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Artificial Intelligence, ESG Performance and Corporate Value: Evidence from Chinese Listed Manufacturing Companies

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Abstract. Against the backdrop of the digital economy, stricter "Dual Carbon" goals and ESG regulations, Chinese A-share listed manufacturing firms face urgent transformation pressure. Previous studies haven't really clarified how AI applications, ESG performance, and corporate value are linked together. They also tend to overlook the behavioral biases that come up in corporate decision-making. This paper tries to fill those gaps by looking into the relationships among the three. Panel data from Chinese A-share listed manufacturing firms between 2009 and 2024, excluding ST companies and those with missing data. The methods include two-way fixed effects regression and a mediation model. The empirical analysis focuses on two aspects: first, how AI applications directly affect corporate value, and second, whether ESG performance plays a mediating role. The underlying mechanism from a behavioral economics perspective. The results show that AI applications significantly boost corporate value at the 1% level. ESG performance turns out to be a notable improvement in ESG outcomes, which in turn raises corporate value. These findings offer some empirical evidence and practical takeaways for firms doing digital transformation and for policymakers working on sustainable development governance.

Keywords: Artificial Intelligence, ESG Performance, Corporate Value, Listed Manufacturing Companies, Mediating Effect

1. Introduction

The Current Trend of AI Empowering Manufacturing Enterprises Amid the Digital Economy Wave; The Overall Status of AI Deployment and Application Among A-Share Listed Manufacturing Companies; Against the backdrop of stricter "Dual Carbon" targets and ESG regulations, the necessity and value of corporate ESG governance have become increasingly evident; Challenges in Integrating AI Technology with ESG Governance: How AI Can Enhance ESG Performance, and How Their Synergy Impacts Corporate Value. Given this background, artificial intelligence, especially in areas like smart manufacturing and environmental monitoring, has become an important driver for transformation in manufacturing firms. At the same time, ESG regulations are getting stricter. In China, the Securities Regulatory Commission (CSRC) now requires

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manufacturing companies to strengthen their ESG disclosures, and the rules are even tighter for high- pollution sub-sectors.

But looking at the existing research, there are two notable gaps. One is that past studies haven't clearly explained how AI actually affects the value of manufacturing firms - the retransmission path remains unclear. The other is that they tend to ignore behavioral biases in corporate decision-making. For example, companies' ESG choices are often shaped by things like social preferences or limited attention, which are exactly the kind of factors behavioral economics focuses on.

Given the practical context and research limitations discussed above, a few core questions stand out. First, does using AI actually raise the value of Chinese listed manufacturing companies? Second, can AI indirectly boost corporate value by improving ESG performance? And third, how can the practical rationality behind this transmission mechanism be explained from a behavioral economics perspective?

2. Literature review and theoretical framework

2.1. Research on the relationship between AI applications and corporate value

A lot of the existing literature points in the same direction: using artificial intelligence (AI) tends to give a clear boost to Environmental, Social, and Governance (ESG) performance. Take Li et al. [1] as an example. They find that AI capabilities can effectively strengthen a firm's ESG outcomes, which highlights the transformative role AI plays in pushing sustainable development goals forward. Similarly, Tian, Wang, and Cai [2] take a different approach, they use machine learning to analyze corporate annual reports and build firm-level AI measures. Their empirical results show that AI adoption clearly improves ESG performance, mainly by easing financing constraints, improving information disclosure quality, and strengthening innovation ability. Then there's Xie and Wu [3], who looked at a large sample of 4,858 Chinese listed firms from 2007 to 2022. They also confirm that AI adoption has a positive effect on corporate ESG performance. Their mechanism tests suggest that AI helps environmental performance through green innovation, boosts social performance via corporate charitable giving, but might hurt governance effectiveness if internal control quality drops. Chen and Ge [4] back up these findings using data from Chinese A-share listed firms. They show that AI significantly promotes ESG improvement by raising operational efficiency and pushing innovation.

2.2. ESG performance and enterprise value

The link between ESG performance and corporate value is another major line of research in this area. Fang and Guo [5] analyzed 4,185 Chinese A-share listed firms during 2017 to 2022 and concluded that good ESG management can effectively lift enterprises' prospective cash flows, long-run value, and market competitiveness. Their research also shows that ESG efforts help create long-term value by lowering the weighted average cost of capital and increasing the return on investment. In the process, market pricing power, measured by the Lerner Index, plays an intermediary role. Zhao et al. [6] provided specific evidence for industrial listed companies, demonstrating that ESG performance and green technological innovation jointly drive corporate value creation.

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2.3. Literature gap

A fair amount of current research has already built a solid empirical link: AI adoption leads to better ESG performance, which in turn boosts corporate value, especially in China's manufacturing sector. That said, most of these studies treat the industry as a whole, and there hasn't been enough specialized work focusing specifically on manufacturing. The typical methods used include panel data regressions with fixed effects, measuring AI adoption based on key words from annual reports and running mediation or moderation models. Looking at the literature we retrieved, one potential gap stands out: very few studies try to identify the full causal chain from AI to ESG to value all within a single, integrated framework.

3. Theoretical analysis and research hypotheses

3.1. The direct impact of AI applications on corporate value

Based on theoretical derivations, this study examines how AI applications enhance corporate value through cost reduction, efficiency improvements, innovation, and risk management, and advances the main hypothesis as follows:

H1: The application of AI Has a Significant Positive Impact on Corporate value.

3.2. The mediating effect of ESG performance

H2: The AI Application Has a Positive Impact on Corporate ESG Performance

H3: ESG Performance Acts as a Mediating Factor Between AI Adoption and Corporate Value (AI Empowers ESG Improvement, and ESG Optimization Further Enhances Corporate Value).

4. Research design

4.1. Sample selection and data sources

The research sample covers manufacturing enterprises listed on China's A-share market from 2009 to 2024. ST and *ST designated firms, delisted companies and entities lacking core data are excluded from the sample.

4.2. Variable definitions and measures

Table 1. Variable definitions and measurement

Variable Type	Name of Variable	Key Metrics
Dependent variable	Corporate Value	Tobin's Q ratio
Explanatory variable	AI Application	Percentage of total assets accounted for by digital assets
Mediating variable	ESG Performance	ESG Composite Rating/Score
Control variable	Company size, debt-to-equity ratio, revenue growth rate, and largest Shareholder Ownership	

Table 1 gives the variable definitions and measurement methods used in this study. The data come from 31,406 firm-year observations of manufacturing firms listed on China's A-share market, covering the period from 2009 to 2024. A few screening steps were applied: first, ST and*ST firms were taken out because their financial status is unusual; second, delisted firms were excluded; third,

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any observations with missing values on key variables were removed. Also, all data have been winsorized. The explanatory variable, ESG, is based on the HuaZheng ESG rating, which has nine levels. Those ratings are converted into numerical values from 1 to 9, so higher numbers reflect better ESG performance among Chinese manufacturing listed firms. All data are sourced from the CSMAR Database, Wind Database, and Bloomberg.

4.3. Model development

Regression approaches are utilized to explore how the deployment of artificial intelligence directly shapes enterprise value. Meanwhile, stepwise regression based on the mediation framework is carried out to analyze the influence of AI on ESG performance as well as the subsequent effect of ESG on corporate value, which helps validate the mediating pathway. Prior to further analysis, we formulate the following two-way fixed-effects model to conduct the baseline regression of AI on firm value:

$$Value_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Here, $Value_{it}$ represents the enterprise value of firm i in year t. AI_{it} is the digitalization level index. $Controls_{it}$ is the set of control variables. μ_i and λ_t denotes firm-specific and year-specific fixed effects, respectively. ε_{it} represents the random error term.

In further regression analysis, following the stepwise regression method proposed by Wen, Zhonglin et al. [7] to test whether AI indirectly promotes firm value by improving ESG levels, the following stepwise regression model is constructed:

$$ESG_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$Value_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 ESG_{it} + \alpha_3 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

Where ESG_{it} represents the ESG level of firm i in year t.

5. Empirical results and analysis

5.1. Descriptive statistics results

Table 2. Descriptive statistics

Variable Type	Name of Variable	Mean	Std. Dev.	Min	Max
Explained variable	Corporate Value	2.0636	1.235	0.871116	7.97378
Explanatory variable	AI Application	0.0072	0.0073	0	0.0439
Mediating variable	ESG Performance	0.8596	4.0939	1.75	6.25
Control variable	Company size	22.0561	1.1603	19.9805	25.6462
	debt-to-equity ratio	0.3907	0.1958	0.0509	0.8751
	revenue growth rate	0.1326	0.3180	-0.5104	1.6915

Table 2 presents the descriptive statistics for all core variables in this study, based on a sample of 31,406 firm-year observations of Chinese manufacturing-listed firms from 2009 to 2024. The table reports the mean, standard deviation (Std. Dev.), minimum (Min), and maximum (Max) values for

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each variable, providing a comprehensive overview of their distribution characteristics and data variability.

The dependent variable, firm value, is proxied by Tobin's Q. Its average value stands at 2.0636, with a standard deviation of 1.234. Since the mean exceeds 1, it suggests that manufacturing firms in the sample generally have a market value higher than their book value, and investors seem to hold positive expectations for them. The main explanatory variable is AI adoption, calculated as the ratio of digital assets to total assets. The average is 0.0072, with a standard deviation of 0.0073. The minimum is 0, and the maximum goes up to 0.0439, so there's quite a big gap across firms. This kind of variation is actually helpful for identifying causal effects.

As for the mediating variable, ESG performance, it's captured by a composite ESG score. The mean is 0.8586, and the standard deviation is 4.0939, with values ranging from 1.75 to 6.25. That range shows that manufacturing firms differ a lot in their environmental, social, and governance practices. The relatively high standard deviation points to noticeable cross-firm differences.

Turning to control variables, firm size has a mean of 22.0561 and a fairly narrow range between 19.9805 and 25.6462, meaning the sample firms are relatively similar in scale. The debt-to-equity ratio averages 0.3907 with a standard deviation of 0.1958, which suggests capital structure varies quite a bit. Other controls, like the largest shareholder's ownership percentage and revenue growth rate, also show reasonable dispersion with no extreme values.

Overall, every variable falls within economically sensible ranges. There's enough variation both across firms and over time to support subsequent regression analysis, and no more severe outliers are present, so the sample data should be reliable.

5.2. Correlation analysis

Table 3. Regression model

	(1) Cooperate Value	(2) ESG_mean	(3) Cooperate Value
AI	532.2061***	3.0569***	522.2349***
	(2.8464)	(3.2399)	(2.7929)
Size of Cooperate	10.2074***	0.3269***	9.1410***
	(5.1387)	(32.6162)	(4.5173)
Debt-to-equity ratio	-4.9273	-1.0313***	-1.5635
	(-0.6627)	(-27.4861)	(-0.2075)
Shareholding percentage of the largest shareholder	-0.4728***	0.0056***	-0.4910***
	(-3.6118)	(8.4220)	(-3.7462)
Revenue Growth Rate	-11.0214***	-0.1127***	-10.6539***
	(-4.4423)	(-8.9986)	(-4.2884)

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Table 3. (continued)

ESG_mean			3.2619***
			(2.7529)
_cons	-150.9591***	-2.8862***	-141.5446***
	(-3.4852)	(-13.2050)	(-3.2581)
year	Yes	Yes	Yes
id	Yes	Yes	Yes
N	31406	31406	31406
r2	0.1736	0.5106	0.1738
F	13.1182	311.5770	12.1975

t-statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3. Analysis of benchmark regression results

Column (1) shows how AI affects firm value. The coefficient is positive and significant ata the 1% level. That fits with digital transformation theory, for manufacturing firms, using AI helps improe operational efficiency through better production scheduling, less material waste, and lower marginal costs, which directly raises productivity and profits. From a capital market angle, the positive coefficient also means investors view AI adoption favorably. Digital transformation signals strong innovation ability and long -term growth potential, which then gets reflected in higher market value, measured by Tobin's Q.

Column (2) reports the impact of AI on ESG performance. The coefficient for AI is 3.0569, again positive at the 1% significance level. So, AI adoption does seem to improve a firm's ESG outcomes by a fair amount. Manufacturing firms usually face more pressure on environmental compliance and from stakeholders. For them, AI can be a powerful tool: it enables real-time monitoring of carbon emissions and energy use to lower the environmental footprints (E dimension), enhances supply chain transparency and labor management efficiency to fulfill social responsibilities (S dimension), and strengthens internal control systems to improve corporate governance quality (G dimension). The large positive coefficient also suggests that AI works particularly well for manufacturing firms trying to meet ESG requirements, a mechanism that often gets overlooked in broad cross-industry studies.

Column (3) includes both AI and ESG_mean. The results show that ESG has a significantly positive effect on firm value, meaning better ESG performance leads to higher market value. The effect of AI on firm value stays consistent with the baseline regression and is still significantly positive. Notably, the AI coefficient decreases slightly from 532.2061 in Column (1) to 522.2349 in Column (3), but it remains statistically significant. That confirms ESG plays a partial mediating role. So AI creates value through two channels that work together. The first is direct: technological efficiency gains. The second is indirect: AI-driven ESG improvements help lower financing costs, reduce regulatory risks, and build stakeholder trust, which then lifts long-term firm value. For manufacturing firms dealing with tighter "Dual Carbon" and ESG rules, this indirect channel is especially important. It turns compliance pressure into a sustainable competitive advantage.

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Collectively, these results back up the proposed theoretical framework in a manufacturing context. They show that AI adoption doesn't just bring immediate operational benefits; it also unlocks long-term value growth through ESG performance. This helps fill the gap in industry-specific research on the AI-ESG-value transmission mechanism.

6. Research findings and policy recommendations

6.1. Key findings

The benchmark regression results show that AI adoption has a favorable and statistically significant effect on the market value of listed manufacturing firms, at the 1% level. So, AI adoption does help raise corporate value. When it comes to mediation effect tests, two main findings emerge. First, AI significantly improves ESG performance with a regression coefficient of 3.0569, also significant at 1%. This means that firms using AI can improve their overall performance in environmental governance, social responsibility, and corporate governance. Second, when both AI and ESG indicators are included in the same model, ESG performance turns out to be positively associated with market value. This suggests that solid ESG governance can effectively lift a firm's market value. At the same time, the positive effect of AI on firm value remains statistically significant, which is consistent with the benchmark results. Putting these together, ESG performance works as a partial mediator between AI applications and enterprise value. In other words, AI not only directly drives value growth for listed manufacturing firms, but also indirectly lifts their value by improving ESG performance.

6.2. Policy recommendations

The government could set up a special support program for AI-driven ESG initiatives. Options include tax breaks, targeted subsidies, or preferential green credit for manufacturing companies that apply AI in areas like green technology innovation, smart environmental protection facilities, workplace safety, or employee welfare [3]. A clear framework for AI usage transparency, data security, and algorithm compliance can really help. It reduces the regulatory uncertainty firms face when they try to use AI to improve ESG performance [8]. Policies also need to fit different regions. Take the central and western parts of the country, or areas where tech density is lower – the government could put more money into infrastructure and talent development there, to help close the digital divide. Regulators and capital markets should also pay more attention to ESG's intermediary role. One simple way is to raise disclosure standards and AI for collecting and reporting ESG data. Once the information becomes more transparent and easier to compare, ESG's effect on corporate value shows up more clearly [9].

Bringing AI and ESG into evaluation and pricing systems also makes sense. Think about credit ratings, refinancing reviews, green bonds, or green supply chain finance. In those contexts, "AI application level + ESG performance" could be explicitly listed as key factors. That way, more capital market returns would go to companies that perform well on both fronts [10]. On the business and industry side, AI investment ought to be directed toward areas with a high ESG multiplier. Manufacturing firms, for instance, could use AI mainly for green innovation and efficiency gains. Research shows AI can significantly boost ESG performance by promoting green tech innovation, improving production and supply chain efficiency, and making information more transparent [3]. Policy tools like pilot projects and industry guidelines could also help.They could steer AI away

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from a narrow focus on cost-cutting and toward green initiatives, social responsibility, and better governance.

Another useful angle is promoting industry self-regulation and competitive pressure. When companies in highly competitive sectors use AI to improve their ESG performance, it tends to prompt other firms to follow suit. That would raise overall ESG standards [11]. Industry associations could also receive support to establish AI+ESG benchmarks and publish rankings. That would strengthen this demonstration-follow-on effect.

6.3. Conclusion

This study focuses only on Chinese manufacturing listed firms. So the sample is limited to a single industry and one country's institutional setting. That means the findings probably don't apply directly to non-manufacturing sectors like services or high- tech industries. They also might not hold for companies in countries with very different regulatory or economic environments. Also, by excluding ST,*ST, and firms with missing data, there's a risk of selection bias. So, the results might not hold for higher-risk companies either.

AI adoption is measured with just one indicator – the ratio of digital assets to total assets. This doesn't distinguish between traditional AI and generative AI, or between R&D – focused AI versus application – based AI. For the mediating variable, only the overall ESG score is used, without looking at whether individual ESG dimensions play different mediating roles. Firm value is captured solely by Tobin's Q, so there's no multi-dimensional view that includes financial value, innovation value, or long-term value.

What's more, the analysis only confirms that ESG performance plays a partial mediating role. Other possible channels, such as financing constraints, green technology innovation, or information transparency, are not examined. And while behavioral economics is brought up as a theoretical lens, the study doesn't actually test how behavioral biases like limited attention or social preferences influence the AI ESG-firm value relationship. So, the theoretical side remains somewhat underdeveloped.

Future work could expand the sample to include all listed firms across industries, and perhaps run cross-country comparisons between emerging markets and developed economies. Adding non-listed firms and small to medium-sized enterprises (SMEs) would also help test whether the AI-ESG-value mechanism holds in broader settings. Researchers might also classify AI more finely, by technology type and application scenario, and test the separate effects of the environmental, social, and governance pillars separately. Using multiple value measures would support a more rounded assessment of value creation.

Chained mediation models could be set up, treating financing constraints, green innovation, and disclosure quality as parallel or sequential paths. Moderators like ownership structure, digital infrastructure, industry competition, and corporate governance could also be introduced. And finally, behavioral economics could be more fully integrated to look at how managerial cognitive biases play a role.

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