CEO Gender and Firm's Adoption of Artificial Intelligence Technology

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Abstract: In this rapidly evolving era, AI is an emerging industry with a significant presence in various industries. Factors affecting the extent to which AI is used in companies have been explored by many researchers, but the factor of CEO gender is rarely mentioned. To test the effect of CEO gender on the degree of corporate use of AI, this paper analyzes the text of corporate annual reports to measure the degree of each company's use of AI by counting the number of times the term AI appears in each annual report. The CEO gender information is manually collected to construct an indicator of the degree of corporate adoption of AI. In this paper, a theoretical hypothesis of the relationship between CEO gender and the degree of corporate use of AI based on the different attitudes of males and females towards ethical behavior and risk will be provided. Then, accorded with the panel data about companies from Chinese a-share non-financial, which was listed from 2000 - 2021, a two-way fixed-effects regression model is used to analyze the effect of CEO gender on the degree of firms' use of AI technology. The study results show that AI usage is higher in male than female CEOs. Based on the above findings, this paper not only reveals the influence of CEO gender on the extent of firms' AI use but also deepens the understanding of the differences in gender characteristics between males and females.

Keywords: Artificial Intelligence, Chief Executive Officer (CEO), Gender

1. Introduction

This study focuses on how the gender of a company's CEO influences whether the company utilizes artificial intelligence. In this era of rapid development, Artificial Intelligence, as an emerging industry, has an essential place in various industries. One of the largest populations in the world, China has a huge market potential. With the continuous growth of China's economy and the advancement of technological innovation, AI has great prospects for development in the Chinese market. Researching China has advantages, including a vast population and diverse industry mix that have the potential to generate huge volumes of data and provide an enormous market [1]. Second, the Chinese government has put forward national development plans, such as the "New Infrastructure" and the AI strategy, to promote the application and dissemination of AI technology. This provides more opportunities for researchers to collaborate with the government, enterprises, and academia to promote the development of the AI field. In addition, conducting AI research in the Chinese market can help

understand the impact of the country's specific cultural, social, and economic factors on AI adoption. Factors such as consumer habits, data privacy issues, and regulatory environment in China may differ from those in other countries, and there is a need to understand the impact of these factors on the adoption of AI technologies. Overall, studying AI in the Chinese market is vital to gain insights into the global trends in AI and the challenges of practical application. It can help promote the development of AI technology in China and facilitate international cooperation and exchange. This shows that the use of artificial intelligence in a company or business has a great deal to do with whether or not a company can proliferate. The CEO, as a major decision-maker in a company, greatly influences whether or not a company uses AI as a technology. The topic of gender is hotly debated today. Since ancient times, many people believed that men were the only ones who could work in the field or hold important positions and that the status of women was underestimated in ancient times. Nowadays, more and more people are advocating for gender equality, and there are more women in the position of CEO. This is one of the reasons why we are researching the topic of the department.

While the Internet is familiar with the impact of AI on humanity, the topic of why people are increasingly inclined to integrate AI into society and businesses has not been widely studied. Studies show CEO gender shapes firm behaviors such as earning management, capital allocation efficiency and firm innovativeness [2-4]. However, relevant research on how CEO gender affects the extent of firms' AI adoption is deficient. Artificial Intelligence has great potential and a wide range of applications. By utilizing AI technology, more efficient and innovative solutions in healthcare, transportation, education, and finance can be achieved. Artificial intelligence enables us to better utilize tools such as big data, automation and machine learning to create more value and convenience for society. Second, AI can also help solve some of the major challenges facing the real world. For example, AI can provide sustainable and intelligent solutions to problems such as population aging, climate change, and urbanization. It can provide more accurate predictions and decision support that can help optimize resource use and improve quality of life. In addition, AI has the potential to drive innovation and economic growth. Many countries and businesses are actively investing in and researching AI technologies in the hope of driving economic and social progress through innovation and development. Integrating AI into society can create new business opportunities for enterprises and create more jobs. Research shows that AI adoption is associated with higher revenue growth but only at high levels of adoption [5]. However, the challenges and risks associated with AI applications must also be aware of, such as privacy protection, ethical issues and employment impacts.

Using data from A-share listed companies from 2007 to 2020 and utilizing a panel two-way fixed-effects model, male CEOs were found to mention 0.297 more words about AI in their company's annual reports compared to female CEOs. In this study, the x-axis examined is the gender of the CEO the y-axis is number of AI-related words are mentioned in the company's annual report.

This study contributes to the literature on how CEO gender affects firms' use of AI. This is more conducive to our study of how CEO gender affects corporate strategy as well as economic outcomes.

Second, this study advances the research on the impact of CEO gender on firms' adoption of AI technology from the perspective of firms' adoption of AI technology. This study expands the understanding of the factors influencing firms' adoption of AI.

The rest of the paper is structured as follows: Hypothesis Formulation section that describes the literature and the formulation of hypotheses. The research design and methodology section recounts the empirical strategy, including the empirical model, sample selection, and variables. The benchmarking empirical results section provides benchmarking results and discusses them.

2. Hypothesis development

2.1. Hypothesis development

Based on prior research studies, differences have been observed in the decision-making processes of chief executive officers (CEOs) due to distinct genders, with a particular focus on their inclinations towards venturesome corporate decisions and ethical concerns.

Empirical evidence has shown that companies headed by female chief executive officers (CEOs) exhibit comparatively lower levels of risk when compared to companies managed by male CEOs [6]. This discrepancy in risk-taking behavior can be attributed to various factors, including variations in risk aversion between genders [7-8], incentive structures, unemployment risk, and societal norms concerning gender responsibilities in society [9-12].

In response to existing research, it has been found that female executives generally display a greater inclination towards risk aversion compared to their male counterparts. Consequently, when assuming the position of Chief Executive Officer (CEO), female executives tend to curtail business risk-taking in order to match with their preferences. Research conducted in the fields of experimental economics and psychology has documented the existence of gender-related disparities in individuals' preferences and levels of risk tolerance. Notable surveys conducted by [8] as well as [7] have contributed significantly to the existing literature base. Numerous studies [13-17] have firmly confirmed the prevailing belief that, overall, women exhibit a lesser propensity for risk-taking compared to men.

Furthermore, research investigations have provided evidence suggesting that chief executive officers (CEOs) who exhibit lower levels of overconfidence tend to favor risk reduction subsequent to their CEO role. In regard to this, behavioral study has found that women often exhibit lower levels of overconfidence than males do [18,19]. Male CEOs often display higher degrees of overconfidence than their female colleagues, according to the findings of [20]. Due to the gap in overconfidence levels, female CEOs may be less likely to participate in transactions like acquisitions and loan issuance.

In addition, study also suggests that gender affects decision-making in companies, with a positive association between corporate risk-taking and the likelihood of a CEO experiencing job termination. It has been observed that women have greater difficulties in securing new employment opportunities compared to men, suggesting they may choose to align with organizations with lower levels of risk or mitigate risk within their enterprises. Phelps and Mason [21] have demonstrated in prior research that women who have previously held managerial positions experience a higher average unemployment rate than their male counterparts.

The societal expectations on women's roles and behaviors (as discussed in 9, 10, and 12) can also potentially influence their employment decisions and the distribution of men and women throughout various industries and organizations. Women may favor low-risk enterprises due to the need to manage high-risk firms, which often involve longer working hours and less flexible schedules. This choice may be influenced by their duties related to child-rearing and home tasks. Akerlor and Kranton's study [9] suggests that individuals experience a drop in utility when they deviate from societal expectations, leading to diminished female engagement in the labor field. This model also provides an explanation for occupational segregation based on gender, as supported by Goldin [22], Altonji and Blank [11], and Bertrand et al.'s findings [23].

Moreover, scholarly investigations show ethical diversity between female and male executives, particularly in lucrative company stock transactions [24]. According to Doan et al. [25], it has been observed that female Chief Financial Officers (CFOs) tend to decrease excess cash holding, address conflicts due to managerial discretion, and enhance dividend distribution. This suggests that female

chief executive officers (CEOs) are more likely to consider ethical issues when making organizational decisions and avoid business activities with a higher risk of harm.

AI has been recognized for its effectiveness [26–28] and contribution to various academic domains [29–31], but it also has risks associated with its adoption in recruitment and selection processes. Research by Ore et al. [32] has shown that AI can lead to fear and distrust among recruiters, and potential moral problems can arise due to the lack of transparency in "black box" algorithms [33]. The development and use of AI involve hiding vast amounts of personal and private data, raising concerns about privacy and data protection [34]. Additionally, AI systems may inherit gender and race biases from the human-made datasets used for training. Larson [35] and Koolen and Cranenburgh [36] have shown that AI systems can exhibit biased predictions based on gender and race. For example, certain software used to predict future criminals has exhibited biased predictions against certain races [37].

Finally, accountability issues arise when AI systems fail to perform a particular assigned task, raising challenges in determining responsibility [33].

Considering the risk-averse behaviors and ethical considerations of female CEOs, their decision-making may negatively impact AI adoption in firms. Their decision-making aligns with the potential problems associated with AI, which they may want to avoid. Therefore, the hypothesis is that CEO gender may negatively affect a firm's AI adoption, meaning that male CEOs tend to adopt more AI and vice versa.

3. Research design and methodology

3.1. Variable description

3.1.1. Control variables

The study incorporated several control variables to account for potential factors influencing a firm's adoption of AI technology, including Firm size, Firm leverage, Book-to-market value, Return on equity, TobinQ, Ratio of shares held by the largest shareholder, and word count of the annual report. Firm size (Size) was measured as the natural logarithm of total assets at the end of the period, Firm leverage (Lev) was measured using the current year's asset-liability ratio. Book-to-market value (BM) was measured using the book-to-market value ratio. Return on equity (ROE) was included to measure a company's profitability and efficiency in generating profits. TobinQ is measured by $\frac{Total\ market\ value\ of\ firm}{Total\ asset\ value\ of\ conpany}$, and the Ratio of shares held by the largest shareholder (%) (named Top1) measures the proportion of shares held by the largest shareholder. The word count of the annual report (Word_of_annual_report) was controlled to address the potential confounding effect stemming from the size of the annual report on the measurement of AI adoption.

3.1.2. Model methodology

To test our hypothesis, we establish the following two-way fixed effect model:

$$AI_{it} = \beta 0 + \beta 1 CEOSEX_{it} + \beta 2 ControlVaribles_i + DateFE_t + FirmFE_i + \varepsilon_{it}$$

Where i denotes the firms in our data source, t denotes time, and $\beta 1$ denotes the average increase in the number of mentions of AI in annual reports for male CEOs relative to female CEOs, holding other variables constant. $CEOSEX_{it}$ denotes the gender of CEO, $ControlVaribles_i$ is the set of control variables we added. $DateFE_t$ denotes year fixed effect, and $FirmFE_i$ denotes firm fixed effect, and ε_{it} is the error terms.

4. Data analysis

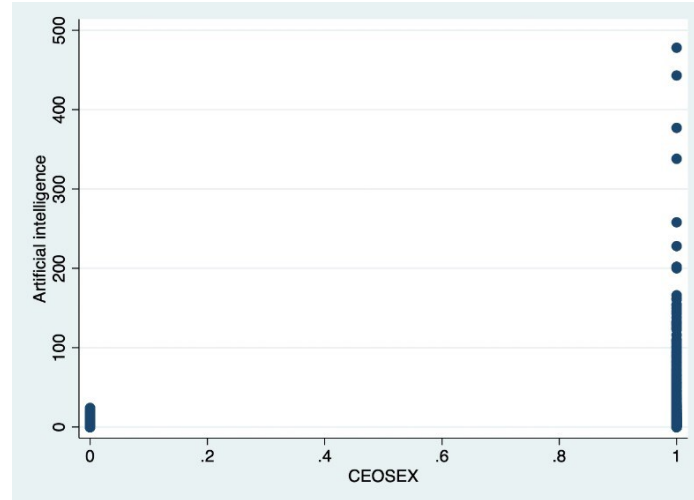### 4.1. Distribution of data

Figure 1: Adoption of AI by CEO of different gender

In Figure 1, the horizontal coordinate and vertical coordinate refer to CEO gender and AI usage correspondingly. 1 represents male, and 0 represents female. Observed from the graph, males exhibit a higher AI utilization than females as the substantial concentration of data points at x=1, all of which possess greater y values. From x=0 to 1, an upward trend can be seen, indicating a greater preference for males to adopt AI.

4.2. Statistical analysis

Table 1: Statistics on AI by year

| Summary	for	variables	AI		
Group	variable	year	(year)		
year	Mean	p50	Min	Max	Growth rate
2006	0	0	0	0	
2007	0.014	0	0	4	
2008	0.0445	0	0	18	217.86%
2009	0.0597	0	0	11	34.16%
2010	0.0954	0	0	72	59.80%
2011	0.0934	0	0	64	-2.10%
2012	0.101	0	0	69	8.14%
2013	0.108	0	0	53	6.93%
2014	0.147	0	0	36	36.11%
2015	0.3	0	0	66	104.08%
2016	0.772	0	0	125	157.33%
2017	1.837	0	0	338	137.95%
2018	2.322	0	0	377	26.40%
2019	2.548	0	0	478	9.73%
2020	2.528	0	0	443	-0.78%
Total	1.044	0	0	478	
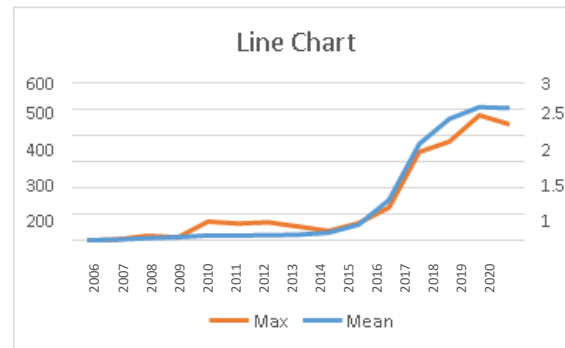
Figure 2: Maximum and average values of AI statistics by year

Panel data of Chinese a-share non-financial listed companies from 2000-2021 was analyzed, and charts were obtained by statistical analysis of the two-term fixed effects model of the data. The charts are about the change in the number of times the term artificial intelligence is mentioned in company annual reports from 2006 to 2020. Table 1 is a chart of statistics on AI by year, and Figure 2 is a line graph of maximum and average values of AI statistics by year. The charts show that AI applications in enterprises have recently developed from weak to strong. This is Evident from the change in the frequency of AI mentioned. In 2006, only a few companies mentioned the term AI in their annual report. In 2007, the term was mentioned for the first time. In 2019, the term AI appeared with an average of 2.548 times in a single company's annual report, whose maximum number was 478 occurrences. The data was the highest number of occurrences from 2006 to 2020. The growth in the extent of AI use is not linear but bimodal. The two peaks were in 2008, with a growth rate of 217.86%, and 2016 with a growth rate of 157.33%. From 2006 to 2020, there were only two negative growth rates, -2.10% in 2011 and -0.78% in 2020. Though there was slight drop, AI has shown an overall upward trend in the number of times mentioned in the company's annual reports from 2006 to 2020.

4.3. Descriptive statistical analysis

Table 2 is a chart of descriptive statistics where 1 is male and 0 is female. The charts are obtained by statistical analysis of the two-term fixed effects model of the panel data. The overall average of the gender of the CEOs in the observable sample of 36,094 is 0.937, which indicates that most of companies have male CEOs and only a small percentage of companies have female CEOs. The average number of times the term artificial intelligence appears in all annual reports is 1.086, with a maximum of 478 occurrences in a single company's annual report, and a standard deviation of 7.491. It can be inferred that a significant difference exists in the degree of AI usage in individual companies and uneven development. Out of the total 33,057 samples involved, the smallest company is 19.406 and the largest is 26.398. In addition, the ROE of each sample company differs but with an average value of 0.068. One of the companies with the highest ROE is 0.446, but the lowest is with a negative value of -1.072, causing a large gap. ROE is one of the leading indicators of the company's operating condition, and such gap signifies the difference in each company's operating condition. To be mentioned, both companies that are doing well and those are struggling are included in the sample.

Table 2: Descriptive statistics

VarName	Obs	Mean	SD	Min	Median	Max
AI	36094	1.049	7.491	0.000	0.000	478.000
CEOSEX	36094	0.936	0.244	0.000	1.000	1.000
Size	33057	22.062	1.291	19.406	21.879	26.398

Table 2: (continued).

Lev	33057	0.429	0.208	0.027	0.423	0.925
BM	33057	0.987	1.111	0.051	0.631	10.142
ROE	33019	0.068	0.134	-1.072	0.076	0.446
TobinQ	32452	2.044	1.390	0.802	1.619	17.729
Top1	33057	0.349	0.149	0.083	0.329	0.758
word_of_annual_report	35865	53779.355	16750.150	2822.000	51450.000	174818.000

4.4. Correlation analysis

Table 3: Correlation coefficient

	AI	CEOSEX	Size	Lev	BM	ROE	TobinQ	Top1
AI	1.000							
CEOSEX	0.013**	1.000						
Size	0.016***	0.038***	1.000					
Lev	-0.036***	0.024***	0.483***	1.000				
BM	-0.035***	0.032***	0.633***	0.539***	1.000			
ROE	-0.017***	-0.014**	0.086***	-0.194***	-0.119***	1.000		
TobinQ	0.024***	-0.021***	-0.371***	-0.227***	-0.412***	0.044***	1.000	
Top1	-0.074***	-0.002	0.194***	0.049***	0.094***	0.147***	-0.125***	1.000

$^*\ p < 0.1,\ ^{**}\ p < 0.05,\ ^{***}\ p < 0.01$

In Table 3, we can see a positive relationship between CEO gender and AI adoption in a company.

4.5. Base regression analysis

Table 4: Base regression

	(1)	(2)	(3)	(4)
VARIABLES	AI	AI	AI	AI
CEOSEX	0.398***	0.387***	0.300*	0.297*
	(3.386)	(3.023)	(1.945)	(1.901)
Size		0.644***	1.008***	0.729**
		(5.353)	(3.591)	(2.503)
Lev		-2.231***	1.644**	1.695**
		(-4.713)	(2.016)	(2.045)
BM		-0.452***	-0.662***	-0.640***
		(-5.530)	(-6.327)	(-6.277)
ROA		-4.555***	-3.131***	-2.739**
		(-4.522)	(-2.636)	(-2.267)
TobinQ		0.100*	-0.018	-0.031
		(1.807)	(-0.488)	(-0.808)
Top1		-4.143***	-2.849**	-2.898**
		(-5.296)	(-2.174)	(-2.188)
word_of_annual_report				0.000***

Table 4: (continued).

				(4.591)
Constant	0.676***	-10.650***	-20.311***	-16.790***
	(8.661)	(-4.516)	(-3.231)	(-2.610)
Observations	36,094	32,451	32,451	32,249
Adjusted R-squared	0.000	0.013	0.385	0.386
YEAR FE	NO	NO	YES	YES
Firm FE	NO	NO	YES	YES

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

In Table 4, the primary function of the first column of this chart is to show the positive correlation between gender of the CEO and the use of AI, as neither control variables nor fixed effects were imposed. The second column controls other variables in the chart, contributing to increased data accuracy. The third column adds firm and year fixed effects to the control variables. The number of words in the company's annual report is controlled in column four to mitigate the influence of the ratio between total number of words and the number of words associated with AI on the overall accuracy. The last column in the chart reveals that companies, on average, mention 0.297 AI-related words. The asterisk in the upper right corner indicates the statistical significance of this variable on AI applications. This finding serves to underscore the meaningfulness and relevance of our study.

5. Conclusions

Given the escalating attention given to AI technology in recent years and the significant role of gender in contemporary society, it becomes imperative to investigate the influence of CEO gender on a firm's adoption rate of AI. Gender equality and diversity have assumed increasing importance within organizations, with a growing recognition of diverse perspective's value to decision-making processes. Moreover, as the AI industry continues to command attention and reshape various sectors, comprehending the relationship between CEO gender and AI adoption offers insights into potential gender disparities in technology adoption and illuminates the role of CEOs in shaping organizational strategies. Consequently, it is crucial to explore the association between CEO gender and a firm's adoption of AI technology. To examine the impact of CEO gender on AI adoption, this paper manually gathers CEO gender information and constructs an index of a firm's AI adoption based on textual analysis of annual reports. Guided by theories on gender preferences and the characteristics of AI technology, this study formulates theoretical hypotheses regarding the relationship between CEO gender and AI adoption. Empirically, a two-way fixed-effect regression model is employed to estimate the effect of CEO gender on AI adoption using panel data from Chinese A-share non-financial listed firms spanning from 2000 to 2021. The empirical results reveal that: (1) Male CEO is positively correlated to higher adoption of AI technology. (2) Robustness checks consistently support our benchmark findings, including altering the sample and introducing control variables such as firm size, return on equity, total number of words in the annual report, and market-to-book ratio. (3) AI application among companies has progressed from limited to extensive adoption in recent years. Building upon previously mentioned research endeavors and outcomes, this paper not only unveils the impact of CEO gender on firms' AI utilization but also contributes to a broader understanding of the intricate interplay between gender, leadership, and the adoption of innovative technologies in the dynamic landscape.

Acknowledgement

References

[1] Barton, D. (n.d.). Artificial Intelligence: Implications for china - mckinsey & company. ARTIFICIAL INTELL IGENCE: IMPLICATIONS FOR CHINA. https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Ch ina/Artificial%20intelligence%20Implications%20for%20China/MGI-Artificial-intelligence-implications-for-Chi na.pdf

[2] Na, K., & Hong, J. (2017). CEO gender and earnings management. Journal of Applied Business Research (JABR), 33(2), 297-308.

[3] Faccio, M., Marchica, M., & Mura, R. (2016). CEO gender, corporate risk-taking, and the efficiency of capital allocation. Journal of Corporate Finance, 39, 193–209.https://doi.org/10.1016/j.jcorpfin.2016.02.008

[4] Expósito, A., Sanchis-Llopis, A., & Sanchis-Llopis, J. A. (2021). CEO gender and SMEs innovativeness: evidence for Spanish businesses. International Entrepreneurship and Management Journal, 1-38.

[5] Yong Suk Lee a, a, b, c, d, AbstractThis paper examines how high-tech venture performance varies with AI-adopti on intensity. We find that firm revenue increases only after sufficient investment in AI, Alekseeva, L., Arora, A., Au gereau, A., Bresnahan, T., Eckhardt, J. T., Greenwood, J., Jovanovic, B., Lee, Y., Acemoglu, D., Aghion, P., Agra wal, A., Aral, S., Atkeson, A., ... Felten, E. W. (2022, July 4). When does AI pay off? AI-adoption intensity, comple mentary investments, and R&D strategy. Technovation. https://www.sciencedirect.com/science/article/abs/pii /S0166497222001377

[6] Khan, W. A., & Vieito, J. P. (2013). CEO gender and firm performance. Journal of Economics and Business, 67, 55-66.

[7] Marianne, B. (2011). New perspectives on gender. In Handbook of labor economics (Vol. 4, pp. 1543-1590). Elsevier.

[8] Croson, R., & Gneezy, U. (2009). Gender differences in preferences. Journal of Economic literature, 47(2), 448-474.

[9] Akerlof, G. A., & Kranton, R. E. (2000). Economics and identity. The quarterly journal of economics, 115(3), 715-753.

[10] Altonji, J. G., & Blank, R. M. (1999). Race and gender in the labor market. Handbook of labor economics, 3, 3143-3259.

[11] Booth, A., & Nolen, P. (2012). Choosing to compete: How different are girls and boys?. Journal of Economic Behavior & Organization, 81(2), 542-555.

[12] Guiso, L., & Paiella, M. (2008). Risk aversion, wealth, and background risk. Journal of the European Economic association, 6(6), 1109-1150.

[13] Hudgens, G. A., & Fatkin, L. T. (1985). Sex differences in risk taking: Repeated sessions on a computer-simulated task. The Journal of Psychology, 119(3), 197-206.

[14] Bruce, A. C., & Johnson, J. E. (1994). Male and female betting behaviour: New perspectives. Journal of Gambling studies, 10(2), 183-198.

[15] Johnson, J. E., & Powell, P. L. (1994). Decision making, risk and gender: Are managers different?. British journal of management, 5(2), 123-138.

[16] Sunden, A. E., & Surette, B. J. (1998). Gender differences in the allocation of assets in retirement savings plans. The American Economic Review, 88(2), 207-211.

[17] Bernasek, A., & Shwiff, S. (2001). Gender, risk, and retirement. Journal of economic issues, 35(2), 345-356.

[18] Lundeberg, M. A., Fox, P. W., & Punćcohaŕ, J. (1994). Highly confident but wrong: Gender differences and similarities in confidence judgments. Journal of educational psychology, 86(1), 114.

[19] Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. The quarterly journal of economics, 116(1), 261-292.

[20] Huang, J., & Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives?. Journal of financial Economics, 108(3), 822-839.

[21] Phelps, S., & Mason, M. (1991). When women lose their jobs. Personnel Journal.

[22] Goldin, C. (1990). Understanding the gender gap: An economic history of American women (No. gold90-1). National Bureau of Economic Research.

[23] Bertrand, M., Goldin, C., & Katz, L. F. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. American economic journal: applied economics, 2(3), 228-255

[24] Sun, F., Dutta, S., Zhu, P., & Ren, W. (2021). Female insiders' ethics and trading profitability. International Review of Financial Analysis, 74, 101710.

[25] Doan, T., & Iskandar-Datta, M. (2020). Are female top executives more risk-averse or more ethical? Evidence from corporate cash holdings policy. Journal of Empirical Finance, 55, 161-176.

[26] Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. Journal of the Academy of Marketing Science, 50(6), 1176-1197.

[27] Li, J., Ma, S., Qu, Y., & Wang, J. (2023). The impact of artificial intelligence on firms' energy and resource efficiency: Empirical evidence from China. Resources Policy, 82, 103507.

[28] Guermazi, A., Tannoury, C., Kompel, A. J., Murakami, A. M., Ducarouge, A., Gillibert, A., ... & Hayashi, D. (2022). Improving radiographic fracture recognition performance and efficiency using artificial intelligence. Radiology, 302(3), 627-636.

[29] Mak, K. K., & Pichika, M. R. (2019). Artificial intelligence in drug development: present status and future prospects. Drug discovery today, 24(3), 773-780.

[30] Baghbani, A., Choudhury, T., Costa, S., & Reiner, J. (2022). Application of artificial intelligence in geotechnical engineering: A state-of-the-art review. Earth-Science Reviews, 228, 103991.

[31] Chadaga, K., Prabhu, S., Sampathila, N., Nireshwalya, S., Katta, S. S., Tan, R. S., & Acharya, U. R. (2023). Application of artificial intelligence techniques for monkeypox: a systematic review. Diagnostics, 13(5), 824.

[32] Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. International Journal of Organizational Analysis, 30(6), 1771-1782.

[33] Timmermans, J., Stahl, B. C., Ikonen, V., & Bozdag, E. (2010, November). The ethics of cloud computing: A conceptual review. In 2010 IEEE second international conference on cloud computing technology and science (pp. 614-620). IEEE.

[34] Wang, W., & Siau, K. (2018). Ethical and moral issues with AI. https://doi.org/10.1080/16081625.2014.1003568

[35] Larson, B. N. (2017). Gender as a variable in natural-language processing: Ethical considerations. Association for Computational Linguistics.

[36] Koolen, C., & van Cranenburgh, A. (2017). These are not the stereotypes you are looking for: Bias and fairness in authorial gender attribution. In Proceedings of the First Ethics in NLP workshop (pp. 12-22). Association for Computational Linguistics (ACL).

[37] Bossmann, J. (2016, October). Top 9 ethical issues in artificial intelligence. In World Economic Forum (Vol. 21).