Enhancing Enterprise Investment Efficiency through Artificial Intelligence: The Role of Accounting Information Transparency

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Abstract: In the post-COVID-19 era, with global economic recovery as a critical goal, the rapid development of artificial intelligence (AI) has emerged as a key driver of economic growth and transformation. AI not only acts as a powerful catalyst for economic development but also significantly impacts enterprise investment efficiency (EIE). This paper explores the influence of AI on EIE, with a focus on the role of accounting information transparency. Using data from Shanghai and Shenzhen A-share listed enterprises between 2010 and 2021, the findings demonstrate that AI development significantly enhances EIE. These results are confirmed through robustness tests, including variable substitution, and addressing endogeneity and sample limitations. Mechanism analysis reveals that AI improves EIE by increasing the transparency of accounting information. Additionally, heterogeneity analysis shows that AI has a greater impact on the investment efficiency of high-tech and technology-intensive enterprises, non-state-owned enterprises, and those located in highly urbanised areas, such as 'Broadband China' pilot cities. This paper examines how AI development affects EIE through the lens of enterprise accounting information transparency, offering actionable insights for enhancing accounting disclosures and serving as a valuable resource for enterprises navigating the technological transformation of the modern era.

Keywords: Artificial intelligence, Enterprise investment efficiency, Accounting information transparency, Listed enterprises

1. Introduction

Since the beginning of the 21st century, continuous technological progress has led to the widespread evolution of digitalisation and the application of big data technology. These advancements have had a far-reaching impact on the world, significantly altering people's ways of life. Digital development has become a global strategic priority, as highlighted in the White Paper on the Global Digital Economy (2023) released by the China Academy of Information and Communications Technology. According to the report, the digital economy of major countries is showing a continuous growth trend. By 2022, the combined digital economy of the five major world economies—China, the United States, Japan, Germany, and South Korea—was projected to reach $31 trillion, with digital economy contributions accounting for 58 per cent of Gross Domestic Product (GDP).

Big data technology has become a focal point in scientific, technological, economic, and social research, and many countries have integrated big data into their national strategies. For instance, China introduced the 'implementation of the National Big Data strategy' in its 13th Five-Year Plan adopted in 2016. The 14th Five-Year Plan, adopted in 2020 further emphasised big data's role, highlighting its transition from an emerging technology industry to a crucial component of social development. The new generation of information technology driven by big data is evolving from 'frontier technology' to 'important application', playing an increasingly vital role.

Artificial Intelligence (AI), a rapidly advancing technology in the context of big data, has garnered significant attention scholars for its applications. The existing literature indicates that AI impacts enterprise data processing, governance, and performance. In data processing and analysis, AI effectively handles and interprets large and complex datasets (Ortega-Calvo et al., 2023; Wang et al., 2023; Zhu et al., 2021). In enterprise governance, AI facilitates timely and rapid decision-making, enhancing governance levels and providing crucial technical support (Dignam, 2020; Zhang et al., 2024; Zhang et al., 2021). Regarding enterprise performance, AI can expand sales channels and create a more conducive working environment, thereby improving performance (Tian et al., 2023; Wen et al., 2021; Zhou et al., 2022).

While extensive research has explored AI's applications in various sectors, its impact on the financial investment sector remains underexplored. Enterprise Investment Efficiency (EIE) is crucial not only for the development prospects of enterprises but also for the stability of the national economy. Most existing research on EIE focusses on traditional factors such as government intervention, corporate governance, and internal control (Ezzi et al., 2023; Hao & Lu, 2018; Zuo et al., 2024), leaving a theoretical gap in understanding the relationship between AI and EIE. In the current post-COVID-19 era, characterised by sluggish economic performance and low investor confidence, improving EIE is paramount for global economic recovery (Shi et al., 2023; Wanke et al., 2024). AI offers precise data analysis and forecasting capabilities, helping enterprises better assess investment returns and risks. By leveraging big data and machine learning technologies, AI can identify market trends, analyse competitors, and conduct risk management (Rodriguez-Garcia et al., 2023; Wang et al., 2023; Yang & Wu, 2022). This capability provides comprehensive decision support, helping enterprises in selecting high-potential investment projects with manageable risks and thus enhancing EIE.

In recent decades, transparency in accounting and financial reporting has become a major concern, especially for economic entities such as small and medium-sized enterprises (Gao, 2023; Lu & Xin, 2023). High transparency in accounting information can decrease the degree of information asymmetry in enterprises, lower external financing costs, and improve EIE by mitigating underinvestment and overinvestment (Biddle et al., 2009). Theoretically, AI can enhance accounting information transparency, which, in turn, enhances EIE. AI enhances the efficiency and accuracy of accounting information systems by automating the processing and analysis of extensive financial data, reducing human error and fraud, and enhancing the reliability and transparency of accounting information. However, the level of accounting information disclosure can directly affect investors' cognition of enterprises and decision-making processes (Adelopo et al., 2021). When businesses provide more accurate and transparent accounting information, investors can better assess the value and risk of the business and make more informed investment decisions (Fulgence et al., 2023). This increased transparency can enhance financing capabilities, reduce financing costs, and attract more investment, further improving EIE (Elemes & Filip, 2022). Therefore, this paper examines the effect of AI on EIE from the perspective of accounting information transparency.

In this context, this paper uses the number of AI patents to measure urban AI levels, focussing on A-share listed companies in Shanghai and Shenzhen from 2010 to 2021. It analyses the impact and mechanism of AI on EIE and investigates the mediating role of accounting information transparency. The research finds that AI development significantly enhances EIE, with results confirmed through robustness tests, such as variable substitution and addressing endogeneity and sample limitations. Mechanism analysis reveals that AI improves EIE by enhancing accounting information transparency. Further heterogeneity analysis shows that AI has a stronger impact on the investment efficiency of high-tech and technology-intensive enterprises, non-state-owned enterprises, and those located in highly urbanised areas, such as 'Broadband China' pilot cities.

The contributions of this paper are as follows: (1) From a research perspective, the world is experiencing sluggish economic performance in the post-COVID-19 era, and AI has emerged as a strategic technology driving the fourth technological revolution. As AI integrates with emerging technologies like 5G, cloud computing, big data, and the Internet, it becomes a significant force in promoting national economic development. While most existing research focusses on improving EIE through traditional factors, this paper is the first to investigate the impact of AI on EIE, providing significant insights for global economic recovery (Li et al., 2021; Lin & Yeh., 2020; Deng et al., 2020). (2) From a research content perspective, this paper delivers a thorough and robust analysis of AI's impact on EIE. It examines the role of accounting information transparency and conducts a detailed mechanism analysis and testing, addressing a notable gap in theoretical research. Additionally, the paper explores AI's heterogeneous effects on EIE and offers precise implications for future policy recommendations. (3) In terms of research methods, this study distinguishes itself from most others by avoiding the use of specific AI branches, such as industrial robot data or AI technology patents, as proxies to measure AI levels (Cheng et al., 2019; Fujii & Managi, 2018). Instead, it employs Python to extract comprehensive patent information from the Wanfang patent database for China from 2010 to 2021. Using Stata software, the study identifies patents related to ten keywords–machine learning, expert systems, robotics, computer vision, natural language processing, big data, virtual reality, cloud computing, intelligent manufacturing, and intelligent language–to accurately assess urban AI levels. To address potential errors in the accounting information transparency model due to variations in stock trading volumes, the paper uses the ratio of daily stock trading volume to the mean daily trading volume over the research period, rather than relying on raw differences.

The remainder of the paper is organised as follows: The second section reviews the literature review and theoretical mechanisms of AI and EIE. The third section covers the measurement model, data, and variables used. The fourth section presents the empirical analysis results. The fifth section includes the mechanism test and heterogeneity analysis. Finally, the sixth section presents the conclusions, theoretical contributions, policy suggestions, and future research avenues.

2. Literature review and theoretical mechanism

2.1 Literature review

AI refers to the intelligent behaviours exhibited by artificial systems, including machines that can perceive, reason, learn, communicate, and act in complex environments. These systems use advanced algorithms and models to simulate human consciousness and thought processes (Jakhar & Kaur, 2020). Despite the wide scope of AI, scholars have yet to reach a consensus on how to consistently measure its development. Most existing research relies on specific branches of AI as proxy variables. For example, Cheng et al. (2019) utilised industrial robot data to measure AI levels and studied its impact on labour markets, while Fujii and Managi (2018) used AI patent data to track global AI development. Although these approaches provide valuable insights, they lack a comprehensive, multidimensional view of AI's impact, especially at the microeconomic level. This paper aims to address this limitation by offering a more granular measurement of AI, specifically its effects on EIE, using patent data and advanced analytical tools like Python and Stata.

As AI continues to drive the fourth industrial revolution, its integration with other emerging technologies, such as big data and the Internet of Things, has deeply affected nearly every global industry, including finance, energy, and manufacturing (Buckmann et al., 2021; Omrani et al., 2024; Yang et al., 2023). However, despite AI's widespread adoption, its micro-level economic impacts on enterprises, particularly in terms of EIE, remain underexplored. Wall (2018) highlighted that AI is reshaping the financial industry by enabling more effective decision-making processes, yet its broader economic implications are still not fully understood. This lack of focus on the microeconomic impacts of AI creates a significant research gap, which this paper aims to address.

EIE has been a long-standing area of interest among scholars, with numerous studies exploring the factors influencing it at both macro and micro levels. At the macro level, Dai et al. (2021) examined the influence of industrial policies on EIE, finding that supportive policies encourage enterprises to invest in targeted areas. Similarly, Huang (2022) investigated fintech's effect on EIE, revealing that fintech developments enhance investment efficiency. At the micro level, studies such as those by Huang et al. (2022) found that stock pledge restrictions reduce overinvestment, which in turn improves EIE. However, while these studies explore various traditional factors affecting EIE, they overlook the potential impact of emerging technologies like AI. The critical question of how AI can enhance or disrupt enterprise investment patterns, especially through mechanisms like accounting information transparency, has yet to be rigorously examined.

The role of digital technology in enhancing EIE has been well-documented, making it a relevant foundation for the study of AI's influence. For instance, Horvitz et al. (1988) argued that digital technologies can improve investment decision-making processes by reducing informational inefficiencies. Digital construction enables enterprises to identify investment opportunities more accurately and address the inherent conflict between limited knowledge and decision-making needs. Balakrishnan et al. (2014) also showed that digital technologies enhance internal information efficiency and transparency between investors and managers, fostering better supervision and reducing the risk of over- or under-investment.

However, while the literature on digital technology offers valuable insights, it primarily focuses on general digital tools, without addressing AI's specific capabilities in improving EIE. Cong and He (2019) demonstrated that digital technologies reduce information opacity, but few studies have examined how AI-driven mechanisms, such as advanced data analytics and machine learning, enhance transparency and lead to more efficient investments. This gap in the literature on AI's direct role in improving enterprise investment transparency and efficiency presents an opportunity for further exploration.

The literature provides a comprehensive view of the factors influencing EIE, including digital technology and fintech. However, the specific role of AI in shaping EIE, especially through its impact on information transparency, remains largely unstudied. Most research focuses on the macroeconomic effects of digital transformation (Lin et al., 2023; Liu et al., 2023) or digitisation in general (Liao et al., 2023; Zhou & Ge, 2023). Fintech's influence on EIE has been explored by Duchin et al. (2017) and Lv & Xiong (2022), but the micro-level impact of AI remains underexplored, particularly in the Chinese context.

In China, AI is regarded as a new generation of information technology with broad applications. Despite this, the economic effects of AI on enterprises, particularly from a micro-level perspective, have not been thoroughly examined. This study focuses on the specific influence of AI on EIE in Chinese micro-enterprises and investigates the underlying mechanisms. By integrating AI and information transparency, this paper seeks to enrich the understanding of AI's role in corporate governance and investment outcomes, thus addressing a critical gap in the current literature.

Furthermore, while existing research on AI measurement methods lacks specificity, this paper addresses this by proposing a detailed AI index. Using Python to capture patent data from China between 2010 and 2021 and employing Stata to filter patents based on ten targeted keywords, this study provides a more accurate characterisation of urban AI levels and their effects on EIE.

2.2 Theoretical mechanisms

Based on the analysis of the literature review, this paper concludes that the effect and theoretical mechanism of AI on EIE remain unclear. Drawing on economic and information theories, this section seeks to explore how AI influences EIE through the lens of accounting information transparency (Figure 1).

AI can enhance EIE, as it is a strategic technology of the fourth technological revolution and a key driver of national economic development. EIE measures the ratio between the economic benefits gained by an enterprise from its investment activities and the resources invested (Verrecchia, 1983). AI enables more precise data analysis and predictive capabilities in enterprise investment decisions, helping enterprises to better assess the potential rewards and risks of investment projects. Ren (2021) found that enterprises relying on traditional approaches to financial decision-making will struggle to enhance their competitiveness. AI technology improves the precision, automation, and timeliness of business decisions. By leveraging big data and machine learning techniques, AI identifies market trends, analyses competitors, manages risks, and more. Wu (2023) integrated AI technology into enterprise data security storage and developed a new secure storage system. According to the results, the new system has shorter delays and minimal data loss compared to traditional methods, effectively ensuring the integrity of enterprise data security storage and reducing the risk of missing financial information. AI provides enterprises more comprehensive decision support, helping them select investment projects with greater potential and manageable risks, thereby enhancing EIE. Based on this, the first hypothesis of this paper is as follows:

Hypothesis 1: AI can enhance EIE.

AI can enhance the transparency of enterprise accounting information. First, it will have an active 'information effect' on enterprises, which will greatly enhance their ability to process and analyse data. Automated data collection and processing can reduce errors and omissions, enhance the timeliness and comprehensiveness of information, and enhance the transparency of enterprise accounting. In addition, AI can provide more accurate financial information and performance forecasts through model forecasting and analysis. AI 'sends' operational data and financial information to external markets in a timely and accurate manner. It reduces the information asymmetry between enterprises and investors and enhances the transparency of accounting information of enterprises (Han et al., 2023; Zhang et al., 2021). Second, AI will have an active 'exposure effect' on enterprises, effectively preventing them from hiding internal information. On the one hand, AI will visualise the business information inside the enterprise. Investors will monitor the earnings management behaviour of enterprises in real time and effectively avoid the discretionary power of managers in choosing accounting policies to enhance the transparency of accounting information (Zhang et al., 2024). On the other hand, the application of AI helps investors identify anomalies in enterprise data, greatly reducing the ability and incentive to hide messages within enterprises. AI will reduce the costs associated with the collection, processing, and identification of target enterprises by external investors, facilitate the timely detection of financial anomalies within enterprises and enhance the transparency of accounting information of enterprises. Finally, AI also has a positive 'agent effect' on enterprises. The advent of AI enhances the information transparency between investors and managers, alleviates agent conflicts, and thus enhances the transparency of enterprise accounting information. With the rapid advancement of AI, enterprise organisational structures have shifted from central control to more networked and flat models. This promotes the effective transmission of information, enhances enterprises' digital analysis capabilities, increases information transparency, and improves their ability to respond to risks in a timely manner (Haefner et al., 2021). AI allows advanced techniques to be applied across various aspects of internal control, comprehensively improving internal control quality and increasing the transparency of enterprises' accounting information.

The transparency of accounting information enhances EIE. In this regard, high transparency reduces the degree of information imbalance between enterprises and investors and decreases the cost of adverse selection between investors and enterprises, making it easier for enterprises to access external funds and increase EIE (Francis, 2005; Verrecchia, 2001). Chen (2017) found that the more transparent the information environment and the stronger the external supervision, the higher the EIE. Efficient accounting information transparency constrains managers from engaging in underinvestment or overinvestment due to personal interests, thereby enhancing EIE. Based on this analysis, AI will have a positive 'information effect', 'exposure effect', and 'agent effect' on enterprises, enhancing the transparency of accounting information of enterprises and thereby improving EIE. Therefore, hypothesis 2 is proposed as follows:

Hypothesis 2: AI can enhance EIE by improving the transparency of enterprise accounting information.

[Insert Figure 1 here]

3. Model, variables, and data

3.1 Model design

In order to analyse the impact of urban AI levels on EIE and verify Hypothesis 1, this paper constructs the following four fixed-effect econometric models to examine the effect of AI on EIE:

$$Inv_{i,t} = \alpha + \beta_1 AI1_{i,t} + \beta_n Controls_{i,t} + FE_{year} + FE_{city} + FE_{indu} + FE_{ente} + \varepsilon_{i,t} \quad (1)$$

where *i* represents the enterprise and *t* represents the year. *Inv* represents the proxy variable of EIE; the smaller the value, the higher the EIE. *AI1* represents the level of AI. *Controls* represents both enterprise-level and city-level control variables. FE_{year}, FE_{city}, FE_{indu}, and FE_{ente} represent time, city, industry, and enterprise fixed effects, respectively. The above four fixed effects are controlled for in this paper to absorb the missing effects as much as possible. Furthermore, *a* is the constant term, and $\varepsilon_{i,t}$ is the random error term. In addition, in all regression equations, robust standard errors are clustered at the industry-year level by default to correct for potential misadjustments in the *t*-statistics.

3.2 Variable descriptions

3.2.1 Explained variable: EIE (Inv)

This paper builds on Richardson's (2006) research to measure EIE. Richardson's (2006) model for measuring EIE is widely used in studies of A-share listed enterprises. The model estimates an enterprise's normal level of investment and uses the residuals to measure EIE:

$$Invest_{i,t} = \delta_0 + \delta_1 Growth_{i,t-1} + \delta_2 Cash_{i,t-1} + \delta_3 Age_{i,t-1} + \delta_4 Size_{i,t-1} + \delta_5 Return_{i,t-1} + \delta_6 Invest_{i,t-1} + \sum_t Year_t + \sum_j Indu_j + v_{i,t} \quad (2)$$

In Model (2), the formula for calculating new investment ($Invest_{i,t}$) is:

$$Invest_{i,t} = \left[CAPEX_{i,t} + Aquisition_{i,t} + RD_{i,t} - SalePPE_{i,t} - InvestMaintain_{i,t}\right] / A_{i,t-1} \quad (3)$$

where $CAPEX_{i,t}$ is capital expenditure, equal to 'cash paid for the purchase and construction of fixed assets, intangible assets, and other long-term assets' plus 'net cash paid by subsidiaries and other business units'; $Aquisition_{i,t}$ is M&A expenditure; $RD_{i,t}$ is R&D expenditure; $SalePPE_{i,t}$ is asset liquidation income, equal to 'net cash recovered from the disposal of fixed assets, intangible assets, and other long-term assets' plus 'net cash received from the disposal of subsidiaries and other business units'; $InvestMaintain_{i,t}$ is replacement investment, equal to 'depreciation of fixed assets, depletion of oil and gas assets, depreciation of productive biological assets' plus 'amortisation of intangible assets' plus 'amortisation of long-term unamortised expenses'; and $A_{i,t-1}$ represents initial total assets.

In Model (2), the other variables are defined as follows: $Growth_{i,t-1}$ is the rate of growth of operating income for the previous period, representing investment opportunities; $Cash_{i,t-1}$ is the cash asset from the prior period; $Age_{i,t-1}$ is the age of the enterprise in the previous period; $Size_{i,t-1}$ is the asset size for the previous period. $Return_{i,t-1}$ is the annualised return on equities for the previous period; $Invest_{i,t-1}$ is additional investments from the prior period; $Year_t$ is an annual dummy variable; and $Indu_j$ is the industry dummy variable.

In this paper, we run an ordinary least squares (OLS) regression on Model (2) and take the absolute value of the regression residuals as a proxy variable to measure EIE, denoted as *Inv*. A larger *Inv* value indicates less efficient EIE, while a smaller *Inv* value signifies more efficient EIE.

3.2.2 Core interpretation variables: Urban AI(AI1)

Referring to Mann and Püttmann (2023), this paper uses the number of AI patents to measure the level of AI in a city. It first combines the previous literature mentioning 'expert systems, robotics, computer vision, machine learning and natural language processing' and the action goals mentioned in the 'Three-year Action Plan to Promote the development of the New Generation of AI industry (2018–2020)'. This paper extracts a total of ten keywords: 'machine learning, expert systems, robotics, computer vision, natural language processing, big data, virtual reality, cloud computing, intelligent manufacturing and intelligent language'. Second, we use Python software to capture all the patent information from China for the years 2010 to 2021 in the Wanfang patent database and use Stata software to screen patents containing one of the above ten keywords. Finally, we obtain the annual number of AI patent grants for each city based on the address information of the patents to determine each city's AI level. The core explanatory variable of this paper, namely urban AI (*AI1*), is obtained by taking the natural logarithm of the AI level for each city.

Figure 2 shows our measurements of the AI level of Chinese cities in 2010, 2014, 2018, and 2021. The figure shows an upward trend in China's AI level over time. The lower AI development level in 2010 is due to China's greater focus on traditional infrastructure prior to 2010. With increased investment from the Chinese government, the level of AI improved by 2014. By 2018, AI had achieved initial maturity and steady development. By 2021, the development of AI had become very mature, reflecting the evolving national conditions in China.

[Insert Figure 2 here]

3.2.3 Control variables

With reference to previous literature (Chen et al., 2011a; Chen et al., 2011b; Richardson, 2006), the following control variables are also added to the regression model: Enterprise size (ln*size*), which represents the natural logarithm of the total assets of the enterprise; the Asset–liability ratio (*lev*), which represents the ratio of an enterprise's total liabilities to its total assets (to be noted that a higher debt ratio is less beneficial to an enterprise's investment capability); Cash holdings (*cash*), which represents the ratio of the sum of cash, bank deposits, and short-term investments of an enterprise at the end of the year to its total assets at the beginning of the period; Listed years (ln*age*), which represents the natural logarithm of the number of years between the date of listing of the enterprise and the date of data collection; the Current assets ratio (*car*), which represents the ratio of an enterprise's current assets to its total assets. Higher current assets can provide more resources and opportunities for investment. Therefore, the coefficient of *car* is expected to be negative in this paper. To control for growth opportunities and profitability, this paper includes book-to-market ratio (*mb*), annual return rate (*ret*), and return on assets (*roa*) as control variables. For cities, the following control variables are used: Science and technology index (*sti*), defined as the ratio of science and technology spending to local general public budget spending; Advanced industrial structure (*ais*), defined as the proportion of tertiary sector value added to secondary sector value added; Degree of government intervention (*gi*), defined as the ratio of general government expenditure to the gross regional product; Human capital level (*hci*), defined as the proportion of college students to the total population at the end of the year.

3.3 Data sources and descriptive statistics

The research sample consists of A-share listed enterprises in Shanghai and Shenzhen, China, with a sample period from 2010 to 2021. Data were collected from the CSMAR database, the CCER database, and the China City Statistical Yearbook. Samples with missing data and missing values of control variables were excluded. The final dataset includes 20,604 observations from 3,196 listed companies. Table 1 shows the descriptive statistics of the results.

[Insert Table 1 here]

Before conducting the empirical analysis, a binscatter linear fitting diagram of urban AI levels and EIE was created, as shown in Figure 3. The figure reveals a significant negative correlation between urban AI (*AI1*) and EIE (*Inv*). This indicates that a lower *Inv* corresponds to higher EIE efficiency. The figure preliminarily suggests that a higher AI level is likely to enhance EIE. However, non-parametric estimation based on scatter plots does not statistically verify the significance of this negative relationship. This result supports Hypothesis H1. Therefore, a more rigorous measurement method will be used to confirm this later.

[Insert Figure 3 here]

4. Empirical results and analysis

4.1 Benchmark regression

Table 2 reports the results of the regression of AI on EIE. Column (1) presents the results of regressing the core explanatory variables on the explanatory variables, showing a regression coefficient for the AI indicator of -0.0049, which is significant at the 1% level. Control variables are further added in Column (2), and cities, years, industries, and fixed effects of enterprises are successively added in Columns (3)–(6). From Table 2, we can see that R^2 increases progressively, indicating that the model's explanatory power improves as more variables are included. Even after adding control variables and fixed effects, the regression coefficient of AI remains negative and significant at the 1% level. These results demonstrate that higher AI levels are associated with smaller *Inv* values, which translates to more efficient EIE. There is a significant positive correlation between AI levels and EIE, strongly supporting Hypothesis H1.

[Insert Table 2 here]

4.2 Robustness analysis

The following robustness tests are conducted in this study to ensure the robustness of the conclusions:

(1) Substitution of core explanatory variables. Among the ten keywords, cloud computing is the most frequently mentioned and representative. As an alternative explanatory variable, the natural logarithm of the sum of cloud computing word frequencies (after +1) is used as a robustness indicator for urban AI metrics (*AI2*). The regression results in Column (1) of Table 3 confirm that the core conclusion, i.e., 'the level of urban AI can help enhance EIE', remains unchanged.

(2) Elimination of outliers. To account for the potential impact of extreme values in macro variable calculations, a 1% tail reduction is applied to both ends of the variables. The regression results in Column (2) of Table 3 show that the core conclusion, i.e., 'the level of urban AI can help enhance EIE', remains unchanged.

(3) Exclusion of samples from municipalities directly under central government. Since municipalities directly governed by the central government (Beijing, Shanghai, Tianjin, Chongqing) may have economic and political advantages, as well as an earlier start in AI development, these cities are excluded from the sample for robustness purposes. The remaining data are re-analysed, and the results in Column (3) of Table 3 indicate that the core conclusion, i.e., 'the level of urban AI can help enhance EIE', remains unchanged.

(4) Change clustering standard error. The clustering level of the standard errors is adjusted to the enterprise level, and additionally to both the enterprise and industry levels. The regression results in Columns (4)–(5) of Table 3 demonstrate that the core conclusion, i.e., 'the level of urban AI can help enhance EIE', remains unchanged.

(5) Change in the index of explained variables. Two new indicators are constructed to measure EIE, following the models proposed by Biddle et al. (2009) and Chen (2011a).

The Biddle model regresses EIE on growth opportunities, where growth opportunities are measured by the sales growth rate. The regression model is as follows:

$$Inv_{i,t} = \beta_0 + \beta_1 SaleGrowth_{i,t-1} + \varepsilon_i \quad (4),$$

where $Inv_{i,t}$ is defined as cash outlays for fixed, intangible and other long-term assets, less cash proceeds from asset sales, divided by total assets at the beginning of year *t*. *SaleGrowth* is the percentage change of sales income from year *t-1* to year *t*. The absolute residual value obtained from the regression estimation is used as a measure of EIE (*Inv1*).

The Chen model accounts for the possibility that the impact of investment may vary depending on whether income increases or decreases. The regression model is as follows:

$$Inv_{i,t} = \beta_0 + \beta_1 NEG_{i,t-1} + \beta_2 SalesGrowth_{i,t-1} + \beta_3 NEG \times SalesGrowth_{i,t-1} + \varepsilon_{i,t} \quad (5),$$

where the definitions of $Inv_{i,t}$ and *SaleGrowth* are consistent with Model (4), and *NEG* is a dummy variable that takes a value of ‘1’ if the growth rate of sales revenue is less than ‘0’, and ‘0’ otherwise. The absolute residual value obtained from the regression estimation is used as the measurement index of EIE (*Inv2*). The regression results after replacing the indicators of the explained variables are shown in Columns (6)–(7) of Table 3. The regression results confirm that the core conclusion, i.e., ‘the level of AI can help enhance EIE’, remains unchanged.

[Insert Table 3 here]

4.3 Endogeneity test

According to the estimation principle of Model (1), the reliability of its estimated results depends on the exogeneity of the urban AI level. However, there may be two key issues that cannot be fully addressed: First, the issue of ‘reverse causation’. While the level of AI may enhance EIE, enterprises with high EIE may also leverage AI to expand sales and capture market share. As a result, they may be more willing to spend more manpower and material resources to enhance the development of the AI level. Second, the issue of ‘missing variables’. Although this paper controls for many other factors that may affect EIE at both the enterprise and city levels, it is impossible to guarantee that all relevant variables are included. Both ‘reverse causality’ and ‘missing variables’ can lead to the endogeneity of the core explanatory variable, AI, and thus bias the estimation results.

(1) Instrumental variable regression. To address the ‘reverse causation’ issue, this paper employs instrumental variables regression methodology. The extreme slope of

cities may influence AI development. Cities with greater slope differences often face challenges in traffic management, building design, and sensor data collection due to terrain complexities. As a result, AI development may be limited by the topography of the city. Given the need for relevance and exclusivity of the instrumental variables, this paper selects the natural logarithm of the difference between the maximum and minimum slopes of the city where the enterprise is located (ln*pd*) as the instrumental variable for AI. Additionally, time-varying instrumental variables are constructed to control for fixed effects, including the product of the slope difference and the time trend term (ln*pd* × *year*) and the product of the slope difference and the geographic distance of each enterprise to Shenzhen and Hangzhou (ln*pd* × ln*dis*). Two-stage least squares estimation (2SLS) instrumental variable regression is applied, and the regression results are displayed in Columns (1)–(3) of Table 4. The Kleibergan–Paaprk LM test rejects the original hypothesis of under-identification of the instrumental variables. The Kleibergen–Paaprk Wald F test also rejects the original hypothesis of weak identification of the instrumental variables, confirming the validity of the selected instrumental variables. After effectively controlling for endogeneity, the regression results for *AI1* in Table 4 (1)–(3) remain significantly negative, indicating that urban AI actively enhances EIE. This is consistent with the benchmark regression results, demonstrating the robustness of the paper's conclusions.

[Insert Table 4 here]

(2) Further control of joint effects. To address the issue of omitted variables, this paper extends the benchmark regression by further controlling for city–enterprise, industry–enterprise, city–industry, and industry–year effects. The regression results are shown in Columns (1)–(4) of Table 5. These results show that the core conclusion of this paper, i.e., that 'the level of AI can help enhance EIE', remains unchanged. Furthermore, the estimated coefficients of the core explanatory variable, AI, are significant at the 1% level. After addressing endogeneity issues stemming from both 'reverse causality' and

'missing variables', the effect of AI on EIE remains significant, supporting the results of the benchmark regression.

[Insert Table 5 here]

5. Mechanism testing and heterogeneity analysis

5.1 Mediation mechanism analysis

(1) Design of intermediary mechanism model. The previous study provides empirical support for the impact of urban AI on EIE. However, the prior analysis only gives a broad overview of the relationship between AI and EIE, without examining the specific mechanism at play. Based on theoretical analysis, it is suggested that AI may improve EIE by increasing the transparency of accounting information. This paper constructs Models (6)–(7), building on the baseline regression, to explore the mediating role of accounting information transparency and to test Hypothesis 2. The models are as follows:

$$KV_{i,t} = \alpha + \beta_1 AI1_{i,t} + \beta_n Controls_{i,t} + FE_{year} + FE_{city} + FE_{indu} + FE_{ente} + \varepsilon_{i,t} \quad (6)$$

$$Inv_{i,t} = \alpha + \beta_1 AI1_{i,t} + \beta_2 KV_{i,t} + \beta_n Controls_{i,t} + FE_{year} + FE_{city} + FE_{indu} + FE_{ente} + \varepsilon_{i,t} \quad (7)$$

where *i* represents the enterprise and *t* represents the year. *Inv* represents the proxy variable of EIE. *AI1* represents the level of AI, and *KV* represents the proxy for accounting information transparency. The greater the *KV*, the less transparent the accounting information. *Controls* represents both enterprise-level and city-level control variables. FE_{year}, FE_{city}, FE_{indu}, and FE_{ente} represent fixed effects for time, city, industry and enterprise, respectively. Furthermore, *a* is the constant term and $\varepsilon_{i,t}$ is the random error term. Additionally, all regression equations employ robust standard errors adjusted for industry-year clustering.

(2) Intermediate variable: accounting information transparency (Trans). This paper refers to the KV index model proposed by Kim and Verrecchia (2001) to measure the transparency of accounting information in enterprises. Considering the significant

variability in stock trading volumes across enterprises, this paper introduces an improved KV index model. The estimation model is as follows:

$$\mathrm{Ln}|(P_t - P_{t-1})/P_{t-1}| = \lambda_0 + \lambda\left(\frac{Vol_t}{Vol_0} - 1\right) + \varepsilon \tag{8}$$

where P_t and Vol_t are the closing price and trading volume (number of shares) of the stock on day t, respectively, and Vol_o is the average daily trading volume for all trading days during the study period. The *KV* index is calculated using the λ value from the OLS regression for each listed enterprise (excluding cases where λ is negative). The smaller the λ, the more transparent the accounting information. In this paper, the *KV* index, denoted as KV, is used as a proxy for accounting information transparency, where a higher *KV* indicates lower transparency.

(3) Result analysis of mediation model. First, the total effect of AI on EIE is significant, as shown in Column (1) of Table 6. Second, the influence of AI on accounting information transparency in Column (2) of Table 6 and the influence of accounting information transparency on EIE in Column (3) of Table 6 are both significant, indicating that the mediating effect is valid. Finally, after accounting information transparency is introduced in Column (3) of Table 6, the coefficient between AI and EIE remains significantly negative, demonstrating that accounting information transparency serves as a mediator between AI and EIE. Thus, AI can enhance EIE by improving the transparency of enterprise accounting information.

[Insert Table 6 here]

5.2 Heterogeneity analysis

5.2.1 Heterogeneity of technological level of enterprises

Based on the industry code, enterprises can be classified as either high-technology (*gaokeji*=1) or non-high-technology (*gaokeji*=0). High-technology enterprises typically leverage newer technologies and products, which generate higher returns. These firms are more competitive than their non-high-technology counterparts and are better able to grow steadily in highly competitive markets. To analyse the heterogeneity of the technological level, this paper introduces an interaction term between the AI index and the enterprise's technology level index in the benchmark model. The results, shown in Column (1) of Table 7, indicate that both the regression coefficients of the AI index and the interaction term are significantly negative. This suggests that, compared with non-high-technology enterprises, AI has a stronger effect on enhancing EIE in high-technology enterprises.

5.2.2 Heterogeneity of enterprise nature

Enterprises can be categorised by their nature as either state-owned or non-state-owned. State-owned enterprises are controlled by the state, with a primary focus on providing services that ensure public welfare, while non-state-owned enterprises primarily focus on profit generation. Unlike non-state-owned enterprises, investments by state-owned enterprises are not considered as risky. To explore the heterogeneity based on enterprise nature, an interaction term between the AI index and the enterprise nature (*govcon*) is introduced into the benchmark model. The results, shown in Column (2) of Table 7, reveal that both the regression coefficient of the AI index and the interaction term are significantly negative, confirming that AI influences EIE differently depending on the nature of the firm. Specifically, AI has a stronger effect on enhancing EIE in non-state-owned enterprises compared to state-owned enterprises.

5.2.3 Differences in factor intensity

According to the China Securities Regulatory Commission (CSRC) 2012 industry classification standard, enterprises can be categorised as capital-intensive (*ziben*=1), labour-intensive (*laodong*=1), or technology-intensive (*jishu*=1). Technology-intensive enterprises, which focus on high-tech products and services, generally have higher levels of research and development, innovation, and competitiveness compared to capital- and labour-intensive enterprises. To examine this heterogeneity, interaction terms between AI indicators and factor-intensive indicators are introduced into the benchmark model. The results, shown in Column (3) of Table 7, reveal that the regression coefficient of the AI index is negative, while the interactions terms for capital-intensive and labour-intensive enterprises are positive. This indicates that AI has a stronger impact on enhancing EIE in technology-intensive enterprises than in capital-intensive or labour-intensive enterprises.

5.2.4 Difference in enterprise registration place

In August 2013, the State Council issued the ‘Broadband China’ strategy and implementation plan, subsequently establishing 117 ‘Broadband China’ demonstration cities. These cities benefit from superior information infrastructure, broader broadband network coverage, and stronger broadband transmission and access capabilities. Based on the enterprise’s registration place, this paper classifies the areas of registration of the enterprises into ‘Broadband China’ pilot cities (*kuandai*=1) and ‘non-Broadband China’ pilot cities (*kuandai*=0). To analyse the heterogeneity based on the enterprise registration place, an interaction item between the AI index and the enterprise registration place index is introduced into the benchmark model. The results, shown in Column (4) of Table 7, reveal that both the regression coefficient and the interaction coefficient of the AI index are significantly negative. This indicates that AI has a stronger effect on enhancing EIE in enterprises registered in ‘Broadband China’ pilot cities compared to those in ‘non-Broadband China’ pilot cities.

5.2.5 Heterogeneity of urbanisation rate level

Based on the median urbanisation rate of the province in which the enterprise is located, local districts are categorised into regions with high urbanisation rates (*chengzhenhua*=1) and those with low urbanisation rates (*chengzhenhua*=0). Regions with high urbanisation levels generally have more developed infrastructure, richer human resources, larger market sizes, and more diversified policy support compared to regions with low urbanisation rates. To examine this heterogeneity, an interaction term between the AI index and the urbanisation rate level index is introduced into the benchmark model. The results, shown in Column (5) of Table 7, indicate that the regression coefficients of both the AI index and interaction term are significantly negative. This suggests that AI has a stronger role in enhancing the EIE in regions with higher urbanisation rates compared to those with lower urbanisation rates.

[Insert Table 7 here]

6. Conclusions, theoretical contributions, policy suggestions, and future research avenues

6.1 Conclusions

This paper examines the significant impact of AI on the efficiency of enterprise investment in China, focusing on the role of accounting information transparency. Using data from 3,196 listed Chinese enterprises between 2010 and 2021, the study offers several key insights. First, AI plays a crucial role in enhancing EIE. This effect remains strong and significant even after a series of robustness checks, such as replacing the core explanatory variable, excluding the sample of the central government and the sample of singular value, replacing the index of the explained variable, and addressing potential endogeneity issues. This highlights a novel approach to improving EIE and introduces a new perspective on AI's role in enhancing investment efficiency. Second, the research demonstrates that AI enhances EIE by improving the transparency of enterprise accounting information. This empirical result clarifies the theoretical mechanism by which AI influences EIE, providing a strong basis for further investigation into AI's role in corporate governance and investment outcomes. Third, the study reveals that AI's effect on EIE varies across different types of enterprises. AI shows a more pronounced impact on high-technology enterprises, technology-intensive firms, non-state-owned enterprises, companies located in highly urbanised regions, and those registered in 'Broadband China' pilot cities. This heterogeneity in AI's influence underscores the importance of considering industry and regional differences when studying the relationship between AI and EIE.

6.2 Theoretical contributions

This study makes several key theoretical contributions. First, it expands the current literature by demonstrating how AI, through the enhancement of accounting transparency, improves EIE. Previous studies largely focused on traditional determinants of investment efficiency, but this research shifts the focus to AI, offering a fresh perspective on its impact within enterprise settings. By empirically validating this relationship, the study adds depth to the theoretical discourse on AI's role in corporate governance.

Second, the study introduces heterogeneity in AI's impact across enterprise types and regions, suggesting that the effects of AI on EIE are not uniform. This contributes to the theory by emphasising the importance of context-specific factors such as industry characteristics, technology intensity, and regional development when analysing AI's impact on corporate performance. These findings encourage further theoretical development to account for the diverse effects of AI across different environments.

6.3 Policy suggestions

In the post-COVID-19 era, the global economy faces significant challenges that require strategic interventions from both governments and enterprises. Based on the research conclusions, several policy suggestions are proposed to leverage the potential of AI to enhance EIE.

At the government level, authorities should prioritise integrating AI into daily operations, using AI technology to supervise enterprises' public information to ensure accuracy and timeliness. Governments should also formulate clear AI development strategies, setting both short- and long-term goals to guide enterprises in adopting AI effectively. Local governments can promote AI adoption by providing incentives, such as tax relief, financial support, and government procurement initiatives, which will encourage enterprises to invest in AI. In addition, governments must establish and refine AI-related laws, regulations, and technical standards to ensure that AI development occurs in a healthy and orderly manner. Support for high-technology transformation is also critical, with governments providing targeted assistance to enterprises in terms of talent acquisition, financial resources, and technological expertise. Furthermore, strengthening regional broadband infrastructure should be a priority, as this will help expand network coverage and enhance broadband transmission capabilities, thereby supporting the broader development of regional information infrastructure. Governments should also focus on improving urban planning and infrastructure, promoting urbanisation, and raising the overall level of development in urban areas.

At the enterprise level, companies should make full use of AI technology to optimise internal controls and improve EIE. By deeply integrating AI into various aspects of their operations, enterprises can strengthen risk management, enhance communication efficiency, and ultimately boost the quality of internal controls. This will contribute significantly to enhancing investment efficiency. Enterprises should also invest more heavily in AI research and development, with a particular focus on attracting and training AI talent to maintain their competitive edge in an increasingly technology-driven market. Using AI to improve the transparency of accounting information is another key strategy for enhancing EIE. Enterprises should regularly produce clear and comprehensive financial reports that disclose essential aspects of their financial position, operating performance, and cash flow. Timely disclosure of important events and changes within the company is also necessary to ensure that investors are well-informed. Companies should also be transparent about their governance structures, including details about board members, compensation policies, and internal controls. Finally, governments should strengthen oversight to ensure that companies are truthful in their external communications, and strict penalties should be imposed on those that release false or misleading information.

6.4 Future research avenues

This paper provides an innovative perspective by examining the mechanisms through which AI influences EIE, using a sample of Chinese micro-listed enterprises. While the study offers preliminary insights into AI's impact, future research is necessary due to data limitations and the complexity of AI's potential pathways. In addition to improving accounting information transparency, AI may affect EIE through unexplored channels, which future studies should investigate. Finally, while the research focuses on China, the findings may not apply universally. Future research should assess the applicability of these conclusions in other countries, considering their unique economic and institutional contexts.

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Table captions

Table 1 **Statistical descriptions of variables**

	N	*Mean*	*S.D.*	*Min*	*Max*
Inv	20604	0.0332	0.0392	0.0004	0.2359
AI1	20604	4.9766	1.9548	0.0000	8.6266
ln*size*	20604	22.3817	1.3405	19.7137	26.4580
lev	20604	0.4465	0.2092	0.0618	0.9531
cash	20604	0.1875	0.1290	0.0144	0.6318
ln*age*	20604	2.3544	0.6607	1.0986	3.3322
ret	20604	0.1526	0.4992	-0.5707	2.1282
mb	20604	0.5690	0.2744	0.0853	1.2083
roa	20604	0.0301	0.0757	-0.3765	0.1956
car	20604	0.5705	0.2027	0.0955	0.9572
sti	20604	0.0457	0.0251	0.0006	0.2068
ais	20604	1.7573	1.0987	0.5665	5.2982
gi	20604	0.1554	0.0490	0.0812	0.2853
hci	20604	0.0475	0.0330	0.0031	0.1311

Table 2 Benchmark regression results

	Univariate regression	Add control variable	Add city FE	Add year FE	Add industry FE	Add firm FE
	Inv	*Inv*	*Inv*	*Inv*	*Inv*	*Inv*
	(1)	(2)	(3)	(4)	(5)	(6)
AI1	-0.0049***	-0.0038***	-0.0040***	-0.0022***	-0.0023***	-0.0036***
	(0.0002)	(0.0002)	(0.0003)	(0.0005)	(0.0005)	(0.0008)
ln*size*		0.0005	0.0005	-0.0002	0.0001	0.0081***
		(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0012)
lev		0.0102***	0.0114***	0.0114***	0.0115***	0.0124***
		(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0036)
cash		0.0122***	0.0146***	0.0180***	0.0204***	0.0186***
		(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0041)
ln*age*		-0.0076***	-0.0074***	-0.0077***	-0.0079***	-0.0147***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0021)
ret		-0.0002	-0.0001	0.0019**	0.0019**	0.0008
		(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
mb		-0.0207***	-0.0202***	-0.0143***	-0.0135***	-0.0114***
		(0.0018)	(0.0017)	(0.0017)	(0.0018)	(0.0028)
roa		0.0148***	0.0169***	0.0162***	0.0158***	0.0452***
		(0.0042)	(0.0042)	(0.0042)	(0.0043)	(0.0060)
car		-0.0395***	-0.0394***	-0.0398***	-0.0428***	-0.0521***
		(0.0020)	(0.0021)	(0.0021)	(0.0023)	(0.0041)
sti		-0.0317**	-0.0590***	-0.0585***	-0.0578***	-0.0908***
		(0.0134)	(0.0209)	(0.0222)	(0.0221)	(0.0239)
ais		-0.0001	-0.0000	0.0000	0.0002	-0.0026**
		(0.0003)	(0.0006)	(0.0006)	(0.0006)	(0.0011)
gi		-0.0197***	0.0033	-0.0201	-0.0177	-0.0317*
		(0.0073)	(0.0155)	(0.0163)	(0.0161)	(0.0185)
hci		-0.0247***	-0.0122	-0.0369	-0.0343	-0.0812*
		(0.0091)	(0.0230)	(0.0229)	(0.0233)	(0.0415)
Constant	0.0577***	0.0925***	0.0877***	0.0967***	0.0902***	-0.0523**
	(0.0010)	(0.0072)	(0.0072)	(0.0070)	(0.0071)	(0.0259)
city FE	*NO*	*NO*	*YES*	*YES*	*YES*	*YES*
year FE	*NO*	*NO*	*NO*	*YES*	*YES*	*YES*
industry FE	*NO*	*NO*	*NO*	*NO*	*YES*	*YES*
firm FE	*NO*	*NO*	*NO*	*NO*	*NO*	*YES*
N	20,604	20,604	20,586	20,586	20,585	20,320
R^2	0.0602	0.1240	0.1551	0.1605	0.1694	0.3661

Note: Robust standard errors, clustered at the city-industry level, are reported in parentheses. Furthermore, ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. This convention applies to all subsequent tables, unless otherwise specified..

Table 3 Robustness analysis results

	Replace *AI* index	Winsorisation	Eliminate Municipalities	Adjust the standard deviation clusters		Investment efficiency proxies	
	Inv	*Inv_w*	*Inv*	*Inv*	*Inv*	*Inv1*	*Inv2*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI2	-0.0015***						
	(0.0004)						
AI1_w		-0.0036***					
		(0.0008)					
AI1			-0.0032***	-0.0036***	-0.0036***	-0.0016**	-0.0016**
			(0.0009)	(0.0008)	(0.0009)	(0.0007)	(0.0007)
Control variable	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
city FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
industry FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
firm FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
N	20320	20,320	15,348	20,320	20,320	19,192	19,173
R^2	0.3657	0.3661	0.3720	0.3661	0.3661	0.4180	0.4015

Note: Due to space limitations, the results for control variables are not reported. This applies to the following tables, as well.

Table 4 Instrumental variable regression results

	IV:ln*pd*	IV:ln*pd*year*	IV:ln*pd**ln*dis*
	Inv	*Inv*	*Inv*
	(1)	(2)	(3)
AI1	-0.0097***	-0.0124**	-0.0132**
	(0.0033)	(0.0054)	(0.0061)
Control variable	*YES*	*YES*	*YES*
city FE	*YES*	*YES*	*YES*
year FE	*NO*	*YES*	*YES*
industry FE	*YES*	*YES*	*YES*
firm FE	*YES*	*YES*	*YES*
N	20320	20320	19434
First stage regression			
IV	-2.8279***	-0.0014***	-0.1307***
	(0.4018)	(0.0002)	(0.0192)
F	49.54***	49.22***	46.48***
Kleibergen–Paap rk LM statistic	37.65***	37.41***	29.917***
Kleibergen–Paap rk Wald F statistic	49.531***	49.223***	46.476***

872 **Table 5 The regression results were further controlled for the combined effect**

	Add city× firm FE	Add industry × firm FE	Add industry × city FE	Add industry × year FE
	Inv	*Inv*	*Inv*	*Inv*
	(1)	(2)	(3)	(4)
AI1	-0.0037***	-0.0039***	-0.0039***	-0.0036***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Control variable	*YES*	*YES*	*YES*	*YES*
city FE	*YES*	*YES*	*YES*	*YES*
year FE	*YES*	*YES*	*YES*	*YES*
industry FE	*YES*	*YES*	*YES*	*YES*
firm FE	*YES*	*YES*	*YES*	*YES*
N	20,262	19,939	19,937	19,837
R^2	0.3657	0.3850	0.3850	0.4196

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Table 6 Mechanism test

	(1)	(2)	(3)
	Inv	*KV*	*Inv*
AI1	-0.0036***	-0.0116***	-0.0035***
	(0.0008)	(0.0027)	(0.0008)
KV			0.0085***
			(0.0019)
Control variable	*YES*	*YES*	*YES*
city FE	*YES*	*YES*	*YES*
year FE	*YES*	*YES*	*YES*
industry FE	*YES*	*YES*	*YES*
firm FE	*YES*	*YES*	*YES*
N	20,320	20,320	20320
R^2	0.3661	0.4509	0.3669

Table 7 Heterogeneity test result

	Enterprise technology level	Enterprise property	Factor intensity	Place of business registration	Level of urbanisation rate
	Inv	*Inv*	*Inv*	*Inv*	*Inv*
	(1)	(2)	(3)	(4)	(5)
AI1	-0.0035***	-0.0039***	-0.0044***	-0.0021**	-0.0030***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0008)
AI1 ×gaokeji	-0.0030***				
	(0.0007)				
AI1 #govcon1_p		0.0007***			
		(0.0003)			
AI1 #ziben			0.0013**		
			(0.0005)		
AI1 #laodong			0.0015***		
			(0.0005)		
AI1 #kuandai				-0.0019***	
				(0.0006)	
kuandai				0.0025	
				(0.0080)	
AI1 #chengzhenhua					-0.0013**
					(0.0005)
chengzhenhua					0.0033
					(0.0031)
Control variable	*YES*	*YES*	*YES*	*YES*	*YES*
city FE	*YES*	*YES*	*YES*	*YES*	*YES*
year FE	*YES*	*YES*	*YES*	*YES*	*YES*
industry FE	*YES*	*YES*	*YES*	*YES*	*YES*
firm FE	*YES*	*YES*	*YES*	*YES*	*YES*
N	20,320	20,203	20,320	20,320	20,320
R^2	0.3667	0.3668	0.3666	0.3666	0.3669

Figure captions

Figure 1 The influence mechanism of AI on EIE

Figure 2 Spatial distribution of urban AI level

Figure 3 The fitting curve of AI and EIE

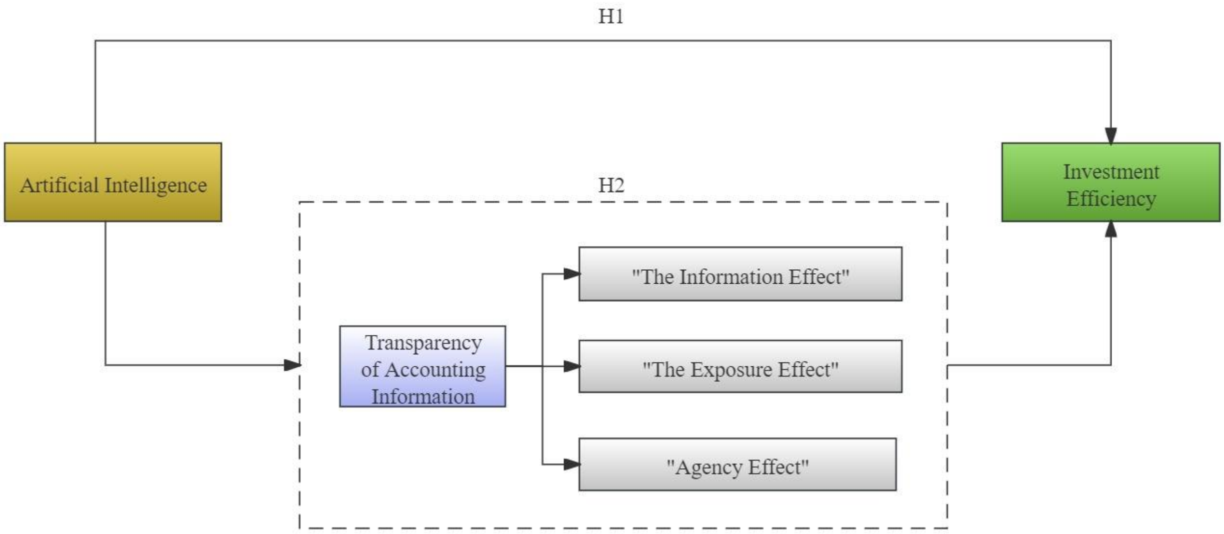
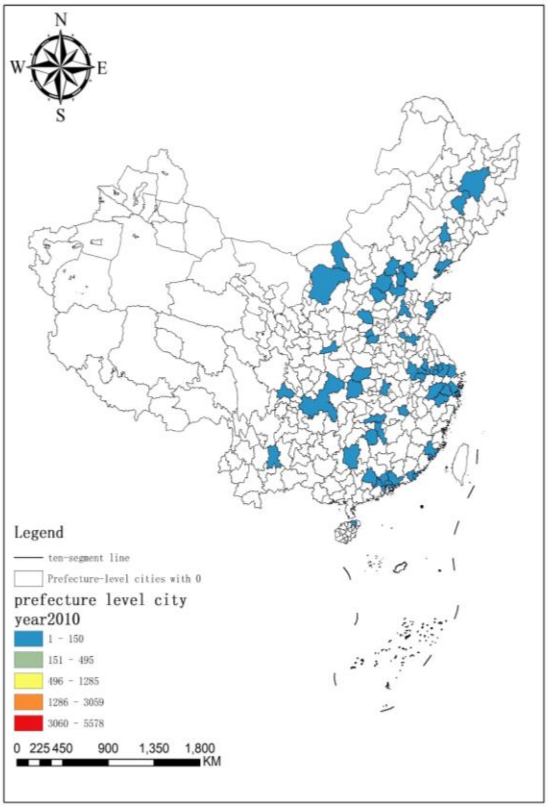
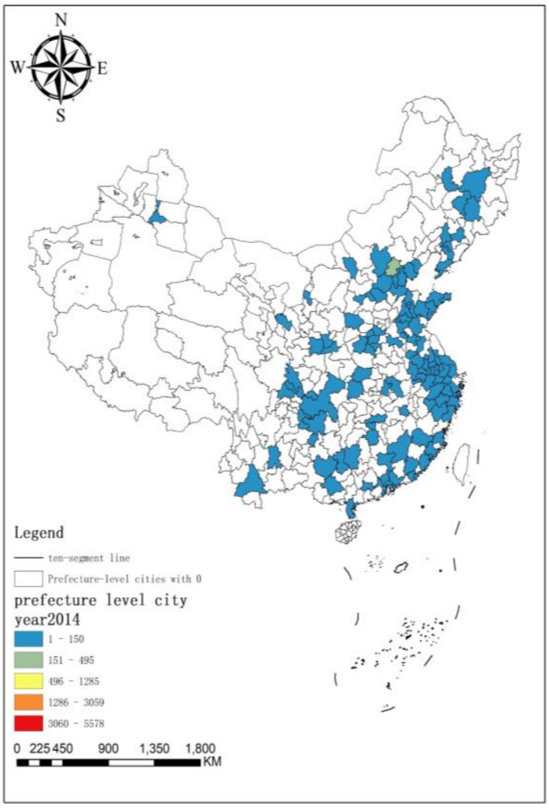
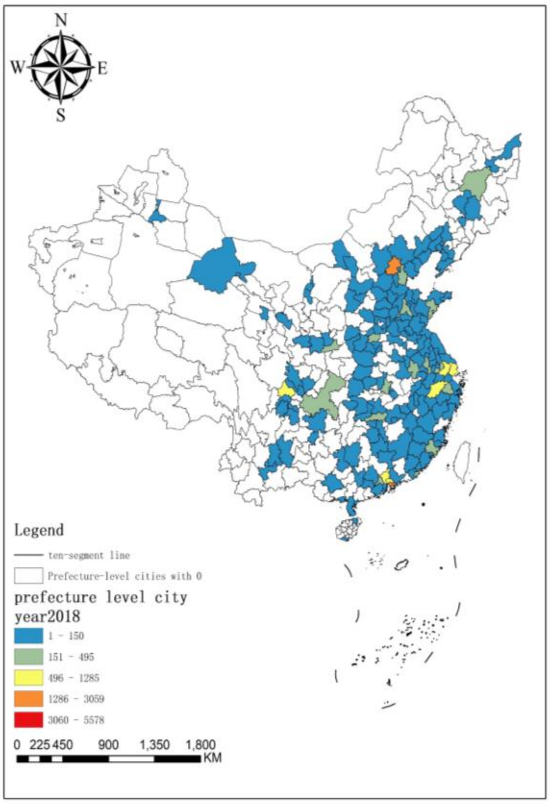


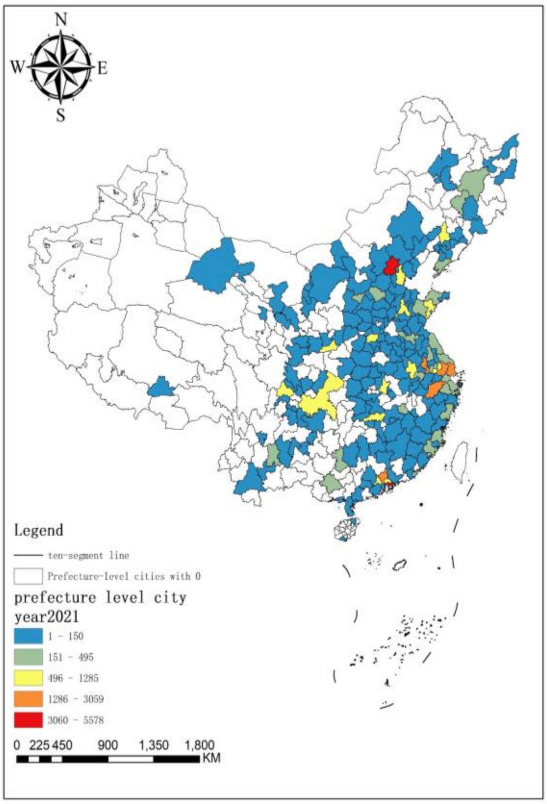
Fig.1 The influence mechanism of AI on EIE





a (2010) b (2014)





c (2018) d (2021)

Fig.2 Spatial distribution of urban AI level

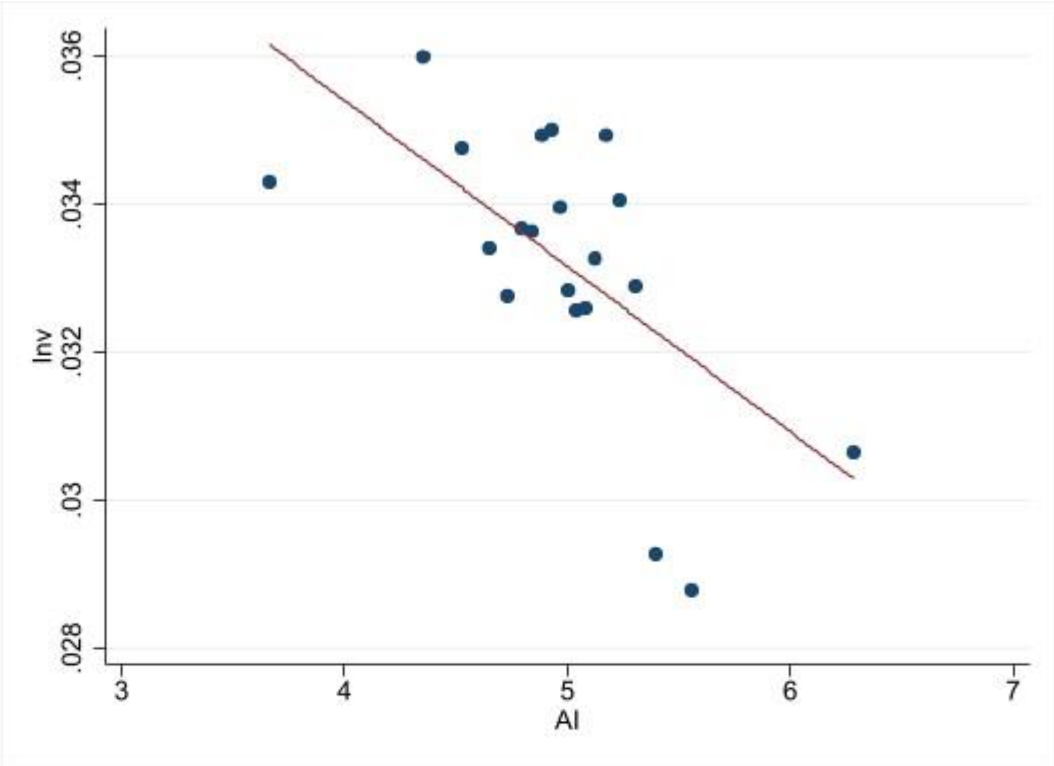


Fig. 3 **The fitting curve of AI and EIE**