THE IMPACT OF EXECUTIVE CHARACTERISTICS ON INVESTMENT STRATEGY EFFICIENCY: EVIDENCE FROM CHINESE A-SHARE LISTED FIRMS

Yiren Wen *

* aSSIST University, Seoul, South Korea
Contact details: aSSIST University, Ewhayeodae 2-gil, 03767 46, Seodaemun-gu, Seoul, South Korea

OPEN ACCESS

How to cite this paper: Wen, Y. (2026). The impact of executive characteristics on investment strategy efficiency: Evidence from Chinese A-share listed firms. *Corporate and Business Strategy Review, 7*(1), 239–249.
https://doi.org/10.22495/cbsrv7i1art21

ISSN Online: 2708-4965
ISSN Print: 2708-9924

Received: 31.07.2025
Revised: 24.11.2025; 13.01.2026
Accepted: 30.01.2026

JEL Classification: G30, M12, O33
DOI: 10.22495/cbsrv7i1art21

Abstract

Investment efficiency is a key parameter in modern business as it reflects the optimisation of capital in ventures taken up by a firm through positive net present value. However, in recent times, it has been understood that Chinese firms have shown traits of underinvestment or overinvestment (Guariglia & Yang, 2016; Gao et al., 2025). This leads to investment inefficiency and a loss in revenue for such firms. As a result, it is necessary to understand the factors responsible for such inefficiencies. The research also used artificial intelligence (AI) adoption as a mediating role in shaping capital allocation efficiency. Using an unbalanced panel dataset of 3773 firms from 2009 to 2023 (27790 firm-year observations), a fixed effects model was used as a baseline model and two-stage least squares (2SLS) regression as a robustness check to address potential endogeneity. The results indicate that chief executive officer (CEO) age has a statistically significant negative effect on investment efficiency, meaning that older CEOs are associated with higher investment efficiency, while overseas experience and academic qualifications do not exert a consistent influence. Additionally, AI adoption also mediates the executive-investment relationship significantly. These results have important implications for corporate governance, strategic leadership, and AI investment strategies in emerging markets.

Keywords: Investment Efficiency, Executive Characteristics, Artificial Intelligence, Corporate Governance, Chinese A-listed Firms

Authors' individual contribution: The Author is responsible for all the contributions to the paper according to CRediT (Contributor Roles Taxonomy) standards.

Declaration of conflicting interests: The Author declares that there is no conflict of interest.

1. INTRODUCTION

The understanding of the investment efficiency of a firm is a key parameter, as it reflects the optimal allocation of capital to various business ventures. Chen et al. (2011) describe investment efficiency as the optimal allocation of capital within the projects of firms, which tends to fetch a positive net present value. This indicates that there is a substantial return to the investments made, and ensures that the firm is in a healthy position financially with the investment function. In the modern global business era, firms face the risk of unproductive costs, which eventually reduce the overall revenue of the firms. This leads to the need to improve the investment efficiency, as it would ensure that the unproductive costs incurred by the firm are bypassed. Therefore, a better project selection and planning would be underway. However, the decisions on investments and the selection of projects depend on the executive board of the firm. As per the study by Al-Matari (2020), the characteristics of the board of directors and top executive management impact the corporate performance of firms. Factors like the size of the board along with the experience of the board play a critical part in determining the decision-making function of the firm.

Furthermore, in the present day, the adoption of artificial intelligence (AI) has also become a benchmark in the enhancement of investment efficiency. Liu et al. (2024) indicate AI integration leads to better data processing levels within firms. Hence, the firms could predict the market trend in a more efficient manner. This AI integration also indicates the firms on projects to invest in. As a result, such influence in the decision-making regarding investments of firms also play a critical role in the operations. Overall, it could be considered that the characteristics of the executive management along with the integration of AI are helpful parameters in influencing the investment activities of the firm.

Despite the rapid financial development of China, there are certain firms that still suffer from sub-optimal investments. Research by Guariglia and Yang (2016), has indicated that there is strong evidence among Chinese listed firms for investment inefficiency. This is caused by several parameters surrounding financial constraints and agency costs, which eventually lead to investment inefficiency. Another study by Gao et al. (2025), have also found instances of overinvestment or underinvestment made by firms towards various ventures. This shows that investment inefficiency has been structurally present within the Chinese A-listed firms. Therefore, it is subsequently necessary to understand the role that the top-level management has on such investment inefficiencies among Chinese firms.

This brings to the research gap, as there is limited evidence of integrated studies that account for the impact of chief executive officer (CEO) characteristics on the firm investment levels while controlling for the integration of AI. As a result, this study bridges the gap and jointly examines executive traits and AI as a mediating factor in the context of Chinese A-share listed firms.

The primary objective of this research is to empirically investigate the extent to which executive characteristics impact the investment efficiency of Chinese A-share listed firms. Additionally, the research also seeks to examine whether the adoption of AI acts as a mediating variable in this relationship, while accounting for firm-specific financial and operational factors.

In order to address the identified gaps and fulfil the research objectives, the following research questions are identified:

RQ1: To what extent do executive characteristics affect the investment efficiency of Chinese A-share listed firms?

RQ2: Does the adoption of AI mediate the relationship between executive characteristics and investment efficiency?

RQ3: How do firm-specific control variables influence investment efficiency?

The study is structured into several sections. Section 1 introduces the background and the problem of the research, Section 2 reviews the relevant literature. Section 3 of the research identifies the research methodology, and Section 4 presents the empirical analysis and provides the research results, whereas the Section 5 proposes the research discussion. Finally, the paper is concluded in Section 6, where the limitations and directions for future studies are also presented.

2. LITERATURE REVIEW

2.1. Theoretical framework

2.1.1. Upper echelons theory

This study, which aims to categorise the impact of executive characteristics of a firm on investment efficiency, uses the theoretical framework of upper echelons. Saiyed et al. (2023) indicate that the managers of the firm play an important role in the operations. This is because the managers are responsible for the strategic decisions of the firms. These also impact the performance of the firm. Under the upper echelons theory, the personal characteristics of a manager define the management style and the business environment followed by the firm (Oppong, 2014). These factors influence the strategic choices made by the managers on behalf of the firm.

The same is further highlighted by the stewardship theory, which mentions that the directors work towards the best interest of the firm (Keay, 2017). Hence, under the upper echelons theory, it would mean that the managers would make decisions for the firm to ensure better organisational performance.

2.1.2. Resource-based view

The resource-based view (RBV) is another important theory that could be used to define the performance of a firm. As per the study by Lockett et al. (2009), the RBV looks into the internal parameters of the firm. These internal parameters are critical to ensure comparative advantage. This indicates that firms with unique internal capabilities could perform better than others. Moreover, Lockett et al. (2009) also indicate that the internal capabilities of the firm is a primary enabler for such firm characteristics. This is shown via the management and the decisions taken by the management towards the firm. A firm with good management would have greater unique capabilities in handling business decisions. Hence, this would lead to efficient operation of the company, leading to a better comparative advantage in the market.

2.2. Impact of investment efficiency on firm performance

The efficiency of investments within a firm impacts the performance of the firm as well. According to the study by Wu et al. (2024), the investment efficiency has 0.1% positive impact on return on assets (ROA), 0.03% positive impact on return on equity (ROE) and 1.2% positive impact on Tobin's Q.

This indicates that as the investment efficiency of the firms improves, the firm performance also improves. The conclusion is drawn upon by analysing 89198 firm-year observations in the United States between 2010–2022. A panel data regression analysis is considered for this analysis with a Hausman test for segregation between fixed effects model (FEM) and random effects model (REM).

Another literature by Salehi et al. (2022), also indicated that an improvement in the investment efficiency of a firm leads to better firm value. The increase in investment efficiency by 1% leads to an enhancement in firm value by 29.8%. Moreover, the second model with additional control variables also indicates that an improvement in investment efficiency leads to an enhancement in firm value by 43.2%. These results were compiled by using generalized least squares approach on data of 177 companies listed in the Tehran Stock Exchange between 2014 and 2021.

The investment levels and efficiency also have a varied impact on the Chinese firms. In accordance with the study by Gao et al. (2025), the degree of overinvestment has a negative impact of 5% on corporate performance and the degree of underinvestment has a 7% negative impact on corporate performance. The results are reached by conducting a panel data analysis on 1918 Chinese firms between 2016 and 2020. This indicates that the investment efficiency is a key parameter for firm performance, as overinvestment and underinvestment both impact the firm performance adversely. Hence, it is necessary to have an efficient investment channel that would eventually enhance firm performance. A similar stance is also presented by Bao and Motlagh (2024), who find no significant impact of firm performance and investment efficiency. This is because of the failure of investment channels by effective leadership to enhance investment efficiency. Moreover, Bao and Motlagh (2024) also showed a negative relationship between overinvestment and firm performance. This further confirms that inefficient allocation of resources leads to market failure, and does not always impact firm performance as indicated.

2.3. Impact of executive characteristics on firm performance

The upper echelons theory as per Oppong (2014) reveal that the executive characteristics are an important element that determines the firm's performance. Moreover, Lockett et al. (2009), further advocate that the executive characteristics operate as internal parameters that impact the competitive advantage of a firm. Hence, this could also indicate that the characteristics of the manager impact the performance of the firm. In accordance with the study by Setiawan and Gestanti (2022), it is understood that a greater educational factor of management has a positive impact on both investment policy and firm performance. As the educational qualification improves by one year, the investing policy improves by 3.9% and the firm's performance improves by 3.3%. Moreover, Setiawan and Gestanti (2022) also show that an increase in the age of the executives leads to a negative impact on the investing policy as well as firm performance. An increase in age of management personnel reduces investment efficiency by 5.4% and the ROA by 1.3%. These results are achieved by analysing firms from Indonesia between 2010 and 2017. Moreover, Setiawan and Gestanti (2022), used a pooled ordinary least squares (OLS) regression model as a methodological approach in their study.

Other studies find that the professional characteristics of the CEO also impact the firm's performance. The study by Queen and Fasipe (2015), concludes that the presence of an insider CEO has a positive impact on the firm's ROE by 2.22%. However, this relation is not statistically viable. On the other hand, the same study by Queen and Fasipe (2015) also revealed that ownership by the CEO leads to a fall in the ROE by 15.42%. This is statistically significant. Moreover, Queen and Fasipe (2015) also found conflicting reports as there was no direct impact of CEO tenure and CEO duality on the firm performance. The results of the study were concluded by conducting a linear regression across 703 observations on top firms rated by the Russell 1000 index.

2.4. Interlink between executive characteristics and investment efficiency

The individual characteristics of the executives who are responsible for the management of a company also impact the investment efficiency of the company. As per the study by Wang et al. (2019), it was concluded that the presence of a male within the executive management had a 0.31% impact on the optimal allocation of investments. However, this parameter is not statistically significant. Moreover, the same study also concluded that the increase in the age of the executive had a negative impact on the investment efficiency by 0.05%. On the other hand, the additional educational years of the management also had a negative impact of 0.12% on the optimisation of investments. The study used data from Shanghai-Shenzhen A-share listed companies from 2010 to 2016. Moreover, least squares regression model was considered as a methodological approach for this paper. An additional study conducted in China by Huang and Qiu (2023), also concluded that executive characteristic score had a negative impact by 0.3% on investment efficiency. This score was calculated using factors such as executive position, executive ability, industry and reputation.

A similar standpoint is also argued by Depperu et al. (2017) also present that managerial contribution is immense in ensuring efficient operations of the firm. Moreover, the same paper also presents the findings that executive characteristics are critical for the initial public offering preference of the company while going public. As a result, it is imperative for firms to look into executive characteristics to ensure efficient investment. Abed and Al-Najjar (2016) also present that voluntary disclosure of forward-looking information as a part of executive decisions are critical for growth opportunities of firm. This ensures that there is no information asymmetry within the stakeholders. This could be leveraged towards the operational and investment efficiency of firms. Thus, this literature also highlights the importance of executive characteristics within firms.

2.5. Adoption of artificial intelligence as a mediator to investment efficiency

In the modern business dynamics, the growth of AI has also impacted the efficiency of investments made. As per the study by Zhao et al. (2024), it has been understood that an increase in AI investment as a mediator has a negative impact on investment levels. As there is an inverse relation between investment levels and investment efficiency. A fall in the investment levels indicates that there is greater capital allocation efficiency within the firms with AI as a mediator. These results were concluded by analysing data from Chinese A-listed firms between 2010 and 2021. Another research by Liu et al. (2024), has conducted a qualitative analysis to understand the impact that AI have on the investment efficiency of firms. The literature found that AI optimisation allows market trend prediction and also helps in portfolio optimisation. This allows the firms to gain better investment efficiency in the markets. As a result, the adoption of AI is integral parameter in enhancing efficient investments. Naeem et al. (2024) also indicates that investment in AI has a positive impact on firm value in Pakistani organisations. This relation is further moderated by human capital, structural capital, and relational capital. Therefore, this indicates that AI-related projects help in improving the internal structure of firms. Moreover, this also helps firm managers and policymakers to understand the importance of AI and intellectual capital in enhancing firm value (Naeem et al., 2024). Therefore, this presents the impact of both AI and executive characteristics.

Another literature by Chen et al. (2025), also analyse the mediating effect of AI on the investment efficiency. The paper reveals that the presence of AI has a negative impact on investment inefficiencies by 1.8%. Moreover, in an alternate model, the AI dummy also show a negative impact on investment inefficiency by 5%. These results are concluded by conducting a two-stage regression and instrumental variables (IV) regression on data from Chinese firms.

2.6. Research gap

The literatures show the nuanced impact that corporate executive characteristics as well as the AI integration have on the optimal investment of firms in China. However, there are substantial gaps in the literature, as there is no integrated study that analyses the impact of executive characteristics as well as AI integration on investment efficiency. For instance, papers like Wu et al. (2024) and Salehi et al. (2022) confirm that investment efficiency enhances firm performance. However, papers like Gao et al. (2025) and Wang et al. (2019) indicate that executive characteristics directly influence investment efficiency in emerging economies. However, the mediating role of AI remains underexplored in an integrated way as literature like Liu et al. (2024) and Chen et al. (2025), isolates and finds the direct effect of AI implementation on investment efficiency only. As a result, by providing an integrated insight, this particular research will bridge the gap. Finally, papers like Wang et al. (2019), use cross-sectional data or simple OLS models. This limits the ability of the study to control for unobserved firm heterogeneity. As a result, this research would also bridge the methodological gap by using a panel data regression approach.

Based on the above, the research hypotheses are as follows:

H1: Executive characteristics have a significant impact on corporate investment efficiency in Chinese A-share listed firms.

H2: AI adoption mediates the relationship between executive characteristics and investment efficiency.

H3: Firm-specific characteristics impact the investment efficiency significantly.

3. METHODOLOGY

3.1. Design of research

The particular study employs a quantitative panel data research design to empirically analyse the impact of executive characteristics and AI adoption on investment efficiency in Chinese listed firms. As denoted by Shi et al. (2017), the use of a quantitative approach in finance is important as it helps to decode the complex nuances within financial data. As per Oppong (2014) and Lockett et al. (2009), this particular study is grounded in agency and upper echelons theory. Hence, longitudinal data and firm-fixed effects models are used in this analysis as it helps control for both observable and unobservable heterogeneity across firms over time.

The research paper uses STATA 14.0 as the core software for the empirical analysis. The summary statistics, correlation analysis, and FEM and IV-two-stage least squares (IV-2SLS) are all analysed using the software.

3.2. Data and selection of sample

The data is selected from China Stock Market & Accounting Research Database[1] and WIND database[2]. A comprehensive coverage of Chinese A-share listed companies is considered from these databases. Data in the research is considered between 2009 and 2023. In a sample selection strategy, observations with missing values for key variables were excluded to ensure data integrity. From the dataset, a total of 3773 firms were included in the study and a total of 27790 firm-year observations were considered for the analysis.

3.3. Variables and proxies

Following variables — dependent variable (*investment efficiency*), independent variables (*CEO age, CEO overseas experience, CEO academic qualification*), mediating variables (*AI adoption*), control variables (*firm size, leverage, ROA, Tobin's Q*) — are used in the research:

Investment efficiency (*INVE*): This is the core dependent variable in the research. The *INVE* is constructed as per the insights by Biddle et al. (2009). The construction of the variable is shown in Eq. (1) and Eq. (2). This variable estimates the expected investment level based on firm fundamentals.

[1] http://www.csmar.com/en/
[2] https://www.wind.com.cn

As a result, a higher *INVE* value indicates greater deviation from the optimal investment level and thus lower corporate investment efficiency. On the contrary, lower *INVE* reflects higher corporate investment efficiency because of better alignment between actual and expected investments.

CEO age (*CAGE*): The CEO age is the age of the CEO in years at the end of each fiscal year. As per Li et al. (2024), *CAGE* is a continuous variable that is measured and used as an independent measure in the research.

CEO overseas experience (*COVR*): This variable indicates the experience of a CEO for working under overseas firms. This is a binary variable which is equal to 1 if the CEO has overseas experience. Otherwise, the value of the variable is 0. Wang et al. (2019) as well as Huang and Qiu (2023) show that executive exposure and characteristics influence investment efficiency. International exposure aligns with these characteristics.

CEO academic qualification (*CACA*): The academic qualification is measured as a dummy variable. It is coded as 1 if the CEO holds a higher academic degree. Otherwise, it is coded as 0. Setiawan and Gestanti (2022) demonstrate that educational qualifications positively impact firm performance and investment policy. Hence, this variable is considered in the research.

AI adoption (*AIA1*): This is the natural logarithm of the frequency count of AI-related terms in the annual reports of enterprise. Zhao et al. (2024) and Chen et al. (2025) confirm AI adoption impacts investment efficiency as a mediator.

Firm size (*SIZF*): This is the natural logarithm of total assets at the end of each fiscal year. This is also a continuous variable that is considered in the research. As per Wu et al. (2024), larger firms generally have more resources and better access to financing. This also impacts investment efficiency.

Leverage (*LEVF*): This is a continuous variable in ratio form. As per Gao et al. (2025), this is a ratio of total liabilities to total assets. The leverage also has an impact on the investment efficiency.

Return on assets (*ROAF*): This is a continuous variable which indicates the net income divided by total assets at the end of the fiscal year. Wu et al. (2024), reveal that investment efficiency is linked with firm performance indicators like ROA.

Tobin's Q (*TOBF*): This is the ratio of market value of equity plus book value of debt to total assets (Gao et al., 2025). It is also a continuous variable which is used as a performance indicator for firm growth opportunities. This also influence investment efficiency.

3.4. Empirical model specification

The research first constructs the investment efficiency of firms. In order to do so, the research follows the insights presented by Biddle et al. (2009). From the same, the paper uses variables regarding firm growth and cash flow and regresses it to the investment made within the firm. The residuals of the regression analysis indicate the investment efficiency of the firm. In order to find the impact of AI integration, a mediation effect is checked upon using the Baron and Kenny (1986) mediation approach.

The optimal investment of the firm is calculated as per Eq. (1):

$$Investment\ Efficiency = |Investment_{it} - \widehat{Investment}_{it}| \tag{1}$$

Here, Eq. (2) indicates the calculation of the residual of investment:

$$\widehat{Investment}_{it} = \alpha_1 + \alpha_2(Growth_{it}) + \alpha_3(Cash\ Flow_{it}) + \alpha_4(Size_{it}) + \alpha_5(Firm\ Age_{it}) + \gamma_j(Industry_j) + \delta_t(Industry_t) \tag{2}$$

With the investment efficiency measured, the various models to test the impact of the independent and mediator variables — impact of *CAGE* in isolation (Eq. (3)), impact of *COVR* in isolation (Eq. (4)), impact of *CACA* in isolation (Eq. (5)), complete model using *CAGE, COVR* and *CACA* (Eq. (6)), *AIA1* as mediating variable (Eq. (7)), complete model using *CAGE, COVR* and *CACA* and *AIA1* as mediating variable (Eq. (8)), IV-2SLS using *CAGE Lag 1* as IV (Eq. (9)), IV-2SLS using *CAGE, COVR* and *CACA* (Eq. (10)), IV-2SLS using *AIA1* as mediating variable (Eq. (11)), IV-2SLS complete model using *CAGE, COVR* and *CACA* and *AIA1* as mediating variable (Eq. (12)) — are as follows:

$$INVE_{it} = \beta_1 + \beta_2(CAGE_{it}) + \beta_3(SIZF_{it}) + \beta_4(LEVF_{it}) + \beta_5(ROAF_{it}) + \beta_6(TOBF_{it}) + \varepsilon_t \tag{3}$$

$$INVE_{it} = \beta_1 + \beta_2(COVR_{it}) + \beta_3(SIZF_{it}) + \beta_4(LEVF_{it}) + \beta_5(ROAF_{it}) + \beta_6(TOBF_{it}) + \varepsilon_t \tag{4}$$

$$INVE_{it} = \beta_1 + \beta_2(CACA_{it}) + \beta_3(SIZF_{it}) + \beta_4(LEVF_{it}) + \beta_5(ROAF_{it}) + \beta_6(TOBF_{it}) + \varepsilon_t \tag{5}$$

$$INVE_{it} = \beta_1 + \beta_2(CAGE_{it}) + \beta_3(COVR_{it}) + \beta_4(CACA_{it}) + \beta_5(SIZF_{it}) + \beta_6(LEVF_{it}) + \beta_7(ROAF_{it}) + \beta_8(TOBF_{it}) + \varepsilon_t \tag{6}$$

$$AIA1_{it} = \varphi_1 + \varphi_2(CAGE_{it}) + \varphi_3(COVR_{it}) + \varphi_4(CACA_{it}) + \varphi_5(SIZF_{it}) + \varphi_6(LEVF_{it}) + \varphi_7(ROAF_{it}) + \varphi_8(TOBF_{it}) + u_{it} + v_{it} \tag{7}$$

$$INVE_{it} = \beta_1 + \beta_2(CAGE_{it}) + \beta_3(COVR_{it}) + \beta_4(CACA_{it}) + \beta_5(AIA1_{it}) + \beta_6(SIZF_{it}) + \beta_7(LEVF_{it}) + \beta_8(ROAF_{it}) + \beta_9(TOBF_{it}) + \varepsilon_t \tag{8}$$

$$CAGE_{it} = \pi_1 + \pi_2(L1\_CAGE_{it}) + \pi_3(COVR_{it}) + \pi_4(CACA_{it}) + \pi_5(AIA1_{it}) + \pi_6(SIZF_{it}) + \pi_7(LEVF_{it}) + \pi_8(ROAF_{it}) + \pi_9(TOBF_{it}) + \upsilon_t \tag{9}$$

$$INVE_{it} = \beta_1 + \beta_2(\widehat{CAGE}_{it}) + \beta_3(COVR_{it}) + \beta_4(CACA_{it}) + \beta_5(AIA1_{it}) + \beta_6(SIZF_{it}) + \beta_7(LEVF_{it}) + \beta_8(ROAF_{it}) + \beta_9(TOBF_{it}) + \varepsilon_t \tag{10}$$

$$AIA1_{it} = \tau_1 + \tau_2(\widehat{CAGE}_{it}) + \tau_3(COVR_{it}) + \tau_4(CACA_{it}) + \tau_5(SIZF_{it}) + \tau_6(LEVF_{it}) + \tau_7(ROAF_{it}) + \tau_8(TOBF_{it}) + u_{it} + v_{it} \tag{11}$$

$$INVE_{it} = \beta_1 + \beta_2(\widehat{CAGE}_{it}) + \beta_3(COVR_{it}) + \beta_4(CACA_{it}) + \beta_5(AIA1_{it}) + \beta_6(SIZF_{it}) + \beta_7(LEVF_{it}) + \beta_8(ROAF_{it}) + \beta_9(TOBF_{it}) + \varepsilon_t \tag{12}$$

3.5. Strategy of estimation

The research uses an FEM under panel data regression as the baseline model. This is highlighted by Biddle et al. (2009). Using the FEM is useful here as it controls for unobserved heterogeneity across firms that is time-invariant. Other papers, like DeHaan (2021), also indicate that FEMs are widely used in financial econometrics. This is also because the FEM eliminate bias caused by omitted variables.

A dynamic panel estimator, such as system generalized method of moments (GMM), could be an alternate methodology given the persistence of investment behaviour and potential endogeneity of executive characteristics. System GMM can control for lagged dependent variables, unobserved heterogeneity, and simultaneity bias using internal instruments (Sahnoun & Idrissi, 2025). However, it requires large cross-sectional dimensions and careful instrument management to avoid overfitting.

3.6. Robustness estimation

As a part of the robustness test, an IV-2SLS has been considered. As per Zahid et al. (2020), the ignorance of endogeneity in finance studies leads to biased results. Hence, an IV-2SLS estimation helps to address the same problem of endogeneity. As a result, under this research strategy, the robustness checks as per IV-2SLS would also validate the results of the FEM. If the results are similar, this would indicate consistency in the model and would also address issues like endogeneity.

4. EMPIRICAL ANALYSIS AND RESULTS

4.1. Statistical summary

The statistical summary of the data used in the research is provided in Table 1.

Table 1. Summary statistics

Variable	*N*	*AVG*	*SD*	*Min.*	*Max.*
INVE	27790	0.0873	0.0881	0.0000	0.9777
CAGE	27793	50.2442	6.7895	25	82
COVR	27793	0.0858	0.2801	0	1
CACA	27793	0.1786	0.3830	0	1
AIA1	27793	1.0846	1.2667	0	4.8122
SIZF	27793	22.3234	1.2852	19.4149	26.4438
LEVF	27793	0.4409	0.2024	0.0274	0.9246
ROAF	27793	0.0374	0.0644	-0.3750	0.2552
TOBF	27793	2.0257	1.2055	0.8445	7.3076

Source: Author's elaboration.

From Table 1, it is evident that the N for *INVE* is 27,790, and the N for the rest of the variables is 27,793. The average values (AVG) for the variables, standard deviation (SD), minimum value (Min.) and maximum value (Max.) for the variables are as follows. For *INVE*, the mean efficiency for the sample is 0.0873. There is a variation noted worth 0.0881 for the variable. The Min.is 0.0000, and the Max. is 0.9777. The average value for *CAGE* is 50.2442 and has a deviation of 6.7895. The range is between 25 and 82 years. For *COVR*, it is understood that 8.58% have overseas experience, 91.42% do not have overseas qualifications. The deviation within the variable is 28.01%. *CACA* is also a categorical variable. The average is 17.86% for individuals with higher academic qualifications for the CEO. On the contrary, 82.14% of individual CEOs do not have the highest academic qualification. The integration of AI is a logarithmic value that is considered for companies and their involvement in AI-based technologies. The *AIA1* has a mean of 1.0846, and the range for the variable is between 0 and 4.8122. *AIA1* also has a deviation worth 1.0846.

The *SIZF* indicates the size of the firm. This is a control variable that accounts for the firm-individual characteristics. *SIZF* has a mean of 22.32. The deviation within the sample is 1.2852, whereas the range is between 19.4149 and 26.4438. The *LEVF* of the firm denotes the leverage. The *LEVF* for the sample is 44.09%. This comes with a 20.24% deviation. Moreover, the variable ranges between 2.74% and 92.46%. The average value for *ROAF* is 3.74%. This comes with a variation of 6.44%. The range for *ROAF* is between -37.50% and 25.52%. Finally, *TOBF* has an average of 2.02%. The SD is 1.2055, and the range is between 0.8445 and 7.3076.

The correlation matrix analysis is also shown as a part of the descriptive statistics. The results of the correlation analysis are shown in Table 2.

Table 2. Correlation analysis matrix

Variable	*INVE*	*CAGE*	*COVR*	*CACA*	*AIA1*	*SIZF*	*LEVF*	*ROAF*	*TOBF*
INVE	1	0.0145	-0.0014	0.0024	0.0139	0.0961	0.0698	0.0570	-0.0957
CAGE	0.0145	1	-0.0379	0.1719	0.0680	0.1218	0.0033	0.0276	-0.0348
COVR	-0.0014	-0.0379	1	0.1060	0.0796	-0.0042	-0.0513	0.0084	0.0463
CACA	0.0024	0.1719	0.1060	1	0.1360	-0.0581	-0.0929	0.0236	0.0474
AIA1	0.0139	0.0680	0.0796	0.1360	1	0.0520	-0.0812	-0.0305	0.0297
SIZF	0.0961	0.1218	-0.0042	-0.0581	0.0520	1	0.4589	0.0509	-0.4117
LEVF	0.0698	0.0033	-0.0513	-0.0929	-0.0812	0.4589	1	-0.3393	-0.3003
ROAF	0.0570	0.0276	0.0084	0.0236	-0.0305	0.0509	-0.3393	1	0.2079
TOBF	-0.0957	-0.0348	0.0463	0.0474	0.0297	-0.4117	-0.3003	0.2079	1

Source: Author's elaboration.

The correlation analysis shows that *CAGE* and *INVE* have a positive correlation. This correlation coefficient is statistically significant at the 95% confidence interval (CI). The other variables, like *COVR* and *CACA,* have a correlation coefficient of -0.0014 and 0.0024, respectively. However, these two variables of *COVR* and *CACA* are not statistically significant at any level. For the *CAGE*, there is a moderately weak correlation between *CAGE* and INVE. The *AIA1,* which acts as a mediator, has a moderately weak positive correlation. The correlation coefficient is 0.0139 and is statistically significant at 99% CI. Finally, the rest of the control variables like *SIZF*, *LEVF*, *ROAF* and *TOBF* are also correlated significantly with the *INVE*. The coefficient for *SIZF* is 0.0961, which indicates a strong correlation. *LEVF* has a moderate positive correlation with a coefficient of 0.0698. The *ROAF* also has a moderately positive correlation with a coefficient of 0.0570. Finally, *TOBF* has a strong and negative coefficient of -0.0957.

4.2. Baseline regression analysis

The Baseline regression analysis checks for the impact of the independent and moderating variables on the *INVE*. The same is shown in Table 3.

Table 3. Impact on *INVE* using fixed effects models

Variable	*INVE*	*p-value*	*INVE*	*p-value*	*INVE*	*p-value*	*INVE*	*p-value*
CAGE	-0.0004	0.0040					-0.0004	0.0030
COVR			-0.0055	0.1080			-0.0060	0.0830
CACA					-0.0009	0.7360	0.0006	0.8250
SIZF	-0.0145	0.0000	-0.0152	0.0000	-0.0154	0.0000	-0.0144	0.0000
LEVF	0.0718	0.0000	0.0724	0.0000	0.0724	0.0000	0.0717	0.0000
ROAF	0.2052	0.0000	0.2062	0.0000	0.2066	0.0000	0.2047	0.0000
TOBF	-0.0027	0.0000	-0.0027	0.0000	-0.0027	0.0000	-0.0027	0.0000
CONS	0.3983	0.0000	0.3936	0.0000	0.3961	0.0000	0.3955	0.0000

Source: Authors' elaboration.

The baseline regression analysis firstly shows the impact of *CAGE* on *INVE* as per Eq. (3). The baseline analysis shows that *CAGE* has a negative impact of 0.0004 percentage on the *INVE*. This estimate is also statistically significant. The rest of the control variables are also statistically significant here. The impact of *COVR* on *INVE,* as per Eq. (4), is also shown in Table 3. The estimate is worth a negative impact of 0.0055. However, this coefficient is not statistically viable. The *CACA* also has a negative impact of 0.009 percentage on the *INVE*. This is as per Eq. (5). This regression estimate is also not statistically significant.

The results of the combined model, as per Eq. (6) is in Table 3. The table indicates that *CAGE* has a negative impact of 0.0004 percentage on *INVE*. The p-value of the same is also less than 0.05, making the relation significant at 95% CI. The other variables like *COVR* and *CACA* have an impact of -0.0060 and 0.0006, respectively. However, these variables have no statistically significant impact. The control variables all statistically impact the *INVE*. *SIZF* has a negative impact of 1.44%, whereas *LEVF* and *ROAF* have a positive impact of 0.0717 and 0.2047, respectively, on *INVE*. *TOBF* also has a negative impact of 0.0027 on *INVE*.

4.3. Extended model with mediator variable

This particular segment of the empirical analysis indicates the impact that the mediator variable of *AIA1* has on the *INVE*. The results are shown in Table 4.

Table 4. Impact on *INVE* using fixed effects models and *AIA1* as a mediating variable

Variable	*AIA1*	*p-value*	*INVE*	*p-value*
CAGE	0.0094	0.0000	-0.0004	0.0100
COVR	0.1236	0.0030	-0.0054	0.1200
CACA	0.0151	0.6260	0.0007	0.8030
AIA1	-	0.0000	-0.0052	0.0000
SIZF	0.6820	0.0000	-0.0108	0.0000
LEVF	-0.4524	0.0000	0.0693	0.0000
ROAF	-1.2266	0.0000	0.1983	0.0000
TOBF	0.0637	0.0000	-0.0024	0.0010
CONS	-14.5115	0.0000	0.3198	0.0000

Source: Authors' elaboration.

Table 4 indicates the impact of *AIA1* as a mediating variable as shown in Eq. (7). The results of Table 4, Eq. (7), reveal that *CAGE* has a positive impact of 0.0094 percentage on *AIA1* and is statistically significant. *COVR* also has a significant impact of 0.1236 percentage. *CACA* do not have a significant impact on *AIA1*. *SIZF* and *TOBF* have a positive impact on *AIA1* by 0.6820 percentage and 0.0637 percentage, respectively. *LEVF* and *ROAF* have a negative impact of -0.4524 percentage and -1.2266 percentage.

Table 4 also indicates the amalgamated impact of the complete model, including the mediator variable of *AIA1* on the *INVE*. The results of the model, as per Eq. (8), indicate that *CAGE* has a negative impact on *INVE* at 0.0004 percentage. The same is statistically significant at 99% CI. The additional independent variables of *COVR* and *CACA* have an impact of -0.0054 and 0.0007, respectively. These regression estimates are, however, not statistically significant. The *AIA1* mediator has a -0.0052 percentage impact on the *INVE*. This is also statistically significant. The *SIZF* variable has a negative impact of 0.0108 percentage on *INVE*. *TOBF* also indicates a negative impact of 0.0024 percentage on *INVE*. The *LEVF* variable has a positive impact of 0.0693, and *ROAF* have a positive impact of 0.1983. These estimates have a statistically significant impact with a p-value under 0.05.

4.4. Robustness check

A robustness check is also provided in the study under Table 5. The robustness check follows an IV-2SLS model, which shows the impact of CEO characteristics on *INVE*, and then checks for the impact of AI as a mediating effect. Finally, the impact on the overall model is also shown in Table 5.

Table 5. Impact on *INVE* using IV-2SLS models

Variable	*INVE*	*p-value*	*AIA1*	*p-value*	*INVE*	*p-value*
CAGE	-0.0004	0.0000	0.0073	0.0140	-0.0005	0.0010
COVR	-0.0014	0.4720	0.2529	0.0000	-0.0012	0.6840
CACA	0.0018	0.2080	0.4158	0.0000	0.0045	0.0470
AIA1	-	-	-	-	-0.0038	0.0000
SIZF	-0.0025	0.0000	0.1528	0.0000	-0.0015	0.0640
LEVF	0.0290	0.0000	-0.9523	0.0000	0.0249	0.0000
ROAF	0.1363	0.0000	-2.2886	0.0000	0.1300	0.0000
TOBF	0.0019	0.0000	0.0788	0.0000	0.0017	0.0140
CONS	0.1391	0.0000	-2.4226	0.0000	0.1266	0.0000

Source: Author's elaboration.

The IV-regression analysis as per Eq. (10) is indicated in Table 5. The robustness check reveals that *CAGE* has a negative impact of 0.0004 percentage on *INVE* and is significant. *COVR* and *CACA* are not statistically viable. *SIZF* has a negative impact on *INVE* at -0.0025 percentage. *LEVF*, *ROAF* and *TOBF* have a positive impact on *INVE* at 0.0290, 0.1363 and 0.0019 percentage, respectively.

Table 5 also indicates the impact of *AIA1* as a mediating variable. This is as per Eq. (11) using IV-2SLS. The model shows that *CAGE* has a positive impact on *AIA1* by 0.0073 percentage. *SIZF* and TOBF have a positive impact on *AIA1*, whereas *LEVF* and *ROAF* have a negative impact on *AIA1*.

The results of the robustness analysis as per Eq. (12) indicate that *CAGE* have a negative and significant impact on *INVE*. The estimate is -0.0005. The *COVR* has a negative impact on *INVE*. The estimate is -0.0012; however, the same is statistically not significant. The *CACA* under Table 5 indicate a positive coefficient which is also statistically significant. The coefficient is 0.0045, and the p-value is less than 0.05. *AIA1* has an impact of -0.0038 percentage on the *INVE*. This estimate is also statistically significant at 95% CI. The *SIZF* has a negative impact of -0.0015 on *INVE*. The same also has a p-value of 0.0640, which makes it statistically significant at 90% CI. The *LEVF*, *ROAF* and *TOBF* also show a positive impact on the *INVE*. The coefficients are 0.0249, 0.1300 and 0.0017, respectively. These estimates are also statistically significant.

4.5. Results

The empirical analysis indicates that Chinese firms in the sample have a Capital allocation efficiency of 8.73%. For the independent variables as well, there is an average age of 50.2442 for *CAGE*. 8.58% of the *COVR* indicate that 8.58% of the CEOs have been abroad for overseas experience, whereas the rest of 91.42% do not have the same. The *CACA* of 17.86% show that there is an academic qualification of 17.86% of CEOs. 82.14% of the CEOs do not have higher academic qualifications. The correlation matrix also indicates that *CAGE* and *INVE* are related weakly. The mediator variable of *AIA1* also has a moderate and significant positive correlation to the *INVE* at a coefficient of 0.0139. The rest of the control variables are also significantly correlated with *TOBF*, showing a negative correlation.

The baseline regression model, as per Table 3 show that only the attribute of *CAGE* is significantly related to *INVE*. The coefficient is -0.0004, and the p-value is less than 0.05. This means that a one-year increase in *CAGE* reduces *INVE* by 0.0004 units, indicating a small improvement in investment efficiency. The combined model, as per Table 3 and Eq. (6), also indicates the same. The addition of the mediating variable of AI, denoted by *AIA1* as per Eq. (7), indicates that older CEOs are associated with higher investment efficiency (lower *INVE*) with a coefficient of −0.0004. *CAGE* also significantly increases the likelihood of *AIA1* by 0.0094 percentage. On the other hand, the increase in AI investment reduces *INVE* by 0.0052 units. This translates into higher corporate investment efficiency. These are the only two independent variables that are completely significant, as the other factors of education and foreign experience are not statistically significant. With respect to the control variables, the increase in the *SIZF* leads to a fall in *INVE*, indicating higher investment efficiency by 1.08%. The *TOBF* indicator rise also leads to a fall in *INVE*. This means greater investment efficiency by 0.24%. *LEVF* and *ROAF* have positive coefficients, meaning they increase *INVE* and, therefore, reduce investment efficiency.

The robustness check analysis also confirms that *CAGE* continues to exhibit a negative and significant impact on *INVE*, indicating higher investment efficiency. *CAGE* has a positive and statistically significant effect on *AIA1* at 0.0073 percentage. This indicates that older CEOs are more likely to facilitate AI integration within firms. *AIA1* is associated with a significant reduction in *INVE*, which in turn indicates improvement in investment efficiency. There is a negative effect of approximately 0.0005 units of *INVE* for each additional year of *CAGE*, indicating improved investment efficiency. Moreover, the integration of *AIA1* also has a negative impact on *INVE* by 0.38%. This means that increased AI integration improves investment efficiency across Chinese firms. In summary, the robustness check confirms that *CAGE* improves investment efficiency (reduces *INVE*), and this effect is partially mediated through increased *AIA1*. The IV-2SLS results support the main findings and mitigate concerns about endogeneity bias.

5. DISCUSSION

The results of the empirical analysis show that CEO age has a negative coefficient on investment efficiency, meaning that older CEOs are associated with higher investment efficiency. A one-year increase in CEO age reduces investment efficiency by approximately 0.0004 units, indicating a small improvement in investment efficiency. This finding contrasts with Setiawan and Gestanti (2022), who reported that increasing CEO age reduces investment efficiency. The difference suggests that the role of CEO age may be context-specific and shaped by institutional factors unique to China. The results also align with the upper echelons theory as indicated by Oppong (2014). This shows that the demographic factors of CEOs, such as age, shape the strategic decisions regarding the firm. One possible explanation for the improvement in efficiency is that older CEOs may rely on accumulated experience and adopt more disciplined investment policies, reducing deviations from optimal investment levels. Hence, this leads to slower adoption of innovative investment strategies, leading to a fall in efficiency.

AI adoption has a significant and negative effect on investment efficiency, indicating that increased AI integration improves investment efficiency. The coefficients on AI adoption (-0.0052 in the FEM and -0.0038 in the IV model) indicate that greater AI adoption consistently reduces investment efficiency. The research by Liu et al. (2024) concluded that the inclusion of AI in the corporation helps optimise the portfolio. Thereby, it also allows better investment efficiency. Hence, AI integration is an important parameter for Chinese firms. The consistent negative effect of AI adoption on investment efficiency is aligned with the RBV, which emphasises that technological capabilities enhance internal resource allocation efficiency.

The usage of the robustness check models reinforces the stability of the CEO age and AI adoption on the investment efficiency. This robustness check also stabilises the methodological reliability over OLS and FEM. This also addresses the methodological gap that had been left by Wang et al. (2019).

6. CONCLUSION

This particular research aimed at analysing the impact of executive characteristics and the adoption of AI on the investment efficiency of Chinese A-listed firms. The study is also built upon the theoretical frameworks of the upper echelons theory and RBV, which indicates the importance of demographic factors of CEOs as an important parameter in managing the operations of the firm. This also indicates that the CEOs are important internal actors of the firm, which eventually drives the direction of progress of the firm.

This particular research analysed a total of 3773 firms across 27790 firm-year observations from China between 2009 and 2023. A panel regression using fixed effects was considered as the baseline methodology for the analysis. Moreover, an additional IV-2SLS was incorporated within the empirical methodology as a robustness check. The analysis shows that CEO age has a negative impact on investment efficiency, meaning that older CEOs are associated with higher investment efficiency. However, the other factors, like overseas experience and academic background, do not have a statistical impact on the efficiency levels of investment within Chinese firms. This leads to the partial acceptance of *H1*, as the age is understood to be the most influential trait among executive characteristics. AI adoption significantly reduces investment efficiency, indicating higher investment efficiency. This confirms its mediating role between executive characteristics and investment outcomes. *H2* is accepted as AI adoption mediates the relation between executive characteristics and investment efficiency. *H3* is accepted as firm-specific characters impact investment efficiency significantly.

Therefore, through AI adoption, the investment efficiency of firms could be improved. Firm-level characteristics also significantly influence investment efficiency. Larger firms and firms with higher Tobin's Q exhibit lower investment efficiency (higher efficiency), whereas firms with higher leverage and profitability display higher investment efficiency (lower efficiency), indicating possible overinvestment tendencies.

The results of this research have certain theoretical and practical implications. The results of the research reinforce the upper echelons theory as managerial demographics shape firm operations. Moreover, the importance of RBV is also stabilised in the paper, as it indicates that CEOs are important aggravators of the internal capability of firms. These actions of the CEOs eventually shape the resource optimisation. Finally, the particular study also addresses prior literature gaps by using panel data analysis with fixed effects and robustness checks. This ensures greater internal validity by accounting for firm-specific heterogeneity over time.

The research also indicates a number of limitations, as the educational factors and international exposure of CEOs might be underreported across the sample database. This leads to insignificant results on the impact of investment efficiency. Moreover, the AI adoption used in the research is measured using a logarithmic value. This could be further improved in future studies by accounting for actual expenditures on AI by firms. This would help provide more robust results. Future studies could explore causal relations between these variables using IV models as well. Moreover, the usage of other mediators like environmental, social, and governance could also be incorporated in future studies.

REFERENCES

Abed, S., & Al-Najjar, B. (2016). Determinants of the extent of forward looking information: Evidence from UK before financial crisis. *Corporate Ownership and Control, 13*(3), 17–32. https://doi.org/10.22495/cocv13i3p2

Al-Matari, E. M. (2020). Do characteristics of the board of directors and top executives have an effect on corporate performance among the financial sector? Evidence using stock. *Corporate Governance: The International Journal of Business in Society, 20*(1), 16–43. https://doi.org/10.1108/CG-11-2018-0358

Bao, Z., & Motlagh, B. P. (2024). How investment efficiency affects firms performance? *Accounting and Auditing with Applications, 1*(1), 17–26. https://doi.org/10.22105/aaa.v1i1.19

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Biddle, G. C., Hilary, G., & Verdi, R. S. (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics, 48*(2–3), 112–131. https://doi.org/10.1016/j.jacceco.2009.09.001

Chen, F., Hope, O.-K., Li, Q., & Wang, X. (2011). Financial reporting quality and investment efficiency of private firms in emerging markets. *The Accounting Review, 86*(4), 1255–1288. https://doi.org/10.2308/accr-10040

Chen, T., Pi, S., & Wang, Q. S. (2025). *Artificial intelligence and corporate investment efficiency: Evidence from Chinese listed companies* (Working Paper No. 5/2025). University of Canterbury. https://repec.canterbury.ac.nz/cbt/econwp/2505.pdf

DeHaan, E. (2021). *Using and interpreting fixed effects models*. https://doi.org/10.2139/ssrn.3699777

Depperu, D., Minciullo, M., & Cerrato, D. (2017). IPO and CEO turnover: An empirical analysis on Italy and UK. *Corporate Ownership and Control, 14*(2–1), 165–180. https://doi.org/10.22495/cocv14i2c1p2

Gao, D., Li, S., & Zhou, Y. (2025). Investment efficiency, ESG performance and corporate performance: Evidence from Chinese listed enterprises. *Chinese Management Studies, 19*(2), 567–599. https://doi.org/10.1108/CMS-06-2022-0210

Guariglia, A., & Yang, J. (2016). A balancing act: Managing financial constraints and agency costs to minimize investment inefficiency in the Chinese market. *Journal of Corporate Finance, 36*, 111–130. https://doi.org/10.1016/j.jcorpfin.2015.10.006

Huang, Y., & Qiu, J. (2023). The power influence of executives and corporate investment efficiency: Empirical evidence from Chinese state-owned enterprises. *Humanities and Social Sciences Communications, 10*, Article 586. https://doi.org/10.1057/s41599-023-02107-w

Keay, A. (2017). Stewardship theory: Is board accountability necessary? *International Journal of Law and Management, 59*(6), 1292–1314. https://doi.org/10.1108/IJLMA-11-2016-0118

Li, Z., Athanasiadis, K. A., Fygkioris, M. I., & Koufopoulos, D. N. (2024). Financial reporting quality, CEO age, and investment efficiency: Evidence from the U.S. market. *New Challenges in Accounting and Finance, 11*, 29–53. https://doi.org/10.32038/NCAF.2024.11.03

Liu, Z., Zhang, K., & Zhang, H. (2024). A new era of financial services: How AI enhances investment efficiency. *International Studies of Economics, 19*(4), 578–588. https://doi.org/10.1002/ise3.97

Lockett, A., Thompson, S., & Morgenstern, U. (2009). The development of the resource-based view of the firm: A critical appraisal. *International Journal of Management Reviews, 11*(1), 9–28. https://doi.org/10.1111/j.1468-2370.2008.00252.x

Naeem, M., Ali, S., Islam, M., & Rehman, A. (2024). Does intellectual capital mediate the relationship of artificial intelligence investment and firm value in Pakistani non-financial firms? *NICE Research Journal, 17*(3), 63–76. https://doi.org/10.51239/nrjss.v17i3.483

Oppong, S. (2014). Upper echelons theory revisited: The need for a change from causal description to causal explanation. *Management: Journal of Contemporary Management Issues, 19*(2), 169–183. https://scispace.com/pdf/upper-echelons-theory-revisited-the-need-for-a-change-from-553tlyp6gl.pdf

Queen, P. E., & Fasipe, O. (2015). Understanding the impact of business complexity on executive management characteristics and firm performance. *Journal of Accounting and Finance, 15*(3), 99–113. http://www.na-businesspress.com/JAF/QueenPE_Web15_3_.pdf

Sahnoun, M., & Idrissi, F. (2025). The role of instrumental variables in addressing endogeneity bias within dynamic panel data frameworks: A comparative analysis of system GMM and difference GMM estimators. *Annual Review of Foundational and Emerging Scientific Methodologies, 15*(5). https://hazeneditions.com/index.php/ARFESM/article/view/Sahnoun2025/5

Saiyed, A. A., Tatoglu, E., Ali, S., & Dutta, D. K. (2023). Entrepreneurial orientation, CEO power and firm performance: An upper echelons theory perspective. *Management Decision, 61*(6), 1773–1797. https://doi.org/10.1108/MD-05-2022-0641

Salehi, M., Zimon, G., Arianpoor, A., & Gholezoo, F. E. (2022). The impact of investment efficiency on firm value and moderating role of institutional ownership and board independence. *Journal of Risk and Financial Management, 15*(4), Article 170. https://doi.org/10.3390/jrfm15040170

Setiawan, R., & Gestanti, L. (2022). CEO characteristics, firm policy, and firm performance. *International Journal of Business and Society, 23*(1), 371–389. https://doi.org/10.33736/ijbs.4620.2022

Shi, X., Zhang, P., & Khan, S. U. (2017). Quantitative data analysis in finance. In A. Y. Zomaya & S. Sakr (Eds.), *Handbook of big data technologies* (pp. 719–753). Springer. https://doi.org/10.1007/978-3-319-49340-4_21

Wang, Z.-Y., Zhu, H., & Wang, Y.-Q. (2019). An empirical study on the background characteristics of executives and enterprise investment efficiency. In *Proceedings of the 5th Annual International Conference on Management, Economics and Social Development (ICMESD 2019)* (pp. 194–199). Atlantis Press. https://doi.org/10.2991/icmesd-19.2019.29

Wu, W., Le, C., Shi, Y., & Alkaraan, F. (2024). The influence of financial flexibility on firm performance: The moderating effects of investment efficiency and investment scale. *Journal of Applied Accounting Research, 25*(5), 1183–1202. https://doi.org/10.1108/JAAR-07-2023-0192

Zahid, M., Rahman, H. U., Khan, M., Ali, W., & Shad, F. (2020). Addressing endogeneity by proposing novel instrumental variables in the nexus of sustainability reporting and firm financial performance: A step-by-step procedure for non-experts. *Business Strategy and the Environment, 29*(8), 3086–3103. https://doi.org/10.1002/bse.2559

Zhao, X., Zhai, G., Charles, V., Gherman, T., Lee, H., Pan, T., & Shang, Y. (2024). Enhancing enterprise investment efficiency through artificial intelligence: The role of accounting information transparency. *Socio-Economic Planning Sciences, 96*, Article 102092. https://doi.org/10.1016/j.seps.2024.102092