Proceedings of ICFTBA 2026 Symposium: Driving Organizational Strategic Change for Financial Gains
DOI: 10.54254/2754-1169/2026.BH37088

The Moderating Role of Workforce Education in the AI Exposure-Tobin's Q Relationship of Listed Firms

Haoran Xu

Department of Accounting and Banking, Hong Kong Chu Hai College, Hong Kong, China
232201204@student.chuhai.edu.hk

Abstract. The rapid diffusion of artificial intelligence (AI) is reshaping how firms create value. Although a growing literature examines the economic consequences of AI, relatively little attention has been paid to how human capital conditions the relationship between AI exposure and firm value. Based on the pro-worker AI framework advanced by Acemoglu, Autor, and Johnson, this study aims to examine whether employee education conditions the relationship between AI exposure and firm value among Chinese listed firms. By using 5,140 firm-year observations from the CSMAR database, it measures Tobin's Q and constructs firm-level measures of AI exposure and employee education. To test these relationships, a cross-sectional OLS model with interaction terms is employed to examine whether employee education and firm size moderate the association between AI exposure and firm value. The results show a positive association between AI exposure and Tobin's Q. The interaction between EDU and AI exposure is positive and significant, indicating that the association between AI exposure and firm value is stronger among firms with higher levels of employee education. In contrast, the interaction between AI exposure and asset size is not statistically significant, suggesting that firm size does not significantly alter the AI-value association in this sample. These findings indicate that workforce characteristics should be considered when evaluating the market implications of AI exposure.

Keywords: AI Exposure, Education Level, Tobin's Q, Interaction Effect, Firm Value

1. Introduction

With artificial intelligence (AI) reshaping economies, AI exposure, defined as the extent to which a firm's tasks could be automated or augmented, has become an important metric for evaluating firms' technological positioning [1]. However, AI exposure alone does not necessarily translate into higher firm value, as it may generate both productivity gains and adjustment costs. Human capital, especially employee education, may influence how effectively firms integrate new technologies, and Acemoglu, Autor, and Johnson argue that the economic effects of technology depend on whether it complements or substitutes for human capabilities [2]. This logic suggests that education may moderate the AI exposure-firm value link, yet systematic empirical tests of this interaction remain scarce. Existing studies have primarily examined AI and human capital as separate factors, while the way workforce capabilities shape the relationship between AI exposure and firm value remains less understood, particularly in China's rapidly evolving AI landscape [3]. This study addresses that gap

DOI: 10.54254/2754-1169/2026.BH37088

by examining whether education level positively moderates the effect of AI exposure on Tobin's Q among Chinese listed firms, and whether asset size further moderates this interaction. Employing a mean-centered interaction model on a large CSMAR sample, this study reduces non-essential multicollinearity between interaction terms and their constituent variables. It highlights the relevance of considering workforce characteristics when examining the relationship between AI exposure and firm valuation. By providing firm-level evidence from Chinese listed firms, this study extends understanding of how human capital is associated with heterogeneity in the AI-value relationship.

2. Literature review and hypotheses

2.1. The relationship between AI exposure and firm value

Firm value is measured using Tobin's Q, a widely used market-based valuation indicator that captures investors' expectations of growth opportunities, intangible assets, and competitive advantages [4, 5]. Specifically, a value above one suggests that the market values the firm above the replacement cost of its assets, reflecting expectations of future performance and growth opportunities.

Against this background, AI exposure, as defined by Felten, Raj, and Seamans, measures the extent to which a firm's occupational tasks are related to current AI capabilities [1]. At the firm level, this measure reflects the proportion of employees engaged in occupations with higher potential AI applicability. The effect of AI exposure on firm value may arise through two competing channels. On the one hand, greater AI exposure may be associated with efficiency improvements, cost reductions, and opportunities for AI-enabled innovation, which could enhance market expectations [3, 6]. On the other hand, higher AI exposure may also be associated with concerns regarding labor substitution, adjustment costs, and organizational disruption arising from workforce restructuring, potentially reducing firm valuation [7]. Thus, because the relative importance of these competing forces may differ across firms and institutional contexts, the overall association between AI exposure and market value remains theoretically ambiguous. Thus, the following non-directional hypothesis is proposed:

Hypothesis 1 (H1): AI exposure is associated with Tobin's Q, but the direction of the association is theoretically ambiguous.

2.2. The function of human capital in realizing the value of AI

A large body of human capital theory demonstrates that employee education enhances productivity, absorptive capacity, and innovative potential [8]. In China, firms with a higher share of bachelor's-degree holders exhibit stronger productivity and market valuation, and better-educated workforces are generally more capable of implementing digital technologies [9, 10]. Nevertheless, education may alter the association between AI exposure and firm value.This effect operates through both positive and negative pathways by influencing how effectively a firm converts AI exposure into market value.

From the perspective of organizational complementarity theory, new technologies generate value when accompanied by adjustments in worker capabilities and organizational practices [11]. In the AI context, highly educated employees may contribute to workflow redesign, interpretation of AI-generated insights, and the development of new tasks through which technology can create rather

DOI: 10.54254/2754-1169/2026.BH37088

than displace labor demand [7]. Similarly, a pro-worker AI perspective emphasizes that directing AI toward augmentation requires complementary investments in worker skills [2].

However, several countervailing mechanisms may weaken this relationship. In particular, highly educated workers typically command wage premiums, and if AI adoption does not generate sufficient productivity improvements, the combination of high AI exposure and a high-cost workforce may compress margins and reduce valuation. Moreover, skilled employees may resist AI-driven process redesign when such changes threaten the value of existing expertise, creating organizational frictions and implementation delays. Also, advanced but misaligned educational backgrounds may reduce workforce redeployment flexibility, turning AI exposure into a source of skill mismatch rather than complementarity. Given the coexistence of these competing forces, education may either strengthen or weaken the association between AI exposure and firm valuation. Therefore, the following non-directional moderation hypothesis is proposed:

Hypothesis 2 (H2): Employee education level moderates the association between AI exposure and Tobin's Q.

2.3. The moderating role of firm size in the AI-value relationship

The AI-value association may differ across firms with different organizational characteristics. Firm size is particularly relevant because it reflects differences in resources, technological capabilities, and organizational flexibility.

Among these organizational conditions, asset size captures both potential resource advantages and organizational constraints. Larger firms have greater financial and technological resources to invest in AI infrastructure, data systems, and employee training, while spreading adoption costs over a broader revenue base [12]. However, large organizations may also face structural inertia, bureaucratic decision processes, and organizational rigidity that slow technological adaptation [4]. In addition, many AI applications, particularly cloud-based services, require relatively limited incremental capital investment, which may reduce the advantage associated with firm scale and allow smaller firms to remain competitive in AI adoption [13]. Thus, the association between AI exposure and firm value may differ depending on firm size.

Beyond firm-level characteristics, geographic location represents another important contextual factor in the Chinese setting. Firms located in major economic centers typically benefit from greater access to talent, knowledge spillovers, and institutional support, which may influence their ability to adopt and utilize emerging technologies [14]. However, these advantages may be accompanied by higher labor costs and greater resource competition. Therefore, city location is included as a control variable rather than a hypothesized moderator. Given these opposing effects of firm size, the following non-directional hypothesis is proposed:

Hypothesis 3 (H3): Firm size moderates the association between AI exposure and Tobin's Q.

3. Methodology

3.1. Sample selection and data collection

The data for this study are drawn from the China Stock Market & Accounting Research (CSMAR) database, a widely used database for research on Chinese listed firms. The initial sample consists of all A-share firms listed on the Shanghai and Shenzhen stock exchanges. To ensure comparability and data quality, this study excludes financial firms (CSRC industry code J), ST and *ST firms, and observations with missing values for key variables. Among these exclusions, financial firms are

DOI: 10.54254/2754-1169/2026.BH37088

excluded due to their substantially different asset structures, liability characteristics, and valuation mechanisms from those of non-financial firms. Moreover, ST and *ST firms are removed because financial distress and delisting risks may lead to abnormal Tobin's Q values and affect the results. Following these exclusions, the final sample contains 5,140 firm-year observations.

3.2. Variable definitions and measurements

The dependent variable is Tobin's Q, obtained from the CSMAR field "Tobin's Q value A." It is calculated as the market value of equity plus the book value of liabilities divided by total assets and is used as a market-based measure of firm valuation.

The first key explanatory variable is firm-level AI exposure, obtained from CSMAR. This measure maps occupational-level AI exposure scores to Chinese occupational classifications and aggregates them to the firm level using employee occupational distributions as weights [1]. Accordingly, higher values indicate greater exposure to occupations with higher potential AI applicability.

The second key explanatory variable is employee education level. Based on CSMAR's workforce education data, educational attainment is classified into seven ordered categories: 1 for secondary school or below, 2 for associate degree, 3 for bachelor's degree, 4 for master's degree, 5 for doctoral degree, 6 for other qualifications, and 7 for MBA/EMBA. These categories are treated as ordered levels following the CSMAR classification. The median education category within each firm is used as the firm-level education measure.

In addition to the main variables, the model includes total assets and city location as control variables. Total assets are measured in RMB using year-end balance sheet data and capture firm scale. City location is a dummy variable equal to one if a firm is located in one of China's top ten GDP cities (Beijing, Shanghai, Shenzhen, Guangzhou, Chongqing, Suzhou, Chengdu, Hangzhou, Wuhan, and Nanjing), and zero otherwise.

3.3. Model specification and estimation methods

To examine the heterogeneous effects of education level and firm size on the relationship between AI exposure and Tobin's Q, a multiple linear regression model with interaction terms is specified and estimated using ordinary least squares (OLS). The empirical model is specified as follows:

$$\begin{gathered} Q_{avg} = \beta_0 + \beta_1 TopCity + \beta_2 EDU + \beta_3 AI + \beta_4 Assets \\ + \beta_5 (EDU \times AI) + \beta_6 (AI \times Assets) + \varepsilon \end{gathered} \tag{1}$$

where β_2 captures the association between education level and Tobin's Q when AI exposure and total assets are held at their sample means, while β_3 captures the association between AI exposure and firm value, corresponding to the baseline AI–value relationship in H1. The interaction coefficient β_5 is the main parameter of interest for H2, indicating whether the relationship between AI exposure and Tobin's Q differs across firms with varying education levels. Similarly, β_6 tests whether firm size moderates the AI-value relationship, as hypothesized in H3. The city location dummy, TopCity, is included as a control variable to account for differences in regional economic conditions and institutional environments. All non-dummy variables (EDU, AI exposure, and asset size) are mean-centered before constructing the interaction terms. Thus, this transformation mitigates non-essential multicollinearity between the main effects and interaction terms and enables

DOI: 10.54254/2754-1169/2026.BH37088

the coefficients of the level variables to be interpreted at the sample mean of the corresponding interacting variables.

It is important to clarify that this model is designed to identify conditional associations rather than causal mechanisms. Given the cross-sectional OLS design, the results may be subject to omitted variables and reverse causality. For example, firms with higher market valuations may be better positioned to attract educated employees and invest in AI-related activities. Therefore, the interaction coefficients reflect heterogeneous AI-value associations rather than causal effects. In addition, all models report heteroskedasticity-robust standard errors to account for potential unequal variance in the cross-sectional data.

3.4. Robustness checks and result validation

To assess the robustness of the main associations, several robustness checks are conducted using alternative measures and sample specifications. Given the right-skewed distribution of total assets, we replace the mean-centered raw measure with the natural logarithm of total assets and examine whether the results remain consistent. Moreover, because Tobin's Q contains extreme observations, the baseline results based on winsorized values at the 1st and 99th percentiles are compared with those using the original unadjusted values. The robustness of the findings is further examined using an alternative measure of employee education, namely the proportion of employees with a bachelor's degree or above instead of the median education category. Besides, variance inflation factors (VIFs) are calculated to assess potential multicollinearity among regressors. These robustness checks are designed to evaluate whether the observed associations between AI exposure, education level, firm size, and market valuation remain stable across alternative specifications and measurement choices. They are interpreted as tests of result stability rather than evidence establishing causal mechanisms.

4. Results and analysis

4.1. The association between AI exposure and firm value

The sample consists of 5,140 firm-year observations. The mean value of Tobin's Q is 2.10 (SD = 1.49), while the mean AI exposure score is 0.49 (SD = 0.16), suggesting substantial variation in firms' exposure to AI-related tasks. Approximately 38 percent of firms are located in the top-10 GDP cities.

To examine the baseline association between AI exposure and firm valuation (H1), the OLS regression results are reported in Table 1. The coefficient on AI exposure is positive and statistically significant ($\beta = 0.0146$, $p < 0.01$), suggesting that firms with higher AI exposure tend to exhibit higher Tobin's Q after controlling for education level, firm size, and city location. This interpretation is consistent with prior research emphasizing the potential productivity and innovation implications of AI adoption [15, 16]. Given the cross-sectional research design, the result should be interpreted as an association rather than evidence of a causal effect.

Table 1. Baseline regression results: AI exposure and firm value

Variable	Coefficient	Robust Std. Error	t-value	p-value
Intercept	-0.0569***	0.022	-2.615	0.009
TopCity	0.1207***	0.036	3.391	0.001
EDU	0.1303***	0.039	3.359	0.001

DOI: 10.54254/2754-1169/2026.BH37088

Table 1. (continued)

AI Exposure	0.0146***	0.001	10.770	<0.001
Asset Size	-7.49×10^{-14}***	2.52×10^{-14}	-2.975	0.003
EDU × AI Exposure	0.0111***	0.003	3.714	<0.001
AI Exposure × Asset Size	-3.10×10^{-15}	2.26×10^{-15}	-1.372	0.170

Note: This table reports the baseline OLS regression results based on 5,140 firm-year observations, with an R^2 of 0.033. Heteroskedasticity-robust standard errors are reported. EDU, AI Exposure, and Asset Size are mean-centered before constructing the interaction terms. Statistical significance is indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

The magnitude of the association is relatively modest. A one-standard-deviation increase in AI exposure corresponds to an increase of approximately 0.002 in Tobin's Q. In addition, the model explains only a limited proportion of the variation in firm valuation ($R^2 = 0.033$), suggesting that AI exposure represents only one of many factors associated with market valuation.

4.2. Education heterogeneity in the AI-value relationship

The interaction between education level and AI exposure is examined to test H2. The coefficient of EDU × AI Exposure is positive and statistically significant ($\beta = 0.011$, $p < 0.01$), indicating that the association between AI exposure and Tobin's Q differs across firms with different levels of employee education. This result is consistent with the hypothesis that education conditions the relationship between AI exposure and firm valuation.

Further analysis of the interaction pattern shows that the association between AI exposure and Tobin's Q becomes more positive as education level increases. Firms with higher employee education levels exhibit a stronger positive association between AI exposure and market valuation, while firms with lower education levels show a weaker relationship. This pattern suggests that the relationship between AI exposure and firm value is heterogeneous across firms with different educational profiles.

This finding is broadly consistent with theoretical perspectives emphasizing the complementary role of human capital in technology adoption and organizational adaptation [17]. Firms with more educated workforces may possess greater capacity to interpret, integrate, and respond to emerging technologies. However, such mechanisms cannot be directly identified in the current cross-sectional setting. Therefore, the results should be interpreted as evidence of education-related heterogeneity in the AI-value relationship rather than causal evidence that education enhances the value associated with AI exposure.

4.3. The role of firm size in the AI-value relationship

To examine whether firm size moderates the AI–value relationship (H3), the interaction between AI exposure and asset size is included in the regression model. The coefficient of AI Exposure × Asset Size is negative but statistically insignificant ($\beta = -3.10 \times 10^{-15}$, $p = 0.170$), indicating that the association between AI exposure and Tobin's Q does not significantly vary with asset scale. Thus, the results provide no evidence that firm size serves as a significant moderator of the AI–value relationship in this sample.

Though larger firms generally have greater financial and organizational resources, the accessibility of AI technologies through scalable digital platforms may reduce the extent to which

DOI: 10.54254/2754-1169/2026.BH37088

firm size determines AI-related value creation. However, this interpretation remains tentative and cannot be directly tested using the current cross-sectional design. Additionally, geographic location is included as a control variable to capture regional differences in economic conditions, talent availability, and institutional environments. The coefficient on TopCity is positive and significant ($\beta = 0.1207$, $p < 0.01$), suggesting that firms located in major economic centers exhibit higher Tobin's Q. However, the underlying mechanisms driving this association are beyond the scope of the current analysis.

Furthermore, additional analyses were conducted to examine whether the main interaction pattern depends on specific model specifications. Specifically, replacing asset size with its logarithmic form, excluding extreme Tobin's Q observations, adopting alternative education measures, and including two-digit industry fixed effects produce similar interaction patterns. These results suggest that the positive association between education and the AI exposure-firm value relationship is not driven by a single measurement choice or model specification.

The findings should be interpreted with caution. The model explains a limited proportion of the variation in Tobin's Q ($R^2= 0.033$), and the cross-sectional OLS framework identifies conditional associations rather than causal relationships. These associations may reflect omitted factors, selection effects, or reverse causality. Future research using longitudinal data and stronger identification strategies can further examine the mechanisms underlying the AI-value relationship.

5. Conclusion

This study examines whether employee education level conditions the association between AI exposure and market valuation among Chinese A-share listed firms. Using a cross-sectional sample of 5,140 firm-year observations, the results show that AI exposure is positively associated with Tobin's Q, and that this association varies with employee education level. Specifically, the positive interaction between AI exposure and education suggests that firms with higher education levels exhibit a stronger AI–value association, whereas this relationship is weaker among firms with lower education levels. In contrast, firm size does not significantly alter the relationship between AI exposure and firm valuation. These findings should be interpreted with caution, as the cross-sectional OLS design identifies conditional associations rather than causal relationships, and the results may also reflect omitted factors, selection effects, or reverse causality. Moreover, the firm-level measures of education and AI exposure may not fully capture differences in workforce capabilities and task characteristics. Future research using panel data, stronger identification strategies, and more detailed organizational measures could further explore the conditions under which AI exposure is associated with higher firm valuation.

References

[1] Felten, E. W., Raj, M., & Seamans, R. (2023). How will language modelers like ChatGPT affect occupations and industries? *SSRN Electronic Journal*.
[2] Acemoglu, D., Autor, D., & Johnson, S. (2026). Building pro-worker artificial intelligence. NBER Working Paper No. 34854.
[3] Brynjolfsson, E., Li, D., & Raymond, L. R. (2025). Generative AI at work. *Quarterly Journal of Economics, 140*(2), 889-942.
[4] Chen, M. J., & Hambrick, D. C. (2017). Speed, stealth, and selective attack: How small firms differ from large firms in competitive behavior. *Academy of Management Journal, 38*(2), 453-482.
[5] Liu, Y., Dong, J. Y., & Wei, J. (2020). Digital innovation management: Theoretical framework and future research. *Management World, 36*(7), 198-217.

DOI: 10.54254/2754-1169/2026.BH37088

[6] Hampole, M., Papanikolaou, D., Schmidt, L. D., & Seegmiller, B. (2025). Artificial intelligence and the labor market. NBER Working Paper No. 33509.
[7] Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488-1542.
[8] Black, S. E., & Lynch, L. M. (1996). Human-capital investments and productivity. *American Economic Review, 86*(2), 263-267.
[9] Zhu, Y. W., & Xu, K. N. (2006). An empirical study on R&D efficiency of China's high-tech industries. *China Industrial Economy*, (11), 38-45.
[10] Chen, J., Huang, S., & Liu, Y. H. (2020). From empowerment to enablement: Enterprise operations management in the digital environment. *Management World, 36*(2), 117-128.
[11] Milgrom, P., & Roberts, J. (1990). The economics of modern manufacturing: Technology, strategy, and organization. *American Economic Review, 80*(3), 511-528.
[12] Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy, 15*(6), 285-305.
[13] Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
[14] Lu, M., & Xiang, K. H. (2014). Resolving the conflict between efficiency and balance: On China's regional development strategy. *Comparative Economic & Social Systems*, (4), 1-16.
[15] Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3-30.
[16] Acemoglu, D., & Johnson, S. (2023). *Power and progress: Our thousand-year struggle over technology and prosperity*. PublicAffairs.
[17] Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128-152.