How does intelligent investment impact the conservation of enterprise resources

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Abstract. The rapid growth of technologies such as big data and AI has made intelligent investment increasingly popular across different sectors. This trend supports the creation of modern industrial systems and the rise of new, high-quality productivity, making intelligent investment crucial for industries to achieve high-quality structural changes and adopt eco-friendly practices. This study delves into the impact of intelligent investment initiatives on resource conservation, utilizing data from China's A-share listed companies between 2007 and 2022. It explores how these activities influence resource-saving measures within companies and examines the role of financing constraints and the potential for variability across different contexts. Findings reveal that intelligent investments significantly bolster a company's resource efficiency. However, it's noted that financial constraints can dampen the positive outcomes of such investments, limiting their effectiveness in promoting resource conservation. Interestingly, the beneficial effects of intelligent investments are not uniform; they are particularly pronounced in industries with high pollution levels and among smaller enterprises. Drawing from these insights, the paper offers strategic recommendations at the enterprise, industry, and policy levels. These suggestions aim to enhance the adoption of intelligent investment strategies, encourage sustainable practices among businesses, and foster the development of resource-efficient enterprises.

Keywords: intelligent investment, resource conservation, financing constraints.

1. Introduction

China is shifting its economic focus from speed to quality, aiming for high-quality growth that emphasizes resource efficiency and environmental sustainability. This move challenges industries to adapt by reducing capacity, saving energy, and following stricter environmental regulations. Scholars stress the importance of using technological innovations to enhance resource efficiency without waste, especially in the context of green development and achieving "dual carbon" goals. The trend towards digital transformation and eco-friendly practices is seen as essential for businesses aiming for sustainable growth and resource conservation. [1]. Furthermore, saving resources doesn't mean reducing their use indiscriminately but rather improving resource utilization efficiency through technology, especially during periods of business growth. Reducing resource waste is crucial during business downturns [2]. Chinese scholars emphasize the importance of adopting green technological innovations and digital transformation for businesses to achieve resource conservation and sustainable development. This approach aligns with the "dual carbon" goal and the increasing focus on environmental friendliness, urging enterprises to shift from being production-centric to resource-efficient. Green technology innovation is highlighted as crucial for enterprises aiming for green transformation and development.

The evolution of smart investing aligns with the green transformation and resource conservation in industries. The rise of technologies like big data and AI is driving the fourth industrial revolution, marked by intelligence, and leading to major global industrial changes. Notably, the US has its "Advanced Manufacturing Strategic Plan," Germany has "Industrialization 4.0," and Japan introduced the "New Robot Strategy." [3]. The initiatives highlight a significant focus on enhancing investments in the intelligence sector, aiming to transform industries and guide enterprises towards advanced intelligent development. The Chinese government's commitment is evident through the

"Made in China 2025" program, which prioritizes intelligent manufacturing. Additionally, the inclusion of the "artificial intelligence +" concept in the 2024 Government Work Report marks an effort to boost the digital economy's innovative growth. This strategy emphasizes the importance of advancing big data and AI research and application, setting a clear direction for future intelligent investments. Intelligent investment is not just about improving production processes; it represents a shift in the "production-technology" paradigm, utilizing data mining and big data technology to efficiently meet consumer needs for specialization and customization, thereby optimizing enterprise resource allocation. [4]. Considering the diverse operational methods and complex cost structures in industries, intelligent investment can greatly change an organization's production, structure, and business behavior. Thus, evaluating its impact on resource utilization and improvement in enterprise resource management is essential. [5].

This paper investigates the effects of intelligent investment activities on the resource-saving behaviors of A-share listed enterprises from 2007 to 2022. It delves into how financing constraints and differences in enterprise sizes and types moderate these effects. The study offers new insights into how intelligent investment can promote resource conservation and green development within enterprises. It stands out by expanding the focus of research on intelligent investments beyond their impact on innovation and performance, to include their role in fostering green practices. Additionally, it explores the complex roles of financing constraints and enterprise diversity, contributing valuable perspectives to the field.

2. Analysis of Action Mechanism

2.1. The Function Mechanism of Intelligent Investment to Enterprise Resource Saving

Enterprises can enhance their resource-saving behavior through two main strategies by leveraging investments in intelligence technology. Firstly, by automating production and operations, companies can significantly boost the efficiency with which resources are used. The integration of intelligent technology into automated production processes and operational management not only reduces labor costs but also increases the efficiency of raw material use. This leads to a decrease in resource waste during production by enhancing overall efficiency [6]. Secondly, the adoption of fine resource management practices is facilitated by intelligent systems. These systems allow for the meticulous management of resources through continuous monitoring and detailed data analysis. By employing big data analytics, companies can keep a real-time check on equipment health, product quality, and supply chain conditions. This enables the optimization of production planning and resource allocation, further cutting down on resource waste and inefficiency [7]. Intelligent technology offers transformative solutions for businesses, enhancing supply chain management by leveraging real-time data analysis and predictive algorithms. This advancement not only improves visibility and flexibility within the supply chain but also significantly reduces inventory levels and transportation costs. Furthermore, it minimizes resource waste resulting from supply chain disruptions and fosters the development of environmentally sustainable management models. Moreover, intelligent technology plays a crucial role in elevating the energy efficiency of enterprises, contributing to energy conservation and environmental protection. By optimizing energy use in production and operational processes, it helps reduce energy consumption and emissions, supporting efforts towards energy conservation and emission reduction [8]. The intelligent energy management system is a game-changer, capable of dynamically adjusting equipment operation based on production demand and energy pricing. This not only optimizes equipment energy efficiency but also lowers energy costs and mitigates environmental impact, promoting resource-saving practices within enterprises.

Given this analysis, the hypothesis is proposed that intelligent investment significantly encourages resource-saving behavior in enterprises and positively impacts it.

2.2. Analysis of Regulation Mechanism of Financing Constraint

When enterprises encounter financing constraints, their ability to invest in intelligent technology can be significantly hampered, even though such investments can lead to substantial savings in resources. The primary issue at hand is the financial limitations themselves. With restricted access to funding, companies may find their plans to delve into the intelligent sector severely compromised. The scarcity of financial backing could force businesses to scale down their investments or postpone their projects. This might result in an inability to acquire the latest intelligent equipment, hire necessary technical staff, or undertake essential research and development activities. Consequently, they fail to fully capitalize on the potential savings that these resources could offer [9]. Moreover, a second crucial factor is the limitation in technical capabilities. Financing constraints can leave enterprises lacking in the necessary technical skills and knowledge, thereby curbing their capability to effectively develop, implement, or maintain intelligent technologies. The absence of an in-house technical team or a capable partner can present significant challenges in navigating the complexities of intelligent technology projects [10], such constraints related to technical proficiency can hinder the successful execution of intelligent technology endeavors, preventing companies from fully leveraging the benefits of these technologies or leading to resource wastage due to flawed technology application.Enterprises often struggle to properly assess the impact of smart technologies due to a lack of necessary technical expertise. This deficiency can lead to unsound investment decisions, negatively affecting the efficient use of resources. Moreover, competitive abilities of enterprises are constrained by financial limitations. These constraints hinder the ability of enterprises to allocate adequate funds and resources promptly for advancing intelligent projects, causing them to miss out on critical development opportunities in the smart technology sector [11]. Additionally, the rapid pace at which competitors invest in intelligent technologies may intimidate enterprises, fearing market marginalization. This fear, in turn, fosters a cautious approach to investing in smart technology projects, creating a negative feedback loop that deters large-scale investment and ultimately compromises their potential to save resources [12,13].

In light of this analysis, the study introduces Hypothesis 2: Financing constraints negatively modulate the impact of intelligent technology investments on the conservation of enterprise resources.

2.3. Heterogeneity Analysis of Firm Nature and Enterprise Scale

The nature of an enterprise's pollution significantly influences its approach to investing in intelligent technologies, which in turn impacts its resource conservation practices. Heavily polluting enterprises, driven by environmental regulations and the need to reduce pollution, are more inclined to invest in intelligent technologies. These technologies are employed to enhance environmental protection efficiency within production processes, such as by minimizing exhaust emissions and improving wastewater treatment. This strategic focus aims to achieve both resource conservation and environmental protection. In contrast, enterprises that are not major polluters tend to prioritize investments in intelligent technologies that boost production efficiency and cost reduction, aiming to strengthen their competitiveness and profitability. Consequently, their contributions to resource saving may not be as pronounced [14].

Based on these observations, the third hypothesis suggests that the intelligent investments of heavily polluting enterprises have a more pronounced effect on promoting resource conservation compared to their less polluting counterparts.

The impact of enterprise scale on intelligent transformation varies significantly between large and small businesses. Large enterprises, with their intricate production processes, extensive organizational structures, and broad supply chain networks, face more substantial challenges during their intelligent transformation journey. Integrating intelligent investment-related technologies into these complex systems often requires the coordination across multiple departments and business lines, leading to a more involved and prolonged transformation process. As a result, realizing the benefits of resource savings may take longer. In contrast, small businesses, characterized by their straightforward organizational structures and simpler production processes, tend to navigate the

transformation more smoothly, allowing them to achieve resource savings more quickly. Additionally, large enterprises are likely to invest more resources, including capital, manpower, and time, into the intelligent investment process.Given their extensive scope, large-scale enterprises may need to undergo comprehensive business process overhauls, system upgrades, and extensive staff retraining during transformation efforts. A failed transformation can lead to substantial losses. As a result, large enterprises typically face higher risks in the transformation process and are more prone to resource wastage. Conversely, small-scale enterprises encounter lower sunk costs in these endeavors [15].

Due to these differences, intelligent investment in small-scale enterprises tends to have a more pronounced effect on promoting resource conservation compared to their larger counterparts.

3. Empirical Analysis

3.1. Data Declaration

This paper evaluates how intelligent investments impact resource conservation in enterprises, focusing on China's A-share listed companies. Excluding financially distressed firms, those in the financial sector, and records with missing or unsuitable data, the analysis covers 3,907 companies from 2007 to 2022, using 28,804 observation values from the Guotai'an database. To improve data reliability, it employs a 1% tail shrinkage method to manage outliers, aiming to accurately assess the effects of intelligent investments.

3.2. Model Setting

According to the research purpose of this paper, the model is set according to the variables set.

In order to study how the explanatory variable affects the explained variable:

$$ENE_{it} = \alpha_0 + \alpha_1 INTV_{it} + \alpha_2 Size_{it} + \alpha_3 Lev_{it} + \alpha_4 ROA_{it} + \alpha_5 Growth_{it} + \alpha_6 Board_{it} + \alpha_7 Top1_{it} + \alpha_8 Dual_{it} + \alpha_9 FirmAge_{it} + \sum year + \sum ind + \varepsilon_{it} \quad (1)$$

To investigate how the effects of the moderating variables are:

$$ENE_{it} = \alpha_0 + \alpha_1 INTV_{it} + \alpha_2 KZ_{it} + \alpha_3 KZ_{it} * INTV_{it} + \alpha_4 Size_{it} + \alpha_5 Lev_{it} + \alpha_6 ROA_{it} + \alpha_7 Growth_{it} + \alpha_8 Board_{it} + \alpha_9 Top1_{it} + \alpha_{10} Dual_{it} + \alpha_{11} FirmAge_{it} + \sum year + \sum ind + \varepsilon_{it} \quad (2)$$

Is the constant term,α_0 is the regression coefficient, and α_1 is the coefficient value that needs to be estimated, i represents the i listed enterprise, t represents the year, that is, the time, represents the random error term, represents the unobserved value that affects the ENE of the enterprise, CV represents the control variable of this paper. year represents the year effect, ind represents the industry effect, controlling the impact of the industry effect and the year effect, making the estimation of the model results more accurate. Since both INTV and KZ are continuous variables, when the interaction effect is carried out, the INTV and KZ indices are centralized and then interacted to prevent the influence of multicollinearity. The specific research variable Settings and corresponding variable names are shown in Table 1.

Table 1 Variable Settings

Property of Variable	Variable Representation	Variable Name	Variable Calculation
Variable Being Explained	Enterprise Resource Saving	ENE	Converted into a unified standard coal total savings
Explained Variable	Intellient Investment	INTV	
Regulated Variable	Financing Constraints.	KZ	Financing constraint KZ index
Control Variable	Enterprise Scale	Size	The natural logarithm of total assets
	Ratio of Liabilities	Lev	Total liabilities/total assets
	Rate of Return on Total Assets	ROA	Net profit/total assets
	Increase Rate of Business Revenue	Growth	(Current operating income - previous year operating income)/ Previous year operating income
	Directorate Size	Board	The natural logarithm of the number of board members
	Ownership Concentration	Top1	Number of shares held by the largest shareholder/total number of shares
	Duality	Dual	The combination of general manager and chairman is 1, otherwise it is 0
	Enterprise Age	FirmAge	The natural logarithm of the age of establishment +1
	Year Effect	year	Year dummy variable
	Industry Effect	ind	Industry dummy variable

3.3. Descriptive Statistics

Descriptive statistics form the base for understanding data by highlighting key aspects like sample size, mean, variation, and range. After initial processing with Stata software, this analysis is conducted to get a basic insight into the data.Specific descriptive statistical results are shown in Table 2 below.

Table 2 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ENE	28804	0.3072	0.1050	0.1076	0.5762
INTV	28804	0.0028	0.0065	0.0001	0.0468
KZ	28804	1.5789	1.8109	-3.5933	5.6571
Size	28804	22.1689	1.2216	19.9907	25.8743
Lev	28804	0.4277	0.1925	0.0620	0.8614
ROA	28804	0.0379	0.0609	-0.2003	0.2027
Growth	28804	0.1564	0.3438	-0.4976	1.8241
Board	28804	2.1253	0.1960	1.6094	2.6391
Dual	28804	0.2762	0.4471	0.0000	1.0000
Top1	28804	33.7329	14.6560	8.9280	72.6376
FirmAge	28804	2.8916	0.3386	1.7918	3.5264

The dataset includes 28,804 samples, examining enterprise operations. The average resource savings is 0.3072, with a range from 0.1076 to 0.5762, showing slight variation. Intelligent investment averages at 0.0028, with a minimum of 0.0001 and a maximum of 0.0468, leaning towards lower values. The financing constraint KZ index has an average of 1.5789, with a wide range from -3.5933 to 5.6571, indicating significant fluctuation. The data also covers enterprise asset scale, averaging at 22.1689, asset-liability ratio at 0.4277, and return on total assets at 0.0379. Additionally, 27.62% of samples are from enterprises with dual roles, with the largest shareholder's average ratio at 33.7329, and the average enterprise age at 2.8916.

3.4. Correlation Analysis

Here's a clearer version of the text: Correlation analysis helps us understand the relationship between two variables by examining their connection without considering additional influencing factors. This approach allows us to make an initial assessment of how these variables might relate to each other, but it's important to note that this analysis alone cannot serve as the definitive result for regression analysis.

The analysis found a positive and significant correlation at the 1% level between the intelligent investment index and enterprise resource saving, with a correlation coefficient of 0.0611. This indicates that increasing intelligent investment can enhance enterprise resource saving. In contrast, the financing constraint negatively impacts the model with a coefficient of -0.2782, signaling a need for further regression analysis to explore this effect. Most control variables show significant correlations with the explained variables, suggesting their appropriateness. There's no strong correlation between explanatory and control variables, minimizing concerns of multicollinearity affecting the results.

3.5. Baseline Regression Result

After completing the above tests, regression analysis of control year dummy variables and industry dummy variables was carried out, and the benchmark analysis results of this paper were obtained, as shown in Table 3.

Table 3 Model estimates

	(1)	(2)
VARIABLES	ENE	ENE
INTV	0.1495**	0.2175***
	(2.0929)	(3.1918)
Constant	0.1331***	0.0824***
	(32.1862)	(7.0555)
Control Variable	YES	YES
YEAR	YES	YES
IND	YES	YES
Observations	28,804	28,804
R-squared	0.4193	0.4468

Note: ***, **, * indicates a significant relationship at the significance level of 0.01, 0.05, 0.1, respectively. The "t" values (presented in parentheses) are adjusted for robust standard errors to correct for heteroscedasticity.

The estimation reveals that the model's R square is 0.4468, indicating a 44.68% goodness of fit for the explanatory and control variables in predicting enterprise resource saving. This level of fit is considered satisfactory for analyzing enterprise data. A key finding is the positive impact of intelligent investment on enterprise resource saving. The regression coefficient for intelligent investment is 0.2175, and it is statistically significant at the 1% level. This result suggests that an increase in intelligent investment leads to an enhancement in enterprise resource saving, with a unit increase in intelligent investment raising enterprise resource saving by an average of 0.2175. This supports the validity of our first research hypothesis. Additionally, all control variables included in the analysis are significant. Specifically, an increase in the asset-liability ratio and the age of the enterprise is associated with a reduction in enterprise resource saving. Conversely, a growth in enterprise scale and total return on assets contributes to an increase in enterprise resource saving. The model also incorporates a dummy variable for the combination of two jobs, indicating that enterprises engaging in two jobs exhibit higher resource saving. This nuanced approach helps in understanding the multifaceted impacts on enterprise resource saving.

3.6. Regulatory Effect Analysis

To understand the influence of financing constraints on regulatory variables, the research conducted an analysis of regulatory effects, as shown in Table 4.

Table 4 Analysis of adjustment effect

	(1)	(2)
VARIABLES	ENE	ENE
INTV	0.9803***	0.9750***
	(11.5474)	(11.5944)
KZ	-0.0137***	-0.0127***
	(-50.5761)	(-31.1293)
KZ*INTV	-0.0139***	-0.0138***
	(-13.0653)	(-13.1162)
Constant	0.1743***	0.1434***
	(42.5415)	(12.2767)
Control Variable	YES	YES
YEAR	YES	YES
IND	YES	YES
Observations	28,804	28,804
R-squared	0.4696	0.4709

Model 2's findings indicate a 47.09% accuracy in fitting the data. It highlights that intelligent investment significantly impacts with a coefficient of 0.9750. However, when considering the interaction with financing constraints, this positive impact decreases, as shown by a -0.0138 coefficient. This supports the theory that financing constraints diminish the benefits of intelligent investment on saving resources, thus confirming Hypothesis 2.

3.7. Heterogeneity Analysis

The analysis demonstrates that the effectiveness of intelligent investment differs based on the business's nature, especially concerning the environmentally friendly practice of resource conservation. Businesses have been divided into two categories: heavy polluters and non-heavy polluters, with the findings detailed in Table 5.

Table 5 Heterogeneity analysis at the enterprise nature level

	Heavy Polluters	Non-heavy Polluters
VARIABLES	ENE	ENE
INTV	0.6123***	0.1060
	(3.8493)	(1.4010)
Constant	0.1151***	0.0715***
	(5.2240)	(5.2409)
Control Variable	YES	YES
YEAR	YES	YES
IND	YES	YES
Observations	6,868	21,936
R-squared	0.4639	0.4340

The analysis indicates that smart investments in heavily polluted sectors significantly enhance resource saving, with an impact coefficient of 0.6123. In contrast, such investments in cleaner sectors have a minimal effect, with a coefficient of 0.1060. This suggests that directing intelligent investments towards more polluted industries can greatly improve resource efficiency. The study also categorizes firms by size for a detailed analysis in Table 6, supporting hypothesis 3.

Table 6 Heterogeneity analysis at firm size level

VARIABLES	Small Scale ENE	Great Scale ENE
INTV	0.3625***	0.1048
	(3.1918)	(1.2212)
Constant	-0.0097	0.0803***
	(-0.3835)	(4.2632)
Control Variable	YES	YES
YEAR	YES	YES
IND	YES	YES
Observations	14,404	14,400
R-squared	0.4330	0.4581

Recent analysis shows that small-scale intelligent investments have a significant impact on saving resources, with an impact coefficient of 0.3625. In contrast, large-scale investments have a lower impact of 0.1048 and do not significantly save resources. This supports the hypothesis that small-scale investments are more effective in resource conservation.

3.8. Robustness Test

Our analysis uses three methods to ensure its strength. First, we look at data from 2020 and 2021, during the epidemic. Second, we delay the explanatory variables by one period to see their effects. Third, we use a bidirectional fixed effect model, considering both year and industry factors, and adjust it for year and individual effects for a robustness test. If the results still show a positive impact of intelligent investment on resource saving, it confirms our model's reliability.

Table 7 Robustness test

	(1)	(2)	(3)
	Remove 2020, 2021	One Phase Lag Explanatory Variable	Alternate Estimation Method
VARIABLES	ENE	ENE	ENE
INTV	0.4047***		0.2811**
	(5.2732)		(2.2702)
L.INTV		0.5690***	
		(4.3970)	
Constant	0.0726***	0.1079***	0.0068
	(5.7280)	(7.8630)	(0.2027)
Control Variable	YES	YES	YES
Year Effect	YES	YES	YES
Industry Effect	YES	YES	NO
Individual Effect	NO	NO	YES
Observations	23,066	22,702	28,804
R-squared	0.4588	0.4197	0.3799
Number of id	3,907	3,907	3,907

When removing data from the epidemic year, intelligent investment continues to show a positive effect, with an initial impact of 0.4047. This positive influence strengthens to 0.5690 when a one-stage lag is applied, a significant finding at the 1% level. This result remains consistent across different estimation methods. Moreover, intelligent investment also positively impacts enterprise resource conservation, reinforcing the study's conclusions.

4. Conclusion and Countermeasure Suggestion

4.1. Conclusion

This study investigates the impact of intelligent investment on resource conservation in Chinese listed enterprises. Key findings include: a direct positive correlation between intelligent investment and resource savings, with a one standard unit increase in investment leading to an average 0.2175 standard unit increase in resource savings. Factors like an enterprise's age and asset-liability ratio negatively affect conservation efforts, while scale and total asset returns have a positive impact. Integrated operations also result in better resource conservation. However, financing constraints can lessen the benefits of intelligent investment, acting as a regulatory deterrent. The effects vary across different enterprises, with polluting and smaller enterprises experiencing more pronounced benefits from intelligent investment in terms of resource conservation.

This study has limitations including a general analysis of intelligent investment, lacking depth in specific dimensions. Future research should explore intelligent investment in more detail and consider the diversity of enterprises, such as science and technology firms, state-owned companies, and private businesses, to gain a more comprehensive understanding.

4.2. Countermeasure Suggestion

To further foster the growth of intelligent investment and support businesses in adopting green development practices, this study offers recommendations at three levels: enterprise strategy, industry foundation, and macro policy.

Companies are encouraged to adopt intelligent technology as a key part of their strategic development. This includes integrating it into development plans with a focus on improving resource efficiency, reducing energy consumption, and cutting pollution. Investment plans should be detailed, aiming to implement these technologies and embed green development principles throughout the supply chain. This approach will enhance transparency, lower costs, and improve management in the supply chain, contributing to reduced carbon emissions and minimized resource waste.

Industry organizations can enhance intelligent technology development by fostering collaboration among companies. This can lead to shared experiences and resources, reducing investment risks and costs while promoting green transformation. Additionally, taking an active role in standardizing intelligent technologies can lower barriers for companies, ensuring uniform application and improving efficiency and sophistication across the industry.

To encourage the adoption of intelligent technology, governments can implement macro policies such as tax incentives, financial subsidies, research grants, and other supportive measures. These policies aim to reduce costs for companies and promote the use of smart technology. Additionally, governments can foster the development of eco-friendly, intelligent industries through supportive industrial policies, encouraging industry clusters, and facilitating company collaboration and innovation. There's also a need to focus on training and recruiting skilled individuals in the intelligent technology field to enhance talent availability and application.

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