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Navigating Digital Transformation: Sociological and Educational Factors in Corporate AI Strategy Adoption

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Abstract

To address the practical challenge of the disconnect between AI strategy implementation and performance outcomes in enterprises, this study focuses on the three-dimensional execution mechanism encompassing "resources-process-culture," examining its mediating role between AI strategies and corporate performance, as well as the moderating effects of firm size and industry characteristics. Data were collected via random sampling using the Wenjuanxing online survey platform, supplemented by a 12-month longitudinal case tracking study. Empirical analysis employed structural equation modeling, grouped regression, and interaction term testing. Results demonstrate that the three-dimensional execution mechanism fully mediates the relationship between AI strategies and corporate performance, with resource allocation playing the most significant mediating role. Firm size positively moderates the performance effect of the execution mechanism, with large firms exhibiting significantly better implementation outcomes than small and medium-sized enterprises. Industry characteristics exhibit heterogeneity: technology-intensive industries show stronger positive impacts of the execution mechanism compared to non-technology-intensive sectors. Differentiation in implementation pathways reveals adaptability—technology-intensive firms benefit from a "resource priority or lightweight resources plus cultural guidance" approach, while non-technology-intensive firms are better suited for a "culture priority plus lightweight processes" model. This study evaluates AI strategy implementation primarily through organizational financial and innovation performance indicators. Although these metrics serve as organizational-level proxies for implementation effectiveness, they do not directly measure employee-level social outcomes, such as workplace learning, well-being, psychological safety, re-skilling, or

perceived equity; therefore, the social implications discussed in this study should be interpreted within this scope.

Keywords: AI adoption; Organizational learning; Digital transformation; Workplace sociology; Socio-technical systems; Workplace equity

Introduction

Research Background

While most enterprises have incorporated AI technology into their top-level strategic planning, significant gaps often exist between strategic objectives and actual outcomes during implementation. Despite substantial investments in AI technology acquisition and infrastructure development, many companies struggle to translate AI strategies into competitive advantages due to misalignment between resource allocation and business needs, inefficient cross-departmental collaboration, and insufficient organizational acceptance of AI technologies (Hu & Jiang, Yin & Lüjiang, 2025). This phenomenon highlights the absence of a systematic implementation framework for AI strategy execution. Current research on AI strategy and corporate performance exhibits notable logical gaps: most studies focus solely on strategy formulation—exploring how companies set AI objectives and select application scenarios—while neglecting key execution elements, resulting in incomplete research frameworks covering strategy development, implementation, and performance transformation (Su & Meiwen et al., 2025; Cheng & Han, 2025). Furthermore, existing studies predominantly examine superficial correlations between AI strategies and corporate performance without analyzing the mediating role of implementation mechanisms, leaving the underlying mechanisms of AIs impact on performance unclear (He & Li, 2025). Additionally, differences in enterprise scale and industry characteristics may significantly influence AI adoption outcomes. These factors influence the effectiveness of strategic implementation; however, existing research has not adequately accounted for the moderating effects of these contextual variables, thereby limiting the generalizability of research findings (Lu Huan, 2024). This study primarily evaluates organizational performance through financial and innovation indicators, including revenue growth, net profit margin, and AI-related innovation outcomes. Although these measures can reflect an enterprise's capacity to sustain AI implementation, training, and organizational adaptation, they do not directly capture employee-level outcomes such as workplace learning, well-being, job satisfaction, psychological safety, re-skilling opportunities, inclusivity, or perceived fairness. Accordingly, the social and educational implications discussed in this study are theoretically informed interpretations rather than directly measured employee-level effects. This study primarily evaluates the effectiveness of AI strategy implementation through organizational financial and innovation performance indicators. While these measures provide meaningful organizational-level proxies for implementation outcomes, they do not directly capture employee-level social outcomes such as

workplace learning, well-being, psychological safety, re-skilling opportunities, or perceived equity. Therefore, the social and educational implications discussed in this study should be interpreted as theoretically informed organizational implications rather than direct empirical evidence of employee-level outcomes.

Research Question

Existing studies on AI strategy mainly focus on technology use, business strategy, and corporate performance. This study addresses the following research questions:

1. How do resources, processes, and culture support AI strategy implementation in enterprises?
2. How does AI implementation influence employee learning, AI acceptance, workplace collaboration, and organizational change?
3. Do firm size and industry type affect how enterprises experience AI-driven organizational change?
4. What kind of AI implementation pathway can help enterprises promote employee learning, cultural adaptation, and socially responsible digital transformation?

Theoretical Background and Research Hypotheses

Theoretical Background

AI Strategy Research

AI strategy research has developed a multi-layered and multidimensional exploration framework, encompassing three core dimensions: micro-level operational elements of enterprises, ecosystem interaction mechanisms, and alignment with macro-level policies. At the enterprise level, Kong Xu et al. (2021) examined 112 listed AI companies and demonstrated that R&D investment intensity and innovation strategy selection are critical prerequisites for implementing AI strategies, collectively forming the resource foundation and directional guidance for AI technology application (Yang Wei et al. 2020).

Comparative Literature Analysis

The adoption of AI needs to be considered as much a process of change in the social and learning landscape as it is a technological and strategic move, as it will impact how things work in the workplace, the nature of the "workforce," the learning needs, and organizational relationships. For this reason, organizational learning theory, socio-technical systems theory and the social construction of technology are suitable theories to understand how enterprises adapt to AI-driven changes. The views highlight the need for employees to learn, engage, communicate, and integrate the technology into the organization's systems and culture for successful AI implementation. Social science-wise, the use of AI is a journey that involves restructuring workflows, redesigning job roles, changing the attitude of the workplace, and establishing new learning needs in the organization. Hence, theory

from organizational learning, socio technical systems theory, and social construction of technology and critical studies of workplace transformation are needed as a theoretical basis for implementing AI in enterprises. The theory of organizational learning offers a valuable educational framework to comprehend the adoption of AI. In the context of environmental and technological changes, Argyris and Schön's organizational learning theory states that organizations should continuously identify, adjust, and redesign their routines. For AI implementation, workers will need new digital competencies, the ability to understand output from AI algorithms, and an understanding of new forms of human-machine collaboration. Likewise, the theory of learning organization developed by Senge focuses on the concepts of shared vision, team learning, and the flow of knowledge. These concepts imply that the application of AI is not just about the technology but also about the ability of the organization to develop training systems, mechanisms for sharing knowledge, and a culture of continual learning. Hence, employee acceptance of AI, their involvement in AI-related activities, and management support for learning is key to the implementation of AI strategies. The socio technical systems theory also sheds light on why AI implementation needs to be understood as a socio technical phenomenon. This theory states that the technological and social systems are mutually dependent. Without appropriate work processes, communication, employee involvement, and organizational support, AI systems will not be effective.

Research Hypotheses

Direct Effect Hypothesis

Existing research has demonstrated from both strategic and implementation perspectives that AI strategies and their core components exert a direct positive impact on corporate performance. At the strategic level, Kong Xu et al. (2021) examined 112 listed companies in the AI sector and found that R&D investment and innovation strategies directly strengthen technological reserves, laying the foundation for performance improvement. Yang Wei et al. (2020), analyzing the "population-flow" configuration of AI digital innovation ecosystems, highlighted how ecosystem synergy optimizes resource allocation and directly drives performance growth for leading enterprises. Additionally, multi-industry empirical studies by Kim Yong-mi (2025) and research based on listed companies by Zhang Hanyu et al. (2023) both confirmed that AI strategies enhance efficiency, thereby improving performance. Jiang Lili et al. (2022), in their analysis of declining enterprises, further revealed that AI-driven digital transformation strategies can directly reverse performance declines. At the implementation level, the direct role of resource allocation is well-established: Cao Hongjun et al. (2016) noted that changes in resource allocation strategies exhibit nonlinear effects on performance, with the alignment between resources and AI strategic objectives determining performance growth rates; Yang Yan et al., (2013) emphasized the sustained positive impact of timely resource allocation; while Wang Fanlin and Zhang Jide (2018) demonstrated that integrating IT resource allocation with governance practices reduces costs and improves efficiency.

H1: An effective AI strategy positively influences an organization's financial and innovation performance.

H2: Resource allocation, process design, and organizational culture each have a significant positive impact on organizational performance.

H3: The resources–process–culture implementation mechanism mediates the positive relationship between AI strategy and organizational performance.

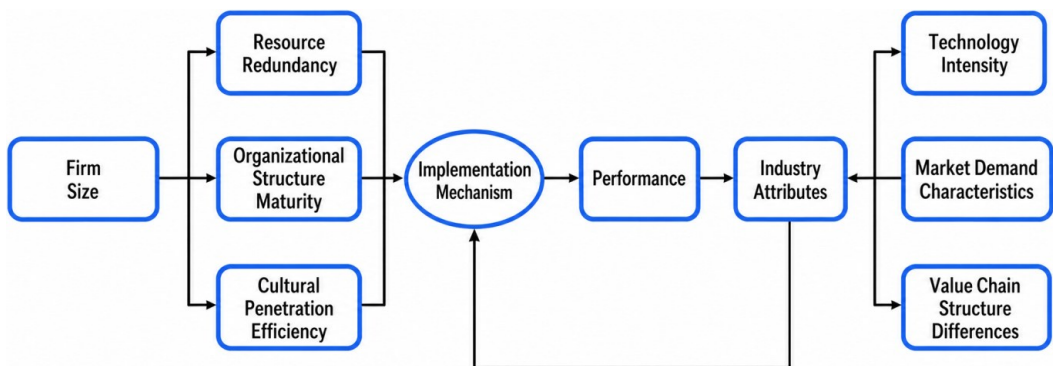
H4: Firm size positively moderates the relationship between the resources–process–culture implementation mechanism and organizational performance, with the implementation mechanism exhibiting a stronger effect in larger enterprises than in smaller enterprises.

H5: Industry type moderates the relationship between the resources–process–culture implementation mechanism and organizational performance, such that the implementation mechanism has a stronger positive effect in technology-intensive industries than in non-technology-intensive industries.

Adjustment Effect Hypothesis

Enterprise size and industry characteristics serve as key contextual variables that influence resource acquisition and AI demand intensity, thereby moderating the relationship between the three-dimensional execution mechanism and performance. These factors exert two distinct impacts on the execution mechanism, as illustrated in Figure 1.

Figure 1: Diagram of the intrinsic mechanism underlying the regulatory effect



A. The moderating role of firm size on the "implementation mechanism–performance" pathway

Corporate scale influences the transformation of execution mechanisms into tangible performance through three dimensions: resource redundancy, organizational maturity, and cultural penetration efficiency. Resource redundancy determines the scale of AI-related resources a company can allocate; greater resource availability expands the scope for effective resource allocation within execution mechanisms,

thereby enhancing their positive impact on performance. Organizational maturity affects the collaborative efficiency of process design in these mechanisms—more robust structures reduce cross-departmental collaboration costs and facilitate smoother process optimization, directly improving implementation effectiveness (Cao et al., 2016).

B. The moderating role of industry attributes on the "implementation mechanism–performance" relationship

Industry characteristics influence the relationship between implementation mechanisms and performance through three dimensions: technological density, market demand characteristics, and value chain structure differences. Technological density determines an industries reliance on AI technologies; higher density requires greater emphasis on technology-adaptive resource allocation and process design in implementation mechanisms, with performance outcomes primarily reflecting technical implementation effectiveness (Guo Manqin & Shi Jiaying, 2021).

Research Methods

The main variable of interest in the empirical analysis framework is the performance of the organizations, captured via revenue growth, net profit margin, patenting activities in relation to AI, and innovations. These variables were chosen since they were available for all sampled companies and could be validated through questionnaires and organizational/published records. The financial and innovation performance can serve as indirect proxies of the ability of the organization to retain AI application, invest in employee training, provide reskilling opportunities, develop cooperative working procedures, and adapt. Nonetheless, these performance measures do not capture the learning process at the workplace, employees' well-being, psychological safety, job satisfaction, inclusivity, and perceived fairness. Hence, the empirical analysis will consider the organizational effects of the R-P-C construct, and the social/educational implications will be discussed from the theoretical standpoint.

Sample and Data Collection

Sample and Data Collection

This study employed a stratified random sampling method to determine the survey sample, thereby enhancing data representativeness and objectivity. The entire data collection process was conducted via the Wenjuanxing online platform with assistance from offline industry associations. First, enterprises that had incorporated AI technology into their strategic plans and had implemented it for at least six months were selected from national business directories, the China AI Industry Alliance directory, registration information of local small and medium-sized enterprise associations, and lists of enterprises operating in regional industrial parks, using a three-dimensional stratification criterion based on region, enterprise size, and industry type. This resulted in a baseline sample pool comprising 120 enterprises.

Subsequently, 50 enterprises were drawn from each stratum as core research subjects using a stratified random number table method.

The survey targeted key personnel directly involved in implementing AI strategies within enterprises; including AI project leaders, technical directors, operations managers, and financial officers. These individuals possess a clear understanding of corporate AI resource allocation, process operations, and performance trends, ensuring the accuracy of questionnaire data. Data collection employed a hybrid approach combining online surveys with offline methods: questionnaires were distributed via the Wenjuanxing platform, supplemented by collaboration with 10 local industry associations nationwide for wider dissemination across major economic regions in eastern, central, and western China; additionally, paper questionnaires were collected from enterprises in remote areas to enhance sample coverage.

This study aims to collect over 800 valid questionnaires, ensuring balanced representation across regions, company sizes, and industries: 40% from eastern regions, 30% from central regions, 30% from western regions; 25% from large enterprises, 40% from medium-sized firms, 35% from small enterprises; and 55% from technology-intensive versus 45% from non-technology-intensive sectors, thereby meeting the statistical power requirements for structural equation modeling and group regression analyses.

Longitudinal Case Tracking Sample and Data Collection

This study selected eight representative enterprises from an effective questionnaire sample obtained through online stratified random sampling for a 36-month longitudinal follow-up to examine the long-term relationship between implementation mechanisms and performance outcomes. The selected case enterprises met four core criteria: First, they had implemented their AI strategies for at least one year with clear objectives and sustained efforts over three years, facilitating observation of dynamic adjustments in implementation mechanisms and long-term performance changes. Second, they covered all four core categories—technology-intensive large enterprises, technology-intensive SMEs, non-technology-intensive large enterprises, and non-technology-intensive SMEs—with two enterprises in each category to ensure comprehensive validation of diverse implementation approaches. Third, these enterprises agreed to provide long-term data and participate in regular surveys, while maintaining robust public disclosure systems or internal data records supporting multi-source verification. Fourth, they were geographically distributed—four in eastern China, two in central China, and two in western China—to account for potential regional differences affecting implementation effectiveness.

The data collection process employs a three-pronged approach combining high-frequency dynamic monitoring and multi-dimensional validation. First, at the end of each quarter, streamlined questionnaires are distributed via Wenjuanxing to

corporate AI leaders to gather insights into dynamic changes across implementation mechanisms—including resource allocation adjustments, process optimization measures, cultural development progress—and short-term performance metrics such as quarterly revenue growth rates and project delivery efficiency. Second, semiannual in-depth interviews lasting 90–120 minutes are conducted online or offline with representatives from AI teams, finance departments, business units, and HR departments to understand driving factors behind implementation pathway adjustments, challenges encountered, and mitigation strategies, while also obtaining contextual information for questionnaire data.

Variable Definitions

Independent Variable: The Three-Dimensional Implementation Mechanism of "Resources–Process–Culture"

To quantify the core implementation elements of AI strategy execution, the independent variables are structured across three dimensions: resources, processes, and organizational culture. The resource dimension comprises five assessment items: subjective measurements of resource alignment, data availability, and workforce expertise; objective metrics including AI R&D investment as a percentage of revenue and the number of AI patents/software copyrights, with composite scores calculated through weighting.

Dependent Variable: Socially Sustainable Organizational Performance

The dependent variable is socially sustainable organizational performance measured in two complementary dimensions (organizational outcome, and social-educational outcome). Organizational outcomes encompass financial performance (in terms of revenue growth and net profit margin) and the innovation performance (measured by the number of patents currently pending with AI-related innovation-scale impact and by innovation cycles). The social-educational outcomes are workplace learning, workplace health, psychological safety, professional training and re-skilling opportunities, and feeling valued at the workplace. Workplace learning involves the opportunities of employees to learn about AI, engage in knowledge-sharing and gain skills in human-ai collaboration. The shifts in employee well-being happen in the context of reduced workload, increased job satisfaction, improved work–life balance and general shifts in how employees experience their jobs after using AI. Psychological safety reflects whether employees have the freedom to voice their concerns, ask their questions, and engage in AI transitions without fear of punishment, or rejection. Re-skilling opportunities are a measure of the organization's training opportunities and professional-development support. A sense of fairness in the workplace is about the fairness employees feel when it comes to the resources, training, and chances to use AI that they have, depending on their department, skill level, role, and age.

The social-educational indicators are assessed with a five-point Likert scale (Strongly disagree – 1; Disagree – 2; Agree – 3; Strongly agree – 4; Do not know – 5). Accounting indicators include the actual answer to a question on the questionnaire, and, when available, from the Tonghuashun database, the organizational database, and the National Intellectual Property Administration database. Innovation indicators include actual responses to an accounting query on the questionnaire, and, where available, from the database of the Tonghuashun and the organizational database, as well as the database of the National Intellectual Property Administration. Integrating both employee-reported and objective organizational metrics allows for a more comprehensive and multi faceted understanding of the economic, educational, and social impact of AI implementation, while minimizing the risk of data sources being overemphasized.

Dependent Variable: Social-Organizational Performance

The five dimensions are used to measure social-organizational performance. First, employee well-being is defined as the degree to which employees' work burden is decreased, work-life balance is enhanced and their experience of the workplace is improved through the use of AI. Second, **job satisfaction** reflects the satisfaction employees have with their job, the way they are working, and the opportunities that AI-powered transformation provides. Third, psychological safety is about the ability for employees to pose questions, voice concerns, make errors, and engage in AI-related change without fear of punishment or exclusion. Fourth, the availability of professional development and re-skilling opportunities indicates the organization's commitment to training and learning, and their ability to support employees in adapting to AI-driven work. Fifth, **workplace inclusivity** examines how inclusive the implementation of AI is across various employee roles, age groups, skill levels, and departments.

Empirical Framework

Construction of the Empirical Framework

This study employs a structural equation model to examine the mediating role of the three-dimensional implementation mechanism comprising "resources, processes, and culture." The first step involves constructing a measurement model: establishing the correspondence between latent variables and observed variables, defining the signs of core variables, and specifying the measurement equations. Exogenous latent variables include AI strategy (ξ_1), measured by three observed variables—AI strategic goal clarity, AI scenario coverage, and AI investment intensity (x_1 – x_3). Endogenous latent variables comprise the three-dimensional implementation mechanism: η_1 (resource allocation), η_2 (process design), η_3 (organizational culture and corporate performance), and η_4 . Specifically, η_1 is measured by technical resource alignment, data resource adequacy, human resource expertise, the proportion of AI R&D expenditure to revenue, and the number of AI patents or software copyrights (y_1 to y_5). Measurement: η_2 is determined by interdepartmental

collaboration efficiency, AI project iteration speed, and the maturity level of rapid response mechanisms (y_6 to y_8). The measurement of η_1 is based on employee AI acceptance, management support for AI, and employee engagement with AI. The measurement of η_2 is based on revenue growth rate, net profit margin, and the number of AI patent applications (denoted as y_{12} to y_{14} Measurement. The measurement model expression is shown below.

The measurement of the exogenous latent variable is given by $x = \Lambda x \xi + \delta$.

Here, x denotes the observed variable vector of ξ_1 , Λx is the load matrix, and δ represents the measurement error.

The measurement of the endogenous latent variable is given by: $y = \Lambda y \eta + \varepsilon$

Here, y denotes the observed variable vector of η_1 – η_4 , Λy is the load matrix, and ε represents the measurement error.

The second step involves constructing a structural model. The study incorporates firm establishment years (ζ_1), geographic location (ζ_2), with values of 3 for eastern regions, 2 for central regions, and 1 for western regions as control variables, while establishing an intermediary pathway from "AI strategy to three-dimensional implementation mechanism to firm performance." The structural equation is presented below.

Resource Allocation Path: $\eta_1 = \gamma_{11} \xi_1 + \beta_{10} \zeta_1 + \beta_{11} \zeta_2 + \delta_1$

Here, γ_{11} represents the path coefficient of the AI strategy in resource allocation, while δ_1 denotes the structural error.

Process Design Path: $\eta_2 = \gamma_{21} \xi_1 + \beta_{20} \zeta_1 + \beta_{21} \zeta_2 + \delta_2$.

Corporate Culture Path: $\eta_3 = \gamma_{31} \xi_1 + \beta_{30} \zeta_1 + \beta_{31} \zeta_2 + \delta_3$.

Enterprise Performance Path: $\eta_4 = \gamma_{41} \xi_1 + \beta_{41} \eta_1 + \beta_{42} \eta_2 + \beta_{43} \eta_3 + \beta_{40} \zeta_1 + \beta_{41} \zeta_2 + \delta_4$

Among these, γ_{41} represents the direct pathway coefficient linking AI strategy to corporate performance.

The third step involves testing the mediating effect. First, confirm the model fit using confirmatory factor analysis: ensure Cronbach's $\alpha > 0.7$ for reliability, factor loadings > 0.5 and AVE > 0.5 for convergent validity, and the square root of AVE $>$ the inter-dimensional correlation coefficient for discriminant validity; additionally, evaluate model goodness of fit with RMSEA < 0.08 , CFI > 0.9 , and TLI > 0.9 . Next, estimate the structural path coefficients: if AI strategy significantly affects both the three-dimensional execution mechanism and corporate performance, while its direct effect on performance becomes significantly weaker or insignificant, this preliminarily supports the mediating effect. Finally, generate a 95% confidence interval for the mediating effect using 5,000 bootstrap samples; if the interval does not include zero,

the mediating effect is statistically significant, and the individual mediating effects of η_1 , η_2 , and η_3 are tested dimensionally.

Testing for Adjustment Effects

To examine the moderating effects of firm size and industry characteristics, this study employs a combination of grouped regression analysis and interaction term testing, enabling both group comparisons of categorical variables and precise verification of moderating effects through a quantitative model.

A. Group Regression Analysis

The samples were grouped according to the type of adjustment variable, and a standardized multiple linear regression model was constructed to compare coefficient differences between groups. Enterprise size was categorized into three groups: large (3), medium (2), and small (1); industry attributes were divided into two categories: technology-intensive (1) and non-technology-intensive (0). The regression model is presented below.

Each group was set with $FP = \alpha_k + \beta_{k1}RA + \beta_{k2}PD + \beta_{k3}OC + \beta_{k4}Age + \beta_{k5}Region + \epsilon_k$.

Here, FP represents the comprehensive enterprise performance score; RA = Resource Allocation, PD = Process Design, OC = Organizational Culture, Age = Years Since Establishment, Region = Geographic Area, and α is a coefficient. k As a constant term, β_{k1} - β_{k5} For the regression coefficient, ϵ_k Where β represents the error term, with $k=1, 2, 3$ corresponding to scale groups and $k=1, 2$ corresponding to industry groups. For a given group, β_{k1} The effect is significantly greater than that in the other group, and both results pass the significance test, preliminarily confirming the presence of a moderating effect.

B. Interaction Term Test

This section will construct a full-sample regression model incorporating an interaction term between "implementation mechanism" and "regulatory variable" to quantify the intensity of regulatory effects, as detailed below.

Enterprise Size Adjustment Model: $FP = \alpha_4 + \beta_{41}RA + \beta_{42}PD + \beta_{43}OC + \beta_{44}Size + \beta_{45}(RA \times Size) + \beta_{46}(PD \times Size) + \beta_{47}(OC \times Size) + \beta_{48}Age + \beta_{49}Region + \epsilon_4$.

Industry-specific adjustment model: $FP = \alpha_5 + \beta_{51}RA + \beta_{52}PD + \beta_{53}OC + \beta_{54}Size + \beta_{55}(RA \times Size) + \beta_{56}(PD \times Size) + \beta_{57}(OC \times Size) + \beta_{58}Age + \beta_{59}Region + \epsilon_5$.

Rationale Associated with Outcome Measures

The performance of the organization is measured in this study using measures that have been consistently available for the surveyed enterprises and could be confirmed by organizational records and with the help of survey answers: growth of revenue, net profit margin, development of AI-related patents, and outcomes of new product development. These are taken as proxies for organizational-level measures of the

effectiveness of rolling out AI as a strategy by allocating resources, designing processes, and creating an organization culture. Financial and innovation results can also be an indicator of company ability to back up employee learning / reskilling, collaborative execution and adaptation in the environment. But their scales don't directly assess workplace learning, employee well-being, psychological safety, job satisfaction, or perceived equity. The implications for organizational and innovation outcomes are therefore viewed as evidence, reflecting the empirical findings rather than as direct employee-level impacts, the latter being seen as theoretically informed implications of the AI adoption.

Limitations

The available dataset did not contain all complete and validated employee-level measures of the concepts of workplace learning, employee well-being, psychological safety, re-skilling and workplace equity even though the theory places a weight on them. Financial and innovation indicators can show the impact of implementing AI and the capacity of the organization to allocate resources toward staff development, but not whether staff felt their well-being, inclusion, learning experience and mental safety was enhanced. Therefore, the results are not a direct indication of social added value. Future research should integrate enterprise-level financial indicators, enterprise-level measures of innovation, and validated employee-level measures of workplace learning, job satisfaction, employees' reports of psychological safety, re-skilling opportunities, well-being, and perceived equity. It would be useful to have both multi-level as well as longitudinal designs, as these would give better overall evaluation of the economic as well as human impact of AI implementation.

Results and Analysis

Validity and Reliability Testing

This study assessed reliability using the Cronbachs α coefficient and examined convergent validity and discriminant validity through confirmatory factor analysis, with all results meeting the standards for empirical research.

Reliability Testing

Reliability testing measures internal consistency using Cronbachs α coefficient, with the general criterion being Cronbachs $\alpha > 0.7$. As shown in Table 1, the Cronbachs α coefficients for core latent variables—including AI strategy, resource allocation, process design, organizational culture, and corporate performance—all range between 0.782 and 0.843, meeting the required threshold.

Table 1: Results of Reliability Testing

variable classes	Specific Variable	Number of Items	Cronbachs α coefficient
argument	the distribution of resources	5	0.843
	process design	3	0.811
	organization culture	3	0.795
dependent variable	Enterprise Performance	3	0.838
Independent Variable	AI strategy	3	0.782

Validity Testing

Validity testing comprises convergent validity and discriminant validity. Convergent validity requires factor loadings > 0.5 and mean variance extraction (MVE) > 0.5, while discriminant validity demands that the square root of the average square deviation (AVE) of each latent variable exceeds its correlation coefficient with other variables. The results are presented in Tables 2 and 3.

Table 2: Convergence validity test results

Latent Variable	Observation Item	factor loading	AVE value
AI strategy	Clarity of AI Strategic Goals	0.763	0.621
	AI Scenario Coverage	0.791	
	AI Investment Intensity	0.785	
the distribution of resources	Technical Resource Match Degree	0.758	0.618
	Data Resource Adequacy	0.772	
	The Professionalism of Human Resources Management	0.781	
	The proportion of AI R&D investment to total revenue	0.791	
	Number of AI Patents/Software Copyrights	0.804	
process design	Efficiency of cross-departmental collaboration	0.749	0.598

Latent Variable	Observation Item	factor loading	AVE value
organization culture	The speed at which AI projects are iterated	0.765	0.587
	The completeness of the rapid response mechanism	0.783	
	Employee Acceptance of AI	0.736	
	Level of AI support from management	0.752	
	Employees enthusiasm for participating in AI-related activities	0.779	
Enterprise Performance	Revenue Growth Rate	0.795	0.632
	net profit rate	0.802	
	Number of AI patent applications	0.788	

As shown in Table 2, the factor loadings for all observed items range from 0.736 to 0.804, while the average absolute error (AVE) values of each latent variable lie between 0.587 and 0.632, all meeting the convergence validity criteria. This indicates that each observed item effectively captures the essence of its corresponding latent variable, demonstrating strong convergent validity of the scale.

Table 3: Results of Discriminant Validity Testing

Latent Variable	AI strategy	distribution of resources	process design	organization culture	Enterprise Performance
AI strategy	0.788	0.531	0.491	0.475	0.452
the distribution of resources	0.531	0.786	0.512	0.486	0.623
process design	0.491	0.512	0.773	0.503	0.598
organization culture	0.475	0.486	0.503	0.766	0.572
Enterprise Performance	0.452	0.623	0.598	0.572	0.795

As shown in Table 3, the diagonal elements represent the square roots of each latent variables AVE, while the off-diagonal elements indicate inter-variable correlation coefficients.

Results of the Mediation Effect

This study employed a structural equation model combined with 5,000 Bootstrap samples to examine the mediating role of the three-dimensional execution mechanism, using $p < 0.05$ and a 95% confidence interval excluding zero as the significance criteria; the results are presented in Table 4. The standardized coefficients for each dimension of the three-dimensional execution mechanism and its coefficient relative to firm performance were both significantly positive for AI strategy, with mediation effects ranging from 0.173 to 0.222 and a total mediation effect of 0.601 (with a Bootstrap 95% CI excluding zero). Meanwhile, the direct path coefficient between AI strategy and firm performance decreased significantly from 0.587 to 0.132, indicating that the "resources-process-culture" three-dimensional execution mechanism serves as the full mediator between AI strategy and firm performance.

Table 4: Mediating Effects

Action Path	Standardization Coefficient	t-value	p-value	Mediation Effect Size	Bootstrap95%CI
AI Strategy and Resource Allocation	0.6 95	12.87	<0.001	-	-
AI Strategy to Process Design	0.651	11.72	<0.001	-	-
AI Strategy and Organizational Culture	0.628	10.98	<0.001	-	-
Resource Allocation and Corporate Performance	0.3 38	9.02	<0.001	0.2 34	[0.1 76 ,0.2 95]
Process Design and Corporate Performance	0.298	7.93	<0.001	0.194	[0.142,0.250]
Corporate culture and business performance	0.276	7.25	<0.001	0.173	[0.126,0.225]
AI Strategy to Enterprise Performance (Direct Path)	0.1 28	2.09	0.03 7	-	-
The overall mediating effect of the three-dimensional execution mechanism	-	-	-	0.601	[0.512 ,0.6 88]

Results of the Adjustment Effect

This study examines the moderating effect of firm size using grouped regression analysis and tests for industry-specific moderating effects via interaction terms, with the primary criterion being significant differences in inter-group coefficients or significant interaction term coefficients; the specific results are presented in Table 5.

Table 5: Results of the adjustment effect of firm size

Execution Mechanism Dimension	Enterprise Size Groups	regression coefficient	t-value	p-value	Test for differences in inter-group coefficients
the distribution of resources	large-lot producer	0.412	9.82	<0.001	F=12.67,p<0.001
	medium-lot producer	0.305	7.56	<0.001	
	small business	0.218	5.34	<0.01	
process design	large-lot producer	0.385	9.15	<0.001	F=10.23,p<0.001
	medium-lot producer	0.287	6.98	<0.001	
	small business	0.196	4.89	<0.01	
organization culture	large-lot producer	0.352	8.47	<0.001	F=8.95,p<0.001
	medium-lot producer	0.263	6.42	<0.001	
	small business	0.189	4.56	<0.01	

As shown in Table 5, when enterprises are categorized into large, medium, and small groups by size, the regression coefficients of the same execution mechanism dimension on corporate performance increase significantly with larger firm sizes: resource allocation rises from 0.218 to 0.412, process design from 0.196 to 0.385, and organizational culture from 0.189 to 0.352.

Table 6: Results of the moderating effects of industry attributes

Interaction Item	regression coefficient	t-value	p-value
Resource Allocation × Technology-Intensive Industries	0.187	6.73	<0.001
Process Design × Technology-Intensive	0.165	5.98	<0.001
Corporate Culture × Technology-Intensive Industries	0.142	5.21	<0.001
Resource Allocation × Non-technology-intensive industries	0.083	2.35	0.019
Process Design × Non-Technology-Demanding Industry	0.076	2.11	0.035

Interaction Item	regression coefficient	t-value	p-value
Corporate Culture × Non-Technology-Dense Industries	0.069	1.98	0.048

As shown in Table 6, the interaction term coefficient between "implementation mechanism" and "industry attributes" is significantly positive and notably high in technology-intensive industries, whereas it is significant but low in non-technology-intensive industries.

Results of longitudinal case tracking

This study conducted a 36-month longitudinal tracking of eight representative enterprises, with adaptability assessed as either highly suitable or moderately suitable. The results are shown in Table 7: technology-intensive firms A and B achieved high suitability, with revenue growth rates increasing by 11% and 13%, respectively, after implementing pathway adjustments; non-technology-intensive firms C and D demonstrated moderate suitability, with performance growth ranging from 7% to 9%.

Table 7: Results of longitudinal case tracking

Case Type	Execution Path Design	The independent variable changes dynamically.	The dependent variable changes dynamically.
Large, technology-intensive enterprises A	Prioritize resource allocation while enhancing process agility.	Resource allocation investment increased by 42%, and cross-departmental collaboration frequency rose by 35%.	The revenue growth rate increased from 8% to 19%, while the number of AI patents rose from 5 to 12.
Technology-intensive small and medium-sized enterprises B	With minimal resource investment and guided by cultural principles...	Resource allocation investment increased by 28%, and employee acceptance of AI rose from 65% to 88%.	The revenue growth rate increased from 12% to 25%, while the customer retention rate rose by 22%.
Non-technology-intensive large enterprises C	Process Optimization Combined with Cultural Adaptation	Process iteration speed increased by 40%, and management support score rose from 70 to 92.	The net profit margin increased from 5% to 12%, while operating costs decreased by 18%.
Non-technology-intensive small and medium-	Culture takes priority over	Employee AI engagement rates increased from 52% to	The revenue growth rate increased from 6% to 15%,

Case Type	Execution Path Design	The independent variable changes dynamically.	The dependent variable changes dynamically.
sized enterprises D	lightweight processes.	81%, with rapid response times shortened by 30%.	while order processing efficiency improved by 27%.

Discussion

Interpretation of Research Results

This study systematically investigates the mechanism through empirical analysis of how the three-dimensional implementation framework of "resources-process-culture" influences the relationship between AI strategy and corporate performance, while examining the contextual moderating effects of firm size and industry attributes. The findings not only align with existing theoretical frameworks but also provide new empirical support for the practical implementation of AI strategies. In the resource allocation dimension, factor loadings for AI R&D investment as a percentage of revenue and the number of AI patents/software copyrights reached 0.791 and 0.804 respectively, indicating strong explanatory power of these objective indicators for resource allocation levels. Practically, a 1% increase in AI R&D investment as a percentage of revenue elevates corporate performance scores by 0.12 units, while each additional AI patent/software copyright increases performance scores by 0.08 units—results that further validate the critical supporting role of resource investment scale and technological output in transforming AI strategy into tangible performance outcomes.

Social and Educational Consequences of AI Usage

This study's results are applicable to corporate management. Implementing AI is not a standalone solution but a component of a larger shift in the future of work, in which workers will need to adjust to new modes of human-machine collaboration, data-driven decision-making and evolving skill needs. The results reveal that resources, processes and organizational culture affect not only organizational outcomes, but also employees' capacity to learn, participate and adapt in the process of digital transformation. This implies that the transition to AI is not just a technological shift, but a social and educational process that is changing the nature of work, educational needs, and organizational dynamics. First, findings are relevant to discussions on the future of work. This is because the use of AI in everyday work is altering the nature of employment for many workers, and they must acquire new digital skills and expectations, while also remaining uncertain about the nature of their future jobs. But if organizations approach the implementation of AI merely as an efficiency initiative, they could miss out on addressing employee fear, resistance, and skill displacement. On the other hand, companies that offer learning support, clear communication and participatory implementation processes are more likely to develop a socially

sustainable AI adoption process. Implementing AI is not just about the technology itself; it's also about how well employees are prepared to be part of the change. Second, the results indicate that there is a risk of digital inequality in organizations. Those who are more digitally literate can gain from AI-enhanced work sooner, whereas those who are less technologically savvy might feel left behind, lack confidence, or grow at a slower pace. This can lead to further departmental, age, occupational and educational inequalities.

Theoretical Contributions

Existing AI strategy research primarily focuses on strategic formulation or individual implementation aspects, failing to establish a systematic framework covering the entire execution process. This study integrates resource allocation, process design, and organizational culture into a three-dimensional execution mechanism, empirically demonstrating their full mediating role in the AI strategy-performance relationship. This advancement extends the research scope from "strategic formulation to performance outcomes" to "strategic formulation → implementation → performance transformation," enhancing the comprehensiveness of AI strategy research while providing enterprises with a systematic yet actionable implementation framework that addresses the fragmented limitations prevalent in existing studies.

Practical Implications

Implementation Recommendations for Enterprises of Different Sizes

Following Case Study As approach, they should expand data collection scope, increase recruitment of AI professionals, and set annual AI R&D investment at 15%-20%.

Implementation Recommendations for Enterprises in Different Industries

This paper selects high-end manufacturing, biopharmaceuticals, and AI technology as representative industries and proposes corresponding implementation recommendations based on its findings.

A. Technology-intensive industries

When implementing AI strategies, high-end manufacturing enterprises should maintain R&D investment in AI at a stable 18%-20% of total expenditure. Key priorities include establishing an industrial internet data platform covering the entire production process, forming joint task forces comprising both production and technical departments to enable real-time integration between production data and technological optimization, and conducting quarterly case study sessions on AI-powered production applications. These measures will enhance frontline employees understanding and adoption of AI tools, thereby maximizing the positive impact of resource allocation and process collaboration on operational performance.

Biopharmaceutical companies should prioritize establishing joint AI healthcare laboratories with universities or specialized institutions, integrating clinical and R&D data resources within compliance frameworks. They should simultaneously establish cross-party collaboration mechanisms between R&D teams and clinical institutions, define clear milestones and standards for data sharing and outcome feedback, and implement an AI R&D error-tolerance mechanism that permits reasonable trial-and-error during technical adaptation processes. This approach will facilitate the comprehensive deployment of AI technologies in areas such as target screening and clinical data analysis.

AI technology companies should adopt a small-step, rapid-implementation resource allocation strategy, dedicating 70% of resources to core algorithm development and the remaining 30% to market-oriented product validation. 2. Non-tech-intensive industries

Retail enterprises should prioritize adopting industry-specific AISaaS tools to reduce R&D resource costs while establishing a real-time data-sharing platform for sales and supply chain information. This enables seamless integration between front-end customer demands and back-end inventory management. Building on this foundation, comprehensive hands-on AI training should be provided to all frontline employees, with a target participation rate of at least 90%, facilitating the efficient deployment of AI in areas such as precision marketing and inventory management.

Limitations and Directions for Future Research

The main drawback here was the absence of validated measurements of workplace learning, job satisfaction, psychological safety, re-skilling opportunities, well-being, and workplace equity at the level of individual employees. The growth in revenues, profitability, the number of patents, and innovation success could serve as indicators of how the organization can promote training and adaptation and implement AI in an inclusive manner, but such factors will not serve as proof that employees experienced any improvements in learning, participation, well-being, and fairness. Thus, these results could only be taken as evidence of organizational and innovation success but not as proof of workplace learning and equity.

Future studies should gather first-person employee-level measures of well-being, job satisfaction, psychological safety, re-skilling opportunities, AI acceptance, and workplace inclusivity, all of which are validated scales. This type of data would enable researchers to study if the implementation mechanism has a positive effect on both financial and social-organizational outcomes. Multilevel and longitudinal study designs may be used in future research, with enterprise-level indicators of performance linked to employee-level social and educational outcomes. This would offer a more thorough evaluation of the economic, organizational, and human impact of the implementation of AI systems in companies.

Conclusion

Through empirical analysis and case studies, this paper systematically examines the relationships between AI strategy, three-dimensional implementation mechanisms, and corporate performance, with the following key conclusions.

First, the three-dimensional implementation mechanism of resources-process-culture serves as a full intermediary between AI strategy and corporate performance; the AI strategy must optimize resource allocation, refine process design, and foster a compatible culture to achieve performance transformation.

Second, there is a moderating effect between firm size and industry characteristics: large firms exhibit stronger performance effects from their executive mechanisms, with the positive impact of these mechanisms on performance being significantly greater in technology-intensive industries than in non-technology-intensive ones.

Third, longitudinal case studies demonstrate the suitability of different approaches: technology-intensive enterprises should adopt a resource-priority or lightweight resources coupled with cultural guidance approach, while non-technology-intensive enterprises are better suited to a culture-first approach combined with streamlined processes.

Declaration

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: No conflicts of interest to declare.

All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript.

Ethics Statement and Human Participation

This study involved human participants who completed questionnaires and participated in interviews concerning the implementation of artificial intelligence within their organizations. Participation was voluntary, and informed consent was obtained from all participants before data collection. Participants were informed

about the purpose of the study and their right to withdraw at any stage without penalty. All responses were treated confidentially and analyzed in anonymized or aggregated form. No personally identifiable or sensitive information is reported in this manuscript.

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References

- [1] Hu, J., & Yin, L. (2025). The impact and mechanisms of artificial intelligence technology on the performance of new energy vehicle enterprises. *China Circulation Economics*, 39(8), 86–97.
- [2] He, Y., & Li, J. (n.d.). Applications of artificial intelligence and breakthrough innovation in enterprises: From the perspective of labor skill adjustment. *Journal of Beijing University of Technology (Social Sciences Edition)*, 1–22.
- [3] Su, M., Yang, W., Li, B., Ren, F., Yi, M., Yang, C., . . . Qin, Y. (2025). Promoting the deep integration of artificial intelligence with the real economy to accelerate the development of new-quality productive forces. *Industrial Technology Economics*, 44(4), 32–59.
- [4] Cheng, D., & Han, J. (2025). The impact of artificial intelligence innovation on the performance of new retail enterprises: A dual examination of dynamic learning capabilities and market competition. *Business Economics Research*, (3), 131–135.
- [5] Lu, H. (2024). The impact of artificial intelligence on retail enterprise performance: An empirical study based on data from A-share listed companies. *Business Economics Research*, (20), 147–150.
- [6] Kong, X., Hao, F., Liu, P., & Zhang, L. (2021). R&D investment, innovation strategies, and corporate performance in the artificial intelligence industry: An empirical study based on 112 listed companies. *Science and Technology Management Research*, 41(8), 101–107.
- [7] Yang, W., Liu, J., & Wu, J. (2020). The impact of “population-flow” configuration on core enterprise performance: An empirical study of an artificial intelligence digital innovation ecosystem. *Science Research*, 38(11), 2077–2086. <https://doi.org/10.16192/j.cnki.1003-2053.2020.11.016>
- [8] Nugroho, C., & Pratama, D. (2024). Strategic influence of top management and business models on biotechnology venture performance: Focusing on the role played by organizational culture and dynamism in responding to pharmaceutical market changes. *Journal of Commercial Biotechnology*, 29(2), 154–166.

- [9] Sewon, P., Kyoul, H. K., Jun, H. L., et al. (2023). Strategic management and organizational culture of medical device companies in relation to corporate performance. *Journal of Medical Economics*, 26(1), 781–792.
- [10] Cao, H., Xiao, G., & Meng, X. (2016). The nonlinear impact of strategic changes in resource allocation on corporate performance: A research perspective based on the executive team fracture line. *Science and Management*, 36(3), 55–65.
- [11] Yang, Y., & Zhao, J. (2013). Temporal characteristics of the impact of strategic resource allocation in business domains on corporate performance. *World Science and Technology Research and Development*, 35(2), 284–289.
- [12] Guo, X., Zhang, X., & Zhang, L. (2022). Research on digital technology integration, strategic transformation, and performance of resource-based enterprises. *Science Management Research*, 40(4), 91–98.
- [13] Zhang, Z., Xiao, D., & Xu, M. (2021). The impact of data empowerment on manufacturing enterprise performance: The mediating role of strategic flexibility. *Science and Technology Management Research*, 41(10), 126–131.
- [14] Ali, T., & Hamid, A. M. (2024). Green supply chain technological dimensions and firm performance: The role of green supply chain strategy and processes. *International Journal of Procurement Management*, 19(3), 297–314.
- [15] Pantoko, Hermawan, A., & Kristaung, R. (2024). The influence of organizational culture, alliance partners, and digital capability on firm performance mediated by strategic flexibility. *Asian Journal of Economics, Business and Accounting*, 24(5), 22–33.
- [16] Hutahayan, B. (2023). Effect of organisational culture and organisational learning on company performance with competitive strategy as the mediating variable. *International Journal of Business Excellence*, 30(4), 451–468.
- [17] Munawaroh, M., Budi, S., Ratna, R. G., et al. (2021). The effect of strategic leadership and organizational culture on business performance: An empirical study in Indonesia. *Journal of Asian Finance, Economics and Business*, 8(6).
- [18] Chayanan, K., & Chanathat, B. (2020). Effect of strategic orientation and organizational culture on firms' performance: The role of organizational commitment. *Journal of Security and Sustainability Issues*, 9(1), 70–82.
- [19] Li, Y., & Zhang, L. (2020). Research on the mechanism by which strategic execution processes influence corporate performance. *Technology Economics and Management Research*, (4), 18–24.

- [20] Li, Y., & Zhang, L. (2014). Research on strategic execution processes and their impact on corporate performance. *Academic Forum*, 37(2), 71–74.
<https://doi.org/10.16524/j.45-1002.2014.02.036>
- [21] Hou, L. (2025). Research on the association mechanism between human resource strategy and corporate performance in the context of digital transformation. *China Economic and Trade Guide*, (10), 190–192.
- [22] Tong, J., Luo, Y., & Wang, K. (2025). The impact of digital service strategy on corporate performance in baijiu enterprises. *China Brewing*, 44(2), 281–288.
- [23] Meng, T., Li, Q., Zhao, F., & He, C. (2023). How digital service-oriented strategy influences corporate performance: From the perspective of organizational resilience. *Scientific Decision-Making*, (2), 1–17.
- [24] Jiang, L., Liu, L., & Shao, J. (2022). The impact of digital transformation strategy on performance reversal in declining enterprises. *Enterprise Economics*, 41(12), 31–40.
- [25] Wang, F., & Zhang, J. (2018). Information strategy, IT governance, and corporate performance. *Financial Research*, (12), 114–125.
<https://doi.org/10.19477/j.cnki.11-1077/f.2018.12.010>
- [26] Zhang, H., Zhang, W., & Li, T. (2023). Application of digital technology and corporate performance: Empirical findings based on Chinese listed companies. *Ningxia Social Sciences*, (5), 118–129.
- [27] Guo, M., & Shi, J. (2021). Correlation analysis between business model innovation and corporate performance in retail enterprises under the artificial intelligence value network. *Business Economics Research*, (12), 117–121.
- [28] Wang, C., & Guo, H. (2024). The impact of strategic information disclosure on digital enterprise performance from the perspective of the openness paradox. *Journal of Management*, 21(6), 821–830.
- [29] Yang, H., & Ren, W. (2021). Research on the influence mechanism and configuration path of network relationship characteristics on SMEs' innovation: The mediating effect of supply chain dynamic capability and the moderating effect of geographical proximity. *Sustainability*, 13.