Artificial Intelligence and Labor Income Share: Labor Substitution or Technological Complementarity?

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Abstract: The rapid advancement and widespread diffusion of artificial intelligence (AI) are transforming labor markets and reshaping traditional patterns of factor income distribution. Using textual data from annual reports of Chinese listed firms and AI-related regulatory documents, this paper constructs a firm-level measure of AI adoption and examines its impact on the labor income share. Results show that AI significantly increases labor's share within firms, with a 10-percentage-point rise in AI intensity linked to a 2.3-percentage-point gain—around 17% relative to the sample mean. Mechanism analyses reveal no evidence of capital-labor substitution but point to capital-skill complementarity, with heterogeneous effects across skill groups. The effect is stronger among rank-and-file workers, in less labor-intensive industries, and in regions with more advanced industrial structures.

Keywords: artificial intelligence; labor income share; capital-labor substitution effect; capital-skill complementarity effect

1. Introduction

With the rapid advancement and widespread adoption of next-generation information technologies, AI (AI) is increasingly integrated into the real economy and emerging as a key driver of high-quality economic growth. The rapid development of AI (AI) technologies is not only reshaping the dynamics of economic growth but also exerting a profound impact on traditional labor market structures and patterns of factor income distribution. Existing literature primarily focuses on AI’s impact on aggregate social labor demand (Acemoglu & Restrepo, 2018a),substitution effects on different types of labor (Frank et al., 2019), and shocks to macroeconomic factor distribution patterns (Acemoglu, 2025). Existing literature examines AI's impact on labor income share, but empirical findings remain highly divergent. The central debate depends on whether AI acts primarily as labor-substituting technology or a productivity-enhancing tool—each implying opposite effects on labor income share.

On one hand, some studies argue that AI displaces human labor by automating routine and low-skill tasks, thereby reducing labor demand, depressing wages, and ultimately lowering labor’s share of income (Acemoglu & Restrepo, 2018a; Frey & Osborne, 2017; Raj & Seamans, 2018). On the other hand, other scholars contend that AI enhances worker productivity—particularly that of high-skilled labor—facilitates the creation of new job categories, and contributes to wage growth, thereby mitigating or even reversing the decline in labor income share (Aghion et al., 2017; Furman & Seamans, 2019; Graetz & Michaels, 2018). Overall, most studies rely on regional- or industry-level proxies for AI development when examining its relationship with labor income share. However, such aggregate approaches are limited in their ability to systematically identify and compare the two core micro-level mechanisms through which AI affects labor income share: the capital-labor substitution effect and the capital-skill complementarity effect. As a result, they tend to offer one-dimensional explanations and overlook firm-level heterogeneity in technology adoption, job restructuring, and labor productivity (Raj & Seamans, 2018). This limitation obscures AI's divergent impacts on labor income share across organizational and technological contexts.

Building on these considerations, this paper leverages textual data from annual reports of Chinese listed companies and AI-related normative documents issued by the State Intellectual Property Office to construct firm-level measures of AI application. It then examines the impact of AI adoption on labor income share and the underlying mechanisms at the micro-enterprise level. Empirical results demonstrate that AI technology significantly increases corporate labor income share. Economically, a 10-percentage-point rise in AI application intensity corresponds to an approximately 2.3-percentage-point increase in labor income share, equivalent to 17.37% of the sample mean. These findings remain robust after addressing endogeneity concerns, using alternative measurement and conducting additional robustness checks. Mechanism analysis indicates that AI primarily enhances labor income share through capital-skill complementarity rather than capital-labor substitution, evidenced by limited displacement of low-skilled labor and substantial growth in the scale and share of high-skilled labor, consistent with skill-biased technological change theory. Heterogeneity analysis further shows that AI significantly increases the labor income share of rank-and-file employees, with minimal effects on executives, and exerts stronger positive impacts in non-labor-intensive industries and regions experiencing advanced industrial upgrading.

This study makes three primary contributions. First, it constructs novel firm-level AI application measures using textual data, overcoming prior reliance on macro-level proxies that yield mixed results due to coarse granularity and confounding factors. Prior empirical work predominantly relies on macro-level indicators—such as regional or industry-level composite indices or AI patent counts—or focuses on specific application scenarios (Beraja et al., 2023; Damioli et al., 2021). These approaches suffer from coarse measurement and confounding macro factors, yielding mixed results with insufficient micro-foundations to establish causality. Second, this paper systematically disentangles the micro-level mechanisms linking AI adoption to labor income share by concurrently examining the capital-labor substitution effect and the capital-skill complementarity effect. It further highlights heterogeneous impacts of AI on high-skilled versus low-skilled labor employment, consistent with the skill-biased technological change framework (Piva et al., 2005). The empirical findings suggest AI in emerging economies remains at a non-autonomous stage without direct low-skilled job substitution (Ide & Talamas, 2024). Third, the study explores firm-level heterogeneity across job hierarchies, factor intensities, and industrial structures, illuminating AI's nuanced productivity effects and broader socioeconomic implications.

The remainder of the paper proceeds as follows: Section 2 reviews literature and develops hypotheses; Section 3 outlines empirical strategy; Section 4 presents results and mechanisms; Section 5 concludes with policy insights.

2. Literature Review and Research Hypotheses

The theory of biased technological change provides a key conceptual framework for analyzing the distributional effects of AI. As a capital-augmenting technology, AI tend to substitute for younger, less-educated, and low-skilled workers while enhancing efficiency. This creates uneven labor market impacts, disproportionately affecting non-skilled labor (Frey & Osborne, 2017; Sachs & Kotlikoff, 2012). Conversely, as a labor-augmenting technology, AI fosters new occupations in data analysis, system architecture, and human-machine interaction. While automating existing tasks, it simultaneously boosts productivity and generates new job categories, driving structural shifts in the labor market (Allam, 2016; Bessen, 2018; Brynjolfsson et al., 2021).

Current empirical AI research predominantly uses industrial robot data or automation indicators, centering on automation's economic implications. In literatures, a prevailing finding is that robot adoption tends to raise the capital share while reducing the labor income share(Autor & Salomons, 2018; Brynjolfsson et al., 2014; DeCanio, 2016; Dinlersoz & Wolf, 2024). However, this conclusion relies on industry-level manufacturing studies, limiting generalizability to broader AI applications across sectors and firms.

Emerging evidence suggests declining labor income share is not inevitable as understanding of industrial AI applications deepens. Some studies argue that the reduction in labor share represents a short-term adjustment driven by automation, particularly through industrial robots. In the long run, robot adoption may enhance productivity, expand production scale, and create new jobs, thereby increasing labor demand and wages while stabilizing the distribution of factor income (Acemoglu & Restrepo, 2018b; Brynjolfsson et al., 2021). Importantly, the impact of AI on labor income share is not linear but depends on the nature of the tasks AI interacts with. While AI can substitute for specific job tasks, this substitution may allow workers to shift toward complementary tasks, mitigating overall displacement effects (Hampole et al., 2025). Moreover, the degree of substitution varies across industries and skill levels: in high-tech or creative occupations, AI tends to complement labor, increase relative demand for skills, and raise wage premiums—ultimately contributing to a higher labor income share (Fan et al., 2025). Based on this theoretical background, the following hypothesis is proposed:

H1. The application of AI technology leads to an increase in corporate labor income share.

The relationship between AI and biased technological change is inherently complex, involving both substitution and complementarity effects. Whether AI functions as a capital-augmenting or labor-augmenting technology depends critically on the elasticity of substitution between capital and labor (Acemoglu & Guerrieri, 2008; Aghion et al., 2017). As a new general-purpose technology, AI inevitably transforms both production processes and production relations, manifesting in capital–labor substitution effects and capital–skill complementarity effects.

On one hand, the application of AI increases automation and replaces certain forms of labor through capital–labor substitution (Acemoglu & Restrepo, 2018b). While this may reduce long-term demand for non-AI tasks, current evidence suggests it has not led to significant employment losses at the industry level (Acemoglu et al., 2022). Substitution effects are particularly salient in routine-intensive occupations—for example, when assembly line workers are replaced by unmanned systems or administrative support is automated via intelligent platforms. Yet task-level complementarities prevent widespread job loss. In fact, in highly automated positions, AI's productivity gains can increase short-term labor demand—creating complementarities that offset substitution and drive net employment growth (Felten et al., 2019).

On the other hand, AI adoption drives technological upgrading, increasing demand for high-skilled labor through capital-skill complementarity and raising labor income share (Fan et al., 2025). These effects are particularly prominent in non-routine and cognitive-intensive tasks, such as those undertaken by engineers, programmers, and data scientists. These high-skilled workers—owing to their specialized knowledge—form effective complementarities with AI systems. In practice, as firms adopt AI to restructure production and marketing, this often requires additional investment in complementary resources, including skilled personnel (Acemoglu et al., 2022). Initial AI deployment necessitates engineers for system maintenance and experts for algorithm optimization—essential for realizing AI's potential. This demand for skilled labor can increase labor income share, especially in digitally transforming or tech-intensive firms. (Aghion et al., 2020). Based on the above analysis, this paper proposes the following hypotheses:

H2. Current applications of AI do not exhibit capital–labor substitution effects and therefore do not result in a decline in corporate labor income share.

H3. The application of AI exhibits capital–skill complementarity effects, thereby contributing to an increase in corporate labor income share.

3. Research Design

3.1 Data Sources

This study uses Chinese A-share listed firms from 2008 to 2022, combining data from four sources: firm fundamentals and geographic coordinates from CSMAR/Wind; AI application metrics constructed via textual analysis of annual reports sourced from Shanghai/Shenzhen stock exchanges; full-text patent data (including classifications) from China's State Intellectual Property Office; and regional characteristics from the China City Statistical Yearbook, supplemented by provincial statistical bureaus for missing values.

The sample is filtered by excluding: (1) financially abnormal ST/*ST firms; (2) financial sector firms due to distinct characteristics; (3) firms with negative net assets; (4) observations with missing key variables; (5) firm-years with anomalous compensation disclosures (employee wages > executive compensation). All continuous variables are winsorized at 1%/99% levels. The final dataset contains 34,105 firm-year observations.

3.2 Variable Definitions

3.2.1 Artificial Intelligence Application

Existing literature predominantly measures AI application or robot usage at regional or national macroeconomic levels (Beraja et al., 2023). Micro-level empirical studies are relatively scarce and often rely on proxies such as information assets or industrial robot counts to capture firm-level AI adoption (Graetz & Michaels, 2018). However, these measures face notable limitations: information asset proxies suffer from confounding macro-level regional factors, obscuring AI's causal impacts and micro-mechanisms at firms. Industrial robot data (e.g., IFR-sourced) are imperfect firm-level AI proxies, as industries increasingly rely on AI algorithms over physical robots, thus robot counts alone understate AI's economic impact.

Some studies use surveys or case studies, measuring AI adoption through indicators like IT investments or IT staff numbers (Beaudry et al., 2010; Michaels et al., 2014). These measures risk significant measurement error, as general IT infrastructure (like hardware or IT staff) reflects basic digitalization, not necessarily AI adoption. Additionally, survey data often lack breadth, limiting large-scale analysis of AI's impact.

To address these issues, this study constructs a relatively objective and comprehensive "AI technology" terminology dictionary based on the keyword descriptions of AI technology in the *Key Digital Technology Patent Classification System (2023)* released by the State Intellectual Property Office in 2023. Using textual analysis methods, we batch-extract the frequency of AI technology-related keywords appearing in the "Management Discussion and Analysis (MD&A)" section of annual reports, constructing a measurement indicator reflecting the degree of enterprise AI application. The specific steps are as follows:

Step 1: Collection and Processing of Listed Company Annual Reports. We utilized Python to collect and organize all annual reports of Shanghai and Shenzhen A-share listed companies from 2008 to 2022. For cases with updated or revised reports, the latest version was used, yielding a total of 45,100 annual reports. The MD&A sections were extracted as the textual analysis corpus. We use the MD&A section because it offers focused disclosures on operations, performance, strategy, and social responsibility, providing key business insights. Unlike full annual reports, it excludes financial statements and audit opinions, improving measurement precision of AI applications.

Step 2: Construction of "AI Technology". Due to the absence of a unified AI terminology dictionary, this study builds one based on the detailed AI technology keyword classifications in the 2023 Key Digital Technology Patent Classification System, a normative document issued by the State Intellectual Property Office. This system categorizes AI technology into three primary branches (hardware platforms, general technologies, key technologies), 14 secondary branches, and 27 tertiary branches, with extensive keyword coverage. The resulting 221-term dictionary enables precise identification of AI technologies while distinguishing them from non-AI technologies (e.g., industrial robots). Using an authoritative source ensures objective term selection, reducing researcher bias prevalent in prior studies.

Step 3: Construction of Enterprise AI Application Degree Indicators. Using Python's "jieba" word segmentation tool, we segmented the MD&A text, pre-loading the AI terminology dictionary as proper nouns to improve accuracy. We then counted the total frequency of AI-related keywords per firm per year. To address the right-skewed distribution of these counts, we applied a log transformation after adding 1, yielding the indicator lnAI. A higher lnAI value indicates a higher level of AI application within the firm.

3.2.2 Labor Income Share

Existing studies typically measure labor income share as the ratio of labor compensation to enterprise value-added. However, methodological differences persist regarding the precise calculation using financial report data from listed firms. Broadly, two calculation approaches dominate the literature. The first approach measures labor income share as the ratio of employee cash compensation to total operating revenue (Autor et al., 2020). The second approach measures labor income share as labor compensation divided by value-added, where value-added comprises labor compensation, operating surplus (revenue minus costs), fixed asset depreciation, and net production taxes (business taxes plus VAT minus subsidies) (Koh et al., 2020). We use the ratio of listed companies' current "cash paid to and for employees" to "total operating revenue" (*LS*) to measure labor income share. Logarithmic transformation is employed to eliminate estimation bias caused by measurement indicator fluctuations within the [0,1] interval, specifically using the natural logarithm of *LS*/(1-*LS*), denoted as *LNLS*.

3.2.3 Control Variables

A series of control variables are included in the model, and measurement methods are detailed in Table 1. Additionally, to control for potential impacts, the regression analysis also controls for firm effects (*Firm*), year effects (*Year*), industry effects (*Industry*), and regional effects (*Province*).

Table 1: Variable Definitions

Type	Symbol	Name	Measurement Method
Explanatory Variable	*lnAI*	AI Application Level	Natural logarithm of total AI-related word frequency in MD&A plus 1
Dependent Variables	*LS*	Labor Income Share	Ratio of labor compensation to total operating revenue
	LNLS	Logarithm of Labor Income Share	*Ln[LS/(1-LS)]*
Control Variables	*Asset*	Firm Size	Natural logarithm of total assets
	Age	Firm Age	Natural logarithm of years since listing
	Leverage	Asset-Liability Ratio	Ratio of total liabilities to total assets
	ROA	Return on Assets	Ratio of net profit to total assets
	Return	Profitability	Ratio of net profit to operating revenue
	Cashflow	Cash Flow	Ratio of net cash flow to total assets
	Cl	Capital Intensity	Ratio of total assets to operating revenue
	Ky	Capital-Output Ratio	Ratio of net fixed assets to operating revenue
	Indep	Independent Director Ratio	Proportion of independent directors on the board
	Ownership	Ownership Concentration	Sum of shareholding ratios of top 5 circulating shareholders
	Dual	CEO-Chairman Duality	Dummy variable: 1 if chairman serves as CEO, 0 otherwise
	Soe	Ownership Type	Dummy variable: 1 if state-owned enterprise, 0 otherwise
	HHI	Industry Competition	Herfindahl-Hirschman Index: sum of squared market shares within industry
	GDP	Economic Development Level	Natural logarithm of provincial GDP per capita
	IS	Regional Industrial Structure	Share of secondary industry in provincial GDP

3.3 Model Specification

To examine the impact of AI Application degree on firm Labor Income Share, this study employs the following model for baseline regression testing:

$$LS_{injt} = \alpha_0 + \alpha_1 lnAI_{injt} + Controls_{injt} + Firm_i + Year_t$$
$$+Industry_n + Province_j + \varepsilon_{injt} \qquad (1)$$

Where *i* represents listed companies, t represents years, n represents industries, and j represents provinces; the dependent variable LS_{injt} represents the Labor Income Share of company i in year t; the core explanatory variable $lnAI_{injt}$ represents the micro-enterprise level AI Application degree, specifically the natural logarithm of the total frequency plus one of AI technology-related keywords appearing in the "Management Discussion and Analysis (MD&A)" section of listed company annual reports; $Controls_{injt}$ represents control variables at the enterprise, industry, and regional levels; $Firm_i$, $Year_t$, $Industry_n$, and $Province_j$ represent fixed effects at the company, year, industry, and regional levels respectively to control for the influence of other unobservable factors; ε_{injt} represents the random error term, with standard errors clustered at the firm level for robust treatment.

4. Empirical Results Analysis

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics for the main variables. After data processing, the final sample comprises 34,105 firm-year observations covering most Shanghai and Shenzhen A-share listed companies from 2008 to 2022. The labor income share (*LS*) exhibits a mean of 0.1323 and a standard deviation of 0.0933. The AI application intensity ($lnAI$) shows a mean of 0.9174 and a standard deviation of 1.2067, indicating substantial heterogeneity in AI adoption across sample firms.

Table 2 Descriptive Statistics

Symbol	Variable	Obs.	Mean	Std. Dev.	Min	Max
lnAI	AI Application Level	34,105	0.9174	1.2067	0	4.5326
LS	Labor Income Share	34,105	0.1323	0.0933	0.0123	0.5541
LNLS	Logarithm of Labor Income Share	34,105	-2.1144	0.8330	-4.3824	0.1349
Asset	Firm Size	34,105	22.1187	1.2947	19.7696	26.1661
Age	Firm Age	34,105	2.0103	0.9406	0	3.3322
Leverage	Asset-Liability Ratio	34,105	0.4219	0.2077	0.0505	0.8929
ROA	Return on Assets	34,105	0.0402	0.0592	-0.2238	0.2014
Return	Profitability	34,105	0.0769	0.1575	-0.7837	0.4958
Cashflow	Cash Flow	34,105	0.1700	0.1350	0.0108	0.6668
Cl	Capital Intensity	34,105	2.4418	1.9644	0.4010	12.9455
Ky	Capital-Output Ratio	34,105	0.4883	0.5791	0.0053	3.6701
Indep	Independent Director Ratio	34,105	37.4089	5.3212	28.57	57.14
Ownership	Ownership Concentration	34,105	54.1226	15.3936	20.2669	88.7396
Dual	CEO-Chairman Duality	34,105	0.2813	0.4497	0	1
Soe	Ownership Type	34,105	0.3831	0.4861	0	1
HHI	Industry Competition	34,105	0.2017	0.1786	0.0380	1
GDP	Economic Development Level	34,105	11.0953	0.5316	9.1796	12.1564
IS	Regional Industrial Structure	34,105	0.4082	0.0927	0.1587	0.6196

4.2 Benchmark Regression Analysis

Table 3 reports the benchmark regression results examining the impact of AI application on firms' labor income share. The univariate tests in columns (1) and (4) show that the coefficient of *lnAI* is significantly positive at the 1% level. Columns (2) and (5) present results after including control variables, while columns (3) and (6) incorporate control variables along with firm, year, industry, and regional fixed effects. The coefficient of *lnAI* remains significantly positive across all specifications, indicating that corporate AI adoption significantly raises labor income share. Specifically, column (3) shows that the coefficient of lnAI on *LS* is 0.0023. From an economic perspective, a 10% upgrading in AI application would increase the firm's labor income share by 2.3% approximately, representing a 17.37% improvement relative to the sample mean ([(0.0023×10)/0.1323]×100%). These findings demonstrate that AI technology significantly increases firms' labor income share, supporting Hypothesis 1 proposed earlier.

Table 3 Regression Results of AI Technology and Corporate Labor Income Share

Variables	（1）	（2）	（3）	（4）	（5）	（6）
	LS	*LS*	*LS*	*LNLS*	*LNLS*	*LNLS*
lnAI	0.0166***	0.0150***	0.0023***	0.1578***	0.1490***	0.0155**
	（17.77）	（17.32）	（4.62）	（21.20）	（21.32）	（3.63）
Asset		-0.0163***	-0.0214***		-0.1558***	-0.2030***

		(-14.52)	(-13.02)		(-14.63)	(-31.89)
Age		0.0000 (0.02)	0.0079*** (5.58)		0.0000 (0.00)	0.0763*** (6.27)
Leverage		-0.0713*** (-10.10)	-0.0190*** (-3.27)		-0.8269*** (-12.99)	-0.2387*** (-5.00)
ROA		0.0325 (1.19)	-0.0349* (-1.87)		-0.2272*** (-1.00)	-1.0711*** (-7.73)
Return		-0.0919*** (-8.69)	-0.0603*** (-7.65)		-0.4495*** (-5.63)	-0.1019** (-1.99)
Cashflow		0.0630*** (7.17)	-0.0010 (-0.19)		0.3691*** (5.47)	-0.0508 (-1.32)
Cl		0.0107*** (14.17)	0.0150*** (19.88)		0.2350*** (36.65)	0.1792*** (34.94)
Ky		0.0096*** (4.68)	0.0175*** (7.45)		0.0806*** (13.27)	0.1370*** (23.79)
Indep		0.0215*** (8.28)	0.0201*** (7.45)		0.2544*** (10.87)	0.1607*** (7.92)
Ownership		-0.0000 (-0.29)	0.0001 (1.43)		0.0001 (0.20)	0.0009 (1.34)
Dual		0.0051** (2.33)	0.0024** (1.98)		0.0565*** (2.96)	0.0237** (2.27)
Soe		0.0106*** (3.96)	0.0027 (0.85)		0.1022*** (3.87)	0.0610** (2.35)
HHI		0.0242*** (2.57)	0.0038 (0.79)		0.1288** (2.33)	0.0615* (1.66)
GDP		0.0182*** (7.41)	0.0040 (0.42)		0.1463*** (6.36)	0.0400 (0.49)
IS		-0.0655*** (-4.06)	-0.0118 (-0.41)		-0.5338*** (-3.86)	-0.1194 (-0.46)
Firm/Year/Industry/Province Fixed Effects	No	No	Yes	No	No	Yes
Observations	34,105	34,105	34,105	34,105	34,105	34,105
Adjusted R^2	0.0461	0.2704	0.3894	0.0522	0.2967	0.4218

*Note: Figures in parentheses represent cluster-robust standard errors at the firm level. ***, *, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The same applies to subsequent tables.

4.3 Endogeneity Treatment

4.3.1 Instrumental Variable Tests.

We adopts the instrumental variable approach following existing literature, and selecting two instrumental variables that consider both industry relevance and historical exogenous shocks:

First, we use the average AI application intensity of other firms in the same industry and region as an instrumental variable (*IV1*). Specifically, we calculate the mean AI application level of other firms in the same year, industry, and registered province, excluding the focal firm itself. Regional economic agglomeration effects and inter-firm interactions influence the specific firm's AI adoption level through spillovers from other local firms, satisfying the relevance condition. However, AI adoption by other local firms in the same industry does not directly affect the target firm's internal income distribution structure, satisfying the exogeneity condition.

Second, we construct an AI instrumental variable based on historical treaty port events during the Qing Dynasty (Fan et al., 2013). We use the interaction between whether treaty ports were opened in an enterprise's city from 1840 to the end of the Qing Dynasty and the natural logarithm of the number of AI enterprises nationwide in year t-1 from the sample as instrumental variable IV2. Whether a city was historically designated as a treaty port may influence regional technology absorption capacity but does not directly affect current labor income share of local enterprises. Meanwhile, the national number of AI enterprises represents the overall development and application trajectory of the AI industry, thus satisfying both relevance and exogeneity conditions.

After conducting weak instrument tests and over-identification tests, Table 4 reports the two-stage least squares (*IV-2SLS*) estimation results. Column (1) shows that both *IV1* and *IV2* are significantly positive in the first-stage regression, while column (2) demonstrates that the coefficient of *lnAI* remains significantly positive, supporting the conclusion that AI promotes increasing in firms' labor income share.

Table 4 The Result of Instrumental Variable Tests

Variables	First Stage	Second Stage	
	(1)	(2)	(3)
	lnAI	*LS*	*LNLS*
lnAI		0.0262* (1.90)	0.1660 (1.44)
IV1	0.1654*** (10.77)		
IV2	0.0396** (2.01)		
Control Variables	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes
Observations	25,033	25,033	25,033
Adjusted R^2	0.2941	0.0742	0.1606

4.3.2 Exogenous Event Shock Test

Furthermore, we employ China's "Intelligent Manufacturing Development Strategy" as a quasi-natural experiment, using the difference-in-differences (DID) method to address potential endogeneity issues. On May 19, 2015, the State Council officially issued "Made in China 2025," launching the intelligent manufacturing development strategy. Compared to previous industrial policies, this strategy iming to achieve breakthrough development in ten key sectors by 2025, and significantly promoting intelligent transformation in key industries and providing support for enterprises to apply AI technology. he ten key industries include: next-generation information technology, high-end CNC machine tools and robotics, aerospace equipment, marine engineering equipment and high-tech ships, advanced rail transportation equipment, energy-saving and new energy vehicles, power equipment, agricultural machinery, new materials, and biomedicine and high-performance medical devices. We employ the following DID model to test the impact:

$$LS_{injt} = \beta_0 + \beta_1 Treat_{inj} \times After_t + Controls_{injt} + Firm_i + Year_t + Industry_n + Province_j + \varepsilon_{injt} \tag{2}$$

Where $Treat_{inj}$ is the identification indicator for treatment and control groups: firms in the ten key industries are classified as the treatment group (Treat = 1), otherwise control group (Treat = 0). $After_t$ is a dummy variable identifying periods before or after the policy. It takes the value 1 for samples from 2015 and later, and 0 for samples before 2015. We focus on the coefficient of the interaction term $Treat_{inj} \times After_t$.

Table 5 presents the test results. Columns (1) and (2) show DID model estimates, where the coefficient of the interaction term *Treat×After* is significantly positive. Columns (3) and (4) present PSM-DID method results. The results also supports the robustness of the core finding.

Table5 Regression Results of DID Model

Variables	DID Estimation		PSM-DID Estimation	
	(1)	(2)	(3)	(4)
	LS	*LNLS*	*LS*	*LNLS*
Treat×After	0.0069*** (3.48)	0.0512*** (2.98)	0.0075** (3.78)	0.0535* (3.10)
Control Variables	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes
Observations	34,105	34,105	33,243	33,243
Adjusted R^2	0.3892	0.4218	0.3839	0.4211

4.4 Additional Robustness Tests

4.4.1 Alternative AI Application Measurement Indicators

The above measurement of AI application is based on two fundamental assumptions: first, the MD&A section of listed companies' annual reports objectively reflects actual operational conditions, and the frequency of AI-related keywords adequately captures the degree of AI application; second, the AI terminology dictionary constructed through text analysis methods is relatively accurate and appropriate for identifying AI-related semantics in textual information. Considering these two aspects, this study employs multiple verification methods to replace AI measurement indicators and further test the robustness of regression results.

Firstly, for avoiding potential impacts of different word frequency counting ranges on research results, we identify and count the total frequency of AI keywords appearing in the full annual report text, and use the natural logarithm of word frequency plus one (*lnAI_FT*) to reflect firms' AI application intensity. Regression results in columns (1) and (2) of Table 6 show that the coefficient of *lnAI_FT* remains significantly positive at the 1% level.

Secondly, to test the sensitivity of our main conclusions to AI keyword selection, we build a second version of the terminology dictionary based on semantic expressions in all national-level AI-related policy documents. We obtain the word frequency and get the natural logarithm of this value plus one (*lnAI_2*) representing firms' AI application intensity. Regression results in columns (3) and (4) of Table 6 are significant, indicating that our main research conclusions do not depend on the specificity of keyword selection.

Finally, we use the number of AI patent as a proxy variable for firms' AI technology level. Through the patent classifications (IPC codes) and keywords related to AI technology in the "Key Digital Technology Patent Classification System (2023)," we precisely identify the number of AI patents applied by listed companies each year, using the natural logarithm of this value plus one (*lnAI_patent*). Using patent data for verification provides mutual validation with AI technology levels disclosed in annual reports, avoiding impacts of factors such as firms "talking without doing" or "following trends with exaggeration" on research results. Regression results in columns (5) and (6) of Table 6 further supporting our main research conclusions.

Table 6 Robustness Test with Alternative AI Technology Measures

Variables	(1) LS	(2) LNLS	(3) LS	(4) LNLS	(5) LS	(6) LNLS
lnAI_FT	0.0031*** (5.55)	0.0233*** (4.89)				
lnAI_ 2			0.0022*** (4.76)	0.0163** (4.01)		
lnAI_patent					0.0025*** (3.95)	0.0227*** (4.51)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,105	34,105	34,105	34,105	34,105	34,105
Adjusted R^2	0.3903	0.4227	0.3894	0.4219	0.3890	0.4219

4.4.2 Alternative Labor Income Share Calculation Methods

To test the sensitivity of our main results to the dependent variable indicator, we employ different methods to measure firms' labor income share. We calculate the labor income share (*LS_2*) measured as the ratio of labor compensation to firm value-added (the sum of four components: labor compensation, operating surplus, fixed asset depreciation, and net production taxes). Additionally, some studies argue that net production taxes belong to government revenue and should be excluded when calculating firm value-added (Smith et al., 2019), hence we also calculate labor income share (*LS_3*) using firm value-added after removing net production taxes. Similarly, to eliminate estimation bias caused by these two indicators fluctuating within the [0,1] interval, we apply logarithmic transformation to obtain *LNLS_2* and *LNLS_3* as auxiliary robustness checks.

Table 7 presents the results. Columns (1) and (2) use labor income share calculated through the value-added method as the dependent variable, while columns (3) and (4) use the labor income share calculated after removing net production taxes from firm value-added. With controlling variables and fixed effects, the coefficients of lnAI are all significantly positive. The promoting effect of AI adoption on firms' labor income share remains statistically.

Table 7 Robustness Tests with Alternative AI Technology Indicators

Variables	(1) LS_2	(2) LNLS_2	(3) LS_3	(4) LNLS_3
lnAI	0.0038*** (5.30)	0.0182*** (5.03)	0.0036*** (4.91)	0.0174*** (4.88)
Control Variables	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes
Observations	34,059	33,949	34,059	33,949
Adjusted R^2	0.3837	0.3962	0.3886	0.4020

4.4.3 Excluding Information Technology Service Company Samples

Considering that the business scope of information technology service companies may encompass cutting-edge digital technologies such as internet, big data, and AI. Therefore, we exclude companies in information transmission, software, and information technology services industries and re-conduct the analysis. Table 8 shows that after removing information technology service company samples, the results obtained from adjusting sample are consistent with previous findings.

Table 8 Regression Tests Excluding Information Technology Service Companies

Variables	(1) *LS*	(2) *LNLS*
lnAI	0.0016** (3.30)	0.0125*** (2.89)
Control Variables	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes
Observations	31,896	31,896
Adjusted R^2	0.4105	0.4320

5. Mechanism Analysis

The theoretical analysis presented earlier suggests that AI application may influence firms' labor income share through "Capital-Labor Substitution Effects" and "Capital-Skill Complementarity Effects". This study employs models 3 and 4 to examine the mechanisms:

$$Mediator_{injt} = \gamma_0 + \gamma_1 lnAI_{injt} + Controls_{injt} + Firm_i + Year_t + Industry_n + Province_j + \varepsilon_{injt} \quad (3)$$

$$LS_{injt} = \delta_0 + \delta_1 lnAI_{injt} + \delta_2 Mediator_{injt} + Controls_{injt} + Firm_i + Year_t + Industry_n + Province_j + \varepsilon_{injt} \quad (4)$$

We focus on the regression coefficient γ_1 in model 3 and coefficients δ_1 and δ_2 in model 4, where the former tests the impact of AI technology on the mechanism channels, and the latter examines how the mechanism channels affect firms' labor income share.

5.1 Capital-Labor Substitution Effect

As AI technology elevates machinery intelligence and automation levels to new stages, unmanned factories, unmanned warehouses, and unmanned delivery systems are becoming widely applied and promoted. Machines can now conduct production activities with minimal human intervention and can even autonomously optimize their programs. If AI technology further enhances machines' automated production capabilities, it would increase capital factor input shares and relatively reduce labor factor input shares through "Capital-Labor Substitution Effects". Conversely, if no significant substitution effect exists, this would suggest that AI applications remain at the stage of augmenting labor tasks rather than causing declines in labor income share or reductions in workforce scale.

To identify and test whether "Capital-Labor Substitution Effects" exist, we use the natural logarithm of firms' net fixed assets divided by total employees *(ln_kl)* to examine the impact. Table 9 presents the regression results. Column (1) shows that AI application significantly reduces firms' fixed capital per worker. Columns (2) and (3) demonstrate that when controlling for firms' capital per worker, the coefficient of *lnAI* decreases compared to benchmark results, and the impact of AI application on labor income share diminishes. This indicates that AI technology may elevate labor income share by reducing capital per worker in enterprises. This outcome indirectly proving that AI application has not triggered significant capital substitution for labor but instead drive a decline in fixed assets per employee.

The underlying reasons for this phenomenon may be twofold. On one hand, AI technology does not directly enhance corporate assets. In most cases, AI technology is not introduced as fixed assets, but rather applied as intangible assets such as intelligent platforms and systems, thus not being fully captured in the growth of corporate fixed assets. On the other hand, current AI technology not only fails to reduce labor but actually increases demand for other positions. In applying and promoting AI technology, enterprises often need to hire talent in related fields, such as engineers and experts to design and maintain intelligent systems. To test whether this logic holds, we use the measuring corporate fixed asset levels with the natural logarithm of net fixed assets (*Ln_FA*) and corporate employment with the logarithm of total employees (*Ln_Em*). Regression results are shown in columns (4) and (5) of Table 9. Column (4) indicates that AI application has no significant impact on corporate fixed asset changes, while column (5) shows that AI application significantly increases corporate employment.

Table 9 Mechanism Analysis：Capital-Labor Substitution Effect

Variables	（1） Ln_kl	（2） LS	（3） LNLS	（4） Ln_FA	（5） Ln_Em
lnAI	-0.0197*** （-3.21）	0.0020*** （4.03）	0.0124** （3.03）	-0.0001 （-0.01）	0.0184*** （3.76）
lnkl		-0.0186*** （-14.07）	-0.1552*** （-12.63）		
Control Variables	Yes	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	34,101	34,101	34,101	34,101	34,105
Adjusted R^2	0.3863	0.4214	0.4528	0.7014	0.5480

Meanwhile, considering the structural impact of AI on labor markets—specifically that high-skilled labor can match with capital while low-skilled Labor has more of a substitution relationship(Acemoglu, 2023). We measure firms' low-skilled labor scale (Low_scale) using the logarithm of total production, business, marketing, and financial personnel, and measure firms' low-skilled labor share (Low_share) as well. Table 10 presents the test results. AI application significantly reduces firms' low-skilled employment share but has no significant impact on low-skilled labor employment scale. AI has not caused large-scale reductions in low-skilled labor, but rather increased employment demand for corresponding high-skilled labor, thereby reducing the proportion of low-skilled workers in relative terms.

Table 10 Mechanism Analysis：impact of AI on Low-Skilled Labor

Variables	（1） Low_scale	（2） LS	（3） LNLS	（4） Low_share	（5） LS	（6） LNLS
lnAI	0.0059 （0.61）	0.0023*** （4.62）	0.0152*** （3.63）	-0.6697*** （-4.62）	0.0023*** （4.53）	0.0153*** （3.59）
Low_scale		0.0034*** （8.30）	0.0388*** （10.33）			
Low_share					-0.0001** （-2.08）	-0.0002 （-0.93）
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,105	34,105	34,105	34,105	34,105	34,105
Adjusted R^2	0.8586	0.3943	0.4304	0.7082	0.3897	0.4218

5.2 Capital-Skill Complementarity Effect

Enterprises are gradually incorporating intangible capital accumulated through big data, unstructured information, and AI technology into production factors. In this process, relative to low-skilled workers, high-skilled labor can more effectively form complementarity effects with capital due to their professional knowledge and skills. To test "Capital-Skill Complementarity Effects", we first incorporate digital intangible assets into models 3 and 4 for mechanism testing, then construct model 5:

$$LS_{injt} = \eta_0 + \eta_1 lnAI_{injt} + \eta_2 lnDA_{injt} \times Low\_scale_{injt} + \eta_3 lnDA_{injt} \times High\_scale_{injt} + Controls_{injt} + Firm_i + Year_t + +Industry_n + Province_j + \varepsilon_{injt} \quad (5)$$

Where $lnDA_{injt}$ represents the logarithm of digital intangible assets, and Low_scale and High_scale represent employment scales of firms' low-skilled and high-skilled labor. We measure firms' low-skilled labor scale using the logarithm of total production, business, marketing, and financial personnel, and measure firms' high-skilled labor scale using the logarithm of total technical and R&D personnel. We focus on regression coefficients η_2 and η_3 in model 5. Due to the differential complementarity between digitized intangible capital and varying skill types, their interaction term coefficients will also differ.

Table 11 presents the test results. AI application has a significantly positive correlation with firms' digitized intangible capital. And the interaction coefficient between high-skilled labor and digitized intangible capital is significantly positive, while the interaction coefficient between low-skilled labor and digitized intangible capital is negative and insignificant, which proving the existence of complementarity between assets and skills.

Table 11 Mechanism Analysis：Capital-Skill Complementarity Effect

Variables	（1） *Ln_DA*	（2） *LS*	（3） *LNLS*	（4） *LS*	（5） *LNLS*
lnAI	0.0470*** （4.22）	0.0017*** （3.38）	0.0112*** （2.61）	0.0013*** （2.64）	0.0074* （1.76）
Ln_DA		0.0058*** （7.64）	0.0575*** （8.44）	0.0033*** （4.25）	0.0331*** （4.77）
Ln_DA ×High_scale				0.0005*** （5.81）	0.0042*** （6.48）
Ln_DA ×Low_scale				0.0001 （1.37）	0.0011** （1.97）
Control Variables	Yes	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	26,918	26,918	26,918	26,918	26,918
Adjusted R^2	0.6488	0.4077	0.4477	0.4156	0.4577

Then, we conduct regression analysis using the logarithm of total technical and R&D personnel

(High_scale) and the ratio of technical and R&D personnel to total employees (High_share). Table 12 presents the test results. AI application increases high-skilled scale and raises high-skilled share, consistent with Table 10 results. Comprehensively, this indicates that current AI technology not only fails to reduce the overall scale of low-skilled labor but actually increases employment demand for high-skilled labor, thereby reducing the proportion of low-skilled labor and increasing the proportion of high-skilled labor.

Table 12 Mechanism Analysis：impact of AI on High -Skilled Labor

Variables	（1） *High_scale*	（2） *LS*	（3） *LNLS*	（4） *High_share*	（5） *LS*	（6） *LNLS*
lnAI	0.0655*** （6.98）	0.0020*** （4.11）	0.0123*** （2.95）	0.8041*** （6.99）	0.0021*** （4.28）	0.0141*** （3.31）
High_scale		0.0044*** （8.76）	0.0485*** （10.46）			
High_share					0.0002*** （3.61）	0.0017*** （3.53）
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,105	34,105	34,105	34,105	34,105	34,105
Adjusted R^2	0.8106	0.3967	0.4341	0.3746	0.3908	0.4229

6. Heterogeneity Analysis

6.1 Ordinary Employees vs. Corporate Executives

In further analyzing the heterogeneity of corporate labor income distribution, it can be divided into two main components: the labor income share of ordinary employees and the labor income share of corporate executives. The former is calculated using the following formula: (Cash paid to employees and payments made on behalf of employees + Ending payable employee compensation - Beginning payable employee compensation - Total executive compensation) / Total operating revenue, denoted as *LLS*, with the corresponding logarithmic transformation denoted as *LNLLS*. The latter is measured as the ratio of total executive compensation to total operating revenue, denoted as *MLS*, with the same transformation as *LNMLS*.

The heterogeneous effects are shown in Table 14. In columns (1) and (2), where the regression coefficients of variable *lnAI* are significantly positive at the 1% level, indicating that AI application has a pronounced positive effect on ordinary employees' labor income share. In columns (3) and (4), where the sign and significance of the regression coefficients of variable *lnAI* are not robust. The possible explanation is that corporate executives typically engage in production decision-making and strategic planning, which are less affected by AI technology.

Table14 Heterogeneity Analysis：Ordinary Employees vs. Corporate Executives

Variables	Ordinary Employees		Corporate Executives	
	（1）	（2）	（3）	（4）
	LLS	*LNLLS*	*MLS*	*LNMLS*
lnAI	0.0020*** (3.63)	0.0140*** (2.84)	-0.0000* (-1.65)	0.0060 (0.98)
Control Variables	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes
Observations	34,056	34,056	34,056	34,056
Adjusted R^2	0.3749	0.4753	0.3807	0.4119

6.2 Industries with Different Labor Intensity

Regarding industries with different labor intensity, labor-intensive industries typically rely heavily on labor in their production processes while having lower dependence on technology and equipment. Following the cluster analysis classification results of industry factor intensity, sample firms are categorized into labor-intensive and non-labor-intensive industries. Labor-intensive industries include agriculture, forestry, animal husbandry and fishery, mining and washing, textile and clothing, food and beverage, footwear, furniture manufacturing, food processing, wood processing and related products, printing, as well as catering and retail services. All other industries are classified as non-labor-intensive industries.

The impact of AI application on labor income share is not significant in labor-intensive industries, but the coefficient is significantly positive in non-labor-intensive industries, as it's shown in table 15. The Chow test also indicates that the impact exhibits statistically significant differences across the two subsamples. This result suggests that compared to labor-intensive industries, AI technology generates more significant "capital-skill" complementarity effects in non-labor-intensive industries, and non-labor-intensive industries should pay greater attention to the high-skilled labor employment demands brought by AI application.

Table15 Heterogeneity Analysis：Different Labor Intensity

Variables	*LS*		*LNLS*	
	（1）	（2）	（3）	（4）
	labor-intensive industries	non-labor-intensive industries	labor-intensive industries	non-labor-intensive industries
lnAI	0.0002 (0.26)	0.0024*** (4.42)	0.0007 (0.08)	0.0160*** (3.64)
Control Variables	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,813	25,292	8,813	25,292
Adjusted R^2	0.4458	0.3837	0.4626	0.4185
Chow Test	7.48		8.04	
P-Value	0.000***		0.000***	

6.3 Regional Industrial Structure

Considering the differences in industrial structure and human capital across regions, the impact of AI technology may vary at the geographical level. We use the ratio of tertiary industry output to secondary industry output for each province. This indicator reflects industrial structure upgrading through the relative development levels of the service and industrial sectors, where higher values signify deeper progression toward a service-oriented and knowledge-intensive regional economy. Based on the median annual industrial structure advancement index by province, we stratify enterprises into regions with relatively advanced industrial structures and those with less advanced industrial structures.

The subsample regression results are shown in Table 16. AI technology has a significant positive impact on firms' labor income share in provinces with relatively advanced industrial structures, while the impact is not significant in provinces with relatively less advanced industrial structures. The Chow test also confirms the regional differences. This phenomenon stems from the interplay between industrial upgrading patterns and AI's skill-biased progress. Industrial structure upgrading typically replaces labor/resource-intensive industries with technology/knowledge-intensive sectors. Regions with advanced industrial structures more effectively develop complementary relationships between AI and worker skills—such as AI-aided engineers optimizing designs or analysts enhancing decision-making efficiency. This synergy significantly boosts labor's marginal output value through a human capital multiplier effect, thereby raising labor income share.

Table16 Heterogeneity Analysis：Regional Industrial Structure

Variables	*LS*	*LNLS*

	（1）	（2）	（3）	（4）
	advanced industrial structures	less advanced industrial structures	advanced industrial structures	less advanced industrial structures
lnAI	0.0028*** (4.51)	0.0008 (1.25)	0.0193*** (3.81)	0.0060 (0.98)
Control Variables	Yes	Yes	Yes	Yes
Firm/Year/Industry/Province Fixed Effects	Yes	Yes	Yes	Yes
Observations	20,183	13,922	20,183	13,922
Adjusted R^2	0.3878	0.4228	0.4296	0.4447
Chow Test	2.59		2.69	
P-Value	0.000***		0.000***	

7. Conclusions

This study utilizes firm-level AI application metrics to examine its impact on corporate factor income distribution. The results demonstrate that AI technology significantly enhances firms' labor income share, a finding robust to endogeneity tests and sensitivity checks. Analysis reveals two primary channels for this effect: firstly, AI adoption has not triggered widespread capital-for-labor substitution, thus avoiding declines in labor income share; secondly, through a capital-skill complementarity effect, digital intangible assets increase the relative income share of high-skilled labor while simultaneously expanding their employment scale and occupational share. Heterogeneity analysis indicates the positive impact on labor income share is more pronounced among ordinary employees, firms in non-labor-intensive industries, and regions with advanced industrial structures.

As AI penetration deepens and evolves across industries, its influence may extend beyond technological substitution to reshape labor markets and factor allocation logic. To foster deep AI-real economy integration and build a development paradigm balancing efficiency with equitable distribution, high-level AI talent is crucial. Policymakers should intensify human capital investment by reforming higher education systems, expanding AI-related programs, and improving training quality to cultivate innovative, practice-ready professionals. Concurrently, attracting top domestic and international talent through diverse channels is essential to build a large, high-caliber workforce combining domestic cultivation and global recruitment. Furthermore, enterprises should be guided to strengthen labor protection systems, safeguarding workers' rights and enhancing welfare. Encouraging vocational training for low-skilled workers to bolster their human-machine collaboration capabilities and basic AI skills is vital to improve adaptability and competitiveness, mitigating potential substitution risks as AI capabilities advance.

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Appendix I: AI Terminology Dictionary Based on the Key Digital Technology Patent Classification System (2023)

Basic Terminology	Artificial Intelligence, AI
Artificial Intelligence Hardware Platforms	Intelligent Chip, Intelligent Integrated Circuit, AI Chip, Intelligent Microcontroller, Brain-Inspired Chip, GPU, Graphics Processing Unit, Image Processor, Vision Processor, Graphics Card Chip, Video Card Chip, ASIC, Application-Specific Integrated Circuit, Application-Specific Large-Scale Integrated Circuit, Application-Specific Integrated Chip, Application-Specific Chip, FPGA, Field-Programmable Logic Device, Field-Programmable Gate Array, Field-Programmable Logic Gate Array, Brain-Inspired Chip, Brain-Inspired Computer, Neural Chip, Neuromorphic, Memristor, NPU, Neural Network Processor
Artificial Intelligence General Technologies	Machine Learning, Reinforcement Learning, Deep Learning, Privacy Computing, Support Vector Machine, Decision Tree, Ensemble Learning, K-Nearest Neighbor Algorithm, Reinforcement Learning, Markov Model, Deep Q-Network, Policy Optimization, Multi-Agent System, Imitation Learning, A3C Algorithm, Deep Neural Network, Multilayer Neural Network, Convolutional Neural Network, Recurrent Neural Network, Knowledge Graph, Knowledge Fusion, Knowledge Extraction, Knowledge Processing, Ontology, Brain-Inspired Intelligent Computing, Brain Simulation, Neural Computing, Brain Model, Artificial Life, Synthetic Life, Virtual Biology, Quantum Intelligent Computing, Superconducting Quantum Processor, Ion Trap Quantum Processor, Silicon-Based Semiconductor Quantum Processor, Optical Quantum Processor, Quantum Machine Learning, Quantum Algorithm, Quantum Programming, Qubit, Quantum Mechanics, Pattern Recognition, Pattern Classification, Pattern Clustering, Signal Pattern Recognition, Object Recognition, Entity Recognition, Swarm Intelligence, Ant Colony Algorithm, Particle Swarm Algorithm, Bat Algorithm, Wolf Pack Algorithm, Fruit Fly Algorithm, Social Simulation, Virtual World, Hybrid Intelligence, Biological Intelligence, Machine Intelligence, Pet Robot, Humanoid Robot
Artificial Intelligence Key Technologies	Natural Language Processing, Semantic Processing, Machine Translation, Character Recognition, Grammatical Analysis, Word Frequency Statistics, Word Segmentation, Natural Language Query, Machine Question Answering, Machine Translation, Automatic Translation, Intelligent Translation, Language Converter, Literal Translation, Rule-Based Translation, Interlingua Translation, Neural Machine Translation, Semantic Understanding, Semantic Recognition, Semantic Analysis, Semantic Retrieval, Semantic Segmentation, Semantic Classification, Semantic Fusion, Intelligent Speech, Speech Sensing, Speech Recognition, Speech Synthesis, Voiceprint Recognition, Speech Retrieval, Voice Control, Voice Navigation, Voiceprint Recognition, Speech Coding and Decoding, Speech Enhancement, Speech Classification, Speech Synthesis, Waveform Concatenation, Neural Vocoder, Text-to-Speech Synthesis, Computer Vision, Image Sensing, Image Recognition, Image Generation, Image Enhancement, Image Retrieval, Image Detection, Image Discrimination, Image Classification, Image Extraction, Image Clustering, Image Matching, Image Semantic Segmentation, Image Enhancement, Image Sharpening, Image Contrast, Image Dynamic Range, Image Filtering, Image Correction, Image Standardization, Image Generation, Image Synthesis, Image Generative Adversarial Network, Animation Production, Image Reconstruction, Biometric Recognition, Fingerprint Recognition, Face Recognition, Iris Recognition, Voiceprint Recognition, DNA Recognition, Behavioral Feature Recognition, Arteriovenous Recognition, Liveness Detection, Fingerprint Input, Fingerprint Extraction, Fingerprint Classification, Fingerprint Verification, Facial Capture, Facial Extraction, Facial Recognition, Expression Recognition, Face Verification, Iris Detection, Retinal Detection, Iris Verification, Voice Recognition, Voiceprint Identification, Voiceprint Concatenation, Voiceprint Waveform, DNA Detection, DNA Encoding and Decoding, DNA Matching, DNA Identification, Motion Capture, Action Recognition, Behavior Monitoring, Virtual Reality, Augmented Reality, Head-Mounted Display, Smart Glasses, Virtual Interaction, Virtual Gaming, Virtual Shopping, Augmented Reality, Virtual Reality, Human-Computer Interaction, Eye Tracking, Eyeball Tracking, Visual Trajectory Tracking, Head Trajectory Tracking, Data Glove, Voice Interaction, Voice Wake-up, Voice Prompt, Human-Computer Dialogue, Voice Analysis, Voice Input, Gesture Interaction, Motion Capture, Motion Sensing, Posture Capture, Posture Sensing, Haptic Feedback, Gesture Interaction, Gesture Tracking, Gesture Recognition, Hand Posture, Brain-Computer Interaction, Brain-Computer Interface, Implantable Brain-Computer Interface, Non-Invasive Brain-Computer Interface

Appendix II: AI Terminology Dictionary Established Based on National-Level Policy Documents

AI, intelligentization, intelligent, smart, brain-inspired, multimodal, swarm intelligence, collective intelligence, machine learning, deep learning, autonomous learning, supervised learning, neural networks, knowledge graphs, computer vision, semantic understanding, natural language processing, natural language understanding, recognition technology, recognition systems, facial recognition, image recognition, speech recognition, visual recognition, pattern recognition, feature recognition, identity recognition, identity verification, identity authentication, biometric recognition, environmental perception, unmanned driving, unmanned systems, autonomous driving, autonomous control, autonomous coordination, adaptive, self-organizing, computational models, algorithmic models, data models, cloud computing, edge computing, human-computer interaction, augmented reality, virtual reality, assisted diagnosis