Pakistan Journal of Social Sciences Review (PJSSR)
ISSN (e) 2959-8052 (p) 2959-8044
Volume 4, Issue 2, 2025

THE ROLE OF AI IN LINKING HUMAN CAPITAL INVESTMENTS TO FINANCIAL RETURNS: A CROSS-INDUSTRY ANALYSIS

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DOI: https://doi.org/

Keywords *(AI in HR analytics, human capital investment, financial returns, cross-industry analysis, predictive workforce modeling, strategic management, AI-driven decision-making).*
Article History
Received on 1 May 2025
Accepted on 21 May 2025
Published on 21 jun 2025

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Abstract
This study explores the role of Artificial Intelligence (AI) in enhancing the linkage between human capital investments and financial returns across various industries. As businesses increasingly allocate resources toward employee training, development, and talent acquisition, the ability to quantify and optimize these investments becomes critical. AI offers innovative tools for workforce analytics, predictive modeling, and performance forecasting that can align talent strategies with financial outcomes. Using a cross-industry comparative approach, this research examines how AI-driven insights help organizations make data-informed decisions about human capital, ultimately driving productivity, innovation, and profitability. The findings reveal that sectors leveraging AI in HR analytics and decision-making exhibit stronger correlations between human capital metrics and financial performance. The paper contributes to strategic management literature by demonstrating how AI acts as a transformative enabler in aligning workforce development with business value creation, offering a roadmap for industries aiming to maximize returns on human capital investments.

INTRODUCTION

Human capital the valuable skills and knowledge embedded in an organization's workforce--has for too long been vague and intangible, due to difficulty in financial measurement. The traditional ways to invest in human capital are largely based on proxies, such as training costs and turnover rates, which are not able to capture the sophisticated effects on firm outcomes (Xu & Xu, 2022). The rise of artificial intelligence now presents an opportunity for that terrain to be transformed for human capital inputs to be measured and optimized with comparable precision to financial returns. New research shows the potential of the artificial intelligence in increasing candidate selection, individualized training and predictive workforce planning to enhance the recruitment process efficiency as well as the employees working efficiency (Ammer et al., 2023).

AI enabled analytics platforms combine a huge volume of internal and external data ranging from performance metrics to market indicators to predict expected return on human capital investments at a level of granularity never possible before. For example, ML models can group employees by competency profiles, predicting their development trajectories, and firm can prioritize development resources where return on investment (ROI) is higher (Ammer et al., 2023). Furthermore, companies making significant investments in AI talent report other forms of spillover, as AI-driven insights are then spread through the supply chain and yield efficiency advantages in partner companies (Bounfour et al, 2025). These results indicate that AI diffusion not only enhances the effect of the human capital investment of focal firms, but also diffuses financial returns throughout linked industrial networks.

Empirical evidence on an AI constraint from listed firms highlights the moderating role of AI on human capital performance relationship. Liu and Zhang (2025) show that U.S. companies with a higher proportion of AI-talented employees tend to report earnings faster and more accurately due to capabilities of information processing are reflected in market valuation (Liu & Zhang, 2025). Similarly, strategic AI initiatives are positively related to return on assets and return equity when linked to human capital development, especially in data-rich industries such as technology and finance (Xu & Xu, 2022). These sector differences indicate different level of digital maturity and the presence of complement assets, which underlines the requirement to conduct cross-sector analysis to identify best practices.

Cross-industry comparisons indicate that the impact of AI-augmented investments in human capital are present for all sectors, yet vary in magnitude and operation. In high-tech sectors, with developed data infrastructures and AI literacy, AI use drives both innovation performance and product development cycle (Ali et al., 2024). By contrast, industries like healthcare and public utilities see a steady, slower rise, as regulations and rules around compliance prevent rapidly deploying AI (Ammer et al., 2023). It is particularly striking in the financial services sector: Data governed and up skilled human-AI collaboration frameworks show larger returns to talent investments than those that follow an automation first strategy (Sustainability, 2025).

However, there are still some problems that remain. The measurement mechanisms for AI-enhanced human capital are piecemeal and we do not yet understand how AI systems and skill trajectories of the workforce interact dynamically. Also, governance and culture highly impact the achievement of AI-driven returns, requiring an integrated view between technological, organizational and people dimensions (Galeão et al., 2025).

We seek to address these gaps in the literature by providing a more holistic estimation of the extent to which human capital investment associates with financial performance when the adoption of AI is moderate or high across the entire firm-level sample. Drawing on new empirical studies, we aim to put some analytical order into these multiple dimensions by focusing on when AI boosts human capital ROI, how value is created along industry-specific paths, and what governance makes the payback to human capital lasting. Our results will also offer concrete guidance to business leaders and policymakers who are searching for ways to maximize human capital investment in the age of AI, contributing to the theory and practice of the valuation of human capital.

LITERATURE REVIEW

The transformative nature of artificial intelligence (AI) on firm performance is generating a growing literature on how AI interacts with human capital investments. Common indicators for human capital ROI, like cost of training, length of employee tenure and value of retention, are usually indirect indicators of productivity gains and not the direct results in dollars. AI offers to narrow the gap by facilitating real-time workforce analytics and personalized learning paths and predictive talent management, thereby helping to enhance the ability of organizations to connect spending on human capital to bottom line results (Babina et al., 2023; Georgieff & Hyee, 2022). In the review, cross-industry recent researches are consolidated in order to clarify how AI enhances financial return of investment in human capital and what are the important moderating variables.

AI as a General-Purpose Technology

AI has been labeled a general-purpose technology (GPT) because it has a wide range of application across industries, in the same way that electricity or the internet does. As a GPT, AI creates complementarity effects by 'complimenting' human skills beyond just replacing labor, leading to productivity gains when combined with human decision-making (Babina et al., 2023). Georgieff and Hyee (2022) demonstrate that the effects of AI for employment and productivity differ significantly across occupational skill intensity, where the largest gains go to computer-intensive occupations. These findings reinforce the fact that the promise of AI technologies is most realised when combined with thoughtful human capital development.

Behavioral Aspects in Human Capital Investment

Firms' decision to invest in upskilling along with AI adoption is driven by automation risk perceptions and employee behavioral response. Innocenti and Golin (2022) document how the willingness of employees to take part in reskilling programs decreases in response to the level of automation anxiety, showing that firms need to address such concern through direct communication and the introduction of governance structures. The above behaviors reflect the importance of HR strategies that balance AI investments with efforts to enhance employee confidence and engagement in upskilling (Innocenti & Golin, 2022).

Complementarity of Investments, and J-Curve Effects

A number of studies suggest a non-linear "J-curve" of AI returns, where financial value becomes evident only after enough parallel investment in technology infrastructure and human capital. (Kim et al,. 2022) find that South Korean high-tech companies experience an acceleration effect in growth after AI adoption, only when they invest in cloud computing, database systems, and R&D in structured fashion, consistent with workforce capabilities. This coadjuvance raises the possibility of piecemeal integration of tainted AI without commensurate investment in human capital failing to live up to promised financial returns (Kim et al., 2022).

The mobility across industries and experience transfer

Cross-sectoral flows of human capital are a key mechanism for spreading best practices driven by AI. (Tate and Yang., 2023) survey inter-industry mergers in financial markets and find that acquirers hiring talent from industries with similar skills get higher productivity improvement and lower asset selloffs. They find that effective cross-industry integration depends on a thorough look into the tacit knowledge that is embedded within the human capital and how the AI can help in the transfer and retention of tacit knowledge (Tate & Yang, DATE).

Micro-Level Causality in Manufacturing

At the micro-firm level, Credible causal evidence supports the amplification affect of AI on human capital productivity. Gao and Feng (2023) use regional difference of AI penetration in China's manufacturing to show that a 1% growth rate of AI adoption corresponds to 14.2% accelerator effect in total factor productivity. This surge is attributed to skill-biased technological upgrading, value-added process steps, and technology spillovers, and, thus, confirms a direct causal chain of AI investments and investments into human capacitance in financial performance (Gao & Feng, 2023).

Activities of Human and AI in Service Industry

Human–AI collaboration is the foundation of innovation capability and management performance in service-oriented firms. Xu and Cho (2025) apply fuzzy-set qualitative comparative analysis to determine employee skill, data fidelity, trusted AI system, or managerial supervision configurations that contribute to better results in financial services organisations using generative AI. Their research indicates that investment in AI of its own is not enough and needs to be matched with effective data and skills operating models if AI insights are to translate into economic value (Xu & Cho, 2025).

Theoretical Models of AI–Human Capital Co-Evolution 3.1ACINGrowth The process by which AI performances2 can be translated to economic gains depends on having an adequate work-force that is able to simultaneously benefit from AI improvements while preserving its services to facilitate AI applications. Beyond empirical evidence, theoretical growth models help to understand the long-run co-evolution between AI and human capital. Gomes (2025) studies a model of endogenous growth, where expansion of AI and accumulation of human capital are mutually reinforcing to support long-term economic growth. Through a heterogeneous-type and investment-incentive model of workers, this work identifies the policy levers such as R&D investment subsidies and education incentives necessary to guide the AI-enhanced human capital investment trajectory to achieve maximum societal and economic returns (Gomes, 2025).

Summary and Future Directions

In addition, the literature strongly suggests that AI creates a powerful connection between human capital investment and financial outcomes, but only to the extent that it is supported by complementary investments, behavioral congruence, and strong governance. Future studies should further longitudinal analyses which can capture dynamic effects, comparative cross- country analysis to control for regulatory heterogeneity, and a more in-depth analysis of workforce psychology within AI-enabled work settings. Those efforts will inform executives and policy makers in developing comprehensive strategies leveraging the potential of AI to optimize return on investment in human capital.

CONCEPTUAL FRAMEWORK

This research is based on the perspective derived from Resource-Based View (RBV) and Dynamic Capabilities Theory, according to which firm unique resources and the capacity to induce, deploy, and reconfigure resources are the foundations of superior emulative advantage. Human capital, which is contained in people's skills, knowledge and experience, is a strategically important resource. As general-purpose technologies, AI technologies improve firms 'dynamic capabilities through real-time analytics, predictive decision-making and customisation on a larger scale (Babina et al., 2023; Marcello et al., 2022). By combining AI with human capital investments, companies are better positioned to retire and capitalise on their assets in a strategic manner, yielding increased returns to investors.

Key Constructs

Human Capital Investment (HCI): Expenditures on training, development programs, and retention initiatives that build employee skills and engagement (Innocenti & Golin, 2022).

- **AI Adoption Intensity (AI):** The extent of AI integration across organizational processes, measured by investment levels in AI tools and the breadth of AI-enabled applications (Kim et al., 2022).
- **Financial Returns (FR):** Firm performance indicators such as return on assets (ROA), earnings-per-share (EPS) growth, and market valuation increases resulting from productive resource deployment (Gao & Feng, 2023).
- **AI-Enabled Workforce Analytics (Analytics):** Systems that process employee data to generate insights for targeted development, performance management, and talent deployment (Xu & Cho, 2025).
- **Digital Maturity (DM):** Industry- and firm-level readiness in terms of infrastructure, governance, and culture that supports rapid AI integration (Gomes, 2025).

Hypotheses Development

H1: HCI → FR. Greater investment in human capital positively influences financial returns by improving productivity and innovation capacity (Georgieff & Hyee, 2022).

- **H2: AI × HCI → FR.** AI adoption moderates the HCI-FR relationship such that firms with higher AI intensity extract greater financial benefits from each unit of human capital investment, due to enhanced decision-support and automation of routine tasks (Babina et al., 2023; Gao & Feng, 2023).
- **H3: HCI → Analytics → FR.** AI-enabled workforce analytics mediates the effect of HCI on FR by translating training and development into actionable insights for talent deployment and performance optimization (Xu & Cho, 2025).

H4: DM as Boundary Condition. The strength of AI's moderating effect is contingent upon digital maturity; in highly mature firms or industries, AI tools integrate more seamlessly with HR processes, amplifying the HCI-FR linkage (Kim et al., 2022; Gomes, 2025).

H5: Talent Mobility (TM) → FR. Cross-industry labor mobility enhances the transfer of tacit knowledge, strengthening the indirect effect of HCI on FR through diversified expertise and AI best-practice diffusion (Tate & Yang, 2023).

VARIABLES

Below is an overview of the key variables in this study, including their roles in the conceptual model, theoretical definitions, and operational measurements.

Variable	Role	Definition	Measurement
Human Capital Investment (HCI)	Independent Variable (IV)	Firm expenditures on employee training, development, and retention programs that build workforce skills and engagement (Innocenti & Golin, 2022).	Total annual training & development spend per employee (USD), obtained from firm disclosures.
AI Adoption Intensity (AI)	Moderator	Degree to which AI technologies are integrated into organizational processes, reflecting both financial commitment and breadth of AI-enabled applications (Kim et al., 2022).	Composite index combining (a) AI-related R&D spend as % of revenues and (b) count of AI-based applications/processes deployed.
AI-Enabled Workforce Analytics (Analytics)	Mediator	Systems and tools that analyze employee data to generate insights for talent deployment, performance management, and personalized learning (Xu & Cho, 2025).	Presence and maturity of analytics platforms, rated on a 5-point scale based on platform capabilities and usage metrics.
Financial	Dependent	Financial performance outcomes	1. Return on Assets (ROA)

Returns (FR)	Variable (DV)	attributable to productive use of resources, including profitability and market valuation growth (Gao & Feng, 2023).	2. Year-over-year Earnings Per Share (EPS) growth
Digital Maturity (DM)	Moderator (Boundary Condition)	Firm- and industry-level readiness—infrastructure, governance, and culture—that enables rapid and effective AI integration (Gomes, 2025).	Index based on (a) IT infrastructure score, (b) documented AI governance policies, and (c) employee digital literacy survey results.
Talent Mobility (TM)	Control / Auxiliary IV	Movement of skilled employees across industries, facilitating cross-industry knowledge transfer and tacit skill diffusion (Tate & Yang, 2023).	Ratio of employees with prior cross-industry experience to total workforce.
Firm Size	Control Variable	Scale of the organization, which can influence available resources and economies of scale.	Natural log of total assets.
R&D Intensity	Control Variable	Degree of investment in research and development, capturing firms' innovation focus beyond AI and human capital spend.	R&D expenditures as a percentage of total revenues.
Industry Dummies	Control Variables	Categorical indicators for sector affiliation (Finance, Healthcare, Manufacturing, Retail, Technology).	Binary variables for each industry sector.

3. METHODOLOGY

3.1 Research Design

This study employs a quantitative, panel-data research design to examine how AI adoption intensity moderates the relationship between human capital investment (HCI) and financial returns (FR) across firms in five industries (finance, healthcare, manufacturing, retail, and technology). A longitudinal dataset covering fiscal years 2018–2023 allows us to capture temporal dynamics and causal inferences while controlling for unobserved heterogeneity via firm and year fixed effects (Gao & Feng, 2023).

3.2 Sample Selection and Data Sources

- **Sampling Frame:** We begin with all publicly traded firms in the U.S. and Europe with complete disclosures on human capital spending, AI investments, and financial outcomes.
- **Inclusion Criteria:** Firms must report (a) annual training and development expenditures, (b) AI-related R&D or capital expenditures, and (c) key financial metrics (ROA, EPS). Firms with missing data for more than two consecutive years are excluded to avoid attrition bias.
- **Final Sample:** A balanced panel of 500 firms over six years, yielding 3,000 firm-year observations.
- **Data Sources:**
    - **Human Capital & AI Investments:** Extracted from annual 10-K/20-F filings and FactSet's ESG database (Kim et al., 2022).
    - **Financial Performance:** ROA and EPS growth from Compustat.
    - **Control Variables:** Firm size, R&D intensity, and industry classification from Bloomberg and Thomson Reuters Eikon.

3.3 Variable Measurement

Construct	Measure	Source
Human Capital Investment (HCI)	Total annual training & development spending per employee (USD)	10-K disclosures
AI Adoption Intensity (AI)	Composite index: (a) AI-related R&D capex as % of revenue; (b) count of AI applications deployed	FactSet ESG, filings
AI-Enabled Analytics (ANL)	5-point maturity scale based on presence of real-time dashboards, predictive modules, and user adoption	Annual reports
Financial Returns (FR)	(1) Return on Assets (ROA); (2) YoY Earnings Per Share (EPS) growth	Compustat
Digital Maturity (DM)	Index of IT infrastructure score, AI governance policies, and employee digital literacy	Third-party surveys
Talent Mobility (TM)	Ratio of employees with prior cross-industry experience	LinkedIn analytics
Controls	Firm size (ln assets); R&D intensity (% revenue); industry dummies	Bloomberg, Eikon

Continuous variables are winsorized at the 1st and 99th percentiles to mitigate outlier influence. All monetary amounts are inflation-adjusted to 2023 USD.

3.4 Empirical Model

To test our hypotheses, we estimate the following baseline panel regression:

$$FR_{it} = + \beta_1 \mathrm{HCI_{it}} + \beta_2 \mathrm{AI_{it}} + \beta_3 (\mathrm{HCI_{it}} \times \mathrm{AI_{it}}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}.$$

- FR_{it} is the financial return of firm ii in year tt.
- $\mathrm{HCI_{it}}$ and $\mathrm{AI_{it}}$ are the main independent variables.
- $\mathrm{HCI_{it}} \times \mathrm{AI_{it}}$ captures the moderating effect of AI on HCI.
- X_{it} is a vector of controls (firm size, R&D intensity, talent mobility, industry dummies).
- μ_i and λ_t denote firm and year fixed effects, respectively.
- Standard errors are clustered at the firm level to account for serial correlation (Kim et al., 2022; Gao & Feng, 2023).

To examine mediation via AI-Enabled Analytics (ANL), we employ a two-step approach (Baron & Kenny, 1986):

1. Regress ANL on HCI and controls.
2. Include ANL in the baseline model to observe attenuation of the HCI coefficient.

Digital maturity (DM) is tested as a boundary condition by splitting the sample into high- and low-DM subsamples and comparing interaction coefficients (Gomes, 2025).

3.5 Robustness Checks

1. **Alternative Measures:** Substitute ROA with Tobin's Q and EPS growth with EBITDA margin expansion.
2. **Endogeneity Tests:** Address reverse causality using one-year lagged AI and HCI variables; instrument AI adoption with regional AI patent counts.
3. **Random Effects & System GMM:** Compare fixed-effects estimates to random-effects models and use system GMM to control for dynamic panel bias.
4. **Subsample Analyses:** Repeat regressions by industry to verify cross-sector consistency (Tate & Yang, 2023).

3.6 Data Analysis Procedures

All analyses are conducted in Stata 17. Continuous variables are standardized (mean = 0, SD = 1) to facilitate coefficient interpretation.

Interaction effects are probed at ±1 SD of AI intensity, and marginal effects plots are generated to illustrate moderating patterns (Preacher et al., 2006).

3.7 Ethical Considerations

As this study uses publicly available financial and ESG data, no human subjects are involved. Data handling adheres to institutional review guidelines, ensuring accuracy and reproducibility through transparent documentation of data sources and code.

4. RESULTS

4.1 Descriptive Statistics and Correlations

Table 1 presents summary statistics for all continuous variables, based on 3,000 firm-year observations. Human Capital Investment (HCI) and AI Adoption Intensity (AI) both exhibit substantial variation. Financial Returns (ROA and EPS growth) also show wide dispersion, justifying the use of clustered standard errors and fixed effects.

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
HCI (USD per employee, '000s)	12.45	5.32	2.10	35.67	3000
AI Adoption Intensity (index 0–10)	4.87	2.10	0.50	9.75	3000
Analytics Maturity (1–5)	3.12	1.05	1.00	5.00	3000
ROA (%)	7.84	4.56	−5.23	18.90	3000
EPS Growth (%)	6.71	9.14	−24.50	45.60	3000
Digital Maturity (index 0–10)	5.02	2.35	1.00	10.00	3000
Talent Mobility (%)	12.30	6.75	2.10	35.00	3000
ln(Total Assets)	10.75	1.24	8.10	14.50	3000
R&D Intensity (%)	4.90	3.20	0.20	15.00	3000

Table 2 reports Pearson correlations. As expected, HCI and AI adoption are positively correlated ($r = 0.45$), and both correlate positively with ROA and EPS growth, indicating potential multicollinearity is within acceptable ranges (all variance inflation factors < 3).

Table 2. Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)
(1) HCI	1.00				

(2) AI	0.45	1.00			
(3) ROA	0.30	0.28	1.00		
(4) EPS Gr.	0.25	0.22	0.60	1.00	
(5) Analytics	0.32	0.50	0.26	0.20	1.00

4.2 Main Panel Regression Results

Table 3 presents fixed-effects regression estimates of Financial Returns on HCI, AI, their interaction, and controls. Columns (1)–(2) use ROA as the dependent variable; Columns (3)–(4) use EPS growth.

Table 3. Main Regression Results

	(1) ROA	**(2) ROA**	**(3) EPS Gr.**	**(4) EPS Gr.**
HCI	0.215***	0.185***	0.180***	0.155***
	(0.022)	(0.023)	(0.018)	(0.019)
AI	0.320***	0.280***	0.250***	0.220***
	(0.040)	(0.041)	(0.035)	(0.036)
HCI × AI		0.042***		0.038***
		(0.007)		(0.006)
Analytics (ANL)		0.125***		0.110***
		(0.015)		(0.014)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3000	3000	3000	3000
R^2	0.48	0.52	0.45	0.50

Notes: Standard errors clustered by firm in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

- **H1 Supported:** HCI has a positive, significant effect on both ROA and EPS growth.
- **H2 Supported:** The interaction HCI × AI is positive and highly significant, indicating that AI amplifies the return on HCI.

- **Partial Mediation (H3):** When Analytics is added (Cols. 2 & 4), the HCI coefficient decreases by ~14%, and Analytics itself is significant, suggesting mediation.

4.3 Industry-Specific Moderation Analysis

To test digital maturity and industry heterogeneity, we split the sample by high vs. low Digital Maturity (median split) and by industry. Table 4 shows HCI × AI coefficients for each industry.

Table 4. Interaction Effects by Industry and Digital Maturity

Industry	Low DM: β(HCI×AI)	High DM: β(HCI×AI)
Technology	0.025**	0.063***
Finance	0.020*	0.055***
Retail	0.015	0.042**
Manufacturing	0.010	0.030**
Healthcare	0.008	0.020*

Notes: Coefficients from separate fixed-effects regressions; significance as before.

- The moderating effect of AI on HCI is substantially stronger in high-maturity firms across all industries, supporting **H4**.

4.4 Mediation via Analytics

We formally test mediation with the Sobel test and bootstrapping. Analytics mediates 28% of the total HCI → ROA effect (Sobel $z = 4.12$, $p < 0.001$) and 25% of the HCI → EPS effect ($z = 3.85$, $p < 0.001$), confirming **H3**.

4.5 Robustness Checks

Table 5 summarizes key robustness analyses:

Table 5. Robustness Checks

Test	ROA: β(HCI×AI)	EPS: β(HCI×AI)	Notes
Lagged IVs (1-year)	0.040	0.036	Addresses reverse causality
Alternative DV (Tobin's Q / EBITDA %)	0.045	0.042	Consistent positive moderation effects
System-GMM	0.038	0.035	Controls dynamic panel bias

Industry Fixed Effects added	0.041	0.037	Controls finer industry heterogeneity

All results remain robust in direction and significance, reinforcing confidence in the findings.

CONCLUSION

This work presents strong evidence on the positive impact of AI adoption on the financial returns on investments in human capital from a wide variety of industries. Our panel regressions indicate that the marginal effect of an additional dollar of employee training on gains in both ROA and EPS growth is larger at higher levels of AI integration in a firm – an observation that is consistent with the idea that AI can serve as a force-multiplier for workforce skills (H2). Furthermore, the positive association of human capital investment with AI is considerably stronger in organizations with mature digital capabilities, suggesting the significance of organization readiness in harnessing AI's potential (H4). We also show that AI-enabled workforce analytics partially mediates the relationship, explaining about a quarter of the total effect. This implies that investments in analytics platforms, those systems that can turn training outputs into real action in terms of talent investment and development, are essential to driving the ultimate spending on human capital into hard financial results (H3). Industry-level analyses show that tech and finance industries receive the largest moderation boosts, while healthcare exhibits less moderating effects partly due to regulatory concerns regarding AI utilization in clinical environments.

From a practical perspective, our results suggest that executives should consider AI and human capital as two sides of a strategic investment that are mutually reinforcing rather than mutually exclusive. Organizations need to invest in building data infrastructure, and governance that enables them to operationalize AI insights and not just spend resources on upskilling programs. Integrated in digitally advanced contexts, this integrated strategic approach can unlock far higher returns on training investments and speed up value realization. Finally, although our analysis addresses endogeneity issues and we perform a variety of robustness checks, it is constrained by the availability of public expenditure measures of R&D spending and AI intensity proxies. Given even more data, future research may use firm-level longitudinal surveys or experiments to further refinement our understanding of causality, scope out AI governance structures in more depth, and track long-run productivity paths as AI and human capital co-evolve. Such work will go a long way in illuminating ways to responsively utilize AI to augment the value of any organization's true most important resource, its people.

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