The Impact of Artificial Intelligence Capability on Market Value

Abstract

This study examines the relationship between country-level artificial intelligence (AI) capability and firm value, as well as the moderating role of country-level technological readiness in this relationship. Using 29,100 firm-year observations across 28 countries, we find that firms in countries with greater AI capability experience higher firm value. Additionally, the positive association between AIC and firm value is more pronounced for firms in countries with greater technological readiness. These findings suggest that investors positively evaluate a country's investment in AI, with the relationship being stronger when firms in that country demonstrate technological readiness. Further analysis indicates that firm-level competitiveness is an underlying channel through which AI capability enhances firm value. Our findings have practical implications for regulators, standard-setters, policymakers, investors, and firms as AI continues to drive global economic momentum.

Keywords: Artificial intelligence, Technological readiness, Firm value, Cross-country

JEL Classification: M14; M40; M41; M49

Data Availability: All data used in this study are publicly available from sources stated in this paper.

1. Introduction

Artificial Intelligence (AI), a transformative and disruptive technology, has garnered significant global attention due to its profound impact on productivity, innovation, and operational efficiency across industries (Gillespie et al., 2023; OECD, 2021). Artificial Intelligence (AI)'s ability to analyse large volume datasets and model complex systems enables firms to make informed decisions and optimise performance (Duan et al., 2019; Fedyk et al., 2022; OECD, 2021). Generative AI technologies, such as ChatGPT, illustrate its growing influence, revolutionising business processes and service delivery (Eisfeldt et al., 2023; Gillespie et al., 2023). The McKinsey Global Institute estimates that AI could contribute an additional $13 trillion to global economic output by 2030, boosting global GDP by approximately 1.2% annually (Bughin et al., 2018). Country-level national AI strategies have emerged as pivotal resources, with governments and firms increasingly recognising AI as a critical driver of economic growth and competitive advantage. Mittal et al. (2022) report that 94% of business executives regard AI as essential to their operations, while Ransbotham et al. (2017) found that 85% of leaders see AI as a means to sustain competitive advantage. These developments underline the need to examine how AI capability impacts firm valuation. Accordingly, this study's central empirical question investigates whether country-level AI capabilities, as external strategic resources, influence firms' market valuation by creating a supportive environment for innovation, operational efficiency, and growth.

Previous studies widely explore the relationship between firm-level AI adoption and organisational outcomes. Research highlights the benefits of AI in enhancing operational efficiency (Ivanov & Webster, 2017), fostering innovation (Mikalef & Gupta, 2021), improving decision-making (Estep et al., 2024), and driving revenue growth (Babina et al., 2024). Firms leveraging AI also report increased customer retention and market share (Syam & Sharma, 2018). However, the literature reveals mixed findings on AI's financial implications. While prior studies suggest that AI adoption boosts firm valuation (Brynjolfsson et al., 2019; Rock, 2019), others highlight potential downsides, including high implementation costs and risks associated with disclosing sensitive AI resources (Lui et al., 2022; Rock, 2019). Despite these insights, limited research investigates the role of country-level AI capabilities as external resources that shape firm valuation. This study addresses this gap by applying the resource-based view (RBV) to explore how national AI investments and strategies enhance firms' competitive advantage and market valuation.

The RBV posits that firms achieve sustainable competitive advantage by leveraging resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Extending this framework to a national context, country-level AI capabilities represent strategic resources that firms can exploit to enhance their performance and valuation. Countries investing in AI infrastructure, research, and talent development create an ecosystem conducive to fostering innovation and operational excellence. For example, countries with robust AI ecosystems enable firms to access advanced research facilities, skilled talent pools, and cutting-edge technologies. These resources empower firms to develop innovative products, reduce costs, and improve customer experiences, aligning with the RBV's principles of resource value and rarity. Moreover, country-level AI strategies that encourage collaboration between academia, industry, and government enhance firms' capacity to innovate, creating competitive advantages that are challenging for rivals to replicate (Rock, 2019).

Firms operating in AI-capable countries benefit from several strategic advantages. First, access to national AI resources facilitates the adoption of state-of-the-art technologies, enabling firms to optimise operations and expand into new markets. Second, the presence of a skilled AI workforce supports firms in implementing complex AI-driven solutions, enhancing productivity and innovation capacity (Rock, 2019). Third, national AI policies often reduce barriers to innovation, such as regulatory uncertainty or infrastructure limitations, further strengthening firms' competitive positioning. Collectively, these factors contribute to firms' market valuation by improving efficiency, driving growth, and mitigating operational risks. The RBV also acknowledges that leveraging AI capabilities involves substantial costs. Implementing AI solutions requires significant investments in infrastructure, training, and compliance with evolving regulations (Bughin et al., 2018; Lui et al., 2022). These costs may constrain short-term profitability, potentially diminishing firms' valuation.

Additionally, firms may face pressure to disclose AI-related capabilities to comply with governance requirements, exposing sensitive strategies and diminishing their competitive advantage (Bock et al., 2020). These challenges highlight the trade-offs firms must navigate when leveraging country-level AI resources to achieve long-term strategic benefits.

Furthermore, the impact of AIC on firm value depends largely on country-level technological readiness, which encompasses the infrastructure, workforce expertise, and digital maturity required to integrate AI effectively. Therefore, we examine country-level technological readiness as a critical moderator in the relationship between AIC and firm value, arguing that AI's benefits are fully realised only when firms operate in digitally mature environments (Bharadwaj, 2000; Bresciani et al., 2021). Firms with high technological readiness can seamlessly deploy AI, enhancing operational efficiency, innovation, and cost reductions (Côrte-Real et al., 2020). Advanced IT frameworks facilitate data management, system interoperability, and scalable AI applications across business functions, amplifying the returns on AI investments. In contrast, firms with insufficient readiness face challenges such as data incompatibility, skill shortages, and cybersecurity risks, limiting AI's scalability and effectiveness (Kane et al., 2015). Technological readiness also enhances firms' strategic agility, allowing them to adapt to market shifts and sustain competitive advantages (Bresciani et al., 2021; Côrte-Real et al., 2020). Grounded in the resource-based view (RBV), technological readiness moderates the relationship between AI capabilities and firm value by ensuring AI resources are optimally deployed. However, achieving readiness requires substantial investments in digital infrastructure and workforce training, necessitating a strategic balance between short-term costs and long-term benefits. Ultimately, firms with robust technological readiness are better positioned to maximise AI's potential, driving superior market valuation, while those lacking readiness may struggle to realise AI's full value.

Using 29,606 firm-year observations from 2017–2021 across 28 countries worldwide, we examine the association between AI capability and firm value and the moderating role of country-level technological readiness in this relationship. We measure firm value using Tobin's Q, while AI capability using the AI Index developed by Stanford University. Our results show a positive association between AI capability and firm value, supporting the benefit perspective of the resource-based view (RBV). This suggests that firms leveraging AI technologies effectively enhance their operational efficiency, innovation capacity, and market competitiveness, which, in turn, boosts firm value. Additionally, our results show that the positive relationship between AI capability and firm value is amplified in countries with higher levels of technological readiness. These findings highlight the critical role of national technological readiness in strengthening the value-creation potential of AI investments, emphasising the interplay between firm-level resources and country-level factors in shaping corporate outcomes. To address potential selection bias, we employ entropy balancing analysis, along with robustness checks, comprising quasi-experimental designs, firm fixed effects, change regression models, and instrumental variable techniques. These methods mitigate endogeneity concerns and ensure the reliability of our findings.

Furthermore, competitive advantage is critical in linking AI capability with firm value. Firms that leverage AI technologies to achieve superior operational efficiency, innovation, and cost-effectiveness often strengthen their competitive position in the market. These capabilities enable firms to differentiate themselves from competitors, respond more effectively to customer needs, and adapt to changing market conditions, thereby creating sustainable value (Barney, 1991). By adopting AI-driven strategies that enhance productivity and foster innovation, firms can establish themselves as industry leaders, a quality increasingly rewarded by capital markets. Accordingly, we examine competitive advantage as a potential channel in the relationship between AI capability and firm value and find that it significantly mediates this association. These findings suggest that the ability to generate and sustain competitive advantage is a key mechanism through which AI capability translates into enhanced firm value.

Previous research emphasises the critical role of country-level factors in shaping the institutional context in which firms operate (Dey et al., 2024; Dhaliwal et al., 2014; Dhaliwal et al., 2012). These factors influence firms' strategic decisions, including adopting and effectively utilising advanced technologies such as artificial intelligence (AI). Building on this foundation, we examine how country-level factors interact with AI capability to influence firm value, focusing on three key moderators: digital development, economic development, and investor rights. Our findings reveal that the positive association between AI capability and firm value is stronger in countries with higher levels of digital development. Advanced digital infrastructure, characterised by widespread internet penetration, mobile connectivity, and broadband access, provides the technological foundation for firms to integrate and scale AI solutions effectively. Similarly, the positive relationship between AI capability and firm value is amplified in countries with higher levels of economic development. Economically developed nations offer better access to financial resources, skilled labour, and market opportunities, enabling firms to maximise the benefits of AI technologies. Finally, we find that stronger investor rights enhance the positive impact of AI capability on firm value. Robust legal protections for shareholders and governance frameworks foster accountability and encourage long-term investments in innovation, further reinforcing the value generated by AI capabilities. These findings highlight the critical interplay between firm-level AI capability and country-level contextual factors. By incorporating digital development, economic development, and investor rights as moderators, our study provides a nuanced understanding of the conditions under which AI investments yield the most significant benefits for firm value. This underscores the importance of aligning technological innovation with supportive institutional environments to enhance corporate outcomes.

Our study contributes to the literature in several ways. Firstly, our study responds to recent calls for a deeper understanding of how AI capability impacts firm value within the broader context of national institutional environments. While previous studies have focused primarily on firm-level drivers of AI adoption, we are among the first to empirically examine the impact of country-level AI capabilities on firm value and the moderating role of country-level technological readiness in this relationship. Secondly, we explore how country-level factors—digital development, economic development, and investor rights—moderate the relationship between AI capability and firm value, addressing a critical gap in prior research primarily focused on firm-level determinants of AI adoption. Our findings reveal that advanced digital infrastructure, financial resources, institutional stability, and stronger investor rights significantly amplify the positive impact of AIC on firm value. These factors enhance accountability, governance, and resource allocation, creating an enabling environment for firms to fully leverage AI technologies. By investigating the moderating effects of these country-level factors, our study offers a new perspective on the interplay between institutional contexts and technological innovation. This research bridges the gap between macro-level environmental factors and micro-level technological outcomes, advancing understanding of the conditions under which AI investments drive optimal firm-level and societal value creation.

Further, we contribute to the existing literature by showing that competitive advantage is a key channel through which AI capability enhances firm value. Firms leveraging AI technologies to achieve superior operational efficiency, innovation, and differentiation strengthen their competitive position, which drives higher market valuation. Finally, our study has important policy implications for fostering the value-creation potential of AI investments. Governments should prioritise AI research, development, and adoption investments to enhance firms' operational efficiency and competitiveness. Building robust digital infrastructure, such as broadband access and internet connectivity, is critical for enabling effective AI integration. Workforce development policies are essential to address AI-related skill gaps and support the growing demand for expertise in AI technologies. Additionally, aligning AI strategies with national economic and technological goals while implementing governance frameworks for accountability and data security will ensure sustainable economic and social progress. These measures collectively create an enabling environment for maximising the benefits of AI investments.

The remainder of the paper is structured as follows: Section 2 presents the literature review and hypotheses development, Section 3 describes the research design, Section 4 reports the empirical results, and Section 5 discusses potential mechanisms that link AI and firm value. Section 6 concludes the paper.

2. Literature Review and hypotheses development

2.1 Literature review

Artificial Intelligence (AI) has been widely recognised as a revolutionary and game-changing technology in the business world (Mikalef & Gupta, 2021). While numerous studies extol AI's transformative potential in enhancing firm performance, limited empirical research examines its impact on capital market outcomes, particularly the long-term effects of country-level AI capabilities on firm valuation. Existing research primarily focuses on event studies and firm-level analyses, often in the context of the U.S., leaving a significant gap in understanding the broader implications of AI capabilities across countries and over time.

Some studies have explored the short-term effects of AI-related technological announcements on market outcomes. Eisfeldt et al. (2023) found that the announcement of Generative AI technology, such as ChatGPT, significantly boosted firm value, with firms highly exposed to ChatGPT outperforming others by over 40 basis points in excess daily returns within two weeks of its release. Similarly, Son et al. (2014) examined market reactions to cloud computing announcements, demonstrating that the stock market positively responds to firm-specific cloud computing initiatives, with the magnitude of the reaction influenced by firm, resource, and vendor-specific factors. These studies underscore the capital market's responsiveness to AI-related announcements but are limited to specific events and technologies.

Other research has investigated the broader relationship between information technology (IT) investments and firm performance. Bharadwaj et al. (1999) found that IT infrastructure investments positively impact firm performance, as measured by Tobin’s Q, suggesting significant intangible benefits from IT investments. Chatterjee et al. (2002) further demonstrated that IT investment announcements lead to abnormal stock returns and increased trading volumes, indicating investor recognition of IT’s strategic value. Similarly, Dehning et al. (2003) and Teo et al. (2016) documented positive abnormal returns from business analytics and other IT-related announcements, emphasising the market’s perception of IT as a driver of more thoughtful decision-making and efficiency.

The growing role of AI as a specific subset of digital technology has also attracted attention. Chen and Srinivasan (2024) analysed non-tech firms’ digital activities, finding that references to AI and related technologies in firms' 10-K reports positively impact firm value. They reported increased valuations of earnings and sales, underscoring AI’s role in driving growth. Similarly, Mishra et al. (2022) found that a firm’s AI focus is associated with improved net efficiency, measured by metrics such as return on sales and marketing investment. Wamba-Taguimdje et al. (2020) highlighted AI’s potential to disrupt ecosystems and provide firms with strategic advantages, increasing market share and firm value.

In addition to performance enhancements, AI investment has been linked to innovation-led growth. Babina et al. (2024) demonstrated that AI-driven product innovation fosters higher sales, employment, and market valuation growth in U.S. firms. Similarly, Alderucci et al. (2020) reported that AI-related innovations significantly accelerate revenue and employment growth, suggesting that AI empowers firms by reducing product development costs and enhancing productivity. However, such advantages are often industry-specific, with firms in manufacturing benefitting more from AI investments than those in other sectors (Lui et al., 2022).

Despite these promising findings, some studies highlight the risks associated with AI and IT investments. Lui et al. (2022) reported negative abnormal stock returns following AI investment announcements, particularly for firms with weak IT capabilities or low credit ratings, reflecting investors' scepticism regarding their ability to successfully implement AI technologies. Similarly, Bose et al. (2011) found that RFID adoption negatively impacts firm market value, suggesting that certain technological investments may be perceived as risky or unprofitable. Dos Santos et al. (1993) offered a nuanced perspective, showing that market reactions to IT investment announcements depend on their innovativeness, with only innovative investments generating positive abnormal returns.

This study seeks to address the limitations of prior research in several ways. First, unlike studies such as Lui et al. (2022), which focuses on short-term event-based impacts; this research investigates the long-term effects of AI capabilities on firm value using a longitudinal approach. Second, while most existing studies are confined to U.S. firms, this study adopts a cross-country perspective, allowing for broader insights into the role of country-level AI capabilities in shaping firm valuation. Finally, this study employs a novel index for measuring AI-related capabilities, providing a robust framework to assess the sustained impact of AI investments and innovations on capital market outcomes. By addressing these gaps, this research contributes to the growing body of literature on AI's economic and market implications, offering insights into how AI capabilities influence firm value across diverse institutional and technological contexts.

2.2 Theoretical background and hypotheses development

This study adopts a market-based approach to investigate the effects of AI capabilities on firm market value. The underlying theoretical premise is that if AI resources are perceived as a source of sustained competitive advantage, they should signal to investors a firm's enhanced prospects for business success and long-term performance (Chatterjee et al., 2002). Investments in AI resources generate direct benefits, such as future cash flows, and indirect advantages, such as creating new investment opportunities for firms (Chen & Srinivasan, 2024; Dos Santos et al., 1993). From a financial theory perspective, firm value is derived from existing assets' discounted future cash flows and the present value of expected investment opportunities (Dos Santos et al., 1993). When an investment's net present value (NPV) is positive—indicating that expected benefits exceed the required rate of return—it is anticipated to enhance the firm's value. This increase is reflected in the firm's market valuation, with stock prices adjusting promptly in an efficient market that incorporates all publicly available information (Fama, 1970). Consequently, investments in AI resources as strategic assets should provide value-relevant information to market participants, with their significance reflected in stock prices (Chatterjee et al., 2002). We, therefore, examine whether AI resources influence a firm's market value.

The Resource-Based View (RBV) has become a widely applied framework in strategic management research to examine how information systems (IS) resources and capabilities affect firm performance (Mikalef & Gupta, 2021; Wade & Hulland, 2004). RBV posits that firm-specific resources contribute to competitive advantage and superior long-term financial performance when these resources are valuable, rare, inimitable, and non-substitutable (Barney, 1991; Mahoney & Pandian, 1992). Applied to AI resources, this framework suggests that investments in AI capabilities can lead to sustained competitive advantage by enabling firms to develop unique, integrated, and context-specific AI platforms that are difficult for competitors to replicate (Ravichandran et al., 2005; Wade & Hulland, 2004). Such platforms result from a combination of technologies, human expertise, and organisational processes that together enhance efficiency and effectiveness (Chatterjee et al., 2002).

Unlike static assets, AI resources represent dynamic capabilities that evolve over time (Teo et al., 2016). These capabilities allow firms to respond to rapidly changing business environments, develop new competencies, and implement innovative strategies. For example, a firm's ability to integrate technologies, databases, skilled human resources, and managerial knowledge into an advanced AI platform reflects its unique capabilities, which competitors may find challenging to imitate. The heterogeneity and complexity of these resources contribute to sustained competitive advantage, as they are deeply embedded in a firm's organisational routines and processes (Ravichandran et al., 2005; Wade & Hulland, 2004).

RBV also emphasises the importance of complementary organisational resources—such as human expertise, managerial strategies, and agility—in leveraging AI investments to achieve competitive advantage (Mikalef & Gupta, 2021). While AI technologies and systems serve as critical inputs, the firm's ability to integrate, deploy, and utilise these resources effectively determines their contribution to firm performance. For instance, skilled human resources and managerial flexibility enable firms to adapt AI capabilities to evolving market conditions, ensuring consistent productivity and rent yields. The interaction of technical and organisational resources enhances the firm's capacity to transform inputs into outputs of greater value, thereby improving firm efficiency and effectiveness (Ravichandran et al., 2005; Wade & Hulland, 2004).

AI resources are expected to complement and enhance a firm's core competencies, contributing to its competitive positioning and market valuation. Investments in AI platforms signal future growth opportunities and the firm's ability to generate superior cash flows over time. However, the value of these investments also depends on the efficient utilisation of AI capabilities. Inefficient deployment or underutilisation may introduce risks that offset the potential benefits, which market participants consider when evaluating the firm's prospects. Stock prices, as reflections of the discounted value of future cash flows, capture this trade-off between the risks and rewards associated with AI investments (Chatterjee et al., 2002). The literature suggests that firms that effectively leverage AI resources—characterised by being firm-specific, valuable, rare, and difficult to imitate—are more likely to achieve sustained competitive advantage and superior market valuation. Conversely, failing to integrate or utilise these resources effectively may lead to diminished market value. Building on these insights, we propose the following hypothesis:

H1: Firms in countries with greater artificial intelligence capability (AIC) have higher firm value.

While AI capabilities hold the potential to automate complex processes, enhance customer experiences, and generate actionable insights, their efficacy largely depends on the supporting technological infrastructure, workforce expertise, and digital maturity of the firm (Bharadwaj, 2000; Bresciani et al., 2021). Technological readiness, defined as the infrastructure and technical skill sets required to deploy, integrate, and leverage advanced technologies like AI, plays a crucial role in unlocking AI's strategic and operational advantages. Without sufficient readiness, firms face barriers that limit AI's contribution to firm value. Firms with high technological readiness are better positioned to translate AI capabilities into tangible outcomes such as operational efficiency, innovation, and cost reductions (Côrte-Real et al., 2020). Robust technological environments—characterised by advanced data management systems, scalable architectures, and cloud computing resources—enable swift and efficient AI deployment. These infrastructures facilitate the management of complex datasets, ensure interoperability between systems, and integrate AI solutions seamlessly across business functions. By accelerating the adoption and utilisation of AI technologies, technological readiness amplifies the return on AI investments, enhancing firm value. For instance, firms equipped with modern IT frameworks can scale AI applications across domains like marketing, finance, and supply chain management while minimising disruptions and costs (Bresciani et al., 2021).

Conversely, firms with insufficient technological readiness face significant challenges in leveraging AI. Issues such as data incompatibility, lack of integration capabilities, and a shortage of skilled personnel can undermine the effectiveness of AI systems, leading to deployment delays and increased operational costs (Kane et al., 2015). These limitations restrict the scalability of AI solutions, confining them to pilot projects and reducing their overall contribution to firm value. Moreover, inadequate technological readiness amplifies the risks associated with AI implementation, such as cybersecurity vulnerabilities, data privacy breaches, and regulatory non-compliance (Bughin et al., 2018; Lui et al., 2022). Firms with weak technological readiness are less equipped to proactively address these challenges, increasing the likelihood of disruptions that may erode the potential benefits of AI investments.

Beyond operational efficiency, technological readiness enhances the strategic agility of firms, enabling them to respond to dynamic market environments and emerging technological opportunities (Bresciani et al., 2021; Côrte-Real et al., 2020). By supporting continuous innovation, technological readiness allows firms to evolve AI applications over time, sustaining competitive advantages and ensuring long-term value creation. Conversely, firms with insufficient readiness struggle to pivot in response to market or technological changes, further limiting AI's potential to enhance firm value. From a theoretical perspective, technological readiness acts as a moderating factor in the relationship between AI capabilities and firm value. While AI resources are valuable, rare, and capable of providing competitive advantages (Barney, 1991; Wade & Hulland, 2004), their impact on firm value is significantly enhanced by the presence of robust technological infrastructure and capabilities. According to RBV, firm-specific resources must be effectively integrated and deployed to generate sustained competitive advantages. Technological readiness enables firms to maximise the utilisation, scalability, and resilience of AI resources, ensuring the realisation of their full potential.

However, achieving technological readiness requires substantial investment in technological upgrades, workforce training, and digital transformation initiatives to establish and sustain the necessary infrastructure for AI. While these investments are essential, they often impose significant short-term financial burdens, compelling firms to carefully balance immediate costs with long-term benefits. Additionally, misalignment between technology and AI strategies can lead to inefficiencies, underscoring the critical need for strategic coherence in leveraging technological readiness to support AI capabilities. Considering these challenges, we posit that the relationship between AI capability and firm value is highly dependent on technological readiness. Firms with robust technological readiness are better positioned to harness the full potential of AI, driving superior market valuation. Conversely, firms with insufficient readiness are likely to face barriers that diminish the effectiveness of AI investments, limiting their contribution to firm value.

H2: Country-level technological readiness positively moderates the positive relationship between AI capability and firm value.

3. Methodology

3.1 Sample and data

Our sample consists of all firms in countries included in the Artificial Intelligence (AI) Index compiled by Stanford University. We collect country-level technological readiness data from the Economist Intelligence Unit (EIU). Furthermore, we obtain firm-level financial accounting data from the Worldscope database and stock market data from the DataStream database. We merged firm-year observations in all the above databases in 2017-2021. Our sampling period is restricted by the limitations of the AIC database as the data on AIC were available only from 2017. After merging these databases and dropping all incomplete observations, we obtained an initial sample of 29,606 firm-year observations from 28 countries. Due to our lead-lag analysis approach, the firm valuation data covers the period from 2018–2022, while independent variables apply to the period from 2017–2021. Table 1, Panel A provides the sample selection process.

[INSERT TABLE 1 HERE]

Table 1, Panel B summarizes the industry distribution of our sample firms. The Financial industry (14.11%) has the highest percentage of observations, followed by computers (10.05%) and Services (9.31%) industries, while Retail: Restaurant (0.80%) has the fewest observations. Furthermore, Table 1, Panel C provides the yearly distribution of our sample firms. The highest number of observations is shown in 2020, followed by 2021, while the lowest in 2017.

3.2 Measure of artificial intelligence capability and technological readiness

We measure artificial intelligence capability *(AIC)* using the Artificial Intelligence Index, developed by Stanford University, which serves as a comprehensive and authoritative resource for tracking and evaluating the development and impact of artificial intelligence globally. The AIC Index's measurement, focusing on the research and development (R&D) and economy pillars, involves a systematic and comprehensive approach to tracking progress and impact in these critical areas. For the R&D pillar, the index measures the volume and quality of AI-related research outputs by analysing the number of peer-reviewed AI publications, conference papers, and patents. It considers contributions from academia, industry, and government institutions, highlighting trends in collaborative research efforts and the geographical distribution of these activities. Key indicators include the growth rate of AI publications, citation impact, and the prominence of AI research in leading conferences and journals. Additionally, the index tracks the evolution of AI-specific academic programs and the production of AI PhD graduates, emphasizing the role of education in advancing AI research.

In the economy pillar, the index evaluates the economic impact of AI through various lenses, including private investment in AI technologies, the proliferation of AI startups, and the integration of AI in different industries. It measures the amount of capital invested in AI-driven solutions, particularly in high-impact areas such as healthcare, drug discovery, and finance. The index also monitors AI-related job postings, hiring trends, and the distribution of AI talent across regions and sectors. This analysis helps to understand the economic dynamics of AI adoption and its contribution to productivity and economic growth. By combining these indicators, the AI Index provides a detailed and nuanced picture of the state of AI in terms of research innovation and economic influence, guiding policymakers, researchers, and industry leaders in their strategic decisions. Stanford University provides a composite index of AI as well as individual measures of AI, as mentioned above. We employ the composite index scaled by 100 to measure AI capability *(AIC)*. We also employ the individual pillars of the AI index (e.g., R&D pillars and economy pillars) as a separate analysis for assessing the robustness of our findings.

Furthermore, we measure technological readiness using the technological readiness ratings by the Economic Intelligence Unit. Technological readiness is a critical measure of a country's ability to integrate and utilise new technologies to drive economic growth and enhance quality of life. It encompasses several key dimensions: internet access, digital economy infrastructure, and openness to innovation. High internet penetration and extensive mobile phone usage indicate a population's readiness to engage with digital technologies. Robust digital economy infrastructure, including efficient e-commerce, comprehensive e-government services, and strong cybersecurity measures, supports seamless digital transactions and safeguards data. Openness to innovation is reflected in high levels of international patents, significant R&D spending, and a strong research infrastructure, all of which foster continuous technological advancements. Countries excelling in these areas are well-positioned to adapt to technological disruptions, driving economic development and improving living standards. We split the technological readiness rating score based on the country-level median to separate firms into higher and lower-level of technological readiness. More specifically, we create an indicator variable of *HIGH_TECH* that takes a value of 1 if the country-level technological readiness is higher than the sample median value of technological readiness and 0 otherwise.

3.3 Measure of firm value

We use Tobin's Q *(TOBINQ)* to measure firm value. *TOBINQ* is calculated as the sum of the book value of total assets and the market value of equity, minus the book value of equity, divided by total assets. We prefer Tobin's Q over accounting-based measures because it reflects a firm's future growth potential and the sustainability of profits (Luo & Bhattacharya, 2006). This metric is risk-adjusted and less affected by changes in accounting practices (Bharadwaj et al., 1999). Additionally, since the share price is a key component in calculating Tobin's Q, changes in share prices may partly indicate investors' reactions to a firm's performance.

3.4 Empirical models

We estimate the following ordinary least squares regression (OLS) model for testing our first hypothesis (H1) that predicts the positive association between artificial intelligence capability (AIC) and firm value:

$$\begin{aligned} TOBINQ_{i,j,t+1} = {} & \beta_0 + \beta_1 AIC_{j,t} + \beta_2 SIZE_{i,j,t} + \beta_3 ROA_{i,j,t} + \beta_4 LEV_{i,j,t} + \beta_5 GROWTH_{i,j,t} + \beta_6 DIVIDEND_{i,j,t} \\ & + \beta_7 RETVOL_{i,j,t} + \beta_8 LIQUIDITY_{i,j,t} + \beta_9 RDINT_{i,j,t} + \beta_{10} CAPIN_{i,j,t} + \beta_{11} INTANG_{i,j,t} \\ & + \beta_{12} FAGE_{i,j,t} + \beta_{13} ESG_{i,j,t} + \sum YEAR_t + \sum INDUSTRY_k + \sum COUNTRY_j + \varepsilon_{i,t} \quad (1) \end{aligned}$$

We include the interaction between AIC and technological readiness (*HIGH_TECH*) in Equation (1) for testing our H2. The model is as follows:

$$\begin{aligned} TOBINQ_{i,j,t+1} = {} & \beta_0 + \beta_1 AIC_{j,t} + \beta_2 AIC_{j,t} \times HIGH\_TECH_{j,t} + \beta_3 HIGH\_TECH_{j,t} + \beta_4 SIZE_{i,j,t} + \beta_5 ROA_{i,j,t} \\ & + \beta_6 LEV_{i,j,t} + \beta_7 GROWTH_{i,j,t} + \beta_8 DIVIDEND_{i,j,t} + \beta_9 RETVOL_{i,j,t} + \beta_{10} LIQUIDITY_{i,j,t} \\ & + \beta_{11} RDINT_{i,j,t} + \beta_{12} CAPIN_{i,j,t} + \beta_{13} INTANG_{i,j,t} + \beta_{14} FAGE_{i,j,t} + \beta_{15} ESG_{i,j,t} \\ & + \sum YEAR_t + \sum INDUSTRY_k + \sum COUNTRY_j + \varepsilon_{i,t} \quad (2) \end{aligned}$$

The measurement of *TOBINQ* and *AIC* is discussed in Sections 3.2 and 3.3, respectively. *HIGH_TECH* in Equation (2) indicates higher technological readiness, also discussed in Section 3.2. We expect a positive coefficient for β1 in Equation (1) and a positive coefficient for β2 in Equation (2) to support our hypotheses. Appendix A provides an explanation of all variables.

Following the prior literature (Bose et al., 2021; Chang & Jo, 2019; Roll et al., 2009), we include several control variables in Equations (1) and (2). We account for firm size *(SIZE)* because larger firms typically benefit from economies of scale (Roll et al., 2009), which enables them to operate more efficiently. Leverage *(LEV)* and profitability *(ROA)* are included in Equation (1) to capture the likelihood of financial distress (Bose et al., 2021; Roll et al., 2009) and investment opportunities, respectively, which may impact firm value (Bose et al., 2021; Roll et al., 2009). We also control for revenue growth *(GROWTH)* to reflect the effect of growth on firm value following Bose et al. (2021).

Furthermore, we control for capital expenditures to capture future growth opportunities, specifically capital expenditure intensity *(CAPIN)*, since firms with better future growth prospects tend to have higher firm value (Roll et al., 2009). Additionally, we account for a firm's dividend payments *(DIVIDEND)* to consider potential overinvestment in marginal projects due to large free cash flows (Roll et al., 2009). Chang and Jo (2019) find that higher market risk exerts greater pressure on firm performance. Hence, we control for market risk *(RETVOL)*. We also control for liquidity *(LIQUIDITY)* to capture the potential effects of stock trading activity on firm valuation (Roll et al., 2009). Furthermore, we control research and development (RDINT) and intangible assets (INTANG), as investments in R&D and intangible assets are crucial for developing intangible knowledge assets or innovations that enhance business performance (Chang & Jo, 2019). We include firm age *(FAGE)* because firms with a longer market presence have a competitive advantage that can affect firm value (Bose et al., 2021). Additionally, we control for industry-adjusted environmental, social and governance (ESG) performance to account for their impact on firm value. We also control for the industry and year in all regression models to account for the impact of industry-specific and time-related factors on our results.

To estimate our research models, we employ the Ordinary Least Squares (OLS) regression method. We mitigate heteroskedasticity and serial correlation issues by using robust standard errors clustered at the country level. Furthermore, we check the Variance Inflation Factor (VIF) values to detect potential multicollinearity problems. Additionally, we winsorise all continuous variables, except those at the country level, at the 1st and 99th percentiles.

4. Empirical results

4.1 Descriptive statistics

Table 2 provides the descriptive statistics for the variables included in Equation (1). The average (median) firm value, measured by Tobin's Q *(TOBINQ)*, is 1.761 (1.074), with a standard deviation of 2.059. The first quartile value of *TOBINQ* is 0.691, while the third quartile value is 1.940, indicating variability in firm valuation across the sample. The mean (median) value of country-level artificial intelligence capability *(AIC)* is 0.413 (0.491), with a standard deviation of 0.289, reflecting differences in AI capabilities across countries. About 83.60% of our sample observations have technological readiness. The mean (median) firm size *(SIZE)*, measured by the natural logarithm of market capitalisation, is 7.684 (7.762), indicating that the average market value of equity (unreported) for the sample observations is US$2,173.30 million. The average (median) value of return on assets *(ROA)* is 0.015 (0.030), with a standard deviation of 0.152, suggesting variation in profitability among the firms. On average, the leverage ratio *(LEV)*, profitability *(ROA)* and intangible assets *(INTANG)* are about 25.40%, 1.50% and 160.50% of total assets, respectively. Moreover, sales growth *(GROWTH)*, capital expenditures (*CAPIN*), and research and development expenditure intensity *(RDINT*, on average, are about 17%, 13.20% and 16.10% of total assets, respectively. Approximately 70.60% of the sample observations paid dividends *(DIVIDEND)*. The average value of stock return volatility *(RETVOL)* is 0.398, with a median value of 0.339 and a standard deviation of 0.221, suggesting notable differences in stock return stability across firms. The average (median) liquidity *(LIQUIDITY)* is 1.459 (0.966), with the first and third quartile values at 0.463 and 1.866, respectively. The natural logarithm of firm age *(FAGE)* has a mean (median) value of 2.94 (3.045), corresponding to an average age (unreported) of approximately 18.90 years. The industry-adjusted ESG index *(ESG_IND)* has a mean (median) value of 0.160 (0.143), with a standard deviation of 0.111, reflecting differences in ESG practices across industries. Definitions of all variables are provided in Appendix A.

[INSERT TABLE 2 HERE]

4.2 Correlation matrix

Table 3 presents Pearson's bivariate correlation matrix for the variables included in Equation (1). The country-level artificial intelligence capability *(AIC)* exhibits a positive correlation with Tobin's Q (r=0.082), growth (r = 0.058), leverage (r=0.016), return volatility (r=0.149), liquidity (r=0.379), R&D intensity (r=0.096), and intangible assets (r=0.011). Conversely, *AIC* is negatively correlated with firm size (r=-0.023), return on assets (r=-0.110), dividend payments (r=-0.187), capital intensity (r=-0.023), firm age (r=-0.108) and industry-adjusted ESG (r=-0.156). All correlations are statistically significant, with at least 10% significance levels. All correlation coefficients are below 0.80, which is consistent with the threshold Gujarati and Porter (2009) suggested to avoid multicollinearity concerns. Additionally, the mean-variance inflation factor (VIF) is 1.88, ranging from 1.06 to 5.88, which is well below the critical value of 10, further confirming that multicollinearity is unlikely to affect the results. These findings suggest that the variables are appropriately suited for regression analysis.

[INSERT TABLE 3 HERE]

4.3 Regression results

Table 4 presents the regression results of the association between artificial intelligence capability *(AIC)* and firm valuation and the moderating role of technological readiness *(HIGH_TECH)*. Column (1) shows the regression results for the effect of *AIC* on firm value without control variables, Column (2) includes control variables in the model, and Column (3) examines the moderating effect of technological readiness on the relationship between *AIC* and firm value. The coefficient on *AIC* is positive and statistically significant across Columns (1) and (2), with [β=0.981, p-value<0.05 in Column (1), β=1.369, p-value<0.01 in Column (2)]. These results suggest that higher artificial intelligence capability at the country level is positively associated with higher firm valuation, supporting our first hypothesis (H1). Specifically, the coefficient in Column (2) implies that a one-standard-deviation increase in *AIC* is associated with a 22.47% increase (1.369×0.289/1.761) in

Tobin's Q, highlighting the economic significance of the findings. These results are consistent with prior studies that emphasise the role of advanced technologies in enhancing firm valuation.

[INSERT TABLE 4 ABOUT HERE]

In Table 4, Column (3), we examine the moderating role of technological readiness *(HIGH_TECH)* in the relationship between *AIC* and firm value. To test the moderation hypothesis, the key variable of interest is the interaction term (*AIC×HIGH_TECH*), which captures the difference in the effects of *AIC* on firm value between firms operating in countries with high and low technological readiness. Additionally, the coefficient on *AIC* captures the impact of *AIC* on firm value for firms in countries with lower technological readiness. The positive coefficient of *AIC×HIGH_TECH* (β=0.368 p-value<0.05) indicates that, after controlling for other factors, the average increase in firm value driven by *AIC* is greater for firms in countries with higher technological readiness. For instance, based on Column (3), a one standard deviation increase in *AIC* leads to a 28.92% increase [(1.762×0.289/1.761)] in the value of Tobin's Q for firms in countries with lower technological readiness. In contrast, a one standard deviation increases in *AIC* results in a 34.96% increase [(1.762×0.289 + 0.368×0.289)/1.761] in the value of Tobin's Q for firms in countries with higher technological readiness. These findings support our second hypothesis, indicating that the interaction between *AIC* and technological readiness *(HIGH_TECH)* positively influences firm value, suggesting that the positive relationship between *AIC* and firm value is more pronounced for firms operating in countries with higher technological readiness.

The control variables in Columns (2) and (3) show consistent and statistically significant results, aligning with expectations from prior literature. For instance, firm size *(SIZE)*, return on assets *(ROA)*, growth *(GROWTH)*, return volatility *(RETVOL)*, and R&D intensity *(RDINT)* positively influence firm value, while leverage *(LEV)*, dividend payments *(DIVIDEND)*, liquidity *(LIQUIDITY)*, intangible assets *(INTANG)*, and firm age (*FAGE)* have negative effects. Overall, the findings highlight the significant role of artificial intelligence capability in driving firm value, particularly when firms operate in technologically advanced environments.

4.4 Endogeneity analysis

4.4.1 Entropy balancing

Our study's findings might be biased if they were influenced by inherent differences in observable firm characteristics. To address this concern, we employed the entropy balancing technique. This approach effectively mitigates imbalances in firm characteristics, ensuring that our results reflect the influence of AI capability rather than underlying differences in firm-level covariates. The entropy balancing results are presented in Table 5, which incorporates weights to adjust for the sample distributions of control observations (Hainmueller, 2012; Hainmueller & Xu, 2013). By balancing covariates on all three moments (mean, variance, and skewness) of the distributions, this method created a "pseudo" control group that minimises differences between treatment and control groups. Underrepresented observations were assigned higher weights, while overrepresented observations were assigned lower weights. The treatment group in our analysis consists of observations with higher levels of artificial intelligence capability *(HIGH_AIC=1)*, while the control group includes observations with lower levels of artificial intelligence capability *(LOW_AIC=0)*. We defined *HIGH_AIC* as an indicator variable equal to 1 when the country-level artificial intelligence capability exceeds the median value for that year, and 0 otherwise.

[INSERT TABLE 5 ABOUT HERE]

Table 5, Panel A, provides the descriptive statistics of the variables before entropy balancing, showing notable differences in firm characteristics between the treatment and control groups. For example, the treatment group has higher R&D intensity *(RDINT)* and liquidity *(LIQUIDITY)* but slightly lower firm size *(SIZE)* compared to the control group. Panel B presents the descriptive statistics after entropy balancing, confirming that the balancing procedure successfully aligns the means, variances, and skewness of all covariates between the treatment and control groups. For instance, the mean, variance, and skewness of *SIZE* are identical across the groups post-balancing, indicating that any differences in firm valuation can now be attributed to AIC rather than covariate imbalances. Panel C of Table 5 reports the regression results using the entropy-balanced sample. In Column (1), the coefficient on *AIC* is positive and statistically significant, indicating that higher artificial intelligence capability is associated with increased firm valuation. In Column (2), the interaction term *AIC×HIGH_TECH*, which captures the moderating role of technological readiness, is positive and statistically significant. This suggests that the positive effect of artificial intelligence capability on firm valuation is amplified in technologically advanced industries. These findings align with previous results, further demonstrating the robust association between artificial intelligence capability and firm valuation, as well as the enhanced impact of technological readiness in this relationship.

4.4.2 Impact Threshold Confounding (ITCV) analysis

We also employ the ITCV technique to assess the sensitivity of our results to potential omitted variable bias. This technique estimates a threshold representing the extent to which a potential confounding variable must influence the independent variable *(AIC)* and the dependent variable *(TOBINQ)* to distort the estimated relationship significantly. Since such confounding variables may not be directly observable and remain unaccounted for in our analysis, the ITCV technique provides a robust validation of the primary regression outcomes (Larcker & Rusticus, 2010). Recent studies have increasingly adopted this method to address concerns about endogeneity (Blaylock et al., 2015; Chapman et al., 2019).

Table 6 reports the raw and partial impacts of the control variables. The findings indicate that, for the inferences of our study to be invalidated, the correlation between *AIC* and *TOBINQ* with an unobserved confounding variable would need to be at least 0.050. Notably, the ITCV exceeds the raw and partial impacts of all control variables, suggesting minimal omitted variable bias and confirming the robustness of our conclusions. For instance, the raw and partial impacts of *SIZE, ROA, LEV*, and *GROWTH* remain small and stable, indicating their limited sensitivity to potential confounding effects. Similarly, while *DIVIDEND, LIQUIDITY,* and *FAGE* exhibit slight reductions in their partial impacts relative to their raw impacts, but these differences are insufficient to challenge the validity of our results. Overall, the ITCV analysis validates that the observed relationship between AIC and firm value is robust to the influence of unobservable confounding variables. This reinforces our conclusion that artificial intelligence capability significantly enhances firm value.

[INSERT TABLE 6 ABOUT HERE]

4.4.3 Change model regression

Furthermore, we implement change model specifications to address endogeneity concerns arising from omitted variable bias related to time-invariant factors that could influence both artificial intelligence capability and firm valuation. In the change regression, we regress the change in firm valuation *(ΔTOBINQ)* on the change in artificial intelligence capability *(ΔAIC)*, as well as the change in control variables. Table 7 reports the regression results. The coefficient on *ΔAIC* is positive and statistically significant, indicating that improvements in AI capability are associated with higher firm value. Moreover, the interaction term *(ΔAIC×ΔHIGH_TECH)* is also positive and statistically significant, suggesting that the relationship between AI capability and firm value is amplified in high-tech industries. These results align with our earlier findings, confirming the robustness of our conclusions and addressing concerns about time-invariant omitted variable bias.

[INSERT TABLE 7 ABOUT HERE]

4.4.4 Instrumental variable analysis

To address potential omitted variable bias and endogeneity concerns in the relationship between artificial intelligence capability *(AIC)* and firm value *(TOBINQ),* we employ an instrumental variable (IV) approach. We employ the number of secure internet servers per million population *(SERVER)* as the instrumental variable due to its strong relevance to *AIC* and its exogeneity concerning firm valuation. Secure servers indicate a country's infrastructure for enabling secure communication, data transfers, and technological advancements, which are critical for AI capability development. However, secure server availability does not directly impact firm valuation, which is primarily influenced by firm-level factors such as financial performance and growth potential. By serving as an external proxy for the technological and infrastructural environment conducive to *AI, SERVER* isolates the impact of *AIC* on firm valuation, addressing potential endogeneity.

Table 8 presents the results from the two-stage least squares (2SLS) regression. In the first stage (Column 1), *AIC* is regressed on *SERVER* alongside control variables. The coefficient of *SERVER* is positive and statistically significant ($\beta=0.006$, $p<0.01$), confirming its strong association with *AIC*. The model diagnostics validate the instrumental variable's relevance, with a Kleibergen–Paap rk LM statistic of 72.161 ($p<0.01$) and a Wald F statistic of 71.052, indicating that *SERVER* is not weakly identified. In the second stage (Column 2), *AIC* (instrumented using fitted values from the first stage) is regressed on *TOBINQ*. The coefficient on *AIC_FITTED* is positive and statistically significant ($\beta=20.761$, $p<0.05$), corroborating the positive impact of AI capability on firm valuation. Further diagnostics confirm the validity of the IV approach. The Durbin–Wu–Hausman test is significant ($\chi2=6.393$, $p<0.05$), supporting the hypothesis that *AIC* is endogenous and justifying the use of the IV method. Additionally, the under-identification test (Kleibergen–Paap rk LM statistic) confirms that the model is well-identified, while the weak identification test statistic (Wald F=71.052) demonstrates the strength of the instrumental variable.

[INSERT TABLE 8 ABOUT HERE]

The results confirm the robustness of our findings, indicating that AI capability significantly enhances firm valuation when potential endogeneity and omitted variable bias are addressed. The use of SERVER as an instrumental variable provides a valid and reliable framework for isolating the causal impact of AI on firm valuation, strengthening the validity of our conclusions.

4.4.5 Quasi-experimental analysis: Introduction of the European Union (EU)'s Green Deal

To address potential endogeneity concerns, we employ a quasi-experimental setting using the introduction of the European Green Deal (EGD) on firm value, focusing on the role of artificial intelligence capability (AIC). The EGD, introduced by the European Commission in December 2019, is an ambitious policy framework to achieve climate neutrality by 2050, promote sustainable economic growth, and accelerate the transition to digital and green technologies. By establishing regulatory pressures, financial incentives, and structural reforms, the EGD presents a quasi-experimental setting to explore how AI capabilities enable firms to adapt, innovate, and generate value in response to sustainability-driven policy shifts. The EGD prioritises investments in green innovation, renewable energy, and digital transformation, all of which require firms to develop advanced technological capabilities to remain competitive. AI has emerged as a critical enabler in this transition, allowing firms to optimise energy consumption, enhance predictive analytics for climate risk management, and automate compliance with new sustainability regulations. Given that the Green Deal includes funding mechanisms such as the Just Transition Mechanism and the EU Sustainable Finance Taxonomy, firms with superior AI capabilities are better positioned to secure funding, implement AI-driven sustainability solutions, and gain competitive advantages in a transitioning economy. Leveraging the staggered implementation of Green Deal initiatives across EU member states, our quasi-experimental approach isolates the causal effect of AI capability on firm value. Firms with higher AI capability are expected to capitalize on Green Deal incentives by improving operational efficiency, optimizing resource allocation, and reducing regulatory compliance costs. Additionally, AI-driven automation enhances firms' ability to meet stringent environmental disclosure requirements, comply with the EU Taxonomy for Sustainable Finance, and integrate climate-related financial risks into decision-making. These advantages translate into higher investor confidence and market valuation, reinforcing the strategic importance of AI in navigating policy-induced sustainability transitions.

Therefore, this regulatory initiative provides a quasi-experimental setting, as it directly affects EU-based firms while firms outside the EU serve as a control group. The variable *TREAT×POST* is defined to capture this regulatory shock, where *TREAT=1* indicates firms domiciled in EU countries, and *POST=1* indicates the post-EGD period (2020-2021). This interaction term isolates the differential impact of the EGD on firm value for treated firms relative to the control group, allowing us to identify the Green Deal's role in shaping firm value within a rapidly evolving regulatory and technological landscape.

Furthermore, to address concerns regarding non-random sample selection and enhance the comparability between the treatment and control groups, we employ a combined DiD analysis and entropy balancing approach using the pre-EGD period (2017-2019). We balance all three moments (mean, variance, and skewness) of the distribution of each control variable, as shown in equation (1). The pre-EGD characteristics are used to align treatment firms with control firms, and these matched pairs are then applied to post-EGD observations to ensure constant treatment-control matches across the pre- and post-EGD periods.

Panels A and B of Table 9 present the descriptive statistics before and after entropy balancing. Following entropy balancing, the treatment and control samples are well-aligned across all covariates, with negligible differences in means, variances, and skewness, confirming improved comparability. Panel C of Table 5 reports the DiD regression results for the entropy-balanced sample over the time from 2017-2021. In Model (1), we present the DiD regression results without entropy balancing for comparison, while Model (2) reports the DiD regression results for the entropy-balanced sample. The coefficient on *TREAT×POST* is positive and statistically significant (β=0.096, $p<0.05$), indicating that the introduction of the EGD positively influenced firm value for EU-based firms relative to the control group.

[INSERT TABLE 9 ABOUT HERE]

Furthermore, we conduct a test of parallel trends in the pre-treatment periods to validate the parallel trend assumption. Following Bertrand and Mullainathan (2003), we employ a dynamic analysis framework by creating four categorical variables to track the impact of the EGD before and after its implementation, using 2019 as the benchmark year. Specifically, we replace the *POST* variable with three pre-EGD indicators—*PRE3, PRE2,* and *PRE1*—and three post-EGD indicators—*POST0,* and *POST1*. These variables are then interacted with the treatment group *(TREAT)*, with

PRE1 serving as the benchmark category. The pre-period interaction terms, *TREAT×PRE3* and *TREAT×PRE2*, allow us to assess whether any firm value effects emerged before the EGD's introduction. If the parallel trend assumption holds, these coefficients should not be statistically significant, indicating no systematic differences between treatment and control firms before the regulatory change. For this analysis, we use the entropy-matched sample discussed earlier. The results, reported in Table 9, show that the coefficients of *TREAT×PRE3* and *TREAT×PRE2* are not significantly different from zero, confirming that there were no pre-event differences in firm value trends between the treatment and control groups. However, the coefficient on *TREAT×POST0* and *TREAT×POST1* are positive and statistically significant, supporting our prediction that the EGD leads to a significant increase in firm value.

4.5. Additional analyses and robustness tests

4.5.1 Role of country-level Institutional Factors in the association between Artificial Intelligence Capability and firm value

Prior studies highlight the critical role of country-level contextual factors in shaping a firm's non-financial information (Bose et al., 2024; Dey et al., 2024; Dhaliwal et al., 2012; Simnett et al., 2009). Therefore, we examine the role of country-level digital development, economic development and investors' rights in the relationship between AI capability and firm value.

Firstly, we examine the role of country-level digital development as a moderator in the relationship between AI capability and firm value, highlighting how a country's digital infrastructure enhances firms' ability to leverage AI technologies. Digital development, measured through internet penetration, mobile cellular subscriptions, and fixed broadband access, creates the foundation for integrating and scaling AI applications (World Bank Group, 2024). High internet penetration fosters better connectivity and data sharing, while mobile and broadband subscriptions provide the infrastructure for real-time AI adoption and advanced analytics (World Bank Group, 2024). In digitally developed countries, firms can more effectively translate AI capabilities into operational efficiency, innovation, and enhanced customer experiences, driving higher market valuations. Conversely, limited digital development constrains firms' ability to fully utilise AI, reducing its impact on firm value. By incorporating digital development as a moderator, our analysis emphasises the critical role of country-level digital infrastructure in enabling firms to maximise the benefits of AI investments. We measure country-level digital development using an index constructed from three key indicators: internet penetration, mobile cellular subscriptions, and fixed broadband access from the World Bank (World Bank Group, 2024). This composite index captures a country's overall digital infrastructure and connectivity. To facilitate analysis, we create an indicator variable, *HIGH_DIGITAL*, which takes a value of 1 if a country's digital development index is above the sample median and 0 otherwise. This binary classification allows us to investigate the differential effects of digital development on the relationship between AIC and firm value.

Secondly, we examine economic development as a moderator in the relationship between AI capability and firm value, emphasising how a country's economic environment influences the extent to which firms can leverage AI technologies. It reflects a country's financial resources, infrastructure, and institutional support, which collectively enable firms to adopt and utilise advanced technologies effectively. In economically developed countries, firms are better equipped to integrate AI into their operations, benefiting from access to capital, skilled labour, and well-established markets (Bughin et al., 2018). These advantages facilitate operational efficiency, innovation, and strategic growth, ultimately enhancing firm value. Conversely, in less economically developed countries, limited financial and institutional resources constrain firms' ability to capitalise on AI, diminishing its impact on firm performance. By incorporating economic development as a moderator, our analysis highlights the critical role of a country's economic environment in enabling firms to maximise the benefits of AI investments. We measure country-level economic development using the natural logarithm of GDP sourced from the World Bank. This measure captures a country's overall economic capacity and development level. To facilitate analysis, we create an indicator variable, *HIGH_EDEV*, which takes a value of 1 if a country's economic development is above the sample median and 0 otherwise. This binary classification allows us to investigate the differential effects of economic development on the relationship between AIC and firm value.

Thirdly, we examine the role of country-level investor rights as a moderator in the relationship between AI capability and firm value, highlighting how better investor protections influence firms' ability to leverage AI technologies effectively. Investor rights, reflecting the strength of legal protections for shareholders and their ability to influence corporate decisions, play a critical role in ensuring accountability and encouraging long-term investments in innovation (La Porta et al., 2000; La Porta et al., 2002). In countries with strong investor rights, firms benefit from enhanced access to capital and better governance mechanisms (La Porta et al., 2000), which facilitates the integration and scaling of AI technologies. These environments enable firms to invest confidently in AI-driven innovation, leading to improved operational efficiency, strategic growth, and higher market valuations. Conversely, in countries with weaker investor protections, firms may face governance challenges and resource constraints, limiting their ability to capitalise on AI capabilities. By incorporating investor rights as a moderator, our analysis underscores the importance of strong legal frameworks in enhancing the value derived from AI investments. We measure country-level investor rights using an index that captures the strength of legal protections for shareholders, including their ability to influence corporate decisions and safeguard their interests. This measure reflects the governance environment and the degree of shareholder protection within a country. To facilitate analysis, we create an indicator variable, *HIGH_INVRIGHT*, which takes a value of 1 if a country's investor rights index is above the sample median, and 0 otherwise. This binary classification allows us to investigate the differential effects of investor rights on the relationship between AIC and firm value.

Table 10 provides regression results of the moderating effects of country-level factors on the relationship between AI capability (AIC) and firm value, through three models examining digital development, economic development, and investor rights. Column (1) investigates the moderating role of digital development. The key variable of interest is the interaction term between AIC and digital development *(AIC×HIGH_DIGITAL)*. The positive coefficient (β=0.643, p-value<0.05) indicates that, after accounting for other variables, the positive relationship between *AIC* and firm value is stronger for firms in countries with higher levels of digital development. This suggests that firms operating in environments with advanced digital infrastructure, such as high internet penetration and broadband access, benefit more from their AI capabilities in terms of firm value compared to those in countries with less developed digital ecosystems.

[INSERT TABLE 10 ABOUT HERE]

Column (2) examines the moderating role of country-level economic development. The interaction term between AIC and higher economic development *(AIC×HIGH_EDEV)* is positive and statistically significant (β=3.124, p-value<0.05), indicating that the positive association between AIC and firm value is stronger in countries with higher economic development. This result implies that firms in economically developed countries are better equipped to translate their AI capabilities into tangible value due to better access to financial resources, infrastructure, and skilled labour. Conversely, in less economically developed countries, resource constraints may limit the effectiveness of AI investments, diminishing their impact on firm value.

Column (3) explores the moderating role of country-level investor rights. The positive coefficient of the interaction term between *AIC* and stronger investor rights *(AIC×HIGH_INVRIGHT)* (β=4.496, *p*-value<0.05) suggests that the positive relationship between *AIC* and firm value is amplified in countries with robust investor protections. This indicates that firms operating in environments with stronger legal frameworks and shareholder protections are rewarded more for their AI investments. In these contexts, AI capabilities are likely to be perceived as credible and aligned with good governance practices, which enhances firm value.

4.5.2 Alternative proxies of artificial intelligence capability and firm value

As outlined in Section 3.2, our measure of artificial intelligence capability (AIC) comprises two pillars: research and development (R&D) and economic. While our primary analyses rely on a composite measure of *AIC* that integrates these two pillars, we further test the robustness of our findings by using each pillar separately as distinct measures of AIC. The findings confirm that the positive association between *AIC* and firm value remains consistent when using either the R&D or economic pillar individually. Specifically, both the R&D and economic pillars independently exhibit positive and statistically significant relationships with firm value, highlighting their respective contributions to the overall AIC construct. These results demonstrate that the observed relationship between *AIC* and firm value is not driven by any single dimension but is robust across different aspects of AI capability. This robustness reinforces the validity of the composite measure and highlights the complementary roles of research and development and economic contributions in driving the value-enhancing effects of AIC.

5. Role of firm's competitive advantage as an underlying mechanism in the relationship between artificial intelligence capability and firm value

In our hypothesis development, we argue that firms with advanced artificial intelligence capabilities *(AIC)* achieve greater firm value through the creation of competitive advantages. In this section, we explore this mechanism through additional analysis. Specifically, we employ path analysis to examine whether AIC drives improvements in competitive advantages, which subsequently enhance firm value. To measure competitive advantages, following Cannon et al. (2020), we employ industry-adjusted gross margin *(ADJ_GM)* and operating margin *(ADJ_OM)*. Following prior studies in accounting and finance that have used mediation analysis (Bose & Hossain, 2024; Cook et al., 2019; DeFond et al., 2016; Lang et al., 2012), we develop the following set of equations to conduct our mediation test:

$$TOBINQ_{i,t+1} = \beta_0 + \beta_1 AIC_{i,t} + \sum CONTROLS_{i,t} + \sum YEAR_{i,t} + \sum INDUSTRY_{i,t} + \sum COUNTRY_{i,t} + \varepsilon_{i,t} \quad (3.1)$$

$$ADJ\_GM_{i,t+1}/ADJ\_OM_{i,t+1} = \gamma_0 + \gamma_1 AIC_{i,t} + \sum CONTROLS_{i,t} + \sum YEAR_{i,t} + \sum INDUSTRY_{i,t} + \sum COUNTRY_{i,t} + \varepsilon_{i,t} \quad (3.2)$$

$$TOBINQ_{i,t+1} = \omega_0 + \omega_1 AIC_{i,t} + \omega_2\, ADJ\_GM_{i,t+1}/ADJ\_OM_{i,t+1} + CONTROLS_{i,t} + \sum YEAR_{i,t} + \sum INDUSTRY_{i,t} + \sum COUNTRY_{i,t} + \varepsilon_{i,t} \qquad (3.3)$$

where *ADJ_GM/ADJ_OM* is the industry-adjusted gross margin/operating margin, which is computed as firm-level gross margin (operating margin) adjusted by industry median within the same country and year. Gross margin is defined as sales revenue minus cost of goods sold scaled by beginning total assets, while operating margin is defined as operating income before depreciation scaled by beginning total assets. A higher value of *ADJ_GM/ADJ_OM* indicates a higher level of competitive advantage. Descriptions of other variables are provided in Appendix A.

In Equation (3.1), the coefficient of $\beta 1$ indicates the overall effect of *AIC* on firm value, while the coefficient of $\gamma 1$ in Equation (3.2) captures the effect of *AIC* on firms' competitive advantage *(ADJ_GM/ADJ_OM)*. Moreover, the coefficient of $\omega 1$ in Equation (3.3) captures the direct effect of *AIC* on firm value after controlling for the mediator variable, *ADJ_GM/ADJ_OM*. Following prior studies(Baron & Kenny, 1986; Wen & Ye, 2014), we consider *ADJ_GM/ADJ_OM* as a mediator variable if: (a) *AIC* is significantly related to *TOBINQ* ($\beta 1 \neq 0$) in Equation (3.1); (b) *AIC* is significantly related to *ADJ_GM/ADJ_OM* ($\gamma 1 \neq 0$) in Equation (3.2); and (c) *ADJ_GM/ADJ_OM* ($\omega 2 \neq 0$) is significantly related to *TOBINQ* after controlling for *AIC* in Equation (3.3). After establishing the relationships, the statistical significance of the average causal mediation effect needed to be established. Furthermore, the Sobel–Goodman test (Preacher & Hayes, 2004) is used to determine the role of the mediator variable in transmitting the effect of the treatment variable to a dependent variable. This test is essential to evaluate the potential relationships between the variables of interest (*AIC*, *ADJ_GM/ADJ_OM*, and *TOBINQ*), given that the three equations [Equations (3.1)–(3.3)] are run simultaneously.

Table 11, Panel A, Models (1)–(3) present the regression results of the mediation effects of *ADJ_GM* on the *AIC*–TOBINQ relationship. The results show that *AIC* has a positive and significant total effect on firm valuation ($\beta=1.425$, $p<0.01$) in Model (1), indicating that firms in countries with advanced AI capabilities achieve higher market valuations. In Model (2), *AIC* is positively and significantly associated with *ADJ_GM* (β=0.069, p<0.05), suggesting that AI capability enhances competitive advantages through improved operational efficiency and cost management. In Model (3), after controlling for *ADJ_GM*, the coefficient on *AIC* remains positive and significant (β=1.177, p<0.01), while *ADJ_GM* is also significantly associated with *TOBINQ* (β=3.596, p<0.01). However, the reduction in the coefficient for *AIC* from Model (1) to Model (3) confirms that *ADJ_GM* partially mediates the relationship between *AIC* and firm valuation.

[INSERT TABLE 11 HERE]

The mediation analysis further reveals that the indirect effect of *AIC* on firm valuation through *ADJ_GM* is significant (β=0.249, z=1.971, p<0.05) and accounts for 17.40% of the total effect. These findings demonstrate that competitive advantages, as reflected in higher industry-adjusted gross margins, are a key mechanism through which AI capability enhances firm valuation. The results highlight the strategic importance of leveraging AI to improve competitive positioning and, in turn, maximize firm value.

Furthermore, Table 11, Panel B, Models (1)–(3) present the regression results of the mediation effects of *ADJ_OM* on the relationship between *AIC* and firm valuation. The coefficient of *AIC* is statistically significant and positive (β=1.438, p<0.01) in Model (1), suggesting that *AIC* is positively associated with firm valuation. Moreover, the coefficient of *AIC* is also positive and statistically significant (β=0.088, p<0.01) in Model (2), indicating that *AIC* is positively associated with the mediator variable, *ADJ_OM*. In Model (3), the coefficient of *AIC* remains positive and statistically significant (β=1.056, p<0.05), while the coefficient of *ADJ_OM* is highly significant and positive (β=4.331, p<0.01). However, the size of the coefficient of *AIC* is reduced in Model (3) compared to Model (1), and the effect of *ADJ_OM* in Model (3) is substantially larger, indicating partial mediation.

Overall, these results demonstrate that competitive advantages, proxied by *ADJ_OM*, mediate the relationship between *AIC* and firm value. Figure 2 illustrates this mediation effect graphically. The findings highlight that AI capability contributes to firm valuation through enhancing competitive advantages, underscoring the strategic importance of leveraging AI to achieve superior market positioning and financial outcomes.

6. Conclusions

In an era of rapid digital transformation, Artificial Intelligence Capability (AIC) has emerged as a critical driver of firm performance and competitive advantage. As countries invest in digital infrastructure, economic development, and governance reforms, firms increasingly leverage AI technologies to enhance operational efficiency, foster innovation, and strengthen market positioning. This study investigates the association between AIC and firm value, moderated by country-level factors such as digital development, economic development, and investor rights, using 29,606 firm-year observations from 2017–2021 across 28 countries. Our findings provide compelling evidence that AIC positively influences firm value, with the impact being significantly amplified in countries with higher levels of technological readiness, economic stability, and robust investor protections. These results underscore the interplay between firm-level AI capabilities and macro-level institutional environments, demonstrating how supportive national contexts enable firms to maximise the value of their AI investments. By fostering advanced digital infrastructure, promoting economic growth, and ensuring strong governance frameworks, countries can create environments where AI adoption thrives, benefiting not only individual firms but also the broader economy.

The study contributes to the literature on technological innovation by highlighting the role of country-level factors in shaping the relationship between AI capability and firm value. It extends existing research by identifying digital development, economic development, and investor rights as critical moderators in this relationship, providing a nuanced understanding of the conditions under which AI investments yield optimal outcomes.

Despite its contributions, the study has limitations. The reliance on country-level indicators may not fully capture firm-specific nuances in AI adoption and implementation. Additionally, while robust methodologies, including entropy balancing and instrumental variable techniques, address potential endogeneity concerns, the observational nature of the study limits the ability to establish definitive causal relationships. Future research could explore firm-level data on AI practices or examine the influence of emerging technologies and evolving global digital policies on firm performance.

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Appendix A: Variable descriptions

Variables		**Explanation**
TOBINQ	Tobin's Q	The sum of the book value of total assets plus the market value of equity minus the book value of equity divided by total assets.
AIC	Artificial Intelligence	Artificial Intelligence Index, developed by Stanford University, which serves as a comprehensive and authoritative resource for tracking and evaluating the development and impact of artificial intelligence globally.
HIGH_TECH	Cyber-risk	An indicator variable that takes a value of 1 if the country-level technological readiness is higher than the sample median value of technological readiness and 0 otherwise.
SIZE	Firm size	The natural logarithm of the market value of equity.
ROA	Profitability	The ratio of net income to total assets.
LEV	Leverage	The ratio of total debts divided by total assets at the end of the fiscal year.
GROWTH	Revenue growth	Percentage change in sales revenue.
DIVIDEND	Dividend	An indicator variable that takes the value of 1 if the firm pays a dividend and 0 otherwise.
RETVOL	Firm risk	The standard deviation of daily stock returns over the fiscal year.
LIQUIDITY	Liquidity	The ratio of the number of shares traded to total shares outstanding at the end of the year.
RDINT	Research and development	The ratio of research and development (R&D) expenditure to total revenue.
CAPIN	Capital intensity	The ratio of capital expenditure to total sales.
INTANG	Intangible assets	The ratio of intangible assets scaled by total assets.
FAGE	Firm age	The natural logarithm of the total number of years since the firm was included in the World Scope database.
ESG_IND	Industry-adjusted ESG performance	Industry-adjusted ESG performance.
SECURE_SRRVER	Secure Internet server	The natural logarithm of the total number of secure Internet servers per million population
ADJ_GM	Adjusted gross margin	Industry-adjusted gross margin, which is computed as firm-level gross margin adjusted by industry median within the same country and year. Gross margin is defined as sales revenue minus cost of goods sold scaled by beginning total assets. A higher value of ADJ_GM indicates a higher level of competitive advantage.
ADJ_OM	Adjusted operating margin	Industry-adjusted operating margin, which is computed as firm-level operating margin adjusted by industry median within the same country and year. Operating margin is defined as operating income before depreciation scaled by beginning total assets. A higher value of ADJ_OM indicates a higher level of competitive advantage.

Table 1: Sample selection and distribution

Panel A: Sample selection	**Firm-year observations**
Data coverage 2017–2021	59,452
Less: Observations due to unavailable	(41,186)
Less: Observations dropped due to insufficient GHG emissions variable	(1,396)
Final test sample	29,606

Panel B: Industry-wise distribution of firms in the sample

Name of industry	**Observations**	**% of sample**
Mining/Construction	1,961	6.62
Food	904	3.05
Textiles/Print/Publishing	815	2.75
Chemicals	911	3.08
Pharmaceuticals	1,403	4.74
Extractive	949	3.21
Manufacturing: Rubber/glass/etc.	523	1.77
Manufacturing: Metal	818	2.76
Manufacturing: Machinery	1,112	3.76
Manufacturing: Electrical Equipment	755	2.55
Manufacturing: Transport Equipment	1,007	3.40
Manufacturing: Instruments	1,026	3.47
Manufacturing: Miscellaneous	141	0.48
Computers	2,974	10.05
Transportation	1,691	5.71
Utilities	1,087	3.67
Retail: Wholesale	756	2.55
Retail: Miscellaneous	1,438	4.86
Retail: Restaurant	237	0.80
Financial	4,176	14.11
Insurance/Real Estate	1,954	6.60
Services	2,757	9.31
Others	211	0.71
Total sample	**29,606**	**100**

Panel C: Year-wise distribution of firms in sample

	Observations	**% of sample**
2017	4,670	15.77
2018	5,327	17.99
2019	6,141	20.74
2020	7,091	23.95
2021	6,377	21.54
Total sample	**29,606**	**100**

Panel D: Country-wise distribution of firms in sample

	Observations	**% of sample**	**AIC**	**TECHREADY**
AUS	1607	5.43	14.513	9.592
AUT	136	0.46	0.906	9.156
BEL	207	0.7	4.775	9.009
BRA	403	1.36	8.364	6.063
CAN	1443	4.87	17.868	8.817
CHN	3364	11.36	54.251	7.064
CZE	14	0.05	9.857	7.398
DEU	868	2.93	17.650	9.396
DNK	228	0.77	4.733	8.828
ESP	309	1.04	9.216	7.927
FIN	243	0.82	7.782	9.479
FRA	686	2.32	9.740	9.288
GBR	1956	6.61	19.052	8.594

IND	640	2.16	34.369	6.186
IRL	197	0.67	9.381	7.853
ISR	129	0.44	15.311	8.594
ITA	416	1.41	10.015	7.430
JPN	2152	7.27	7.386	9.304
KOR	578	1.95	20.422	9.092
MYS	475	1.6	0.806	7.341
NLD	296	1	8.178	9.387
NOR	260	0.88	8.563	8.313
POL	169	0.57	1.115	7.358
PRT	51	0.17	6.489	6.858
RUS	174	0.59	2.348	7.129
SGP	320	1.08	12.863	9.630
SWE	590	1.99	6.615	9.690
USA	11695	39.5	72.767	9.250
Total	**29,606**	**100**	**41.343**	**8.768**

Table 2: Descriptive statistics

Panel A: Full sample descriptive statistics						
	N	**Mean**	**Std. Dev**	**Median**	**1st Quartile**	**3rd Quartile**
TOBINQ	29,606	1.761	2.059	1.074	0.691	1.940
AIC	29,606	0.413	0.289	0.491	0.126	0.707
HIGH_TECH	29,606	0.836	0.370	1.000	1.000	1.000
SIZE	29,606	7.684	1.710	7.762	6.546	8.822
ROA	29,606	0.015	0.152	0.030	0.005	0.071
LEV	29,606	0.254	0.206	0.229	0.077	0.382
GROWTH	29,606	0.170	0.766	0.065	-0.031	0.191
DIVIDEND	29,606	0.706	0.456	1.000	0.000	1.000
REVOL	29,606	0.398	0.221	0.339	0.246	0.483
LIQUIDITY	29,606	1.459	1.585	0.966	0.463	1.866
RDINT	29,606	0.161	0.924	0.000	0.000	0.026
CAPIN	29,606	0.132	0.365	0.036	0.016	0.089
INTANG	29,606	0.165	0.209	0.061	0.009	0.268
FAGE	29,606	2.94	0.598	3.045	2.565	3.401
ESG_IND	29,606	0.160	0.111	0.143	0.069	0.234

Panel B: Mean and median test						
	HIGH_AIC		**LOW_AIC**		**Mean-test (p-value)**	**Median-test (p-value)**
	Mean	**Median**	**Mean**	**Median**		
TOBINQ	1.872	1.157	1.651	1.009	0.000	0.000
HIGH_TECH	0.861	1.000	0.811	1.000	0.000	0.000
SIZE	7.643	7.703	7.725	7.825	0.000	0.000
ROA	0.004	0.026	0.026	0.034	0.000	0.000
LEV	0.259	0.230	0.249	0.227	0.000	0759
GROWTH	0.191	0.078	0.149	0.052	0.000	0.000
DIVIDEND	0.642	1.000	0.769	1.000	0.000	0.000
REVOL	0.418	0.353	0.377	0.326	0.000	0.000
LIQUIDITY	1.953	1.493	0.971	0.632	0.000	0.000
RDINT	0.210	0.000	0.112	0.000	0.000	0.000
CAPIN	0.126	0.034	0.137	0.039	0.012	0.000
INTANG	0.162	0.057	0.168	0.064	0.007	0.000
FAGE	2.903	3.045	2.976	3.045	0.000	0.000
ESG_IND	0.147	0.130	0.173	0.157	0.000	0.000

Variable definitions are provided in Appendix A.

Table 3: Correlation matrix analysis

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
TOBINQ	[1]	1.000													
AIC	[2]	0.082***	1.000												
SIZE	[3]	0.068***	-0.023***	1.000											
ROA	[4]	0.055***	-0.110***	0.307***	1.000										
LEV	[5]	-0.098***	0.016***	0.073***	-0.091***	1.000									
GROWTH	[6]	0.079***	0.058***	-0.078***	-0.076***	-0.059***	1.000								
DIVIDEND	[7]	-0.144***	-0.187***	0.365***	0.354***	0.014**	-0.133***	1.000							
RETVOL	[8]	0.071***	0.149***	-0.434***	-0.356***	-0.018***	0.177***	-0.447***	1.000						
LIQUIDITY	[9]	0.078***	0.379***	0.070***	-0.066***	0.073***	0.040***	-0.163***	0.329***	1.000					
RDINT	[10]	0.126***	0.096***	-0.159***	-0.505***	-0.100***	0.122***	-0.238***	0.267***	0.064***	1.000				
CAPIN	[11]	0.005	-0.023***	-0.097***	-0.150***	0.073***	0.059***	-0.067***	0.085***	-0.023***	0.227***	1.000			
INTANG	[12]	0.077***	0.011*	0.058***	0.055***	0.135***	-0.024***	-0.077***	-0.038***	-0.014**	-0.070***	-0.152***	1.000		
FAGE	[13]	-0.160***	-0.108***	0.243***	0.175***	-0.012**	-0.155***	0.284***	-0.249***	-0.034***	-0.157***	-0.121***	-0.030***	1.000	
ESG_IND	[14]	-0.012**	-0.156***	0.185***	0.053***	0.029***	-0.030***	0.100***	-0.081***	-0.078***	-0.068***	0.031***	0.036***	0.126***	1.000

Table 4: Regression results between artificial intelligence capability and firm valuation and the role of technological readiness

	Dependent variable=*TOBINQ*$_{t+1}$		
	Column (1)	**Column (2)**	**Column (3)**
AIC	0.981**	1.369***	1.762***
	(2.321)	(3.255)	(4.131)
AIC×HIGH_TECH		—	0.368**
			(2.045)
HIGH_TECH		—	0.006
			(0.077)
SIZE		0.212***	0.214***
		(15.667)	(15.688)
ROA		2.247***	2.259***
		(8.454)	(8.504)
LEV		-0.439***	-0.441***
		(-3.587)	(-3.596)
GROWTH		0.073***	0.073***
		(3.696)	(3.700)
DIVIDEND		-0.296***	-0.294***
		(-5.902)	(-5.855)
RETVOL		0.683***	0.729***
		(5.837)	(5.914)
LIQUIDITY		-0.042***	-0.044***
		(-2.879)	(-3.006)
RDINT		0.222***	0.222***
		(6.265)	(6.253)
CAPIN		0.010	0.010
		(0.183)	(0.180)
INTANG		-0.944***	-0.942***
		(-7.864)	(-7.848)
FAGE		-0.456***	-0.455***
		(-11.933)	(-11.909)
ESG_IND		0.074	0.070
		(0.501)	(0.475)
Intercept	0.493**	0.145	-0.203
	(2.523)	(0.610)	(-0.777)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Observations	29,606	29,606	29,606
R-squared	0.197	0.261	0.261

Notes: This table shows the regression results between artificial intelligence capability and firm value and the role of technological readiness in this association between artificial intelligence capability and firm value. Column (1) shows the regression results between artificial intelligence capability and firm value without control variables. Column (2) shows the regression results between artificial intelligence capability and firm value including control variables. Column (3) shows the regression results of the moderating role of technological readiness in the association between artificial intelligence capability and firm value. Robust *t*-statistics are shown in parentheses. Superscript ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Appendix A.

Table 5: Entropy balancing analysis

Panel A: Descriptive statistics before entropy balancing

	Treatment			Control		
	Mean	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
SIZE	7.643	2.999	-0.005	7.725	2.847	-0.286
ROA	0.004	0.027	-3.300	0.026	0.018	-3.539
LEV	0.259	0.048	0.828	0.249	0.036	0.757
GROWTH	0.191	0.632	7.990	0.149	0.543	8.351
DIVIDEND	0.642	0.230	-0.592	0.769	0.177	-1.279
RETVOL	0.418	0.054	1.589	0.378	0.042	1.859
LIQUIDITY	1.953	3.062	2.015	0.971	1.493	3.586
RDINT	0.210	1.115	6.693	0.112	0.592	9.495
CAPIN	0.127	0.116	6.382	0.137	0.149	5.955
INTANG	0.162	0.042	1.376	0.168	0.045	1.384
FAGE	2.903	0.374	-0.689	2.976	0.340	-0.752
ESG_IND	0.147	0.011	0.702	0.173	0.014	0.524

Panel B: Descriptive statistics after entropy balancing

	Treatment			Control		
	Mean	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
SIZE	7.643	2.999	-0.005	7.643	2.999	-0.005
ROA	0.004	0.027	-3.300	0.004	0.027	-3.300
LEV	0.259	0.048	0.828	0.259	0.048	0.828
GROWTH	0.191	0.632	7.990	0.191	0.632	7.990
DIVIDEND	0.642	0.230	-0.592	0.642	0.230	-0.592
RETVOL	0.418	0.054	1.589	0.418	0.054	1.589
LIQUIDITY	1.953	3.062	2.015	1.953	3.062	2.015
RDINT	0.210	1.115	6.693	0.210	1.115	6.693
CAPIN	0.127	0.116	6.382	0.127	0.116	6.382
INTANG	0.162	0.042	1.376	0.162	0.043	1.376
FAGE	2.903	0.374	-0.689	2.903	0.374	-0.689
ESG_IND	0.147	0.011	0.702	0.147	0.011	0.702

Panel C: Regression results between artificial intelligence capability and firm valuation and the role of technological readiness using entropy-balanced samples

	Dependent variable = $TOBINQ_{t+1}$	
	Column (1)	**Column (2)**
AIC	0.211^{***}	0.022
	(2.731)	(0.137)
AIC×HIGH_TECH	—	0.270^{*}
		(1.705)
HIGH_TECH	—	-0.129
		(-1.186)
SIZE	0.247^{***}	0.248^{***}
	(11.953)	(11.970)
ROA	1.850^{***}	1.843^{***}
	(6.827)	(6.801)
LEV	-0.398^{**}	-0.401^{**}
	(-2.473)	(-2.487)
GROWTH	0.067^{***}	0.068^{***}
	(2.777)	(2.838)
DIVIDEND	-0.377^{***}	-0.378^{***}
	(-4.885)	(-4.894)
RETVOL	0.597^{***}	0.612^{***}
	(4.162)	(4.059)
LIQUIDITY	-0.034^{*}	-0.036^{*}
	(-1.903)	(-1.950)

RDINT	0.177***	0.179***
	(4.545)	(4.594)
CAPIN	-0.014	-0.015
	(-0.176)	(-0.199)
INTANG	-0.935***	-0.935***
	(-5.701)	(-5.693)
FAGE	-0.497***	-0.497***
	(-9.250)	(-9.249)
ESG_IND	0.087	0.084
	(0.355)	(0.341)
Intercept	0.509***	0.585**
	(2.589)	(2.526)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Observations	29,606	29,606
R-squared	0.255	0.255

Notes: This table shows the entropy balanced analysis. Panel A shows descriptive statistics before entropy balancing. Panel B shows the descriptive statistics after entropy balancing. Panel C shows the regression results between artificial intelligence capability and firm value and the role of technological readiness in the association between artificial intelligence capability and firm value. Robust t-statistics are shown in parentheses. Superscript ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Appendix A.

Table 6: Analysis of the impact of unobservable confounding variables

	Dependent Variable = $TOBINQ_{t+1}$	
	Impact (Raw)	**Impact (Partial)**
AIC		
SIZE	-0.002	0.002
ROA	-0.006	-0.006
LEV	-0.002	0.001
GROWTH	0.005	0.001
DIVIDEND	0.027	0.013
RETVOL	0.011	-0.002
LIQUIDITY	0.029	0.011
RDINT	0.012	0.004
CAPIN	-0.000	0.000
INTANG	0.001	0.000
FAGE	0.017	0.008
ESG_IND	0.002	-0.000
Impact Threshold for Omitted variable (ITCV)	0.003	
The required correlations between *AIC* and *TOBINQ* with the unobserved confounding variable to overturn results	0.050	

Notes: This table reports results of the impact of unobservable confounding variables. Variable definitions are provided in Appendix A.

Table 7: Change-specific regression results between artificial intelligence capability and firm value and the role of technological readiness

	Dependent variable=$TOBINQ_{t+1}$	
	Column (1)	**Column (2)**
ΔAIC	0.025^{**}	-0.028
	(1.970)	(-0.964)
ΔAIC×ΔHIGH_TECH	—	0.067^{**}
		(2.099)
ΔHIGH_TECH	—	0.055
		(1.597)
ΔSIZE	-0.079^{**}	-0.077^{**}
	(-2.464)	(-2.423)
ΔROA	-0.190	-0.189
	(-0.972)	(-0.971)
ΔLEV	-0.033	-0.037
	(-0.162)	(-0.180)
ΔGROWTH	-0.017	-0.017
	(-0.992)	(-0.971)
ΔDIVIDEND	-0.111^{**}	-0.110^{**}
	(-2.290)	(-2.268)
ΔRETVOL	0.335^{***}	0.353^{***}
	(4.228)	(4.285)
ΔLIQUIDITY	-0.036^{***}	-0.038^{***}
	(-3.272)	(-3.368)
ΔRDINT	0.257^{*}	0.257^{*}
	(1.651)	(1.653)
ΔCAPIN	-0.139^{*}	-0.138^{*}
	(-1.925)	(-1.911)
ΔINTANG	-0.537^{*}	-0.542^{*}
	(-1.936)	(-1.951)
ΔFAGE	-0.754^{***}	-0.748^{***}
	(-3.498)	(-3.467)
ΔESG_IND	0.132	0.132
	(1.268)	(1.272)
Intercept	0.307^{***}	0.303^{***}
	(6.638)	(6.557)
Year Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Observations	21,738	21,738
R-squared	0.047	0.047

Notes: This table shows the change-specific regression results between artificial intelligence capability and firm value and the role of environmental innovation in this association between cyber security awareness and firm value. Column (1) shows the change-specific regression results between artificial intelligence capability and firm value. Column (2) shows the change-specific regression results of the moderating role of technological readiness in the association between artificial intelligence capability and firm value Robust t-statistics are shown in parentheses. Superscript ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Appendix A.

Table 8: Instrumental variable analysis

	First-Stage	Second-Stage	Lewbel (2012)
	Dependent variable =AIC	Dependent variable =$TOBINQ_{t+1}$	Dependent variable =$TOBINQ_{t+1}$
	Column (1)	Column (2)	Column (3)
AIC		20.761**	4.222***
		(2.455)	(2.718)
SIZE	-0.000**	0.232***	0.216***
	(-1.982)	(22.124)	(25.750)
ROA	-0.001	2.360***	2.228***
	(-0.565)	(11.539)	(12.707)
LEV	0.004***	-0.607***	-0.459***
	(6.402)	(-6.748)	(-6.552)
GROWTH	0.000	0.085***	0.077***
	(1.131)	(3.460)	(4.110)
DIVIDEND	-0.001***	-0.270***	-0.284***
	(-3.080)	(-7.022)	(-9.346)
RETVOL	-0.004***	1.382***	0.690***
	(-3.717)	(10.232)	(7.987)
LIQUIDITY	-0.001***	-0.034**	-0.039***
	(-5.274)	(-2.553)	(-4.044)
RDINT	0.000	0.226***	0.222***
	(1.075)	(7.720)	(9.186)
CAPIN	-0.001	-0.012	0.013
	(-1.527)	(-0.241)	(0.300)
INTANG	-0.001	-0.953***	-0.950***
	(-0.703)	(-11.947)	(-13.918)
FAGE	0.000	-0.485***	-0.462***
	(0.115)	(-18.008)	(-20.237)
ESG_IND	0.002	0.103	0.058
	(1.394)	(0.929)	(0.619)
SECURE_SERVER	0.006***	—	
	(8.429)		
Intercept	0.103***	-2.016	-2.412**
	(14.883)	(-1.477)	(-2.205)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Observations	23,229	23,229	29,606
R-squared		0.240	0.079
Underidentification test:			
Kleibergen–Paap rk LM statistic		72.16***	2628.02***
Weak identification test:			
Cragg-Donald Wald F statistic		101.03	402.67
Stock-Yogo critical values		16.38	11.52

Table 9: Quasi-experimental analysis: Introduction of European Green Deal

Panel A: Descriptive statistics before entropy balancing						
	Treatment			**Control**		
	Mean	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
SIZE	7.804	2.451	0.037	7.618	2.778	-0.099
ROA	0.032	0.013	-4.627	0.012	0.025	-3.610
LEV	0.283	0.031	0.559	0.253	0.044	0.808
GROWTH	0.139	0.087	6.870	0.162	0.487	8.741
DIVIDEND	0.817	0.150	-1.636	0.718	0.203	-0.969
RETVOL	0.321	0.022	3.099	0.370	0.031	2.003
LIQUIDITY	0.568	0.593	3.655	1.529	2.270	2.394
RDINT	0.112	0.641	9.534	0.171	0.921	7.479
CAPIN	0.109	0.078	7.001	0.141	0.141	5.839
INTANG	0.228	0.049	0.867	0.157	0.043	1.481
FAGE	3.021	0.346	-0.914	2.922	0.362	-0.703
ESG_IND	0.195	0.016	0.321	0.155	0.012	0.647
Panel B: Descriptive statistics after entropy balancing						
	Treatment			**Control**		
	Mean	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
SIZE	7.804	2.451	0.037	7.804	2.451	0.038
ROA	0.032	0.013	-4.627	0.032	0.013	-4.627
LEV	0.283	0.031	0.559	0.283	0.031	0.559
GROWTH	0.139	0.087	6.870	0.139	0.087	6.871
DIVIDEND	0.817	0.150	-1.636	0.816	0.150	-1.634
RETVOL	0.321	0.022	3.099	0.321	0.022	3.100
LIQUIDITY	0.568	0.593	3.655	0.569	0.594	3.657
RDINT	0.112	0.641	9.534	0.112	0.641	9.534
CAPIN	0.109	0.078	7.001	0.109	0.078	7.001
INTANG	0.228	0.049	0.867	0.228	0.049	0.868
FAGE	3.021	0.346	-0.914	3.021	0.346	-0.912
ESG_IND	7.804	2.451	0.037	7.804	2.451	0.038

Panel C: Difference-in-differences (DiD) regression analysis with entropy-balanced sample		
	Dependent variable = $TOBINQ_{t+1}$	
	Full sample	**Entropy-matched sample**
	Column (1)	**Column (2)**
TREAT×POST	0.129^{***}	0.121
	(3.009)	(1.126)
POST	0.018	0.113^{**}
	(0.255)	(2.563)
Intercept	1.669^{***}	1.744^{***}
	(11.499)	(6.290)
Control variables	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Observations	29,606	26,808
R-squared	0.265	0.295

Panel D: Parallel trend analysis with entropy-balanced sample	
	Dependent variable = $TOBINQ_{t+1}$
	Column (1)
TREAT×PRE3	-0.060
	(-0.989)
TREAT×PRE2	-0.025
	(-0.444)

TREAT×PRE1	——
TREAT×POST0	0.080*
	(1.657)
TREAT×POST1	0.131**
	(2.092)
Intercept	1.749***
	(6.251)
Control variables	Yes
Year Fixed Effects	Yes
Industry Fixed Effects	Yes
Country Fixed Effects	Yes
Observations	26,808
R-squared	0.295

Notes: This table shows the differences-in-difference (DiD) analysis using entropy balancing analysis. Panel A shows descriptive statistics before entropy balancing. Panel B shows the descriptive statistics after entropy balancing. Panel C shows the DiD regression results between of the impact of the introduction of European green Deal on firm value. Robust t-statistics are shown in parentheses. Superscript ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Appendix A.

Table 10: Regression results between artificial intelligence capability and firm valuation: Role of various institutional factors

	Dependent variable=*TOBINQ*$_{t+1}$		
	Column (1)	**Column (2)**	**Column (3)**
AIC	1.051	0.572	-3.073
	(1.067)	(0.534)	(-1.583)
AIC×HIGH_DIGITAL	0.643**	—	—
	(2.106)		
HIGH_DIGITAL	0.114	—	—
	(0.640)		
AIC×HIGH_EDEV	—	3.124**	—
		(2.655)	
HIGH_EDEV	—	-0.519***	—
		(-4.177)	
AIC×HIGH_INVRIGHT	—	—	4.496**
			(2.590)
HIGH_INVRIGHT	—	—	0.970***
			(8.261)
SIZE	0.213***	0.215***	0.212***
	(5.744)	(5.765)	(5.770)
ROA	2.245***	2.251***	2.246***
	(3.135)	(3.141)	(3.131)
LEV	-0.436	-0.443	-0.440
	(-1.136)	(-1.151)	(-1.139)
GROWTH	0.073***	0.073***	0.073***
	(4.432)	(4.473)	(4.476)
DIVIDEND	-0.298***	-0.292***	-0.295***
	(-3.473)	(-3.319)	(-3.377)
RETVOL	0.689***	0.727***	0.684***
	(4.983)	(4.589)	(4.907)
LIQUIDITY	-0.043	-0.044	-0.042
	(-1.240)	(-1.274)	(-1.171)
RDINT	0.222***	0.222***	0.222***
	(2.922)	(2.911)	(2.926)
CAPIN	0.009	0.009	0.010
	(0.122)	(0.132)	(0.144)
INTANG	-0.945***	-0.942***	-0.943***
	(-3.569)	(-3.548)	(-3.552)
FAGE	-0.456***	-0.456***	-0.456***
	(-6.190)	(-6.248)	(-6.209)
ESG_IND	0.074	0.066	0.075
	(0.359)	(0.324)	(0.363)
Intercept	1.054**	1.236***	0.215
	(2.204)	(3.754)	(0.550)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Observations	29,606	29,606	29,606
R-squared	0.262	0.262	0.261

Notes: This table shows the regression results between artificial intelligence capability and firm value and the role of technological readiness in this association between artificial intelligence capability and firm value. Column (1) shows the regression results between artificial intelligence capability and firm value without control variables. Column (2) shows the regression results between artificial intelligence capability and firm value including control variables. Column (3) shows the regression results of the moderating role of technological readiness in the association between artificial intelligence capability and firm value. Robust *t*-statistics are shown in parentheses. Superscript ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. Variable definitions are provided in Appendix A.

Table 11: Mediation role of firm' competitive advantages in the association between artificial intelligence capability and firm value

Panel A: Mediation role of firm' competitive advantages in the association between *AIC* and firm value using industry-adjusted gross margin as a proxy for competitive advantage

	DV=*TOBINQ*$_{t+1}$	DV=*ADJ_GM*$_{t+1}$	DV= *TOBINQ*$_{t+1}$
	Model (1)	**Model (2)**	**Model (3)**
AIC	1.425***	0.069**	1.177***
	(3.020)	(1.980)	(2.599)
ADJ_GM	—	—	3.596***
			(22.652)
Intercept	0.393*	0.159	-0.179
	(1.900)	(3.730)	(-0.820)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Observations	25,488	25,488	25,488
R-squared	0.236	0.139	0.310
Mediating effects			
Indirect effect – *AIC*×*ADJ_GM*		0.249**	
z-statistic for indirect effect – *AIC*×*ADJ_GM*		(1.971)	
Direct effect		1.177	
Total effect		1.425	
% of total mediated effect		17.40%	

Panel B: Mediation role of firm' competitive advantages in the association between *AIC* and firm value using industry-adjusted operating margin as a proxy for competitive advantage

	DV=*TOBINQ*$_{t+1}$	DV=*ADJ_OM*$_{t+1}$	DV= *TOBINQ*$_{t+1}$
	Model (1)	**Model (2)**	**Model (3)**
AIC	1.438***	0.088***	1.056**
	(3.000)	(3.600)	(2.283)
ADJ_OM	—	—	4.331***
			(17.366)
Intercept	0.235	-0.030**	0.366*
	(1.100)	(-2.280)	(1.808)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Observations	23,719	23,719	23,719
R-squared	0.235	0.274	0.276
Mediating effects			
Indirect effect – *AIC*×*ADJ_OM*		0.382***	
z-statistic for indirect effect – *AIC*×*ADJ_OM*		(3.525)	
Direct effect		1.056	
Total effect		1.438	
% of total mediated effect		26.60%	

This table reports the mediating role of firms' competitive advantage in the association between artificial intelligence capability and firm value. Panel A reports the mediating role of firms' competitive advantage industry-adjusted gross margin as a proxy for competitive advantage. Panel B reports the mediating role of firms' competitive advantage industry-adjusted operating margin as a proxy for competitive advantage. DV=dependent variable. Numbers in parentheses are *t*-statistics. All variables are described in Table 3. Superscript ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.