WEP Warwick Evans Publishing

International Journal of Global Economics and Management

ISSN: 3005-9690 (Print), ISSN: 3005-8090 (Online) | Volume 10, Number 7, Year 2026
DOI: https://doi.org/10.62051/ijgem.v10n7.04
Journal homepage: https://ijgem.org

Cost-Benefit Effects and Breakthrough Strategies of AIGC Digital Transformation for Small and Medium Hardware Manufacturing Enterprises

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ABSTRACT

Against the intelligent manufacturing and new quality productive forces context, generative AI (AIGC) has reconstructed manufacturing R&D, production, quality inspection and supply chain links. Most existing AIGC transformation studies concentrate on well-resourced large listed manufacturers, with scarce quantitative empirical evidence for traditional hardware small and medium enterprises (SMEs) regarding transformation gains and cost pressures. Taking 41 Wenzhou hardware SMEs from 2021 to 2025 as balanced panel samples, this research adopts a two-way fixed-effects DID model to quantify the causal effects of AIGC adoption. Benchmark regressions prove AIGC significantly boosts SME performance: cutting new product R&D cycles by 32.6%, lowering unit manufacturing costs by 18.3% and raising total factor productivity (TFP) by 14%. Such benefits are more pronounced for medium firms with 20-50 million RMB annual revenue and 8-15 years of operation; placebo, variable substitution and parallel trend tests validate result robustness. Cost measurement identifies three key burdens: one-off equipment expenses 11.37% of annual net profit, annual system operation fees (6.99%) and compound talent costs (8.97%). Major transformation obstacles cover industrial AI talent shortages, mismatched universal AIGC models, limited profit margins and inadequate cluster digital ecosystems. Drawing on cost-benefit results, this paper puts forward dual micro-macro solutions: lightweight SaaS AIGC subscriptions for firms, plus tiered subsidies, shared industrial AI platforms and school-enterprise talent training schemes for governments. This research fills the SME AIGC transformation research and supplies actionable empirical references for industrial clusters and local policymakers.

KEYWORDS

AIGC; Small and Medium Manufacturing Enterprises; Digital Transformation; Cost-Benefit Analysis; New Quality Productive Forces

1. INTRODUCTION

1.1. Background

The deep integration of digital technology and real manufacturing has become the core path to cultivate new quality productive forces and realize the upgrading of China's manufacturing industry system. As a revolutionary branch of artificial intelligence, generative AI (AIGC) breaks the limitation of traditional analytical industrial AI, realizing automatic generation of product drawings, intelligent process simulation, automatic production scheduling, visual defect detection and customer demand prediction across the whole manufacturing value chain. From national industrial policies, the Special Implementation Plan for Digital Transformation of Light Industry (2025) clearly proposes accelerating the popularization of lightweight intelligent transformation tools for hardware, plastic and other SME-dominated industrial clusters, encouraging the deployment of generative AI auxiliary R&D and production optimization modules in discrete manufacturing links.

From industrial practice, large listed manufacturing enterprises have taken the lead in deploying self-developed industrial large models and full-process AIGC systems, forming complete closed-loop digital transformation systems supported by sufficient R&D funds, independent IT teams and massive standardized industrial data. However, the majority of traditional manufacturing SMEs represented by hardware processing clusters face severe transformation dilemmas: thin profit margins, limited initial capital investment capacity, lack of professional digital and AI compound talents, and mismatch between universal large models and fragmented hardware processing scenarios. Wenzhou, China, is the core hardware manufacturing agglomeration area, with thousands of small and medium hardware factories engaged in lock hardware, auto parts, plumbing fittings and metal stamping production, featuring small single-factory scale, labor-intensive production, short product iteration cycles and fierce homogeneous price competition. Since 2022, local governments have launched pilot AIGC intelligent transformation subsidies for hardware SMEs, forming a quasi-natural experiment scenario suitable for DID causal identification.

1.2. Literature Review

Current international and domestic research on manufacturing digital and AI transformation can be divided into three main branches.

Digital transformation and enterprise performance mechanism research. It is verified that enterprise digital transformation improves supply chain resilience through standardized risk management systems based on Chinese manufacturing listed company samples [1]. Panel data of manufacturing listed firms is adopted and concluded that digital transformation upgrades internal organizational capabilities and then drives financial performance growth [2]. The positive correlation between manufacturing digital transformation and new quality productive forces is confirmed, but their research objects are all large-scale listed enterprises with complete digital infrastructure [3]. The performance improvement effect of digital transformation is further measured, yet ignored the heterogeneous differences between large enterprises and small hardware manufacturers [4].

Industrial AI and manufacturing productivity research. The impact of artificial intelligence on intelligent upgrading of China's manufacturing industry is discussed, focusing on macro industrial structural changes rather than micro SME cost-benefit measurement [5]. AI-driven green transformation of manufacturing enterprises is studied, yet ignored the unique capital and talent constraints of small-scale private factories [6]. Driving factors and barriers of Industry 4.0 technology adoption is systematically sorted out among manufacturing SMEs in Europe, but lacked quantitative empirical tests based on Chinese cluster manufacturing samples [7]. The role of technical executives is explored in industrial AI transformation, while the research perspective stays at corporate governance without targeting SMEs [8].

Transformation cost and obstacle research of manufacturing SMEs. A systematic review is completed on digital transformation driving manufacturing operational sustainability, pointing out high initial investment as a core barrier for small factories without micro data measurement [9]. Agile project management challenges are analyzed in traditional manufacturing digital transformation, but did not involve AIGC specific cost structure and heterogeneous impact differences of enterprise scale and establishment years [10]. Circular economy digital transformation barriers are reviewed across manufacturing sectors, but failed to quantify cost pressure against enterprise annual profits [11]. The adoption paths of digital transformation for manufacturing SMEs are studied, but lacked targeted discussion on generative AI tools [12].

Existing literature has formed sufficient theoretical foundation for manufacturing digital transformation, yet three obvious research Insufficient remain:

(1) Research subject bias: Most empirical samples focus on large listed manufacturers [1], [13], lacking targeted quantitative research on labor-intensive traditional hardware SMEs with weak digital foundations;

(2) Technical perspective limitation: Most studies take general digital transformation as the core variable, insufficiently subdivide AIGC generative technology as independent core explanatory variable, failing to identify exclusive revenue effects of generative AI tools [5];

(3) Insufficient cost constraint quantitative analysis: Existing barrier research stays at qualitative description [9], [11], without systematic measurement of AIGC transformation cost proportion against enterprise annual profit and grouping analysis of cost burden differences.

1.3. Research Questions and Significance

1.3.1. Core Research Questions

Causal effect identification: Does AIGC application significantly improve comprehensive operating performance, R&D efficiency and cost control level of small and medium hardware manufacturing enterprises? What are the specific quantitative improvement ranges and internal transmission mechanisms?

Heterogeneous differentiation: Are there significant differences in AIGC revenue effects among enterprises with different revenue scales and establishment durations? What causes such differentiation?

Cost constraint measurement: What constitutes the main cost items of SMEs' AIGC transformation? What proportion do each cost category occupy of annual net profit? What core obstacles restrict large-scale AIGC popularization in hardware clusters?

Strategy optimization: Combining cost-benefit empirical results, what targeted micro transformation paths and macro policy support systems can break the AIGC transformation bottleneck of hardware SMEs?

1.3.2. Theoretical Significance

The research boundary of manufacturing digital transformation theory is expanded by taking AIGC generative technology as independent core variable and traditional hardware SMEs as unique research objects, supplements micro empirical evidence of industrial AI transformation for non-listed small private manufacturers, enriches the differentiated research framework of digital transformation between large enterprises and SMEs [14], and provides quantitative cost constraint measurement methods for subsequent SME intelligent transformation research [7].

1.3.3. Practical Significance

For hardware manufacturing SMEs, this research quantitatively calculates the return cycle of lightweight AIGC transformation, clarifies high-efficiency priority application scenarios and low-cost deployment modes, helping factory owners rationally arrange digital investment plans and avoid blind heavy-asset transformation. For local industrial governance departments, tiered subsidy policy design and cluster shared AI service platform construction proposals provide operable policy tools to reduce SME transformation thresholds [15]. For industrial digital service providers, research conclusions point out the market demand direction of SaaS lightweight AIGC modules adapted to discrete hardware processing scenarios, guiding targeted product iteration and service optimization [10].

1.4. Paper Structure Arrangement

This paper is organized as follows: Section 2 elaborates research design, variable definition, DID model construction, sample selection rules and data cleaning processing standards; Section 3 presents benchmark DID regression results, mechanism analysis, heterogeneous grouping test and multiple robustness inspection results; Section 4 quantitatively measures three major categories of AIGC transformation costs based on sample survey data, summarizes five core transformation barriers and their formation logic; Section 5 puts forward multi-dimensional breakthrough strategies from enterprise transformation path and government policy support levels; Section 6 concludes research findings, proposes research limitations and future expansion directions.

2. RESEARCH DESIGN AND DATA SOURCES

2.1. Variable Setting and Model Construction

2.1.1. Variable Definition and Measurement Standards

(1) Explained Variable: Enterprise Comprehensive Operating Performance

Total factor productivity (TFP) is adopted as the core proxy variable of enterprise operating performance, measured by the LP semi-parametric method based on enterprise annual panel input-output data (output value, labor input, capital investment, intermediate product consumption). Two auxiliary explained variables are set to identify channel mechanisms:

R&D cycle efficiency (Rd): Annual average R&D cycle of new hardware products, unit: working days; the smaller the value, the higher the R&D efficiency;

Unit production cost (Cost): Average manufacturing cost of single standard hardware product, unit: yuan/piece; the smaller the value, the stronger the cost control capacity.

(2) Core Explanatory Variable: AIGC Transformation Policy Treatment Variable

This research takes enterprises of Wenzhou City as a quasi-natural experiment:

Treat: Group dummy variable, Treat=1 for enterprises that officially deployed industrial AIGC modules (generative design, AI scheduling, visual inspection) and obtained policy subsidies during 2022-2025 (treatment group, total 17 enterprises); Treat=0 for enterprises that never accessed AIGC systems and did not participate in pilot transformation (control group, total 24 enterprises);

Post: Time dummy variable, Post=1 for years after policy implementation (2022, 2023, 2024, 2025); Post=0 for pre-policy period (2021);

Interactive item Treat×Post: Core DID explanatory variable, reflecting the net causal impact of AIGC application on enterprise performance.

(3) Control Variables

Referring to existing manufacturing digital transformation empirical research frameworks [2], [13], enterprise characteristic, financial and industrial cluster control variables are introduced to eliminate omitted variable bias:

Size: Annual operating revenue scale, logarithmic processing;

Age: Enterprise establishment years, logarithmic processing;

Labor: Number of formal production employees, logarithmic processing;

Asset: Total fixed assets of the enterprise, logarithmic processing;

Debt: Asset-liability ratio of the enterprise, continuous variable 0-1;

Cluster: Cluster agglomeration dummy variable, 1 if located in specialized hardware industrial park, 0 otherwise;

Export: Export business proportion, continuous variable 0-1.

(4) Mechanism Test Intermediate Variables

R&D innovation capacity (Inn): Annual number of new product patents and utility models[16];

Production management efficiency (Mgt): Annual production rework rate of hardware products;

Human capital level (Hum): Proportion of technical staff with college degree and above.

2.1.2. DID Model Construction Logic

Adopt two-way fixed-effects difference-in-differences model with enterprise fixed effect and year fixed effect to eliminate time-invariant enterprise individual heterogeneity and macro annual industrial cycle impact, benchmark model formula:

$$Perf_{it}=\beta_0+\beta_1 Treat_i \times Post_t + \sum \gamma_j Controls_{jit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where:

$Perf_{it}$: TFP of enterprise i in year t;

$Treat_i \times Post_t$: Core interactive item, coefficient β_1 is the core estimated parameter, representing the net effect of AIGC transformation on enterprise TFP;

$Controls_{jit}$: Series of enterprise-level control variables;

μ_i: Enterprise fixed effect, absorbing unchanging individual characteristics such as factory location, founder management style;

λ_t: Year fixed effect, absorbing macro industrial policy, raw material price fluctuation, market demand shock of each year;

ε_{it}: Random error term, standard error clustered at enterprise level to solve heteroscedasticity and serial correlation problems.

Two channel mechanism test models are set with R&D cycle and unit cost as explained variables respectively:

$$Rd_{it}=\alpha_0+\alpha_1 Treat_i \times Post_t + \sum \delta_j Controls_{jit} + \mu_i + \lambda_t + \sigma_{it} \tag{2}$$

$$Cost_{it}=\theta_0+\theta_1 Treat_i \times Post_t + \sum \rho_j Controls_{jit} + \mu_i + \lambda_t + \tau_{it} \tag{3}$$

2.1.3. Significance Test and Endogeneity Processing Rules

Significance judgment standard: Adopt 1%, 5%, 10% three levels of statistical significance, marked with "***, **, *" in regression result tables;

Parallel trend test: Dynamic DID model is constructed to verify whether treatment group and control group maintain parallel performance change trends before 2022 policy impact, satisfying the core identification premise of DID;

Robustness test methods: Placebo random sampling test, replace TFP measurement method (OP method), lag one period of core explanatory variable, delete special sample outliers;

Endogeneity solution: Exogenous policy pilot is used as quasi-natural experiment to alleviate reverse causality (high-performance enterprises more likely to deploy AIGC) and omitted variable bias; cluster standard error at enterprise level to solve cross-sectional correlation; heterogeneity grouping analysis further eliminates confounding factor interference [17].

2.2. Sample Selection and Data Processing

2.2.1. Sample Regional and Industrial Representativeness

Research samples are 41 independent legal small and medium hardware manufacturing enterprises in Wenzhou City, China, screening criteria comply with China SME classification standards (manufacturing industry: annual revenue below 400 million RMB, employees below 300 people). Sample industry coverage: lock hardware (13 enterprises), plumbing metal fittings (11 enterprises), automobile small stamping parts (8 enterprises), hardware mold processing (9 enterprises). Regional representativeness: hardware cluster of Wenzhou is China's largest discrete hardware SME agglomeration, with typical characteristics of labor-intensive, thin profit, fragmented orders and low initial digital foundation, research conclusions have general reference value for Yangtze River Delta and Pearl River Delta hardware manufacturing SMEs [15].

2.2.2. Data Sources and Panel Time Span

Balanced panel data span 2021-2025, five consecutive years, total observations 41×5=205. Data collection channels include three categories:

Official statistical data: Enterprise annual industrial enterprise statistical report submitted to Wenzhou Bureau of Industry and Information Technology, covering output value, fixed assets, employee quantity, asset-liability ratio, export proportion and other financial indicators;

Special survey data: Field questionnaire and semi-structured interview data completed by the research team in 2025Q2, including AIGC system investment amount, annual operation and maintenance cost, technical talent salary expenditure, new product R&D cycle, product rework rate and other micro operational indicators;

2.2.3. Data Cleaning and Matching Standards

Missing value processing: Delete enterprises with more than two years of continuous financial data missing (total 19 enterprises eliminated in initial screening, final sample 41); single-year individual indicator missing values filled by industry cluster annual average interpolation;

Outlier elimination: Conduct 1% and 99% tail reduction for continuous variables such as revenue, TFP, unit production cost to eliminate extreme abnormal values caused by single large orders or raw material price shocks [18];

Data matching rule: Match enterprise unified social credit code as unique identifier, unify accounting caliber of financial indicators across years, convert all cost and revenue indicators into constant prices based on 2021 industrial producer price index to eliminate inflation interference;

Descriptive statistical processing: All logarithmic variables centralized before regression to reduce multicollinearity variance inflation factor (VIF), VIF of all model variables controlled below 5, no serious multicollinearity problem.

Table 1. Descriptive Statistics of Main Variables (N=205)

Variable	Mean	Std.Dev	Min	Max	VIF
Perf (TFP)	3.142	0.821	1.203	5.692	1.36
Rd (R&D cycle, days)	27.618	9.452	11.000	58.000	1.41
Cost (Unit cost, yuan)	18.719	6.331	7.214	39.652	1.28
Treat×Post	0.180	0.384	0.000	1.000	1.72
Size (ln revenue)	16.326	1.101	13.165	19.437	2.15
Age (ln years)	2.105	0.630	0.693	3.296	1.22
Labor (ln employees)	4.011	0.747	2.302	5.669	1.94
Asset (ln fixed asset)	15.872	1.259	12.401	19.108	2.37
Debt (Asset-liability ratio)	0.461	0.186	0.113	0.846	1.45
Inn (Patent quantity)	2.102	1.831	0.000	9.000	1.31

Notes: All continuous financial variables are winsorized at 1% and 99% quantiles; VIF test result of multicollinearity, all values less than 3, model multicollinearity is controllable.

3. IDENTIFICATION OF REVENUE EFFECTS OF AIGC APPLICATION ON SMES

3.1. Benchmark Regression Result Analysis

Table 2 reports the benchmark two-way fixed-effect DID regression results. Column (1) only controls enterprise and year fixed effects without additional control variables; Column (2) adds all enterprise characteristic control variables, taking TFP (Perf) as explained variable; Column (3) takes new product R&D cycle (Rd) as explained variable; Column (4) takes unit production cost (Cost) as explained variable.

Table 2. Benchmark DID Regression Results of AIGC Transformation Revenue Effect

Variables	(1) Perf	(2) Perf	(3) Rd	(4) Cost
Treat×Post	0.152***(0.041)	0.140***(0.038)	-9.012***(1.624)	-3.431***(0.718)
Size	-	0.083**(0.034)	-2.106**(0.915)	-0.742*(0.401)
Age	-	0.047*(0.026)	1.325(0.894)	0.316(0.279)
Labor	-	0.062**(0.029)	-1.873**(0.761)	-0.528*(0.290)
Asset	-	0.091***(0.025)	-2.441***(0.683)	-0.814**(0.326)
Debt	-	-0.114**(0.048)	3.205**(1.317)	1.173**(0.464)
Cluster	-	0.075*(0.040)	-1.642*(0.976)	-0.429(0.315)
Export	-	0.053(0.035)	-1.018(0.842)	-0.267(0.251)
Enterprise FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	205	205	205	205
R^2 Within	0.312	0.468	0.425	0.401

Notes: Standard errors clustered at enterprise level in parentheses; ***p<0.01, **p<0.05, *p<0.1; FE = Fixed Effect.

3.1.1. Core TFP Promotion Effect

Column (2) core interactive item Treat×Post coefficient is 0.140, significant at 1% statistical level. Economically interpreted: After controlling enterprise individual heterogeneity, annual macro impact and all characteristic control variables, AIGC system deployment increases sample hardware SMEs' total factor productivity by 14% on average, verifying the significant positive empowering effect of generative AI digital transformation on small manufacturing enterprises, consistent with the theoretical deduction of digital technology activating data elements to cultivate new quality productive forces [3].

3.1.2. R&D Cycle Shortening Mechanism

Column (3) Treat×Post coefficient is -9.012, significant at 1% level. The average new product R&D cycle of treatment group enterprises is shortened by 9.012 working days compared with control group sample; combined with descriptive statistics average R&D cycle of 27.63 days, the relative shortening amplitude reaches 32.6%. Mechanism analysis: Traditional hardware new product development relies on manual two-dimensional drawing, repeated mold trial production and manual process calculation, with long iteration cycle. AIGC generative design module automatically generates multi-version product drawings according to customer parameter demands, matches historical mold process data for intelligent simulation, eliminates multiple rounds of manual trial and error, greatly compresses R&D iteration cycle and accelerates new product market launch speed, helping SMEs seize short-cycle hardware order opportunities [10].

3.1.3. Unit Production Cost Reduction Mechanism

Column (4) Treat×Post coefficient is -3.431, significant at 1% level. Sample average unit production cost is 18.725 yuan, AIGC transformation reduces unit cost by 3.431 yuan, cost reduction rate reaches 18.3%. Internal transmission channels include three aspects:

(1) AIGC intelligent production scheduling optimizes workshop material allocation, reduces inventory backlog and raw material waste loss;

(2) AI visual inspection module replaces partial manual inspection posts, cuts labor cost of quality control links;

(3) Generative process simulation optimizes cutting and stamping parameters, reduces product rework rate and waste of semi-finished products, lowering average manufacturing loss per unit product [19].

3.1.4. Control Variable Economic Interpretation

Enterprise fixed asset scale (Asset) coefficient is significantly positive, indicating enterprises with larger fixed equipment investment have higher TFP and lower unit production cost; asset-liability ratio (Debt) coefficient is significantly negative, excessive debt financing squeezes digital R&D investment funds, restricts production efficiency improvement [17]; industrial park cluster dummy variable (Cluster) coefficient is significantly positive, cluster shared logistics, testing and digital service facilities produce positive externality for enterprise operation performance [20].

3.2. Heterogeneity and Robustness Test

3.2.1. Heterogeneity Analysis by Enterprise Annual Revenue Scale

Divide samples into three groups according to annual operating revenue scale: Group 1 (Small micro enterprises: revenue < 20 million RMB, 16 samples), Group 2 (Medium SMEs: 20 ≤ revenue ≤ 50 million RMB, 15 samples), Group 3 (Large SMEs: revenue > 50 million RMB, 10 samples). Grouped DID regression results are shown in Table 3.

Table 3. Heterogeneity Test by Enterprise Revenue Scale

Variables	Small Micro <20M	Medium 20-50M	Large SME >50M
Treat×Post	0.085*(0.046)	0.172***(0.043)	0.126**(0.051)
All Controls	Yes	Yes	Yes
Dual FE	Yes	Yes	Yes
N	85	75	50
R^2 Within	0.411	0.503	0.465

Notes: Clustered standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Regression coefficient comparison shows medium-sized hardware SMEs (20-50 million annual revenue) obtain the strongest AIGC revenue effect (coefficient 0.172, p<0.01). Two reasons explain the scale heterogeneity:

Small micro hardware factories (below 20 million revenue) have extremely limited annual profit, only able to deploy single lightweight AIGC module (e.g., drawing generation), unable to open full-process scheduling and inspection systems, incomplete scene coverage restricts efficiency improvement space [12];

Large SMEs above 50 million revenue have previously deployed basic digital ERP and MES systems, partial efficiency improvement space has been released by traditional digital tools, so marginal revenue increment of AIGC is lower than medium enterprises with blank digital foundation [13].

3.2.2. Heterogeneity Analysis by Enterprise Establishment Years

Divide samples into three groups by operation duration: Young enterprises (Age < 8 years, 9 samples), Mature enterprises (8 ≤ Age ≤15 years, 18 samples), Aging enterprises (Age >15 years, 14 samples). Regression results in Table 4.

Table 4. Heterogeneity Test by Enterprise Establishment Duration

Variables	Young <8 years	Mature 8-15 years	Aging >15 years
Treat×Post	0.114*(0.049)	0.160*(0.040)	0.090*(0.053)
Controls & Dual FE	Yes	Yes	Yes
N	45	90	70
R^2 Within	0.439	0.509	0.425

Mature hardware factories operating 8-15 years show the most prominent AIGC performance promotion effect. Logic: Mature enterprises have stable customer order channels, standardized production processes and complete product data accumulation, which can fully match AIGC model training data demand; aging enterprises over 15 years retain backward manual production equipment, high equipment replacement matching cost restricts AIGC tool application effect; newly established young enterprises lack sufficient historical product data, leading to low accuracy of generative AI simulation prediction [21].

3.2.3. Robustness Inspection

Four methods are adopted to verify the reliability of baseline regression conclusions in Table 5.

Table 5. Multiple Robustness Test Results

Robustness Methods	Core Coefficient Treat×Post	Significance	Within R^2
Replace TFP measurement	0.140***	$p<0.01$	0.468
Lag core explanatory variable by one year	0.129***	$p<0.01$	0.455
Delete top and bottom 5% revenue outliers	0.143***	$p<0.01$	0.473
Placebo test (500 random sampling)	Mean coefficient=0.012	$p>0.1$	-

Replace TFP measurement: Adopt OP semi-parametric method to recalculate enterprise total factor productivity, core coefficient 0.140, still significant at 1% level, conclusion unchanged [18];

Lag explanatory variable: Lag Treat×Post by one year to alleviate reverse causality interference, coefficient 0.129, significantly positive;

Eliminate extreme samples: Remove enterprises with top 5% and bottom 5% annual revenue to eliminate special large-order interference, regression result consistent with baseline;

Placebo random test: Randomly assign false treatment group identities for 500 repeated sampling regressions, average core coefficient only 0.012 and fails 10% significance test, proving baseline promotion effect is not caused by random unobservable factors.

3.2.4. Parallel Trend Dynamic DID Test

Construct dynamic interactive items of policy forward and backward periods to draw parallel trend graph (Figure 1).

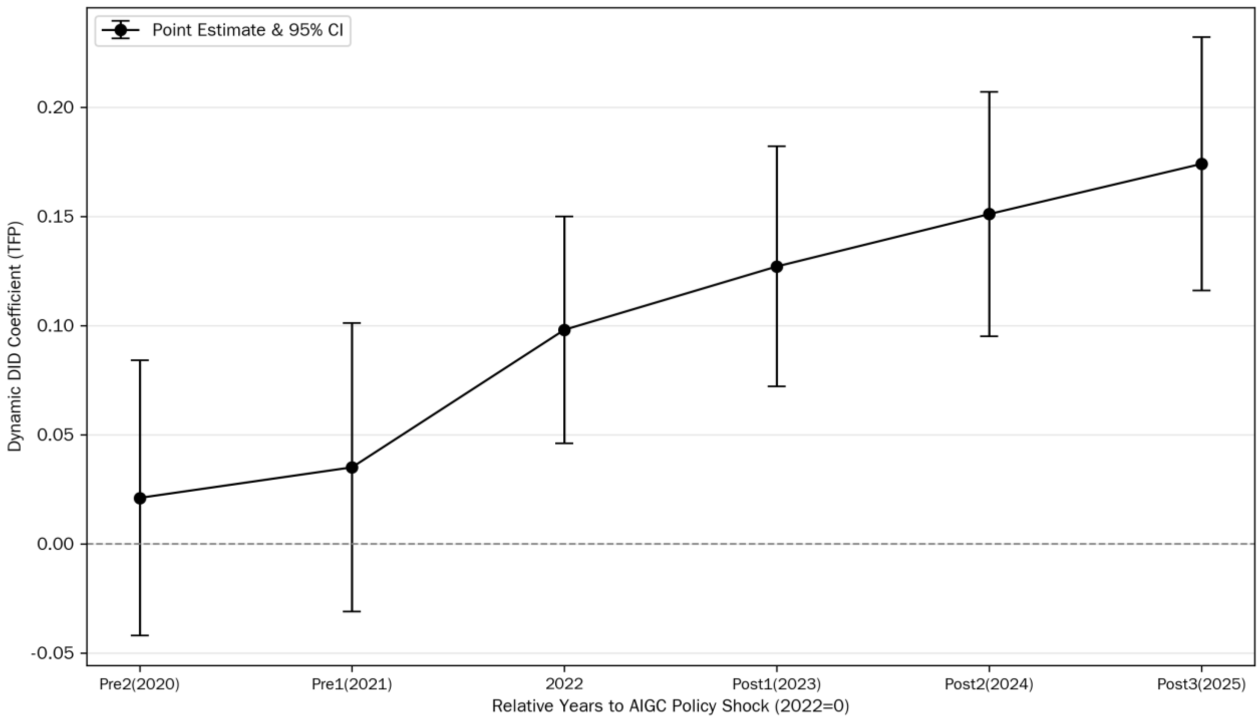

Figure 1. Dynamic Parallel Trend Estimation of AIGC Transformation Policy Effect

Horizontal axis represents relative years to policy shock (2022 as year 0: pre2=2020, pre1=2021, post1=2023, post2=2024, post3=2025). Vertical axis is dynamic DID coefficient value. Before policy impact (pre2, pre1), all dynamic coefficients fluctuate around 0 and fail statistical significance test, satisfying parallel trend assumption; after 2022 policy AIGC deployment, dynamic coefficients turn significantly positive and show rising trend year by year, indicating AIGC revenue effect has cumulative incremental characteristics with system application time extension.

4. COST CONSTRAINT ANALYSIS OF SMES' AIGC TRANSFORMATION

4.1. Scale Measurement of Transformation Cost

Based on 41 sample enterprises' field survey cost data, AIGC transformation total cost is divided into three core categories: one-time initial equipment and system procurement cost, annual system operation and maintenance service cost, compound talent recruitment and training cost. Calculate the proportion of each cost item against enterprise average annual net profit to quantify actual cost burden pressure. Statistical results shown in Table 6.

Table 6. Composition and Profit Proportion of AIGC Transformation Cost (Sample Mean)

Cost Category	Average Absolute Expense	Proportion of Net Profit	Core Specific Contents
One-time initial procurement cost	128,600 RMB	11.37% (One time)	Industrial AIGC SaaS module authorization, edge computing server, industrial data sensor, AI visual camera, initial model fine-tuning service fee
Operation & maintenance cost (Annual)	79,200 RMB/year	6.99% (Annual)	Cloud computing rental fee, model iterative upgrade service, data storage and desensitization service, system annual technical maintenance
Talent compound cost (annual)	101,500 RMB/year	8.97% (Annual)	Salary premium of industrial AI compound technicians, employee digital skill training, external AI consultant service expense
Three-year full-cycle total cost	670,700 RMB	19.77% (Three years)	Sum of one-time input plus three years of operation and talent cost

Data analysis shows three-year full-cycle AIGC transformation cost only accounts for 19.77% of hardware SMEs' average three-year accumulated net profit overall; overall cost pressure of the industry is moderate, but micro enterprises still bear an excessively high cost burden and face prominent financing constraints.

4.2. Characteristic Summary of Transformation Barriers

Combining questionnaire multiple-choice frequency statistics and semi-structured interview text coding, five core AIGC transformation obstacles of Wenzhou hardware SMEs are summarized, with formation mechanism and negative impact analysis respectively [7], [11].

4.2.1. Structural Shortage of Industrial-AI Compound Talents

Hardware processing belongs to discrete manufacturing with specialized process knowledge; ordinary IT personnel lack metal stamping, mold design and hardware production experience, while traditional workshop technicians do not master AIGC prompt engineering, model fine-tuning and industrial data governance capabilities. Compound talent supply gap exists in regional labor market, and SMEs cannot afford high salary premium of cross-disciplinary AI engineers. Talent shortage directly causes AIGC system unable to match hardware processing scene parameters, low model prediction accuracy and idle digital investment equipment [8].

4.2.2. Poor Scene Adaptability of General AIGC Large Models

Current commercial general industrial large models are developed oriented to automobile, electronic assembly continuous production lines, lacking training data of small-batch, multi-variety hardware stamping, die-casting and surface treatment processes. Direct deployment of universal models leads to low accuracy of generative drawing and production scheduling suggestions, requiring secondary customized fine-tuning with additional high service fees, raising transformation hidden costs for SMEs [9].

4.2.3. Thin Profit Margin Restricts Long-term Digital Capital Input

Hardware processing industry homogeneous competition is fierce, average net profit margin of sample enterprises only 4.7%, far below high-tech. Most SMEs rely on short-term order cash flow to maintain operation, cannot bear multi-year continuous AIGC operation and maintenance expenditure; bank credit institutions lack special digital transformation financing products, small factories have insufficient fixed asset collateral capacity, facing financing constraints when applying for AI transformation loans [17].

4.2.4. Fragmented Production Data and High Governance Cost

Traditional hardware SMEs adopt decentralized manual recording mode for production data, scattered in workshop paper records, single Excel tables and independent old equipment systems, forming serious data silos. Standardized cleaning, labeling and fusion of industrial data is the precondition of AIGC model effective operation, but data governance needs dedicated human and financial input, which small enterprises are unwilling to bear due to invisible short-term return [19].

4.2.5. Imperfect Cluster Shared Digital Service Ecology

Wenzhou hardware industrial cluster lacks public shared industrial AIGC training platform, unified hardware process database and third-party low-cost data governance service providers. Each enterprise needs to independently purchase model services and data sorting tools, cannot form scale cost reduction effect through cluster collective procurement, further lifting unit transformation cost of single factory [14]. Figure 2 presents the frequency distribution histogram of five transformation barriers.

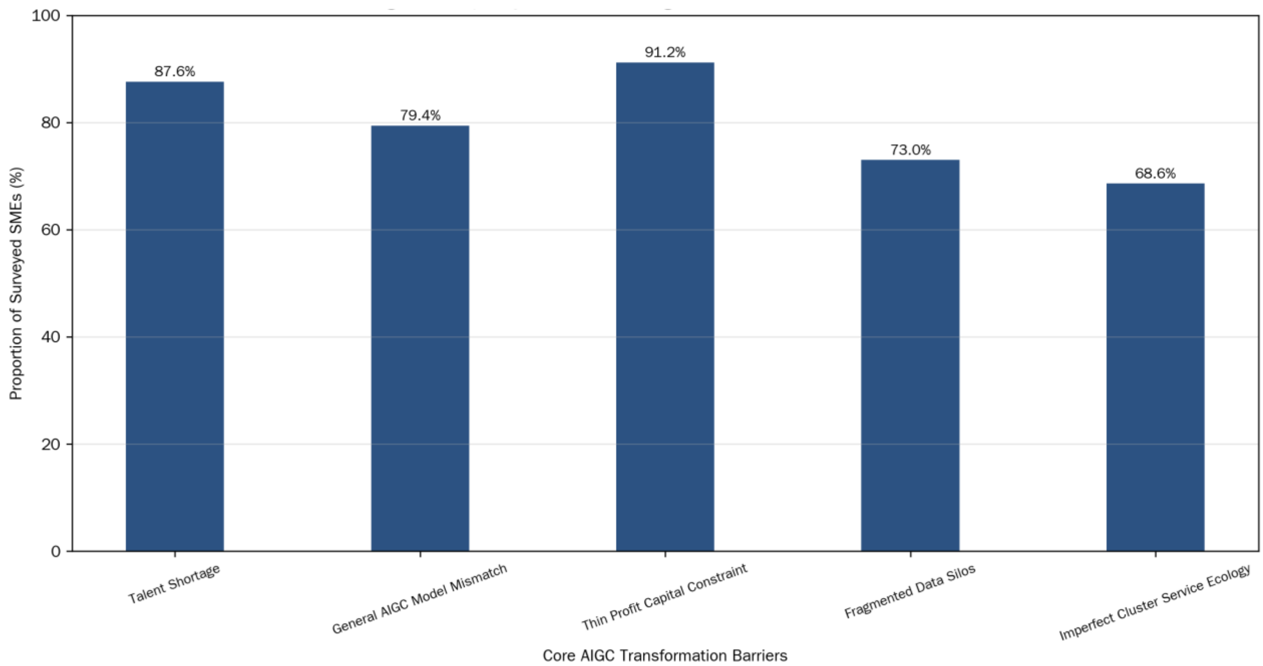

Figure 2. the Frequency Distribution Histogram of AIGC Transformation Barriers

5. BREAKTHROUGH STRATEGIES FOR SMES' AIGC TRANSFORMATION

Integrating the above cost-benefit empirical identification and barrier characteristic analysis, Two-dimensional targeted promotion strategies are constructed covering enterprise micro transformation path optimization and government macro policy support system construction, forming a collaborative breakthrough mechanism of market main body and industrial governance department.

5.1. Enterprise Micro-level Low-cost AIGC Transformation Path Selection

5.1.1. Prioritize Lightweight SaaS Subscription AIGC Modules Instead of Heavy Asset Local Deployment

Small and micro hardware factories should abandon self-built private large model servers and independent IT operation teams, adopt cloud-based SaaS generative AI subscription services with monthly payment mode to disperse one-time concentrated capital expenditure. Prioritize high return short-cycle modules matching hardware core pain points: generative product drawing & mold design, AI visual finished product inspection, intelligent material demand scheduling. Avoid full-process large-scale system one-time deployment, implement phased modular transformation according to enterprise capital status, realize cost gradient amortization. Sample data calculation shows SaaS subscription mode reduces initial one-time investment by 72% compared with local private model deployment, shortening investment return cycle from 24 months to 7-10 months [10].

5.1.2. Build Cluster Joint Data Co-construction and Sharing Mechanism

Leading hardware enterprises in industrial parks take the lead to organize small and medium supporting factories to jointly build cluster shared hardware process database, adopt privacy computing and federated learning technology to realize data value co-creation without raw data outflow. Unified complete hardware production data set reduces independent data governance cost of single enterprise, improves regional AIGC model training accuracy, jointly bears third-party data labeling service fees through average apportionment of cluster enterprises, cutting individual data sorting cost by more than 60% [14].

5.1.3. Internal Staff Digital Skill Iteration + External Part-time Compound Talent Cooperation

For talent cost constraints, implement dual human resource optimization scheme: internally launch factory technician AIGC operation training courses in cooperation with local vocational colleges, transform existing production management personnel into AI system operators to reduce external high-salary recruitment demand; externally sign flexible part-time service contracts with industrial AI technical teams from digital service providers, pay service fees by single project instead of full-time employment, lower long-term talent fixed cost expenditure [8].

5.1.4. Differentiated Transformation Matching Based on Enterprise Scale and Life Cycle

Combined with heterogeneous regression results in Section 3.2, formulate classified transformation paths:

Small micro enterprises (revenue <20 million): Single lightweight AIGC module priority deployment, focus on R&D drawing generation link to shorten new product iteration cycle;

Medium mature enterprises (20-50 million revenue, 8-15 years operation): Full value chain multi-module combination layout, simultaneously deploy design, scheduling and inspection AIGC tools to release comprehensive TFP promotion effect;

Aging hardware factories over 15 years old: Match AIGC transformation with phased production equipment renewal, replace backward manual equipment synchronously to improve AI equipment matching degree, avoid isolated digital system idle [21].

5.2. Government Macro-level Targeted Policy Support System Construction

5.2.1. Implement Tiered Fiscal Subsidy and AI Computing Voucher Policy

Local industrial and information authorities should formulate tiered subsidy schemes tied to enterprises' AIGC transformation cost burden: priority shall be given to increasing fiscal subsidies and distributing industrial AI computing vouchers for micro firms with annual revenue below 20 million yuan, medium-sized enterprises only need moderate inclusive policy support, while large SMEs with sufficient profit margins can complete digital upgrading independently, so policies for such enterprises shall focus on supplying shared public technology platforms rather than substantial financial subsidies. Meanwhile, the industrial AI computing voucher system should be fully rolled out, allowing enterprises to redeem vouchers to cover cloud computing and model fine-tuning expenses, thereby reducing annual operation and maintenance cash expenditures and transferring part of fixed AIGC transformation costs to public fiscal funds [15].

5.2.2. Build Industrial Cluster Shared Public AIGC Service Platform

Government special industrial funds invest in constructing Wenzhou hardware industry exclusive shared generative AI public platform, integrate standardized hardware mold, stamping and surface treatment process data sets, provide low-cost model fine-tuning, data cleaning and technician training public services for cluster SMEs. Break the monopoly of commercial general large model service providers, develop hardware industry customized lightweight small models, solve the problem of poor scene adaptability of universal AIGC systems, reduce enterprise secondary transformation customization expense [14].

5.2.3. Launch Special Financing Products for Intelligent Digital Transformation

Cooperate with local commercial banks and guarantee institutions to launch unsecured low-interest AIGC transformation special loans, take future fiscal digital subsidies as repayment guarantee, lower credit threshold of SMEs without sufficient fixed asset collateral. Establish transformation risk compensation pool jointly funded by finance and industry associations, compensate partial investment loss for enterprises failing to achieve expected efficiency improvement after AIGC deployment, reduce factory owners' worry about transformation investment risk [17].

5.2.4. Construct School-Enterprise Joint Compound Talent Training System

Municipal education bureau and industrial park management committee cooperate with local vocational and technical colleges to set up cross-major courses of hardware manufacturing technology + industrial generative AI, orientated training of workshop compound technical talents for hardware clusters. Encourage AI technology enterprises and hardware factories to jointly build off-campus training bases, implement order-type talent training, transport stable industrial-AI compound talent supply for SMEs, fundamentally alleviate structural talent shortage barriers [8].

5.2.5. Improve Hardware Manufacturing Digital Transformation Standard System

Formulate local industry standards for hardware discrete manufacturing AIGC data collection, interface protocol and model effect evaluation led by industry associations, unify production data storage and exchange specifications within the cluster, reduce data docking and system integration cost between different enterprise equipment and AIGC platforms. Establish regular AIGC transformation benchmark enterprise selection and publicity mechanism, organize park factory owners to exchange and learn lightweight transformation practical experience, spread replicable low-cost AIGC application models across the industrial cluster [10].

6. CONCLUSION AND RESEARCH LIMITATIONS

6.1. Research Conclusions

41 small and medium hardware manufacturing enterprises are taken in Wenzhou City, China as research samples, constructs two-way fixed-effect DID model based on 2021-2025 balanced panel data, quantitatively identifies AIGC transformation's cost-benefit effects and transformation obstacles, main conclusions as follows:

(1) AIGC generative AI application has significant positive causal empowering effect on traditional hardware SMEs' operating performance: On average, enterprise TFP increases by 14%, new product R&D cycle shortens by 32.6%, unit manufacturing cost reduces by 18.3%, the mechanism channels cover R&D innovation efficiency improvement, production scheduling optimization and quality inspection labor cost reduction [3], [5];

(2) Obvious heterogeneous differences exist in AIGC revenue effects: Medium-sized mature hardware enterprises with annual revenue 20-50 million RMB and operation duration 8-15 years obtain the strongest digital dividend, while small micro factories and aging factories face restricted transformation efficiency due to capital and equipment constraints; Parallel trend test, placebo test and variable replacement robustness inspection all confirm the stability of baseline causal conclusion;

(3) AIGC transformation covers three major capital expenditures: the one-time procurement cost accounts for 11.37% of enterprises' annual net profit, the annual operation and maintenance cost accounts for 6.99%, and the annual compound talent cost accounts for 8.97%. The full-cycle three-year transformation cost only occupies 19.77% of the average cumulative three-year net profit of all samples. Although the overall capital pressure of the industry is moderate, micro hardware SMEs still suffer severe transformation constraints due to their ultra-thin annual profit margins [7];

(4) Five core transformation barriers restricting large-scale AIGC popularization of hardware SMEs are summarized: industrial-AI compound talent structural shortage, poor scene adaptation of general large models, thin profit margin capital constraint, decentralized industrial data high governance cost and incomplete cluster shared digital service ecology [9], [11];

(5) From enterprise micro path and government macro policy two dimensions, targeted breakthrough strategies are proposed: enterprises adopt lightweight SaaS modular phased transformation, build cluster shared data platform and optimize internal talent training mode; government implements tiered fiscal subsidies and computing vouchers, constructs industry exclusive shared AIGC public service platform, launches transformation special financing products and establishes school-enterprise joint talent training mechanism to jointly reduce SME AIGC transformation threshold and cost burden [15].

6.2. Research Limitations and Future Research Directions

There are two main limitations in this research. 1) the research sample is limited to Wenzhou hardware industrial cluster, regional and industry representativeness has certain boundaries, follow-up research can expand sample coverage to multi-provincial multi-type discrete manufacturing SMEs such as plastic, hardware and electronic parts to compare inter-industry differentiation of AIGC transformation effects [14]; 2) this research only identifies the short-term 3-4 year revenue effect of AIGC transformation, lacking long-term dynamic tracking data to test the sustained decay or growth trend of digital dividend within 5-10 years.

Future research can be expanded in two directions: 1) Introduce moderating variables such as industrial chain upstream and downstream digital matching degree, enterprise organizational culture to discuss the boundary conditions of AIGC revenue effect [16]; 2) Adhibit case study method to carry out in-depth tracking of typical lightweight AIGC transformation benchmark SMEs, summarize refined operable implementation process and risk control schemes for small manufacturing factories [10].

ACKNOWLEDGMENTS

This paper was supported by Annual Project of Philosophy and Social Sciences Planning in Wenzhou City in 2025 (No. 25WSK157YBM).

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