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RESEARCH ARTICLE

Artificial Intelligence and Team Spirit: Evidence from Listed Companies in China*

LI Tao[a], ZHAO Shengkun[a], BAO Endeer[a]

Abstract

Excellent corporate culture embodies an enterprise's values and represents a crucial informal institutional factor driving its high-quality development. Artificial intelligence (AI) is deeply integrated into various sectors of the Chinese economy, and corporate culture inevitably evolves alongside changes in organizational production modes. From the perspective of team spirit, this study empirically examines whether and how the adoption of AI influences corporate culture. The findings indicate that the adoption of AI substantially enhances team spirit within enterprises, and this effect remains robust after a battery of endogeneity and robustness checks. Mechanism analyses reveal that AI promotes team spirit through income creation, human capital upgrading, and increased market attention. Moreover, this positive effect is more pronounced in regions where Confucian cultural influence is weaker, and elevated team spirit boosts enterprises' market valuation. In the era of the digital economy, therefore, the deployment of AI actively shapes team spirit, thereby providing a scientific basis for cultivating an exemplary corporate culture aligned with socialist core values.

Keywords artificial intelligence (AI); corporate culture; team spirit; text analysis; large language model

1 Introduction

Artificial intelligence (AI) is "a strategic technology that leads this wave of scientific and technological revolution and industrial transformation, exhibiting a strong 'leading goose' spillover effect, " according to Chinese President Xi Jinping.[1] China's AI industry is growing at an astonishing pace, has joined the world's leading ranks, and is increasingly woven into multiple economic sectors. Existing evidence shows that AI not only considerably enhances enterprises' production efficiency (Chen & Qin, 2022; Graetz & Michaels, 2018; Koch et al., 2021) and innovation performance (Feng et al., 2023) but also exerts profound effects on the labor market (Acemoglu & Restrepo, 2019, 2020; Dixon et al., 2021; Wang & Dong, 2020). However, these studies have focused primarily on the hard capabilities of corporate operations; it remains unclear whether AI likewise exerts a subtle influence on enterprises'

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[a] School of Economics, Central University of Finance and Economics, Beijing 102206, China

[1] Speech by Xi Jinping at the ninth group study session of the Political Bureau of the 19th Central Committee of the Communist Party of China (October 31, 2018).

cultural, or soft capabilities.

Conceptually, corporate culture refers to the set of behavioral norms and values widely endorsed and adhered to by managers and employees across an enterprise (O'Reilly & Chatman, 1996). It is regarded as a key intangible asset that permeates management decisions, operations, organizational coordination, and brand marketing, and a strong corporate culture often correlates closely with market value (Guiso et al., 2015). As it lacks formal enforcement mechanisms, corporate culture is frequently treated as an informal institution that provides essential soft environment support for economic activities (Graham et al., 2022). As the digital economy spreads globally, underpinned by advanced communication technologies, a revolution in digital technologies that integrates industrial robotics, AI-driven decision-making, and virtual reality is transforming how employees interact, work, and contribute value (Gorton et al., 2022). Consequently, the behavioral norms and values upheld by enterprises are bound to evolve alongside changes in their production modes. How, then, will advanced digital technologies, epitomized by AI, shape corporate culture? When concerns about labor displacement by machines abound, will enterprises' team spirit strengthen or weaken? This study seeks to assess the effect of AI adoption on corporate culture from the perspective of team spirit.

Team spirit is a fundamental component of exemplary corporate culture, expressed through employees' collaboration under shared values and a strong sense of collective belonging. Such behaviors and mindsets reflect the values or vision upheld by an enterprise (Guiso et al., 2015). Robust team cohesion serves as an indispensable internal driver that enables an enterprise to operate sustainably and stably and to create core value amid intense domestic and international competition. Extant literature on antecedents of team spirit is limited, focusing primarily on how employees' motivation influences teamwork (Chen et al., 2016; Hochberg & Lindsey, 2010; Meng et al., 2019) and has yet to address how digital technology transformations reshape team spirit. This study employs text analysis methods on annual reports of A-share listed companies from 2008 to 2022 to measure enterprises' AI adoption and team spirit and to determine whether and how AI shapes team spirit.

In terms of measurement, this study draws on the Management Discussion and Analysis sections of annual reports, employs a Word2Vec algorithm to construct a proxy for team spirit, and adopts the method of Jin et al. (2024) to identify AI adoption among enterprises. The empirical findings indicate that AI adoption meaningfully enhances enterprises' team spirit, and this finding remains robust across a series of endogeneity and robustness checks. Mechanism analysis reveals that AI adoption enhances team spirit through income creation, human capital upgrading, and increased market attention. Moreover, this positive effect is especially pronounced in regions with relatively weaker Confucian cultural heritage, and the strengthened team spirit, in turn, significantly boosts enterprises' market valuation.

The marginal contributions of this study are twofold. First, from the perspective of corporate culture, it demonstrates how advanced productive forces shape an enterprise's informal institutional environment. Although existing micro-level research has examined AI's

effects on production efficiency and the labor market, it has yet to address how AI influences corporate culture as a soft power environment. Through the novel lens of team spirit, this study systematically identifies AI's impacts, underlying mechanisms, and economic consequences. Second, this study extends research on the determinants of corporate culture. Prior work has largely focused on how corporate culture affects managerial decisions and economic performance, with limited attention to its antecedents. In the era of the digital economy, shifts in production modes also transform organizational structures and corporate culture. By analyzing the linkage between digital technologies, exemplified by AI, and corporate culture, this study enriches the literature on the digital economy and cultural economics. It provides a scientific basis for simultaneously advancing enterprises' soft and hard capabilities.

2 Literature Review and Research Hypotheses

2.1 Literature Review

As a profound transformation of production mode, AI markedly enhances enterprises' production efficiency and innovation capability, while also imposing substantial shocks on the labor market (Aghion et al., 2017). In terms of productivity, AI-enabled operations can raise labor productivity, total factor productivity (TFP), and innovation performance (Feng et al., 2023; Graetz & Michaels, 2018; Koch et al., 2021). From the perspective of the labor market, scholars generally recognize both the displacement and creation effects of AI: While robotics can reduce enterprises' demand for labor (Acemoglu & Restrepo, 2019, 2020; Wang & Dong, 2020), they can also, through productivity and scale effects, increase labor demand (Dixon et al., 2021; Koch et al., 2021), with these impacts varying notably across different skill types and levels. Unfortunately, existing studies remain anchored at the level of tangible economic activities, paying little attention to whether and how corporate culture evolves in their wake.

Corporate culture reflects the system of shared norms and values formed within an enterprise and serves as a key influence on employees' behavioral standards (Gorton et al., 2022). As a core component of corporate culture, team spirit represents the unification of individual and collective interests, which encapsulates employees' sense of the bigger picture, collaborative mindset, and service orientation to ensure the organization operates with high efficiency. At the individual level, team spirit implies loyalty, altruism, and helping behaviors; at the collective level, it signifies cohesion and shared emotions, values, and beliefs among members (Leighton, 1949). When facing complex and diverse tasks and challenges, the role of team spirit becomes even more critical (Fahn & Hakenes, 2019). Evidence indicates that enterprises with higher levels of team spirit tend to exhibit stronger collaborative capabilities and greater productivity (Adhvaryu et al., 2023; Hamilton et al., 2003) and can also effectively enhance innovation efficiency and output (Pan et al., 2019).

However, research on the determinants of team spirit remains limited. Chen et al. (2016)

find that comprehensive employee benefit programs enhance job satisfaction and teamwork and positively affect enterprises' innovation performance and market value. Meng et al. (2019) and Hochberg and Lindsey (2010) report that implementing employee stock ownership plans, which align the interests of enterprise and employees, markedly fosters collaboration among staff. In the wake of global digitalization, enterprises' strategic objectives, governance structures, and internal management have undergone profound shifts. As a leading exemplar of digital technology innovation, AI thus poses a critical question: Can it drive the development of exemplary corporate culture and strengthen team cohesion?

2.2 AI and Team Spirit: Theoretical Analysis and Research Hypotheses

Corporate culture, as a form of soft environment, evolves in tandem with an enterprise's development trajectory. Although no direct evidence yet delineates the link between AI and team spirit, the suite of tangible economic transformations driven by AI, including technological innovation, efficiency gains, and performance improvements, will inevitably reshape employees' behavioral norms and values. Theoretically, AI's influence on team spirit manifests in at least three channels: income creation, human capital upgrading, and increased market attention.

Income creation. Employees' work motivation and sense of team belonging are closely tied to the compensation they receive. When employees perceive that their efforts contribute to enterprises' profit growth and that their contributions are appropriately rewarded, they develop a stronger sense of team belonging (Chen et al., 2016), thereby reinforcing team spirit. Empirical evidence shows that enterprises using AI for automation, data analytics, and decision-making optimization achieve significant gains in productivity and higher input-output ratios (Acemoglu & Restrepo, 2020). For example, machine learning algorithms can forecast market trends and optimize inventory management, while automation tools reduce human error and accelerate production cycles. These efficiency improvements enable enterprises to produce more goods and services at a lower cost and faster pace (Huang et al., 2019). Increased enterprise revenues then drive up the share of labor income and wage levels. For instance, Graetz and Michaels (2018) find that across 17 countries, greater industrial robot adoption raises average hourly earnings.

Human capital upgrading. The overall skill level of employees is a key determinant of team cohesion. Generally, well-educated and highly skilled employees contribute more to organizational management and operations and, in turn, receive higher compensation, which enhances their sense of belonging and alignment with enterprises' norms and values. On one hand, the AI revolution displaces lower-educated workers engaged in routine tasks. On the other hand, technological advances generate new tasks that create demand for high-skill positions, driving an upgrade in the human capital structure (Acemoglu & Restrepo, 2018; Graetz & Michaels, 2018). This shift prompts enterprises to invest more heavily in employee training, thus fostering interdepartmental learning and collaboration that strengthens

communication and teamwork among members (Tsai & Ghoshal, 1998). At the same time, enterprises offer competitive salaries and benefits to retain talent, which further motivates employees and deepens their sense of belonging (Sauermann & Cohen, 2010).

Increased market attention. From the perspective of the capital market, the adoption of AI draws greater market attention to enterprises. By improving organizational coordination and workflow efficiency, AI-driven productivity gains make capacity expansion more effective, thereby signaling growth potential and future returns to investors (Chen & Srinivasan, 2024). The empowerment provided by AI technology can attract increased market attention to enterprises and potentially enhance enterprises' team spirit on two fronts. First, high-profile enterprises build strong reputations that enable them to offer attractive job opportunities and competitive compensation, thereby attracting well-educated, highly skilled talent who readily embrace the enterprise's values and norms, thus reinforcing cohesion. Second, increased market attention places greater external pressure on managers regarding enterprises' reputation and strategic conduct (Bednar et al., 2013). Under such pressure, managers, who seek to safeguard their reputations and sustain market value growth, cultivate a tight-knit team spirit culture to signal positive performance to stakeholders and enhance favorable market expectations.

In light of the foregoing, this study proposes the following research hypothesis:

H1: The use of AI technology significantly stimulates team spirit among enterprises.

3 Model Specification and Data Description

3.1 Model Specification

Ordinary least squares (OLS) is used for baseline regression, specified as equation (1):

$$Team\_Spirit_{it} = \beta_0 + \beta_1 AI\_Adoption_{it} + \beta_n Controls_{it} + \gamma_t + \eta_j + \mu_p + \varepsilon_{it}, \quad (1)$$

where $Team\_Spirit_{it}$ denotes the team spirit score for enterprise i in year t; $AI\_Adoption_{it}$ is a binary indicator equal to 1 if enterprise i adopts AI technology in year t, and 0 otherwise; $Controls_{it}$ is a vector of time-varying, enterprise-level control variables that may influence team spirit. Table 1 presents the definitions and calculation methods of the main variables. γ_t, η_j, and μ_p represent year, industry, and province fixed effects, respectively; ε_{it} is the idiosyncratic error term. Standard errors are clustered at the enterprise level. The coefficient β_1 measures the effect of AI adoption on enterprises' team spirit.

Table 1 Main Variables: Names, Definitions, and Descriptive Statistics

Variable	Definition & measurement	Observations	*M*	*SD*	*Min.*	*Max.*
Team_Spirit	Team spirit index	35,319	2.525	0.747	0	5.756
AI_Adoption	If AI is adopted	35,319	0.459	0.498	0	1
Size	Natural log of total assets	35,319	22.125	1.327	15.710	28.610

(*To be continued*)

(*Continued*)

Variable	Definition & measurement	Observations	*M*	*SD*	*Min.*	*Max.*
Lev	Leverage	35,319	2.034	0.932	0	3.497
Age	Natural log of (years since listing + 1)	35,319	0.424	0.214	0.052	0.990
Growth	Growth rate of sales revenue	35,319	0.375	1.028	–0.689	7.268
Liquidity	Current ratio	35,319	2.543	2.591	0.248	15.340
TBQ	Market-to-book ratio	35,319	2.828	2.125	0.859	13.030
ROA	Return on assets	35,319	0.038	0.068	–0.348	0.279
RD	R&D expenditure ÷ total revenue	35,319	0.032	0.043	0	0.232
CF	Operating cash flow	35,319	0.047	0.072	–0.204	0.266
Board_Size	Natural log of board size	35,319	0.287	0.452	0	1
Indep_Ratio	Proportion of independent directors	35,319	2.242	0.177	1.609	2.944
Duality	Chair-CEO duality	35,319	0.374	0.055	0	0.800
CEO_Age	Age of the CEO	35,319	49.823	6.786	24	82
CEO_Gender	Gender of the CEO (1 = male; 0 = female)	35,319	0.934	0.248	0	1

3.2 Sample and Variables

3.2.1 Data Sources and Sample Treatment

This study initially samples Chinese A-share listed enterprises for the period 2008–2022 and applies the following filters: (1) exclude enterprises in the financial sector; (2) remove abnormal listings, such as ST, ST*, and PT; (3) drop observations with missing values on key variables; and (4) winsorize continuous variables at the 1st and 99th percentiles to mitigate outlier effects. The two core variables, team spirit and AI adoption, are measured using text analysis methods; all other variables are drawn from the Wind and China Stock Market & Accounting Research (CSMAR) databases. After processing, the final panel comprises 35,319 observations.

3.2.2 Definitions and Development of Variables

Following Jin et al. (2024), the indicator of AI adoption is developed using supervised machine learning with a fine-tuned Chinese large language model, ERNIE, to measure AI adoption ($AI\_Adoption_{it}$) among A-share listed enterprises in China; the procedure comprises three steps. In the first step, sentences are labeled: Through manual review and cross-validation, we annotate 38,994 sentences from annual reports to form the training set. In the second step, the ERNIE model is trained and its parameters calibrated, after which it is applied to the annual report texts of all listed enterprises to predict whether each enterprise adopts AI

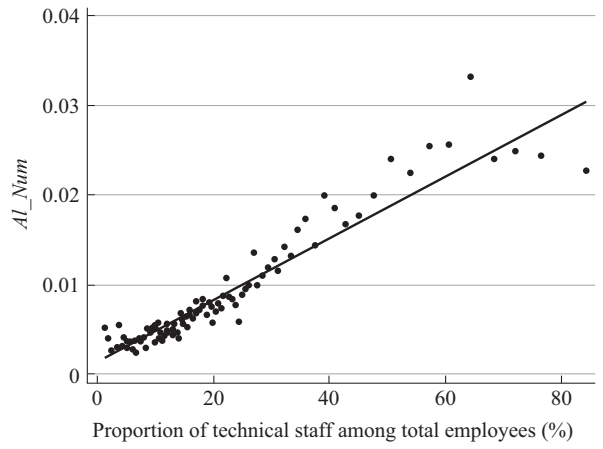
in the given year. The model attains a precision above 80% and an accuracy exceeding 90%. In the third step, three measures of AI adoption are created based on the model's predictions: a binary indicator denoting whether the enterprise adopts AI (*AI_Adoption*), the share of words in the annual report texts that refer to AI relative to the total word count (*AI_Length*), and the share of sentences that refer to AI relative to the total sentence count (*AI_Num*). In the empirical analysis, *AI_Adoption* serves as the primary explanatory variable, while *AI_Length* and *AI_Num* are reserved for robustness checks.

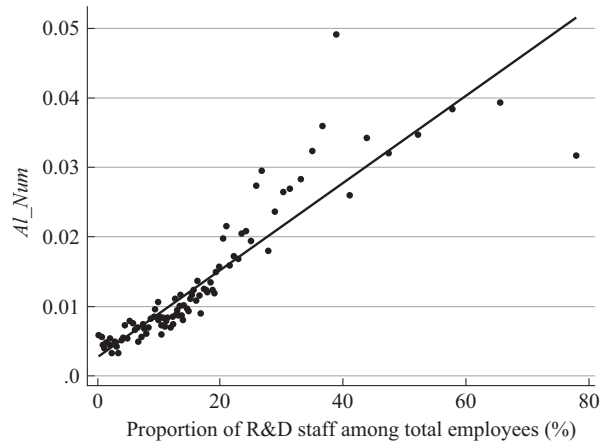
To assess the validity of these indicators of AI adoption, we also conduct a verification. As shown in Figure 1, we plot company-level scatter plots of the AI intensity indicator (*AI_Num*) against the proportion of technical staff, the proportion of R&D staff, and R&D investment intensity among listed companies. The figure shows that as AI intensity rises, the shares of technical personnel, R&D personnel, and R&D intensity likewise increase, exhibiting a clear positive correlation. This result corroborates the scientific rigor and soundness of the indicator developed herein.

The team-spirit measure draws on Li et al. (2021) by using a purpose-built keyword lexicon to gauge listed companies' team-spirit levels via keyword frequency counts. The construction proceeds in three stages. In the first stage, we compile an initial list of 19 seed words by referencing Fiordelisi and Ricci (2014), Li et al. (2021), and relevant entries in the *Modern Chinese Dictionary*, thereby establishing a benchmark for the subsequent lexicon. In the second stage, we train a Word2Vec model on the Chinese Wikipedia corpus to expand this list: For each seed word, the model identifies its five most closely associated synonyms, from which we remove semantically irrelevant and duplicate terms to yield a final lexicon of 35 keywords.[2] In the third stage, we preprocess the annual report texts using Python's Jieba module for tokenization while filtering out sentences containing negation markers (e.g., "no," "not really"). Sentences containing both a team spirit keyword and a negation term are excluded from the frequency count. We then count the occurrences of all keywords related to team spirit per company per year, sum these counts, and take the natural logarithm after adding one to obtain the team spirit indicator, $Team\_Spirit_{it}$.

Descriptive statistics for the core variables are reported in Table 1. *Team_Spirit* has a mean of 2.525 and a standard deviation of 0.747, indicating substantial variation in team spirit across enterprises in the sample. The overall mean of *AI_Adoption* is 0.459, suggesting that, on average, nearly half of the enterprises employed advanced AI technologies in their operations over the 15-year period. Figure 2 presents AI adoption among Chinese A-share listed companies. Overall, AI adoption has become markedly more widespread: In 2008, fewer than 10% of the enterprises had adopted AI, whereas by 2022, adoption reached 80%.

[2] These keywords include: team, team spirit, cooperation, unity, joint action, coordination, collaboration, synergy, joint effort, combined effort, mutual assistance, sharing, shared benefit, working together, communication, exchange, win-win, the masses, organization, group, hand in hand, together, mutual cooperation, standing united, united at heart, united collaboration, mutual coordination, joining forces, together, concerted effort, all with one heart, mutual understanding, mutual respect, collective, and collectivism.





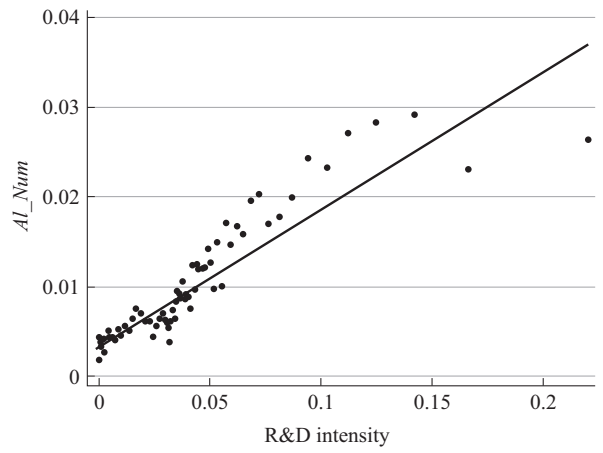


Figure 1 Validation of the AI Adoption Indicator for Listed Companies

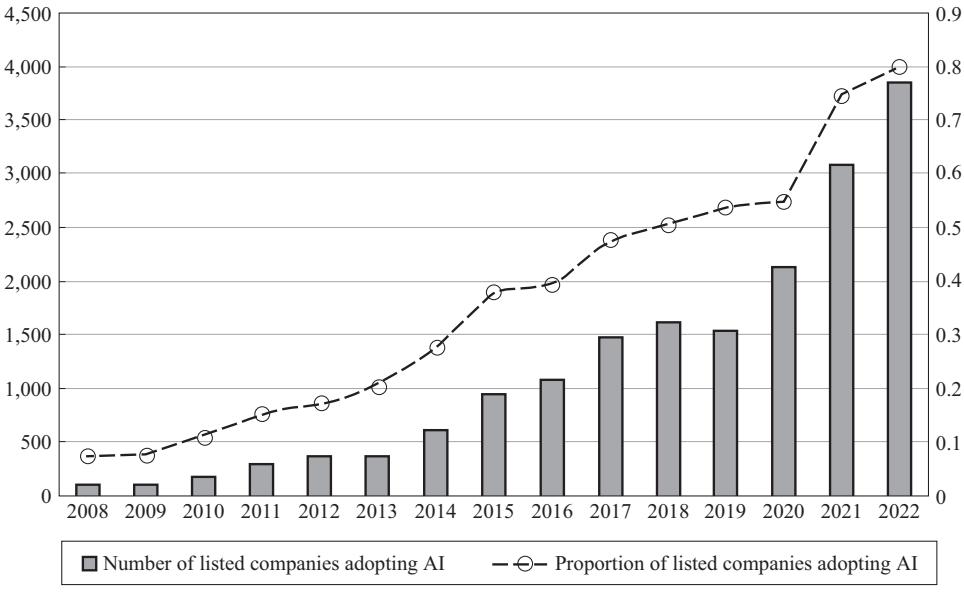


Figure 2 AI Adoption by A-Share Listed Companies, 2008–2022

4 Empirical Findings and Analysis

4.1 Baseline Regression Results

The baseline regression estimates of AI adoption on enterprises' team spirit are reported in columns (1) and (2) of Table 2. In column (1), only industry, province, and year fixed effects are included; column (2) further adds enterprise-level control variables. In both specifications, the coefficient on the key explanatory variable, *AI_Adoption*, is positive and significant at the 1% level, indicating that AI adoption significantly enhances enterprises' team spirit. According to the estimate in column (2), ceteris paribus, enterprises that adopt AI exhibit a 0.317 increase in team spirit. Relative to the sample mean of 2.525, this represents a 12.55% uplift.

To examine the persistence of this effect, we broaden the temporal scope of the regression analysis. To be specific, we replace the dependent variable (*Team_Spirit*) with team spirit at $t + 1$ and $t + 2$. The results are presented in columns (3) and (4) of Table 2. In both cases, the coefficient on *AI_Adoption* remains positive and significant at the 1% level. This not only confirms the robustness of the baseline findings but also demonstrates that AI's effect on team spirit is not ephemeral; it endures over time. Taken together, the baseline regressions support *H1*: AI adoption significantly enhances team spirit among enterprises and provides compelling evidence of how digital technology transformation shapes corporate culture in listed companies.

Table 2 Baseline Regression: AI Adoption and Enterprise Team Spirit among Enterprises

Variable	(1) $Team\_Spirit_{it}$	(2) $Team\_Spirit_{it}$	(3) $Team\_Spirit_{it+1}$	(4) $Team\_Spirit_{it+2}$
$AI\_Adoption_{it}$	0.3170*** (0.0127)	0.2781*** (0.0124)	0.2306*** (0.0135)	0.2193*** (0.0143)
Controls	No	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes
Province-fixed effects	Yes	Yes	Yes	Yes
N	35,319	35,319	28,301	24,435
R^2	0.251	0.273	0.270	0.246

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All regressions report standard errors clustered at the enterprise level.

4.2 Endogeneity Treatment

The baseline regression results may be biased by potential endogeneity. Unobserved factors correlated with either corporate culture or AI adoption could introduce omitted variable bias. In addition, enterprises with higher team spirit often exhibit stronger performance and thus possess greater resources and incentives to adopt new technologies, giving rise to reverse causality. To address these concerns, this study employs five different methods to mitigate potential endogeneity.

First, we include enterprise-fixed effects to control for time-invariant, enterprise-level influences. As shown in column (1) of Table 3, after adding enterprise-fixed effects, the positive effect of AI adoption on enterprises' team spirit remains significant.

Table 3 Endogeneity Treatment: Enterprise-Fixed Effects, Within-Group Differencing, IV Regression, PSM Matching, and DID

Variable	Individual FE	Within-group difference	IV regression	PSM matching	DID
	(1)	(2)	(3)	(4)	(5)
	$Team\_Spirit_{it}$	$\Delta Team\_Spirit_{it}$	$Team\_Spirit_{it}$	$Team\_Spirit_{it}$	$Team\_Spirit_{it}$
$AI\_Adoption_{it}$	0.1353*** (0.0097)		0.3703*** (0.0306)	0.2807*** (0.0131)	0.1041*** (0.0141)
$\Delta AI\_Adoption_{it}$		0.0801*** (0.0076)			
Controls	Yes	Yes	Yes	Yes	Yes
Enterprise-fixed effects	Yes	No	No	No	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	Yes	Yes	Yes	No

(*To be continued*)

(*Continued*)

Variable	Individual FE	Within-group difference	IV regression	PSM matching	DID
	(1)	(2)	(3)	(4)	(5)
	$Team\_Spirit_{it}$	$\Delta Team\_Spirit_{it}$	$Team\_Spirit_{it}$	$Team\_Spirit_{it}$	$Team\_Spirit_{it}$
Province-fixed effects	No	Yes	Yes	Yes	No
K-PLM (*P*-value)			0.0000		
C-D Wald F			60.740		
N	35,347	31,034	24,969	24,956	35,347
R^2	0.244	0.104	0.046	0.259	0.240

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All regressions report standard errors clustered at the enterprise level.

Second, we apply a within-group differencing approach to eliminate time-invariant unobservables; the results in column (2) of Table 3 continue to support our conclusions.

Third, following the method of Lewbel (2012), we construct instruments using heteroskedasticity-based identification and perform an instrumental-variables (IV) regression. The second-stage estimates are reported in column (3) of Table 3, and the core findings remain unchanged.

Fourth, we employ propensity score matching (PSM). Enterprises that adopt AI are designated as the treatment group, while those that do not adopt it are the control group. All control variables enter the propensity-score model as covariates, and we select the subset that maximizes the likelihood for optimal fit. Using these covariates, we perform 1 : 4 nearest-neighbor matching. Figures 3 and 4 show kernel-density estimates of the propensity scores for the treatment and control groups before and after matching, demonstrating a clear improvement in distributional balance post-matching. The regression results in column (4) of Table 3 show that both the sign and significance of the AI adoption coefficient remain unchanged relative to the baseline regression.

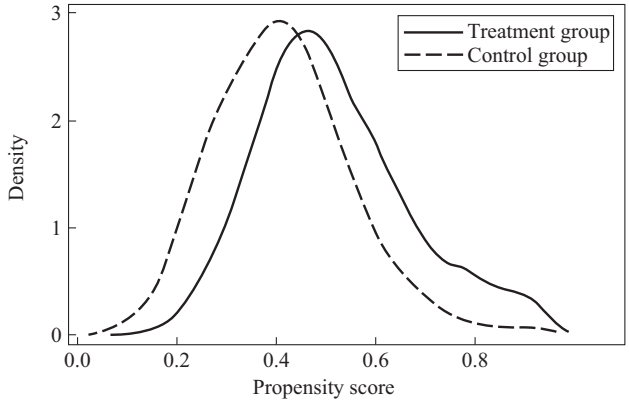


Figure 3 Kernel-Density Distribution (Before Matching)

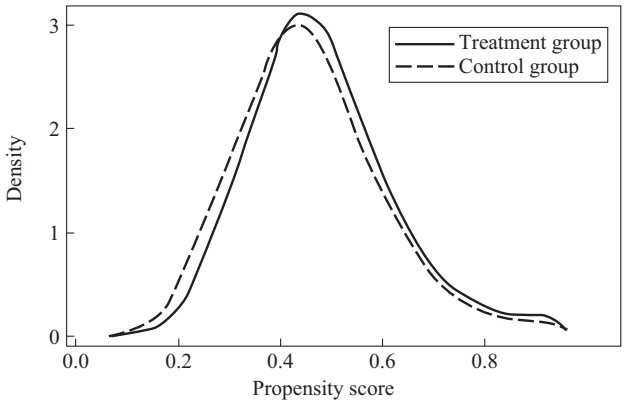


Figure 4 Kernel-Density Distribution (After Matching)

Fifth, we implement a difference-in-differences (DID) approach. Specifically, we construct a multi-period DID model, designating enterprises that adopt AI as the treatment group ($Treat_i = 1$) and those that do not as the control group ($Treat_i = 0$), thereby more clearly isolating the effect of AI adoption on enterprises' team spirit. The model is specified as follows:

$$Team\_Spirit_{it} = \beta_0 + \beta_1 Treat_i \times Post_t + \beta_n Controls_{it} + \gamma_t + \lambda_i + \varepsilon_{it}, \quad (2)$$

where $Treat_i$ is an enterprise-level dummy variable, and $Post_t$ is a time dummy variable. We assign $Post_t$ a value of 1 for treatment enterprises in the year of their first AI adoption and all subsequent years, and 0 otherwise. The terms λ_i and γ_t denote enterprise- and year-fixed effects, respectively. Our primary parameter of interest is the coefficient β_1 on the interaction $Treat_i \times Post_t$, which captures the change in team spirit levels before and after AI adoption. These regression results are reported in column (5) of Table 3. Further, we implement an event-study approach to conduct a parallel trends test, confirming that treatment and control enterprises exhibit similar team spirit trends prior to AI adoption. Figure 5 presents the parallel trends test. Prior to AI adoption, the coefficient on *AI_Adoption* is close to zero and statistically insignificant, indicating no pre-treatment differences in team spirit between the treatment and control enterprises. In terms of dynamic effects, the coefficient becomes positive and significant after AI adoption and persists over time, further demonstrating that AI adoption exerts a positive, lasting effect on corporate culture.

To ensure the robustness of these results, we perform a battery of additional tests: We remeasure both the dependent and key explanatory variables; control for the background and characteristics of the CEO; employ alternative regression specifications; exclude potential confounding effects of other digital technologies; and drop observations from the information technology sector. In every case, the main conclusions hold. Due to space constraints, detailed steps and results of these robustness checks are available from the authors upon request.

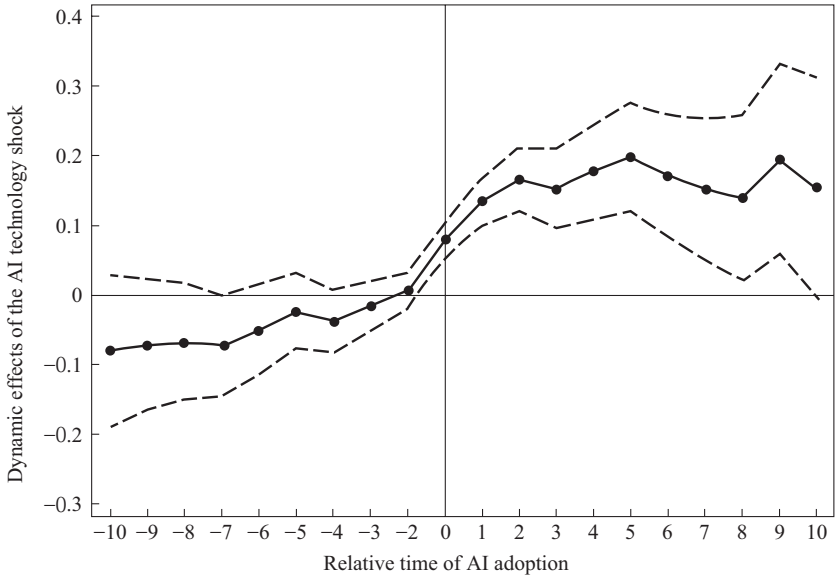


Figure 5 Parallel Trends Test and Dynamic Effects of AI Adoption on Team Spirit

5 Mechanism and Heterogeneity Analyses

5.1 Mechanism Analysis

5.1.1 Income Creation

This study first tests the effect of AI adoption on enterprises' productivity and total output. We compute *TFP* for listed companies using the Levinsohn-Petrin (2003) method and measure total output (*Income*) as the natural log of main business revenue. Following the procedure in Jiang (2022), we regress *TFP* and *Income* directly on *AI_Adoption*. As shown in columns (1) and (2) of Table 4, AI adoption significantly increases enterprises' productivity and raises their total output by 1.17%.

Next, we examine the effect of AI adoption on labor income share and employee compensation. Drawing on the method of Xiao et al. (2022), we measure labor income share in two ways: *LaborShare*1, the ratio of cash paid to employees during the period to total operating revenue; and *LaborShare*2, calculated as (ending accrued employee compensation minus beginning accrued employee compensation plus cash paid to employees during the period) divided by total operating revenue. We also compute average wages for managers and for employees in listed companies. Average managerial pay (*AMP*) is defined as total compensation for managers divided by (total number of directors, supervisors, and senior managers minus number of independent directors minus number of directors or supervisors who did not receive compensation). Average employee pay (*AEP*) is the natural logarithm of [(ending accrued employee compensation minus beginning accrued employee compensation plus cash paid to employees during the period minus total compensation for managers) ÷ total number of employees]. The results are shown in columns (3)–(6) of Table 4. AI adoption increases labor income share, *AMP*, and *AEP* by approximately 0.8%, 2.51%, and 3.15%,

respectively. Overall, these findings support the income creation effect of AI, indicating that higher compensation for managers and employees can foster stronger team spirit.

Table 4 Mechanism Test Ⅰ: Income Creation Effects of AI Adoption

Variable	(1) TFP_{it}	(2) $Income_{it}$	(3) $LaborShare1_{it}$	(4) $LaborShare2_{it}$	(5) AMP_{it}	(6) AEP_{it}
$AI\_Adoption_{it}$	0.0479***	0.0117*	0.0076***	0.0079***	0.0251***	0.0315***
	(0.0126)	(0.0066)	(0.0016)	(0.0017)	(0.0093)	(0.0122)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-, industry-, and province-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	32,105	35,347	35,318	35,055	26,140	25,998
R^2	0.716	0.958	0.371	0.371	0.509	0.525

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All regressions report standard errors clustered at the enterprise level.

5.1.2 Human Capital Upgrading

We first examine changes in the educational composition of employees. As shown in columns (1)–(5) of Table 5, AI adoption significantly upgrades an enterprise's human capital structure. Specifically, compared with enterprises that have not adopted AI, those that have exhibit a 0.66% and 2.49% higher share of employees with postgraduate and bachelor's degrees, respectively, while the proportion of employees with a high school education or below falls by 1.89%. In terms of occupational categories, the share of technical staff rises by 2.64%, whereas the share of production workers declines by 4.28%.

Table 5 Mechanism Tests Ⅱ & Ⅲ: Human Capital Upgrading and Market Attention Effects of AI Adoption

Variable	(1) Postgraduate	(2) Bachelor	(3) High school or below	(4) Technical staff	(5) Production staff	(6) Employee welfare	(7) *Analysts*	(8) *Report*
$AI\_Adoption_{it}$	0.6641***	2.4909***	–1.8850***	2.6392***	–4.2805***	0.0078**	0.3481*	1.0351**
	(0.1310)	(0.2910)	(0.5551)	(0.3051)	(0.4385)	(0.0039)	(0.2007)	(0.5184)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-, industry-, and province-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,688	24,023	14,171	25,306	22,672	22,634	19,512	19,750
R^2	0.334	0.510	0.399	0.485	0.338	0.118	0.364	0.337

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All regressions report standard errors clustered at the enterprise level.

In addition, we examine whether AI adoption prompts management to place greater emphasis on human capital development and training. We proxy management's focus on human capital using the ratio of trade union funds and employee training expenditures to total operating revenue. The results in column (6) of Table 5 indicate that AI adoption not only upgrades enterprises' human capital but also significantly increases management's attention to human capital. This heightened focus, in turn, helps cultivate stronger belonging and team spirit among employees. These empirical findings support the human capital upgrading effect of AI.

5.1.3 Market Attention

We capture market attention to listed companies using two indicators, namely, analyst coverage (*Analysts*) and research report coverage (*Report*), and empirically test the market attention effects of AI adoption. As shown in columns (7) and (8) of Table 5, the coefficient on *AI_Adoption* is positive and significant at the 10% and 5% levels, respectively, thus supporting the mechanism of market attention effects.

5.2 Heterogeneity Analysis Based on Confucian Cultural Variations

Corporate culture is often deeply intertwined with local cultural traditions. A pertinent question is whether AI's effect on corporate culture varies across regions with different cultural backgrounds. We focus on Confucian culture, which exerts the most widespread and enduring influence in China. Following the method of Xu and Li (2019), we proxy regional Confucian influence using two indicators at the prefecture level: the number of historic academies and the number of the Ming and Qing dynasties *jinshi* (successful imperial examination candidates). A higher tally on either metric indicates stronger Confucian cultural influence. We split the sample at the median of each indicator and re-estimate the baseline regression for each subsample. These results are presented in columns (1)–(4) of Table 6. The estimated coefficient on the core explanatory variable *AI_Adoption* indicates that AI adoption has a more pronounced effect on enterprises located in regions with relatively weaker Confucian cultural influence. One possible explanation is that, in regions with relatively weaker Confucian influence, enterprise managers place comparatively less emphasis on team spirit, which is anchored in collectivism and cooperative values, making such enterprises more responsive to the empowering effects of AI.

5.3 Performance Implications of Team Spirit

Finally, we examine how the AI-driven enhancement of team spirit feeds back into operational performance. Drawing on the model of Dai et al. (2021), we estimate the following specification to assess the synergistic effects of digital technology adoption and

team spirit on next-period market value (TBQ_{it+1}). Our primary interest lies in the coefficient β_3 on the interaction term, which captures how AI-induced improvements in team spirit translate into changes in enterprises' market valuation.

$$TBQ_{it+1} = \beta_0 + \beta_1 AI\_Adoption_{it} \times Team\_Spitrit_{it} + \beta_2 AI\_Adoption_{it} + \beta_3 Team\_Spitrit_{it} + \beta_n Controls_{it} + \gamma_t + \eta_j + \mu_p + \varepsilon_{it}. \quad (3)$$

The regression results for the performance implications are shown in columns (5) and (6) of Table 6. The interaction-term coefficient is positive and statistically significant, indicating that AI-driven enhancements in team spirit materially improve enterprises' capital market performance. Moreover, the results in column (6) reveal that AI adoption not only directly boosts economic efficiency but also elevates enterprises' value by fostering a positive corporate culture.

Table 6 Heterogeneity and Economic Performance Tests

Variable	(1) $Team\_Spirit_{it}$	(2) $Team\_Spirit_{it}$	(3) $Team\_Spirit_{it}$	(4) $Team\_Spirit_{it}$	(5) TBQ_{it+1}	(6) TBQ_{it+1}
$AI\_Adoption_{it}$	0.2496*** (0.0108)	0.3187*** (0.0129)	0.2386*** (0.0112)	0.3221*** (0.0122)	–0.4786*** (0.1097)	–0.3242*** (0.1166)
$I\_Adoption_{it} \times Team\_Spirit_{it}$					0.1589*** (0.0409)	0.0981** (0.0438)
$Team\_Spirit_{it}$					–0.0924*** (0.0321)	–0.1026*** (0.0342)
Controls	Yes	Yes	Yes	Yes	No	Yes
Year-, industry-, and province-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	20,723	14,596	19,284	16,035	26,140	25,998
R^2	0.273	0.288	0.284	0.282	0.509	0.525
P-value (heterogeneity)	0.0058		0.0006			

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. All regressions report standard errors clustered at the enterprise level.

6 Conclusions and Policy Recommendations

AI is a pivotal driver of the current scientific and technological revolution and industrial transformation, fundamentally reshaping how we work and live. Extending prior studies, this study employs text analysis methods to construct proxy measures for enterprises' AI adoption and team spirit and empirically examines how AI shapes team spirit. Four key findings emerge. First, AI adoption significantly enhances enterprises' team spirit, and this result remains robust after a battery of endogeneity and robustness checks. Second, AI fosters

positive team spirit through three channels: income creation, human capital upgrading, and increased market attention. Third, the effect of AI on team culture is more potent in regions with weaker Confucian influence. Finally, AI-driven improvements in team spirit translate into higher market valuation of enterprises.

Based on the foregoing analysis, we offer three policy recommendations. First, efforts should be made to actively guide the development and adoption of AI, since its deployment not only enhances team spirit but also converts cultural gains into higher market value, an essential driver of exemplary corporate culture and high-quality development in the digital economy era. Second, attention should be given to the cultivation and development of human capital. As AI shapes corporate culture through income creation, human capital upgrading, and increased market attention, a robust supply of high-end digital technology talent and a competitive support system are critical to realizing AI's full potential. Beyond optimizing compensation schemes and talent retention strategies to reinforce corporate culture, support measures should facilitate and accelerate education system reforms to meet the burgeoning demand for skilled human capital. Third, technology promotion policies should be tailored to local cultural contexts. In regions where cultural norms are relatively weak, particular emphasis should be placed on encouraging the adoption of AI.

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