pilot zones established in 2020 included Beijing, Shanghai, Tianjin, Shenzhen, Hangzhou, Hefei, Huzhou, Chongqing, Chengdu, Xi'an, Jinan, Guangzhou, and Wuhan. The second batch established in 2022 included Suzhou, Changsha, Zhengzhou, Shenyang, and Harbin. Because CFPS public-use data remove identifying information below the provincial level, such as detailed addresses and employers, individuals in provinces containing new-generation AI pilot zones are treated as the treatment group.

6. Occupations are classified by the female worker share. Occupations with a female share below 30 percent are male-dominated; those with a female share between 30 and 60 percent are gender-neutral; and those with a female share above 60 percent are female-dominated.

7. CFPS asks respondents about educational expectations. Response options include no schooling, primary school, junior secondary school, senior secondary school, junior college, undergraduate education, master's degree, and doctoral degree.

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